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Joint estimation of the Lerner index and cost efficiency using copula methods

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Abstract This paper deals with the estimation of market power, measured by the Lerner index, and cost efficiency at the bank level, using the stochastic frontier (SF) methodology. Both market power and cost efficiency are estimated jointly in a single step. We use the copula method to incorporate dependence between market power and cost efficiency. In contrast to earlier works that used a two-step approach, the SF approach used herein estimates a bank-specific nonnegative Lerner index free from random shocks. We showcase the advantages of our proposed methodology in terms of an empirical study on the banking sectors of five former communist countries during the period 2000–2008. Compared to the conventional approach, our model gives higher mean values of the Lerner index and smaller standard deviations. Further, we find a significant positive relationship between cost efficiency and market power of banks, thereby rejecting the "quiet life hypothesis."

Keywords Copula methods · Cost efficiency · Lerner index · Market power · Quiet life hypothesis

JEL Classification C31 · C51 · G21 · L11

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1 Introduction

Two measures of competition are typically used in the existing literature to gauge competitiveness of the banking industry. These are commonly known as the structural and non-structural approaches and are built on different theoretical foundations. The traditional industrial organization theory, often classified as a structural method, focuses on the structure–conduct–performance (SCP) paradigm. It uses market concentration measures as the proxy for market power, including market shares, concentration ratios for the largest firms (CR ratios), and the Herfindahl–Hirschman index (HHI). However, these measures have been shown to be ambiguous indicators of market power.[1]

Non-structural approaches such as the Panzar and Rosse (1987) H-statistic and the Lerner index (Lerner 1934) of market power were developed in the context of the New Empirical Industrial Organization (NEIO) literature. Both methods assess competition and test the competitive conduct of firms directly without using explicit information about the structure of the market. The Panzar and Rosse (PR) approach is based on the idea that market power is measured by the extent to which changes in input prices are reflected by the equilibrium revenues received by a specific firm.[2] The drawback of the PR approach is that the competition condition inferred from the H-statistic depends on the presumption of long-run equilibrium. This requires a separate test to check whether this condition is satisfied or not. Moreover, the estimated H-statistic is measured at the industry level, not at the individual firm level.

More and more studies in recent years have turned their attention to another indicator of market structure, the Lerner index, which is a well-established measure of market power at the firm level.[3] The Lerner index takes the idea that market power is implied by the disparity between a firm's output price (P) and its marginal cost (MC) (the Lerner index is formally defined as (P − MC)/P). The index is expected to be nonnegative. A zero value of the index implies that the market is perfectly competitive, while a positive value refers to non-competitive market.[4] It assesses a firm's capacity for setting the output price above the MC, which is intimately linked with the competitive conditions faced by the firm. The higher the Lerner index is, the larger the dispersion between the output price and the MC is, and hence, the higher, the firm's market power. Firms operating in a perfectly competitive market equate output price to the MC (to maximize profit), so that the Lerner index is equal to 0. Conversely,

1 Berger et al. (2004), Maudos and Fernández de Guevara (2004, 2007), Fernández de Guevara et al. (2005), Beck et al. (2006), and Alegria and Schaeck (2008) show the limitations of using concentration measures as indicators for the degree of competition in the banking industry.

2 The H-statistic has been popularly used as a direct measure of the degree of competition in the recent literature on bank competition. See for example, Bikker and Groeneveld (2000), De Bandt and Davis (2000), Bikker and Haaf (2002), Gelos and Roldós (2004), Claessens and Laeven (2004), Al-Muharrami et al. (2006), Casu and Girardone (2006), Staikouras and Koutsomanoli-Fillipaki (2006), Yeyati and Micco (2007), Turk-Ariss (2009), Carbó et al. (2009), and Delis (2010), among others.

3 See for example, Prescott and McCall (1975) for US banks; Shaffer (1993) for Canadian banks; Carbó et al. (2003) for Spain; Angelini and Cetorelli (2003) for Italian banks; Carbó et al. (2009), Fernández de Guevara et al. (2005, 2007), and Maudos and Fernández de Guevara (2004, 2007) for the cases of European countries; Berger et al. (2009) for the case of 23 different industrial countries; Turk-Ariss (2010) for developing countries; and Agoraki et al. (2011) for the case of 13 CEE transition countries.

4 Agoraki et al. (2011) claim that if the index is equal to 1, then the market is a pure monopoly.

monopolists exercise market power, charging output prices greater than their MCs and consequently pushing the Lerner index close to 1.[5] The advantage of the Lerner index is that it provides observation-specific estimates of market power, which can be used in any subsequent analysis, as opposed to country-level indicators such as conventional concentration ratios (HHI and CR) and the PR H-statistic.

The existing literature does create some potential problems with the way it measures the conventional Lerner index. Computation of the conventional Lerner index is done in two steps. The first step estimates the (translog) cost function in order to derive the MC. The second step computes the Lerner index using the estimated MC and the observed output price, which for banks is obtained by taking the ratio of total revenues to total assets (see, for example, Berger et al. 2009, Turk-Ariss 2010). Koetter et al. (2012) propose an adjusted Lerner index that requires estimation of the profit frontier so that the average revenue (which is treated as the output price) can be estimated. Because the output price and MC are derived from two separate sources, the resulting Lerner index is not guaranteed to be nonnegative for all observations, meaning that the output price charged might be below the MC and hence lacks economic implications. Second, the estimation of market power that ignores cost (or technical) inefficiencies may be severely biased, as Berg and Kim (1998), Delis and Tsionas (2009), and Koetter and Poghosyan (2009) claim. However, almost all previous studies on market power failed to take the correlation between market power and inefficiency into account. For example, Koetter et al. (2012) regress efficiency on market power (Lerner index), among other things, to test the "quiet life" hypothesis. However, in estimating the cost function, inefficiency is assumed to be independent of everything (assumed to be half-normal, independently and identically distributed)—that is, no correlation between the Lerner index and inefficiency is allowed in estimating the model. The problem is that the Lerner index is calculated from the estimated cost function, and therefore, it cannot be used to explain cost efficiency in the first step where a cost function is estimated. In fact, if market power affects cost efficiency, then it is necessary to allow them to be correlated; otherwise, estimates of the Lerner index as well as cost efficiency might be wrong.

In order to resolve the above problems and consistently estimate bank-specific market power (that may change over time), we propose a copula-based simultaneous stochastic frontier model (CSSFM) that consists of a stochastic cost frontier and a stochastic output price frontier[6] from which an observation-specific markup measure (Lerner index) is estimated. This method views both total costs and output price as dependent variables, and their regression counterparts contain composed errors. The composed error in the cost function includes cost inefficiency and noise, while the composed error in the price function includes a markup factor and noise. These two composed errors are allowed to be correlated. The joint probability density function (PDF) of the composed errors is derived using the copula method, which allows arbitrary correlation. After estimating the two equations jointly by the maximum likelihood

[5] This corresponds to a negative value of the H-statistic in the PR model.

[6] Like the stochastic cost frontier, the stochastic output price frontier is defined as $P = \text{MC} + \text{noise}$ which gives the minimum price that a firm charges without market power. The noise term is added to include possible measurement error in P.

(ML) method, the cost frontier is used to estimate cost efficiencies, and the price frontier is used for estimating the Lerner index, both at the firm level. Since one-sidedness of the Lerner index is built in the simultaneous equations model, its estimate using the Jondrow et al. (1982) procedure is guaranteed to be nonnegative.

Our new approach has the following advantages. First, we borrow the stochastic frontier tool to construct an output price frontier as a function of the MC, derived from the partial derivative of the cost frontier with respect to the output. The nonnegative one-sided error in this equation represents the gap between the output price and the MC. We then measure the Lerner index as the ratio of the gap to the output price, which will be bounded above zero. Second, our model is able to relate the output price set by a firm to its MC (following the definition of the Lerner index), which highlights the fact that firm's pricing decision should be related to production costs. We add stochastic noise to this to allow for possible mistakes in pricing decisions. Since the two frontiers are simultaneously estimated by the ML method, the endogeneity of output price is automatically taken into account. Third, the two sets of error components embedded in these frontiers are allowed to be correlated in an arbitrary manner when deriving their joint PDF (and therefore, the log-likelihood function). These features are at the heart of our modeling approach and are used in the estimation of the Lerner index.

A firm can charge a higher price if it has market power and if by doing so its profit (or any other objective it pursues) increases. It is not clear whether an inefficient firm will raise the price more, ceteris paribus. On the contrary, according to the quiet life hypothesis a firm with market power has the luxury of being inefficient, ceteris paribus. An easy way to test this hypothesis is to test for positive correlation between market power and inefficiency. Testing this in a second-stage regression (as done in the banking literature) is wrong, because both inefficiency and the markup factor are estimated from the cost function, and their correlation is not explicitly introduced in the model.

Our proposed model is a seemingly unrelated stochastic frontier regression with correlated composite errors, developed by Lai and Huang (2013).[7] The joint PDF of the frontier equations can be derived by using copula methods.[8] The difficulty in deriving the copula-based joint PDF is that one needs to compute the cumulative distribution function (CDF) of the composite errors, which has no closed-form expression and hence involves numerical integration procedures, making implementation of the ML estimation procedure somewhat difficult. We instead follow Tsay et al. (2013) to approximate the CDF of the composite error by an analytical closed-form formula. Tsay et al. (2013) show by simulations that the finite sample performance of the resulting ML estimates is very promising. Furthermore, Lai and Huang (2013) check the consequences of ignoring the dependence between the frontier equations via Monte Carlo simulations and find that the resulting estimators are inefficient and the estimates of technical efficiency are severely biased.

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7 They apply the model to study Taiwan's hotel industry and simultaneously estimate two production frontiers, representing the technologies of accommodation and restaurant divisions of a hotel.

8 The copula approach, introduced by Sklar (1959), has been widely employed in multivariate analysis and recently extended to the area of productivity and efficiency analysis, e.g., Smith (2008), Carta and Steel (2012), Shi and Zhang (2011), and Amsler et al. (2014).

We exemplify our model by examining the market power of banks during 2000–2008, before the occurrence of the subprime crisis, in five former communist countries: Bulgaria, Czech Republic, Latvia, Poland, and Russia. Banks in these East European transition countries have gone through financial liberalization in the early 1990s. The deregulations were aimed at transforming socialist banking systems into market-oriented ones by means of, for example, removing barriers to entry. New privately and foreign-owned banks entered these markets, intensifying the competition among banks. It is widely believed in the industrial organization literature that the enforcement of various privatization and deregulation measures strengthens the competitive conditions and reshapes the market structure. Whether these reform policies enhance banking competition, leading to a better performance by banks in transition countries, is an important question and has attracted much attention of researchers.[9] We therefore examine whether the market structure of banks in these transition countries changed toward being more competitive during the sample period. We also make comparisons of the estimates of cost efficiency and the Lerner index between our new approach and the conventional one.

We also test for the presence of a negative relationship between market power and cost efficiency, i.e., the "quiet life hypothesis" for banks in these transition countries. This study, to our knowledge, is the first that tests the "quiet life hypothesis" using a system approach and data from transition countries. The results may be important to policymakers of these countries, because their banking systems have recently undergone major changes and restructurings through privatization and financial liberalization.

The rest of the paper is organized as follows. Section 2 formulates the seemingly unrelated regression model with error components and derives their joint PDF using copula methods. Section 3 reports results from the empirical study on the banks of five East European countries, while the last section concludes the paper.

2 The econometric model

2.1 Simultaneous modeling of costs and the output price

The Lerner index signifies the markup of an output price over the marginal cost and is an indicator of the degree of market power. The traditional Lerner index (L) is defined as[10]:

$$L_{it} = (P_{it} - \mathrm{MC}_{it})/P_{it} \tag{1}$$

where P_{it} is bank i's output price at time t, calculated by the ratio of total revenues (including interest and non-interest income) to total assets, and MC is the marginal

[9] See, for example, Gelos and Roldós (2004), Drakos and Konstantinou (2005), Fries and Taci (2005), Mamatzakis et al. (2005), Yildirim and Philippatos (2007), and Delis (2010), among others.

[10] Note that the adjusted Lerner index proposed by Koetter et al. (2012) is expressed as $L_{it}^{\text{adjusted}} = (\mathrm{AR}_{it} - \mathrm{MC}_{it})/\mathrm{AR}_{it}$, where AR_{it} denotes the estimated average revenue that is equal to the ratio of predicted total costs (TC) from (2) plus predicted total profits (TP) derived from an alternative profit function to total assets, i.e., $\mathrm{AR}_{it} = (\mathrm{TC}_{it} + \mathrm{TP}_{it})/\mathrm{TA}_{it}$.

cost of output, proxied by total assets, which is indirectly derived from the following translog cost function with a single output:

$$\begin{aligned}\ln \mathrm{TC}_{it} &= \alpha_0 + \alpha_1 \ln Q_{it} + \frac{1}{2}\alpha_2 \ln Q_{it}^2 + \sum_{k=1}^{3} \eta_k \ln W_{k,it} \\ &\quad + \frac{1}{2}\sum_{k=1}^{3}\sum_{h=1}^{3} \beta_{kh} \ln W_{k,it} \ln W_{h,it} + \sum_{k=1}^{3} \gamma_k \ln Q_{it} \ln W_{k,it} + \omega_1 \mathrm{Trend} \\ &\quad + \frac{1}{2}\omega_2 \mathrm{Trend}^2 + \omega_3 \mathrm{Trend} \times \ln Q_{it} + \sum_{k=1}^{3} \varphi_k \mathrm{Trend} \times \ln W_{k,it} + \varepsilon_{1it} \end{aligned} \quad (2)$$

where TC denotes the total costs, Q stands for the single output (total assets),[11] W_k $(k = 1, 2, 3)$ corresponds to the price of labor, capital, or funds, identified by the current paper as inputs, Trend is the time trend reflecting technical change over time, and $\varepsilon_1 = v_1 + u_1$ represents the composed error term consisting of v_1—the random noise, and u_1—the cost inefficiency.

Following the SF literature, we assume that the random variable v_1 is assumed to be independent of the cost inefficiency term u_1. We further assume that $v_1 \sim i.i.d.N(0, \sigma_{v1}^2)$ and $u_1 \sim i.i.d.\left|N(0, \sigma_{u1}^2)\right|$. Finally, $\alpha, \beta, \eta, \gamma, \omega, \varphi, \sigma_{v1}^2$, and σ_{u1}^2 are unknown parameters to be estimated. Note that some parametric restrictions required by the production theory, such as symmetry $(\beta_{kh} = \beta_{hk}, \forall k \neq h)$ and homogeneity of degree one in input prices $(\sum_{k=1}^{3} \eta_k = 1, \sum_{k=1}^{3} \gamma_k = 0, \sum_{k=1}^{3} \varphi_k = 0$, and $\sum_{k=1}^{3} \beta_{kh} = 0, \forall h)$, are to be imposed before estimating (2). These constraints can be directly imposed on equation (2). A simpler and equivalent way of imposing the homogeneity constraint is to normalize TC, W_1, W_2, and W_3 by one of the three input prices.

Once the unknown parameters are estimated, they can be used to estimate/predict cost inefficiency using the formula $E\left(u_{1it}|\varepsilon_{1it}\right)$.[12] The implied MC function by (2) can be obtained by taking the partial derivative of the cost function with respect to the output, i.e.,

$$\mathrm{MC}_{it} = \frac{\mathrm{TC}_{it}}{Q_{it}}\left[\alpha_1 + \alpha_2 \ln Q_{it} + \sum_{k=1}^{3} \gamma_k \ln W_{k,it} + \omega_3 \mathrm{Trend}\right] \quad (3)$$

Formula (1) requires information on output price and the MC. Unfortunately, both variables come from separate channels and are subject to the influence of random shocks, which may lead to counterintuitive results, i.e., the computed Lerner index using (1) may be negative for some observations. This implies that the firm is setting

[11] See, e.g., Berg and Kim (1994), Angelini and Cetorelli (2003), Berger et al. (2009), and Turk-Ariss (2010), who define total assets as the single output.

[12] This conditional expectation is $E\left(u_{1it}|\varepsilon_{1it}\right) = \mu_{1*it} + \sigma_{1*}\frac{\phi(-\mu_{1*it}/\sigma_{1*})}{1-\Phi(-\mu_{1*it}/\sigma_{1*})}$, where $\sigma_{1*}^2 = \sigma_{1u}^2\sigma_{1v}^2/\sigma_1^2, \sigma_1^2 = \sigma_{1u}^2 + \sigma_{1v}^2, \mu_{1*it} = -\sigma_{1u}^2\varepsilon_{1it}/\sigma_1^2$, and $\phi(.)$ and $\Phi(.)$ are the PDF and CDF of the standard normal random variable, respectively (see Kumbhakar and Lovell 2000 for details).

its output price below the MC, which contradicts the behavior of a profit-maximizing firm. To mitigate such a problem, we suggest adding a price frontier function that follows from the definition of a markup factor. The Lerner index estimated from the stochastic price frontier analysis is guaranteed to be nonnegative for each observation.

In a non-competitive market, a profit-maximizing firm equates MC to the marginal revenue (MR).[13] Since $P \geq \mathrm{MR}$, we have the following inequality:

$$P \geq \mathrm{MR} = \mathrm{MC} \tag{4}$$

Adding a nonnegative random variable of $u_2 \sim \left|N(0, \sigma_{u2}^2)\right|$ to the right-hand side of (4), the inequality sign can be replaced by an equality sign, viz.

$$P_{it} = \mathrm{MC}_{it} + v_{2it} + u_{2it} \tag{5}$$

where the extra noise term of $v_2 \sim N(0, \sigma_{v2}^2)$ is appended to take care of statistical noise affecting output price. We assume it to be independent of u_2. The composed error term $\varepsilon_2 = v_2 + u_2$ can be correlated with the composed error term ε_1 in (2). The $MC + v_2$ term forms the stochastic price frontier akin to the stochastic cost frontier. Note that the MC function has no additional parameters, i.e., the parameters in MC are part of the parameters in TC, as shown in (3). The advantage of using (5) in addition to (2) is that it uses the link between P and MC explicitly in estimation. It also allows systematic departure of P from MC, indicated by the nonnegative u_2 term.[14]

It is interesting to note that the one-sided random term u_2 measures the deviation of the price from the MC. This gap can be estimated by the conditional expectation, $E\,(u_{2it}|\varepsilon_{2it})$. The larger the estimated difference is, the stronger is the markup (market power). A zero value of estimated u_2 implies that the bank is charging a competitive price (absence of market power). Even in this case, output price can still differ from the MC, albeit randomly, due to the presence of the v_2 term in (5). Specifically, P may be temporarily less than MC due possibly to large and adverse shocks of v_2,[15] which results in the estimated value of $E\,(u_{2it}|\varepsilon_{2it})$ to be equal to zero and implies that the market is competitive. However, the fall of P below MC is not profitable and hence cannot last long, unless governments subsidize the industry.

It should be emphasized that both composed error terms ε_1 and ε_2 in (2) and (5) are allowed to be correlated, in that banks with higher market power may set favorable prices in response to higher costs arising possibly from cost inefficiencies. Hence, the composite errors in (2) and (5) are allowed to be correlated and this assumption

[13] In a non-competitive market, one can show that $\mathrm{MR} = P\,(1 + 1/e)$, where $e(\leq 0)$ denotes the price elasticity of demand. By equating MC = MR, we obtain $\frac{P-\mathrm{MC}}{P} = \frac{1}{-e}$, which relates the Lerner index to the price elasticity of demand.

[14] There are several papers that impose regularity (monotonicity and concavity) conditions on a cost function (Griffiths et al. 2000; Terrell 1996) that can guarantee $\mathrm{MC} \geq 0$. However, the Lerner index is implied by equation (4): $P \geq \mathrm{MR} = \mathrm{MC}$, or equivalently, $P - MC \geq 0$. Since P does not appear in the cost function, it is not clear whether the above inequality constraint can be directly imposed on the cost function of (2). Even if it is done, since $P - MC$ can be affected by measurement error in P, it may not be appropriate to use the difference (normalized by P) to estimate the Lerner index.

[15] For example, a large bank may decide to take predatory pricing to drive competitors out of the market.

is, in fact, testable.[16] Therefore, Eqs. (2) and (5) should be simultaneously estimated to take advantage of efficiency gains and to avoid potentially biased estimates of technical efficiency scores, as Lai and Huang (2013) mention. The estimation results are therefore preferred to those obtained from the equation-by-equation estimation that ignores the dependence of ε_1 and ε_2. We suggest estimating (2) and (5), where MC is replaced by (3), in a simultaneous framework with dependent composite errors.[17]

The Lerner index is computed by the ratio of the gap $E\,(u_{2it}|\varepsilon_{2it})$, evaluated from (5), to the output price, i.e., $L_{it}^{\text{New}} = E\,(u_{2it}|\varepsilon_{2it})/P_{it}$. The so-derived Lerner index (henceforth, the new Lerner index) distinguishes itself from the conventional one in several aspects. First, equations (2) and (5) are jointly estimated by the ML method, so that the resulting parameter estimates are more efficient. This procedure explicitly recognizes the dependence between a firm's production costs and its pricing strategy. Second, since the inequality $P \geq \text{MC}$ is built into Eq. (5), the implied new Lerner index is guaranteed to be nonnegative. Third, the new index is less affected from random shocks than the traditional one due to the fact that the former is based on (5), which separates u_2 from v_2. Conversely, the latter is, in essence, measured by $[P - (\text{MC} + v_2)]\big/P$, which is confounded with random error v_2. It is then expected that the variation of the estimated new Lerner index will be smaller than that of the traditional one that absorbs an extra random error.

Aigner et al. (1977) and Meeusen and Van den Broeck (1977) derive the PDF of the single composite errors and the corresponding log-likelihood function. However, it is a little cumbersome to get the joint PDF and the corresponding log-likelihood function for the dependent composite errors in (2) and (5). This difficulty can be solved by relying on copula methods. We discuss this procedure below.

2.2 Copula-based joint PDF and the likelihood function

A copula, dated back to Sklar (1959), is a multivariate joint distribution function for a group of random variables given their marginal distributions. It is especially useful in the case of skew-normal distributions of the composite errors. Sklar (1959) theorem provides the theoretical underpinnings to derive the joint CDF of several random variables, which can be formulated as a function of its own one-dimensional marginal distributions.[18] Since the marginal CDFs range from 0 to 1, the copula function can be regarded as a multivariate distribution of uniform variables with the dependence parameter ρ, for example. The main advantage of the copula function is that it separates modeling of marginals and the dependence structure and can capture

[16] The correlation in the composed errors may stem from (1) the correlation between v_1 and v_2, and (2) the correlation between u_1 and u_2. Unfortunately, we are unable to separate these two sources of correlation in our model. We would argue, in terms of our application, that v_1 and v_2 are not correlated because v_2 represents noise in output price, whereas v_1 is the noise in cost, and therefore, there may not be anything common between them. Since we are not certain on this, we investigate the nexus between market power and cost efficiency in Sect. 3.3 by testing the quiet life hypothesis.

[17] Note that the joint estimation of (2) and (5) will give parameter estimates in (2), σ_{u2}^2 and σ_{v2}^2 in (5), and the correlation coefficient between (2) and (5), to be specified shortly.

[18] For a detailed presentation of copula functions, readers are suggested to refer to Sklar (1959), Joe (1997), Frees and Valdez (1998), Cherubini et al. (2004), and Nelsen (2006).

both linear and nonlinear relationships (Shi and Zhang 2011). The copula method has been widely employed in finance. Recently, it has been gaining popularity among applied researchers in the productivity and efficiency field, mainly because of its ability to handle the dependence structure of the error components (Smith 2008; Carta and Steel 2012; Lai and Huang 2013; Shi and Zhang 2011; Amsler et al. 2014).

In what follows, we focus only on the bivariate case that will be utilized to perform the empirical study.[19] Let $F_1(\varepsilon_{1it})$ and $F_2(\varepsilon_{2it})$ be the respective marginal CDFs of the composite errors in (2) and (5) with the dependence parameter ρ. According to Sklar's theorem, the joint CDF of ε_{1it} and ε_{2it} can be expressed as:

$$F(\varepsilon_{1it}, \varepsilon_{2it}) = C\left(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \rho\right) \tag{6}$$

where $C(\cdot)$ is the copula function of ε_{1it} and ε_{2it} and is unique, if $F_1(\varepsilon_{1it})$ and $F_2(\varepsilon_{2it})$ are continuous. The dependence parameter ρ measures dependence between the marginal CDFs. The corresponding joint PDF to (6) is shown to be:

$$f(\varepsilon_{1it}, \varepsilon_{2it}) = c\left(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \rho\right) \times \prod_{j=1}^{2} f_j(\varepsilon_{jit}) \tag{7}$$

where $c\left(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \rho\right) = \partial^2 C\left(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \rho\right) \big/ \partial F_1(\varepsilon_{1it}) \partial F_2(\varepsilon_{2it})$ is the copula density and $f_j(\varepsilon_{jit})$ is the marginal PDF.

There are several copula functions in the literature, viz. multivariate Student's t copula, Archimedean copula, Gumbel n-copula, and Clayton n-copula. Each of them imposes a different dependence structure. See Cherubini et al. (2004) for a complete review of the copula functions. Further extensions of our proposed approach to other copula functions should follow the same procedure with a similar calculation. Following Lai and Huang (2013), this article selects the Gaussian copula to derive the bivariate distribution function of (6), which takes the form[20]:

$$\begin{aligned} C\left(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \boldsymbol{\Omega}\right) &= \Phi_2\left(\Phi^{-1}(F_1(\varepsilon_{1it})), \Phi^{-1}(F_2(\varepsilon_{2it})); \boldsymbol{\Omega}\right) \\ &= \int_{-\infty}^{\Phi^{-1}(F_1(\varepsilon_{1it}))} \int_{-\infty}^{\Phi^{-1}(F_2(\varepsilon_{2it}))} \frac{1}{2\pi \left|\boldsymbol{\Omega}\right|^{1/2}} \exp\left[\frac{-1}{2} \boldsymbol{Z}' \boldsymbol{\Omega}^{-1} \boldsymbol{Z}\right] \mathrm{d}Z_1 \mathrm{d}Z_2 \end{aligned} \tag{8}$$

where $\Phi^{-1}(\cdot)$ is the inverse of the CDF of the standard univariate normal distribution, and $\Phi_2(\cdot)$ is the standardized bivariate normal distribution function of the random variables $\Phi^{-1}(F_1(\varepsilon_{1it}))$ and $\Phi^{-1}(F_2(\varepsilon_{2it}))$ with the 2×2 correlation matrix $\boldsymbol{\Omega}$ that is specified by:

[19] The analysis can be easily generalized to cases with higher dimensions above two, which are more complicated and require more elaboration, as discussed in Aas et al. (2009).

[20] See Chap. 4.8.1 of Cherubini et al. (2004) for a detailed description on the Gaussian copula. Amsler et al. (2014) point out an important feature of copula functions, i.e., they contain different range of dependence. The Gaussian, Frank, and Plackett copulas are comprehensive copulas, covering the entire range of dependence, while the Farlie–Gumbel–Morgenstern copula can model limited correlations, ranging between about −0.3 and +0.3.

$$\boldsymbol{\Omega} = \begin{pmatrix} 1 & \Omega_{12} \\ & 1 \end{pmatrix} \tag{9}$$

where the off-diagonal elements of $\boldsymbol{\Omega}$ are the correlation coefficients between the two variables. The corresponding Gaussian copula density of (8) is:

$$c\left(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \boldsymbol{\Omega}\right) = \frac{1}{|\boldsymbol{\Omega}|^{1/2}} \exp\left(-\frac{1}{2}\boldsymbol{\zeta}'_{it}\left(\boldsymbol{\Omega}^{-1}\text{-}\boldsymbol{I}_2\right)\boldsymbol{\zeta}_{it}\right) \tag{10}$$

where $\boldsymbol{\zeta}_{it} = \left[\Phi^{-1}\left(F_1\left(\varepsilon_{1it}\right)\right)\ \Phi^{-1}\left(F_2\left(\varepsilon_{2it}\right)\right)\right]'$ and $\boldsymbol{I}_2$ is a 2×2 identity matrix.

The joint PDF of the composite errors in (7) is thus:

$$\begin{aligned} f(\varepsilon_{1it}, \varepsilon_{2it}) &= c\left(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \boldsymbol{\Omega}\right) \times \prod_{j=1}^{2} f_j(\varepsilon_{jit}) \\ &= \frac{1}{|\boldsymbol{\Omega}|^{1/2}} \exp\left(-\frac{1}{2}\boldsymbol{\zeta}'_{it}\left(\boldsymbol{\Omega}^{-1}\text{-}\boldsymbol{I}_2\right)\boldsymbol{\zeta}_{it}\right) \times \prod_{j=1}^{2} f_j(\varepsilon_{jit}) \end{aligned} \tag{11}$$

and the log-likelihood function of our model can be expressed as:

$$\begin{aligned} \ln L(\boldsymbol{\theta}) &= \sum_{i=1}^{N}\sum_{t=1}^{T} f(\varepsilon_{1it}, \varepsilon_{2it}) \\ &= \sum_{i=1}^{N}\sum_{t=1}^{T} \ln c\left(F_1\left(\varepsilon_{1it}\right), F_2\left(\varepsilon_{2it}\right); \boldsymbol{\Omega}\right) + \sum_{j=1}^{2}\sum_{i=1}^{N}\sum_{t=1}^{T} \ln f_j\left(\varepsilon_{jit}\right) \\ &= \frac{-NT}{2}\ln|\boldsymbol{\Omega}| - \frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\boldsymbol{\zeta}'_{it}\left(\boldsymbol{\Omega}^{-1} - \boldsymbol{I}_2\right)\boldsymbol{\zeta}_{it} \\ &\quad + \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\ln f_1\left(\varepsilon_{1it}\right) + \ln f_2\left(\varepsilon_{2it}\right)\right] \end{aligned} \tag{12}$$

where $\boldsymbol{\theta} = \left(\boldsymbol{\theta}'_1, \boldsymbol{\theta}'_2; \Omega_{12}\right)'$ and $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ are the vectors of unknown parameters of the stochastic frontier functions in (2) and (5), respectively.[21]

[21] Although this article assumes that the composed error terms are independent over time, the parameter estimates from such quasi-maximum likelihood (QML) estimation are consistent even when the dependence exists, so long as the likelihood for each observation is correctly specified. Note that the conventional standard errors are invalid and need to be modified. Based on (12), the standard ML estimator has the inverse of the Fisher information matrix $I(\boldsymbol{\theta}) = -E\left(\partial^2 \ln L(\boldsymbol{\theta}) / \partial\boldsymbol{\theta}\, \partial\boldsymbol{\theta}'\right)$ as the covariance matrix of the estimator $\hat{\boldsymbol{\theta}}$. The covariance matrix of the QML estimators has the so-called sandwich form: $I^{-1}(\boldsymbol{\theta})\, E\left[S(\boldsymbol{\theta})\, S'(\boldsymbol{\theta})\right] I^{-1}(\boldsymbol{\theta})$, where $S(\boldsymbol{\theta}) = \partial \ln L(\boldsymbol{\theta}) / \partial\boldsymbol{\theta}$ is the score function. Johnston and DiNardo (1997), pp. 428–430, provide a brief discussion of the QML estimation of misspecified models and the derivation of the covariance matrix.

The ML estimation of (12) requires an evaluation of the PDF, $f_j(\varepsilon_{jit})$, $j = 1, 2$, and the inverse of the distribution functions $\boldsymbol{\zeta}_{it} = \left(\Phi^{-1}(F_1(\varepsilon_{1it}))\ \Phi^{-1}(F_2(\varepsilon_{2it}))\right)'$. The derivation of $f_j(\varepsilon_{jit})$ is already known (Aigner et al. 1977), i.e.,:

$$f_j(\varepsilon_{jit}) = \frac{2}{\sigma_j}\phi\left(\frac{\varepsilon_{jit}}{\sigma_j}\right)\Phi\left(\frac{\lambda_j\varepsilon_{jit}}{\sigma_j}\right), j = 1, 2 \tag{13}$$

where $\lambda_j = \sigma_{u_j}/\sigma_{v_j}$ and $\sigma_j^2 = \sigma_{v_j}^2 + \sigma_{u_j}^2$. However, the computation of $F_j(\varepsilon_{jit})$ is difficult due to the fact that $f_j(\varepsilon_{jit})$ does not have a closed-form expression. Green (2003) suggests using the simulated ML method, and Amsler et al. (2014) applied numerical integration procedure to approximate the integration in computing $F_j(\cdot)$ while applying copulas to ε_j. On the other hand, Lai and Huang (2013) utilize an approximation function proposed by Tsay et al. (2013) to obtain the closed-form CDF of ε_j. We follow the approach of Tsay et al. (2013), who show that the approximation is quite accurate, in obtaining the CDF $F_j(\cdot)$.

Given the PDF $f(\varepsilon_{it})$ in (13), the implied CDF $F(Q_{it})$ of ε_{it} at point Q_{it} is written as:

$$F\left(Q_{it}\right) = \int_{-\infty}^{Q_{it}} f\left(\varepsilon_{it}\right)d\varepsilon_{it} = \frac{2}{\sigma}I(Q_{it}) \tag{14}$$

where $I(\cdot)$ is defined by:

$$I\left(Q_{it}\right)=\int_{-\infty}^{Q_{it}}\left[\int_{-\infty}^{\frac{\lambda\varepsilon_{it}}{\sigma}}\phi\left(\xi\right)\mathrm{d}\xi\right]\phi\left(\frac{\varepsilon_{it}}{\sigma}\right)\mathrm{d}\varepsilon_{it} = \int_{-\infty}^{Q_{it}}\left[\int_{-\infty}^{a\varepsilon_{it}}\phi\left(\xi\right)\mathrm{d}\xi\right]\phi\left(b\varepsilon_{it}\right)\mathrm{d}\varepsilon_{it} \tag{15}$$

with $a = \lambda/\sigma > 0$ and $b = 1/\sigma > 0$. The derivation of $I\left(Q_{it}\right)$ is more involved and requires tedious work.

The integration of (15) cannot be performed analytically. Following Tsay et al. (2013), it can be approximated by $I_{\text{app}}(Q_{it})$[22]:

$$I_{\text{app}}(Q_{it}) = \frac{1}{2b}\text{erf}\left(\frac{bQ_{it}}{\sqrt{2}}\right)\left(\frac{1+\text{sign}(Q_{it})}{2}\right)+\frac{1}{4\sqrt{b^2-a^2c_2}}\exp\left(\frac{a^2c_1^2}{4(b^2-a^2c_2)}\right)$$
$$\left\{1-\text{erf}\left[\frac{-ac_1+\sqrt{2}Q_{it}(b^2-a^2c_2)\text{sign}(Q_{it})}{2\sqrt{b^2-a^2c_2}}\right]\right\} \tag{16}$$

where $c_1 = -1.09500814703333$, $c_2 = -0.75651138383854$, $\text{sign}(Q_{it}) = 1, 0, -1$ depending, respectively, on $Q_{it} >, =, < 0$, and the error function $\text{erf}(z)$, $z \geq 0$, is given by:

$$\text{erf}(z) = \frac{2}{\sqrt{\pi}}\int_0^z e^{-t^2}\mathrm{d}t = 2\int_0^{\sqrt{2}z}\phi\left(t\right)\mathrm{d}t = 2\Phi\left(\sqrt{2}z\right) - 1$$

[22] Readers are suggested to refer to the appendix of Tsay et al. (2013) for a detailed derivation of $I_{\text{app}}(Q_i)$.

$$\approx 1 - \exp\left(c_1 z + c_2 z^2\right) = g(z) \tag{17}$$

Tsay et al. (2013) show that the choice of constants c_1 and c_2 is to ensure that the error function $\mathrm{erf}(z)$ can be well approximated by $g(z)$, for $z \geq 0$. The introduction of the error function and $g(z)$ into (16) and (17) is novel, and the integration of $I(Q_{it})$ in (15) can then be analytically approximated by $I_{\text{app}}(Q_{it})$. Substituting $I_{\text{app}}(Q_{it})$ into (14), the CDF of $F(.)$ is approximated by:

$$F_{\text{app}}(Q_{it}) = \frac{2}{\sigma} I_{\text{app}}(Q_{it}) \tag{18}$$

Tsay et al. (2013) conduct Monte Carlo simulations to verify the finite sample performance of the ML estimators, based on $F_{\text{app}}(Q_{it})$. Simulation results are found to be very encouraging under various model specifications.

3 Empirical application

3.1 Data description

We conduct an empirical study to showcase the advantages of the new approach of estimating the Lerner index over the conventional one. The sample period covers from 2000–2008 (before the global financial crisis) and include five former communist countries: Bulgaria, Czech Republic, Latvia, Poland, and Russia. The choice of these countries is dictated by the fact that their financial markets experienced deregulation in the 1990s. The competitive conditions of these markets are worth examining and comparing with each other. We use the 2009 BankScope database CD-ROM, provided by Fitch-IBCA (International Bank Credit Analysis Ltd.), to compile bank-level data from unconsolidated balance sheets and income statements. The unbalanced panel data include 1133 commercial banks, and the total number of bank-year observations is 4716.

Table 1 summarizes the descriptive statistics of the relevant variables for each country. Russia has the highest number of observations in our sample, and Bulgaria and Czech Republic are at the other end. There are considerable variations across countries for all the variables we use. Specifically, Czech banks have the highest mean values of total revenues, total assets, and total costs, followed by Polish and Latvian banks. This implies that the scale of individual Czech banks is the largest among the five countries on average, followed by Polish and Latvian banks, while Bulgarian and Russian banks are at the other end of the spectrum. Moreover, the output and input prices vary across the five countries, meaning that banks in different countries might have different technologies and they might also be operating under different market conditions for inputs and outputs. Specifically, Russian banks pay the highest average wage to their employees, followed by Bulgarian, Polish, Latvian, and Czech banks. Polish banks pay the highest average input prices to capital and funds, followed by Russian and Czech banks. To adapt themselves to these heterogeneous circumstances, banks in the sample countries employ their individual market power to set their own

Table 1 Descriptive statistics

	Bulgaria	Czech Republic	Latvia	Poland	Russia
Total revenues (TR)[a]	49,243.576	305,186.709	56,736.754	234,876.511	50,312.412
	(83,636.599)	(532,081.569)	(93,825.699)	(408,943.812)	(296,509.347)
Total assets (TA)[a]	641,222.941	5,076,984.995	845,389.997	2,720,737.040	307,535.701
	(1,066,101.093)	(8,420,807.915)	(1,379,234.756)	(5,204,536.950)	(1,289,859.880)
Total costs (TC)[a]	33,945.677	216,554.140	39,691.568	185,862.796	40,102.125
	(50,857.995)	(355,134.448)	(64,219.388)	(298,146.050)	(270,220.651)
Price of labor (W_1)	0.022	0.010	0.016	0.020	0.041
	(0.025)	(0.013)	(0.012)	(0.020)	(0.034)
Price of capital (W_2)	1.496	3.173	1.635	5.614	4.565
	(1.638)	(3.909)	(1.370)	(7.863)	(7.405)
Price of funds (W_3)	0.026	0.027	0.023	0.054	0.049
	(0.022)	(0.020)	(0.012)	(0.041)	(0.054)
Output price (P)	0.083	0.065	0.075	0.103	0.177
	(0.032)	(0.073)	(0.061)	(0.061)	(0.134)
No. of banks	20	24	22	57	1,010
No. of observations	139	139	180	193	4,065

Numbers in parentheses are standard deviations
[a] Thousands of real US dollars with base year 2005

output prices. The highest average price is charged by Russian bank, followed by Polish, Bulgarian, Latvian, and Czech banks. A question that is often raised is whether a higher output price is consistent with a higher market power. We shall come back to this later.

3.2 Results

Table 2 reports the estimation results of the CSSFM for each country. Instead of pooling all the countries together, we estimate the seemingly unrelated stochastic frontier regression equations in (2) and (5) simultaneously for each country. By doing so, we take into account the potential dependence between the errors in these two equations and in particular the correlation between inefficiency and market power. It can be seen that the country-specific translog cost frontiers are fitted reasonably well, because most of the coefficient estimates attain statistical significance. In addition, the coefficient estimates are used to check the regularity conditions implied by the production theory on the cost function, such as non-decreasing and concavity in input prices.[23] Most of the observations are found to satisfy the required conditions. Finally, we estimate the conventional cost frontier (2) alone and check the same regularity conditions.[24] The results reveal that more observations satisfy the required regularity conditions in the CSSFM than in the traditional model, which only estimates the cost function. This arises possibly from the fact that the coefficient estimates are more accurately estimated by the CSSFM than the conventional model, due to more information being employed in estimation, such as the impositions of cross-equation restrictions and of the correlated errors.[25]

It is worth emphasizing that the estimated dependence parameter ρ in the Gaussian copula for each country is statistically significant at least at the 10 % level. The dependence between the production costs and output price indeed exists, confirming the advantage of the CSSFM that takes account of the mutual dependency over the equation-by-equation estimation procedure that ignores the potential dependence. Note that the estimated dependence parameter of Bulgaria is equal to -0.319, out of the range of ± 0.3 (see footnote 20), implying that the chosen Gaussian copula is likely to capture the dependence appropriately. Moreover, the sign of $\hat{\rho}$ has different economic implications. A firm with higher costs arising from production inefficiency may charge either a higher or a lower price depending upon its market power. Table 2 shows that $\hat{\rho}$ is significantly negative in the banking markets of Bulgaria, Czech, Poland, and Russia, indicating that inefficient banks in these markets are less likely to exercise market power in setting favorable prices, perhaps for fear of losing markets to the

[23] The monotonicity condition requires $\partial \mathrm{TC}/\partial W_k \geq 0, \forall k$. The concavity condition requires the cost function to be concave in input prices, i.e., the Hessian matrix is negative semi-definite. Readers are suggested to refer to, e.g., Varian (1992), for those properties of the cost function.

[24] The estimation results for the standard model are not shown to save space, but are available upon request from the authors.

[25] We also estimate a simplified model that imposes the independence assumption between ε_1 and ε_2 in (2) and (5). The results show more violations of the regularity conditions compared to the CSSFM.

Table 2 Joint estimation results of the CSSFM

Variables	Bulgaria	Czech Republic	Latvia	Poland	Russia
Constant	6.781***	0.988	0.366	−7.771	1.188
	(0.297)	(0.673)	(0.642)	(5.453)	(0.745)
$\ln Q$	0.038***	0.882***	1.103***	2.212***	1.081***
	(0.005)	(0.084)	(0.099)	(0.688)	(0.057)
$\ln Q^2$	0.054***	0.015	−0.014	−0.086**	−0.020***
	(0.009)	(0.010)	(0.009)	(0.040)	(0.002)
$\ln W_2$	−0.286***	0.212	−0.053	0.654*	−0.026
	(0.021)	(0.362)	(0.103)	(0.357)	(0.059)
$\ln W_3$	0.198***	0.727***	0.832***	−1.024***	0.095*
	(0.014)	(0.205)	(0.149)	(0.307)	(0.051)
$\ln W_2 \times \ln W_2$	−0.093***	0.006	−0.026*	−0.019	0.013***
	(0.014)	(0.094)	(0.014)	(0.029)	(0.003)
$\ln W_3 \times \ln W_3$	−0.055***	0.331***	0.247***	−0.026	0.065***
	(0.009)	(0.099)	(0.030)	(0.045)	(0.002)
$\ln W_2 \times \ln W_3$	0.069***	−0.059	−0.044**	0.071***	0.002
	(0.012)	(0.065)	(0.017)	(0.018)	(0.001)
$\ln Q \times \ln W_2$	0.085***	−0.008	0.017**	−0.057	0.001
	(0.010)	(0.006)	(0.007)	(0.037)	(0.001)
$\ln Q \times \ln W_3$	−0.005	−0.028***	−0.023**	0.130***	0.029***
	(0.007)	(0.007)	(0.010)	(0.022)	(0.002)
t	0.315***	−0.027	−0.073**	−0.377**	−0.423***
	(0.094)	(0.152)	(0.031)	(0.164)	(0.098)
t^2	0.018**	0.008	−0.78E-03	−0.039***	0.056***
	(0.005)	(0.006)	(0.003)	(0.004)	(0.007)
$t \times \ln Q$	−0.021***	−0.002	0.004*	0.039***	0.011***
	(0.009)	(0.008)	(0.002)	(0.012)	(0.003)
$t \times \ln W_2$	−0.043***	−0.007	0.004	0.032***	0.016***
	(0.006)	(0.011)	(0.003)	(0.004)	(0.005)
$t \times \ln W_3$	−0.004	0.035***	−0.007	−0.115***	−0.013***
	(0.009)	(0.013)	(0.007)	(0.010)	(0.004)
ρ	−0.319	−0.197*	0.142*	−0.251***	−0.025***
	(0.256)	(0.117)	(0.084)	(0.091)	(0.009)
λ_1	1.960**	3.889	2.874**	1.067	2.623***
	(0.904)	(16.799)	(1.230)	(3.107)	(0.160)
λ_2	1.064***	1.601***	2.833***	0.646**	1.133***
	(0.095)	(0.533)	(0.923)	(0.322)	(0.025)
σ_1	0.284***	0.200	0.208***	0.196	0.755***

Table 2 continued

Variables	Bulgaria	Czech Republic	Latvia	Poland	Russia
	(0.054)	(0.135)	(0.020)	(0.124)	(0.017)
σ_2	0.044***	0.016***	0.046***	0.052***	0.044***
	(0.006)	(0.001)	(0.002)	(0.003)	(0.0001)
Log-Likelihood	283.370	519.712	476.710	422.225	4700.940

The QML sandwich form estimated standard errors are shown in parentheses.
W_1 is arbitrarily selected as the numeraire to satisfy the homogeneity restriction in input prices.
$\lambda_j = \sigma_{uj}/\sigma_{vj}$ and $\sigma_j = \sqrt{\sigma_{vj}^2 + \sigma_{uj}^2}$, where $j = 1, 2$
*, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively

more efficient banks.[26] On the contrary, $\hat{\rho}$ is significantly positive in Latvia, implying that Latvian banks with higher market power are apt to set favorable prices in response to higher costs due to inefficiency. This claim appears to be supported by the results in Table 3, in which Latvian banks have the highest average value of the estimated new Lerner index.

Table 3 reports the summary statistics of the estimated Lerner index and cost efficiency scores for the sample countries, evaluated by both the CSSFM and convention models. Dissimilarity in the estimated Lerner index between the two models is clear, especially in Bulgaria, Latvia, and Poland. The conventional model tends to underestimate the Lerner index due to, at least partially, the problem of a negative estimated index for some observations. Specifically, the conventional model suggests that financial markets in Bulgaria and Poland are fairly close to competitive, while the results of the CSSFM indicate that banks in these two countries operate under imperfect market conditions. In addition, the conventional model leads to a number of negative estimated indices in every country, ranging from 17 (Latvia) to 323 (Russia), while the CSSFM does not. This is because the new Lerner index is internally built in the CSSFM, allowing it to resolve the problem of negative estimates of the index. According to the CSSFM, Latvian banks have the highest market power among the five countries, as its average new Lerner index is the largest, followed by Bulgarian, Polish, Russian, and Czech banks in sequence, whereas the conventional model gives a different ranking.

Recall that a negative value of the Lerner index corresponds to the situation in which the bank is setting its output price below its MC—a contradiction to the behavior of a profit-maximizing firm. Many previous studies utilize the conventional Lerner index as a proxy for market power to test for the quiet life hypothesis (Maudos and Fernández de Guevara 2007; Turk-Ariss 2010), the competition–fragility nexus or competition–stability nexus (Berger et al. 2009; Turk-Ariss 2010), and to investigate the relationship between regulation, market power, and risk taking (Agoraki et al. 2011). Consequently, the inferences drawn from these studies may not reflect the true conditions due to their

[26] Another possible explanation is that even though they have more or less market power, the incumbent banks might set their output prices close to the competitive level due to the risk of potential entrants, complying with the feature of a contestable market.

Table 3 Summary statistics of various Lerner index and cost efficiency measures

	Bulgaria			Czech Republic			Latvia			Poland			Russia		
	CSSFM	Conventional	Koetter et al. (2012)	CSSFM	Conventional	Koetter et al. (2012)	CSSFM	Conventional	Koetter et al. (2012)	CSSFM	Conventional	Koetter et al. (2012)	CSSFM	Conventional	Koetter et al. (2012)
Lerner index															
Mean	0.2788	0.0576	0.2186	0.1763	0.1619	0.2658	0.3014	0.2176	0.3445	0.2375	0.0503	0.1814	0.2160	0.2014	0.1154
SD	0.0871	0.4148	0.4261	0.0679	0.1827	0.2349	0.1122	0.2004	0.2378	0.0859	0.4649	0.4024	0.1077	0.3372	0.5016
SE	0.0142	0.0111	1.5055	0.0231	0.0125	5.6218	0.0061	0.0074	0.0779	0.0454	0.0118	0.0978	0.0029	0.0025	0.0143
Min	0.0430	−2.8335	−2.8228	0.0121	−0.6723	−1.1629	0.0321	−0.9157	−0.7872	0.0488	−4.3027	−1.5230	0.0037	−10.3784	−5.2615
Max	0.5233	0.6498	0.8882	0.3552	0.5530	0.5776	0.6846	0.6260	0.6334	0.4349	0.6240	0.6137	1.0000	0.9089	0.9740
No. of total obs.	139	139	139	139	139	139	180	180	180	193	193	193	4,065	4,065	4,065
No. of negative obs.	0	45	40	0	18	14	0	17	13	0	57	34	0	323	858
Cost efficiency															
Mean	0.8187	0.8094	0.8094	0.8632	0.8958	0.8958	0.8704	0.8544	0.8544	0.8938	0.8598	0.8598	0.6624	0.7245	0.7245
SD	0.0930	0.1196	0.1196	0.0864	0.0582	0.0582	0.0829	0.1023	0.1023	0.0431	0.0781	0.0781	0.1347	0.1278	0.1278
SE	0.0258	0.0210	0.0210	0.0550	0.0163	0.0163	0.0166	0.0156	0.0156	0.0448	0.0378	0.0378	0.0062	0.0066	0.0066
Min	0.2967	0.2318	0.2318	0.3892	0.5029	0.5029	0.4733	0.4288	0.4288	0.7036	0.5537	0.5537	0.1411	0.1738	0.1738
Max	0.9481	0.9955	0.9955	0.9804	0.9739	0.9739	0.9762	0.9854	0.9854	0.9701	0.9748	0.9748	0.9583	1.0000	1.0000

use of the conventional Lerner index measures to proxy for the degree of competition in banking markets.

The mean values of the new Lerner index in all countries are larger than those of the conventional model and have smaller standard deviations. Such a smaller variation is primarily attributed to the fact that the new Lerner index is nothing but the estimate of u_2 in (5), which is distinguishable from the noise term v_2. The new Lerner index is free from random shocks, while the conventional Lerner index is usually confounded by such shocks, since it relies on the direct calculation of (1) without the need of estimating (5). The P_{it} term in (1) thus contains the random noise v_2, making the variation of the conventional Lerner index greater than that of our new Lerner index.

Table 3 also includes summary statistics of the adjusted Lerner index, proposed by Koetter et al. (2012).[27] The standard deviations of the adjusted Lerner index in all countries are found to be larger than those of the CSSFM. Moreover, it is noticeable that there are quite a few negative estimates for the adjusted Lerner index in every country, ranging from 13 (Latvia) to 858 (Russia). This means that the adjusted Lerner index suffers from the same problem as the conventional one, i.e., the computed output price (average revenue) might be less than the estimated MC for some banks.

So far as the estimated cost efficiency is concerned, the two models yield similar average values and standard deviations for each of the countries. The omission of the simultaneity in cost and output price does not affect the mean cost efficiency scores much. However, we find evidence of an underestimation of the Lerner index. To put it differently, the conventional model has a tendency to support the view that output markets are somewhat competitive.

It may be interesting to examine the observed output prices in light of competitive market conditions. According to Table 1, an average Czech bank charges the lowest price to its customers, perhaps because this market is most competitive relative to the other four banking industries on the basis of their estimated new Lerner indices. For the remaining four markets, Table 1 shows that Russian banks set the highest average output price, but operate in the most competitive market due to its low average value of the new Lerner index. This might result from the lack of cost efficiency in these banks, since the average value of it equals 0.6626, or other institutional factors such as interest rates regulation imposed by the authorities. Conversely, Latvian banks set the lowest output price and operate in the least competitive market (highest new Lerner index measure). From this, one might conclude that a small number of Latvian banks are operating in a contestable market and they behave competitively due to free entry and exit.

Table 4 presents the evolution of the Lerner index in each of the countries over the period 2000–2008. We also compute the 3-year average value of the index for each country and show them at the bottom of the table. This helps us to detect possible trends in the markup factor. The conventional model gives negative average values of the Lerner index for Bulgaria and Poland at the beginning and in the middle of the sample period, which is inconsistent with the profit-maximizing behavior. The Koetter

[27] The parameter estimates of the alternative profit frontier are not shown to save space, but are available upon request from the authors.

Table 4 Estimates of various Lerner indices over time

	Bulgaria			Czech Republic			Latvia			Poland			Russia		
	CSSFM	Conventional	Koetter et al. (2012)	CSSFM	Conventional	Koetter et al. (2012)	CSSFM	Conventional	Koetter et al. (2012)	CSSFM	Conventional	Koetter et al. (2012)	CSSFM	Conventional	Koetter et al. (2012)
2000	0.1634	−0.3155	−0.1388	0.1160	0.0233	0.0777	0.3385	0.2050	0.2053	0.1382	0.0442	0.0570	0.2263	0.0873	0.1272
2001	0.1998	−0.1781	−0.1136	0.1348	0.1096	0.1849	0.3480	0.3213	0.2556	0.1412	0.0130	0.0702	0.2481	0.2228	0.2392
2002	0.2604	−0.0478	0.0696	0.1660	0.1508	0.2076	0.2889	0.1876	0.3943	0.1798	0.0405	0.1112	0.2583	0.1914	0.2340
2003	0.2558	−0.1755	−0.1392	0.1701	0.1391	0.1703	0.2719	0.1799	0.4033	0.2668	−0.0399	0.1700	0.2722	0.2334	0.2513
2004	0.3075	0.2095	0.3697	0.1892	0.1611	0.2866	0.3019	0.2383	0.4204	0.2587	−0.0344	0.2175	0.2216	0.2319	0.2224
2005	0.3078	0.2444	0.4227	0.1833	0.1968	0.2666	0.2641	0.1934	0.4074	0.2663	0.0158	0.1822	0.2330	0.2465	0.2243
2006	0.3303	0.2096	0.4472	0.2054	0.2271	0.3841	0.2834	0.1591	0.3353	0.2878	0.1821	0.3256	0.2442	0.2207	0.2345
2007	0.3469	0.2463	0.4598	0.2077	0.2367	0.3958	0.3262	0.2747	0.3643	0.2839	0.1572	0.2379	0.2389	0.2462	0.2581
2008	0.2995	0.2075	0.4654	0.2024	0.1716	0.3909	0.2946	0.1985	0.2928	0.3066	0.1084	0.2142	0.1040	0.0477	−0.4997
2000–2002	0.2102	−0.1741	−0.0560	0.1384	0.0929	0.1549	0.3249	0.2385	0.2864	0.1539	0.0334	0.0803	0.2467	0.1754	0.2086
2003–2005	0.2910	0.0989	0.2259	0.1817	0.1678	0.2468	0.2793	0.2039	0.4104	0.2637	−0.0165	0.1917	0.2324	0.2398	0.2261
2006–2008	0.3271	0.2208	0.4563	0.2057	0.2200	0.3900	0.3016	0.2112	0.3321	0.2889	0.1614	0.2737	0.2045	0.1836	0.0455
Average	0.2788	0.0576	0.2186	0.1763	0.1619	0.2658	0.3014	0.2176	0.3445	0.2375	0.0503	0.1814	0.2160	0.2014	0.1154

et al. (2012) model also gives negative mean values of the Lerner index for Bulgaria over the periods of 2000-2001 and 2003 and for Russia in 2008.

The new Lerner index, based on the CSSFM, is found to increase over time for Bulgaria, Czech Republic, and Poland, thereby meaning that the banking output markets in these three countries have become less competitive over time, while Russian banks have become more competitive. The index for Latvia varies over time without any clear trend. It is interesting to note that the conventional and CSSFM models give similar trends for Bulgaria, Czech Republic, and Latvia, but their average values are quite different from one another. The Koetter et al. (2012) model has the same increasing trend for Bulgaria and Czech Republic as the other two models, while different patterns are found for the other three counties.

3.3 Market power and bank efficiency

As mentioned earlier, a number of previous studies have employed the conventional Lerner index to measure the degree of market power for the purpose of testing the "quiet life hypothesis" (Maudos and Fernández de Guevara 2007; Turk-Ariss 2010).[28] The inferences drawn from these studies might not reflect the true conditions due to the fact that the conventional Lerner index tends to overestimate the degree of market competition. We use estimates of cost efficiency and the Lerner index from the CSSFM to investigate the nexus between market power and cost efficiency. No other studies have addressed this issue in transition countries, except for Turk-Ariss (2010).[29]

Figure 1 is a scatter plot diagram in which each point corresponds to a combination of an estimated efficiency score and a Lerner index measure. We also plot the simple regression line obtained by pooling all sample points together. The estimated slope parameter of this line is 0.34 and is significantly different from zero at the 1 % level. We thus reject the "quiet life hypothesis," implying that banks with higher market power also have higher cost efficiency.[30] This outcome can be explained by contestable markets and the entry of foreign banks.

Our findings are consistent with Maudos and Fernández de Guevara (2007) for European banking.[31] Koetter et al. (2012) derive adjusted Lerner indices for US banks and find a positive association between market power and cost efficiency, as well. On the contrary, Berger and Hannan (1998), Delis and Tsionas (2009), and Turk-Ariss

[28] The quiet life hypothesis posits that the higher a firm's market power is, the lower is the effort by managers to achieve maximum operating efficiencies, and so there is a negative relationship between the degree of market power and managerial efficiency.

[29] Most of the previous studies that tested the quiet life hypothesis mainly focus on banking systems in developed countries. For example, Berger and Hannan (1998) and Koetter et al. (2012) study US banking; Maudos and Fernández de Guevara (2007) and Delis and Tsionas (2009) examine European banking; Turk-Ariss (2010) explore the banking industries of 60 developing countries.

[30] We also examine the association for each country and find the slope parameters to be positive and significant, ranging from 0.12 to 0.39, except for Latvia's slope parameter estimate that is as low as 0.07 and insignificant. It is worth mentioning that if we regress the conventional measure of the Lerner index on technical efficiencies, then the estimate of the slope parameter is as low as 0.056, although significant at the 1 % level.

[31] Maudos and Fernández de Guevara (2007) provide several reasons to explain this positive effect.

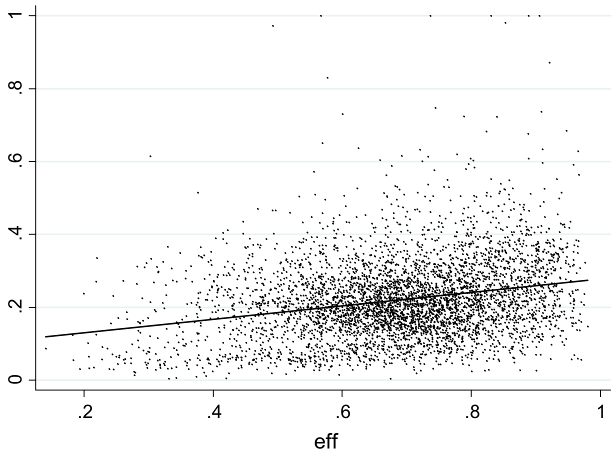

Fig. 1 The relationship between market power and cost efficiency

(2010) note a negative relationship between market power and cost efficiency in the US, as well as in European and developing countries, respectively, verifying the quiet life hypothesis.[32]

4 Concluding remarks

This paper proposes an econometric framework for the joint estimation of bank-level market power and cost efficiency using copula methods. Our model consists of a cost frontier and an output price frontier. The cost frontier allows us to estimate cost efficiency, and the price frontier allows us to derive the Lerner index at the bank level. The novelty of our approach lies in the construction of the output price frontier, which uses the MC function that is implied by the cost frontier. Therefore, it is preferred to estimate both frontiers in a simultaneous system so that the dependence between both frontiers can be explicitly taken into account. In addition, the Lerner index measure is guaranteed to be nonnegative, since it is internally built-in. Conversely, the conventional Lerner index measure and the adjusted Lerner index of Koetter et al. (2012) are based on a two-step procedure. Consequently, the resulting estimates might not be all positive.

Our proposed method, in sum, has the following advantages: (1) It relates the output price to MC, in which the gap between output price and MC reflects the markup. (2) The built-in Lerner index measure is calculated as the ratio of the gap to the corresponding output price, which is not confounded with random shocks. (3) The dependence between the output price and production costs is characterized by a simultaneous equations model in which correlation between inefficiency and markup is introduced through copula functions. (4) The joint density and the likelihood functions are derived using the copula method, and the model is estimated by the MLE.

32 Berger and Hannan (1998) utilize the Herfindahl–Hirschman index to represent market power.

We apply the new approach to estimate cost efficiency and the Lerner index for five former communist countries from 2000–2008. We find the estimated dependence parameters in the Gaussian copula to be statistically significant for each country, implying the existence of dependence between the costs and output price. A bank with higher costs arising from operating inefficiency can pass on some of the cost to consumers, depending on competitiveness of the market. Studies on market power suggest to model the mutual dependency between the output price and production costs in order to gain further insight into the behavior of market competition.

We find that the mean value of the new Lerner index in each country is larger (with smaller standard deviations) than those from the conventional model. Variations in the adjusted Lerner index from Koetter et al. (2012) are also found to be larger than those of the CSSFM in all countries. These results may be attributed to the fact that the new Lerner index obtained from our CSSFM allows for the separation of random shocks from the error term, while the other two models are likely to be affected by random shocks. The conventional model tends to underestimate the Lerner index due, at least partially, to the presence of some negative values for the estimated Lerner index. This indicates that the conventional model is likely to overestimate market competition and likely to mislead the regulators in giving them a false impression about market competition.

Our CSSFM suggests that most banks in the five transition countries are operating under moderately competitive market conditions. The estimated new Lerner index shows an increasing trend for Bulgaria, Czech Republic, and Poland, thereby meaning that the banking sectors in these countries are getting less competitive over time. The reverse is true for Russian banks. We note a significantly positive relationship between market power and cost efficiency for banks operating in the transition countries. This finding rejects the quiet life hypothesis—that is, banks operating in markets with higher market power are also operating more efficiently.

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