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Competition, efficiency, and innovation in Taiwan's banking industry — An application of copula methods☆

Tai-Hsin Huang[a,*], Chu-Nan Hu[a], Bao-Guang Chang[b]

[a] Department of Money and Banking, National Cheng-Chi University, Taipei, Taiwan
[b] Department of Accounting, Tamkang University, New Taipei City, Taiwan

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ABSTRACT

This paper proposes a simultaneous stochastic frontier model that consists of a cost frontier and an output price frontier that relates a firm's output price (P) to its marginal cost (MC). The gap between P and MC reflects a firm's degree of market power, and the Lerner index (LI) is equal to the ratio of the gap to P. The salient feature of our model permits LI to be internally determined by the simultaneous equations model, which avoids obtaining negative estimates of the index. The joint probability density function of the composed errors can be derived in the context of copula methods. Our model is applied to study the competitive conditions of Taiwan's banking industry. Findings show that: (1) the quiet life hypothesis is rejected; (2) the relationship between financial innovation, measured by the technology gap ratio of Huang et al. (2014), and our LI is U-shaped, which is robust over different specifications; and (3) the nexus between innovation and competition is inverted-U shape and consistent with Aghion et al. (2005) and Bos et al. (2013).

1. Introduction

The issue of a causal link between innovation and market competition has drawn much attention from many economists and can be dated back to Schumpeter (1942) who posited that product market competition discourages innovation by diminishing monopoly rents. Conversely, Aghion, Harris, Howitt, and Vickers (2001) claimed that competition is likely to nurture innovation in order to escape competition. Aghion and Griffith (2005) and Aghion, Bloom, Blundell, Griffith, and Howitt (2005) developed a theoretical model to describe an inverted-U relationship between competition and innovation, which is capable of reconciling the above two controversial assertions. An escape competition effect tends to dominate at the outset until competition intensifies to some extent to which the rent dissipation effect prevails.

Traditional industrial organization theory, often classified as the structure method, focuses on the structure–conduct–performance (SCP) paradigm that uses market concentration measures as the proxy for market power, including market shares, concentration ratios for the largest several firms (CR ratios), and the Herfindahl–Hirschman index (HHI). However, these measures have been shown to be ambiguous indicators. Berger, Demirgüç-Kunt, Levine, and Haubrich (2004), Maudos and Fernández de Guevara (2004), Fernández de Guevara, Maudos, and Pérez (2005), Beck, Demirgüç-Kunt, and Levine (2006), and Alegria and Schaeck (2008) presented the restrictions of using concentration measures as indicators for the degree of competition in banking industry.

Non-structural approaches have been developed in the context of the New Empirical Industrial Organization literature, such as the Panzar and Rosse (1987) H-statistic and the Lerner index (LI) of market power. Both methods assess degrees of competition and test the competitive conduct of firms directly without using explicit information about the market's structure. 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.[1] The drawback

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* Corresponding author.
E-mail addresses: thuang@nccu.edu.tw (T.-H. Huang), 102352507@nccu.edu.tw (C.-N. Hu), baog@mail.tku.edu.tw (B.-G. Chang).

[1] The H-statistic was popularly used as a direct measure of the degree of competition in the recent literature on bank competition. See for example, Bikker and

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of the PR model is that the valid competition condition inferred from the H-statistic depends on the presumption of the long-run equilibrium. This requires a separate test for whether this condition is satisfied or not. Moreover, the estimated H-statistic is measured at the industry level, instead of at the individual firm level.

More and more studies are turning their attention to another indicator of market structure, i.e., LI, which is a well-established measure of market power at the firm level.[2] It assesses a firm's capacity for setting the price above the marginal cost (MC), which is intimately associated with the competitive conditions faced by the firm. A perfectly competitive firm's LI is equal to 0, while a monopolist has the index close to 1.[3] However, some past works, such as Berger, Klapper, and Turk-Ariss (2009), Turk-Ariss (2010), and Agoraki, Delis, and Pasiouras (2011), obtained negative estimates of LI for some observations, implying that the output price is charged below MC, which is a contradiction to economic theories. Moreover, their estimation of market power ignored potential technical inefficiencies, which may lead to biased parameter estimates such that the subsequent calculations using these estimates are also distorted, as claimed by Berg and Kim (1998), Delis and Tsionas (2009), and Koetter and Poghosyan (2009). Almost all of the previous studies on market power did not address the issue of negative LIs, nor did they consider technical inefficiencies concurrently.

Koetter, Kolari, and Spierdijk (2012) regressed efficiency on market power (measured by the old LI), along with some control variables, to test for QLH. In their estimation of the cost function, inefficiency is implicitly assumed to be independent of LI. The potential problem is that LI is derived from the estimated cost function, and therefore the same index should not be used to explain cost efficiency in the previous step where a cost function is estimated. It is crucial to allow market power and cost efficiency to be correlated, if the former impacts the latter; otherwise, estimates of LI and cost efficiency might be false.

In order to appropriately resolve the above problems and make progress in the consistent estimation of bank-level market power, we propose a simultaneous stochastic frontier model that consists of a cost frontier and an output price frontier. In this manner, both total costs and output price are viewed as dependent variables and their regression equations contain composed errors. The joint probability density function (pdf) of the composed errors can be derived in the context of copula methods. This model has recently been applied by Huang, Liu, and Kumbhakar (2016) to study the banking sectors of five former communist countries during the period 2000–2008. Huang, Chiang, and Chao (2016) further extended it to allow for measuring LI under the framework of multiple outputs, instead of the conventional single output case.

Our proposed model can be referred to as seemingly unrelated stochastic frontier regressions with correlated composite errors, first developed by Lai and Huang (2013).[4] The joint pdf of the dependent frontier equations can be derived by using copula methods.[5] The difficulty of 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 and hence involves numerical integration procedures. This makes it hard to implement the maximum likelihood (ML) estimation procedure.

We follow Tsay, Huang, Fu, and Ho (2013) to approximate the CDF of the composite error by an analytical closed-form formula.[6] Tsay et al. (2013) proved by simulations that the finite sample performance of the resulting ML estimates is very promising. Furthermore, Lai and Huang (2013) checked consequences of ignoring the dependence between the frontier equations via Monte Carlo simulations and concluded that the resulting estimators fail to be efficient and that the estimates of technical efficiency are severely biased.

We first apply our model to examine the market power and cost efficiency of Taiwan's banking sector over the period 1997–2011. The estimates of efficiency scores and LI are next used to test for QLH. Finally, we examine the nexus between financial innovations and competition under the framework of generalized method of moments (GMM). Two hypotheses are tested: (1) the Schumpeterian (1942) hypothesis (SH), which suggests that product market competition discourages innovation due to the decrease in monopoly rents, and (2) the "escape competition hypothesis" (ECH), which asserts that competition may stimulate innovation as firms try to escape competition, e.g., Aghion et al. (2001), Aghion and Griffith (2005), Aghion et al. (2005), and Bos, Kolari, and van Lamoen(2013).[7]

The potential contribution of this article to the competition/innovation literature is two-fold. First, we develop a new approach to calculate the Lerner (1934) index (henceforth, new LI) that is used to gauge market power (or the inverse of market competition). This new LI is derived in the context of simultaneous equations and does not suffer from having negative values for some observations. By contrast, the conventional LI (henceforth, old LI) may involve negative values for some observations, which is implausible. Second, we establish a new innovation measure against the stochastic metafrontier cost function that represents the potentially lowest production cost a firm can reach, should it adopt the most advanced technology. Specifically, our stochastic metafrontier cost function extends the stochastic metafrontier production function of Huang, Huang, and Liu (2014), which differs from the one proposed by Battese, Rao, O'Donnell (2004) and O'Donnell, Rao, and Battese (2008) whose metafrontier is in essence deterministic, instead of stochastic. We combine the resulting innovation measure with the competition in dex to test for some important hypotheses, e.g., the quiet life hypothesis (QLH) and the inverted-U relationship, and draw economic implications

Groeneveld (2000), De Bandt and Davis (2000), Bikker and Haaf (2002), Gelos and Roldós (2004), Claessens and Laeven (2004), Ai-Muharrami, Matthews, and Khabari (2006), Casu and Girardone (2006), Staikouras and Koutsomanoli-Fillipaki (2006), Yeyati and Micco (2007), Turk-Ariss (2009), Carbó, Humphrey, Maudos, and Molyneux (2009), and Delis (2010), among others. However, Bikker, Shaffer, and Spierdijk (2012) showed that neither a price equation nor a scaled revenue function produces a valid measure for competitive conduct, and an unscaled revenue function generally requires additional information about costs and market equilibrium to deduce competitive conditions.

[2] See for example, Prescott and McCall (1975) for U.S. banks; Shaffer (1993) for Canadian banks; Maudos and Pérez (2003) for the case of Spain; Angelini and Cetorelli (2003) for Italian banks; Carbó, Humphrey, and Rodríguez (2003, 2009) for Spanish banks; Fernández de Guevara et al. (2005, Fernández de Guevara, Maudos, and Pérez, 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.

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

[4] They applied the model to study the hotel industry in Taiwan and simultaneously estimate two production frontiers, representing the technologies of accommodation and restaurant divisions of a hotel.

[5] The copula approach, introduced by Sklar (1959), has been widely employed in multivariate analysis and recently it is 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).

[6] Greene (2003, 2010) proposed the use of simulation to approximate the integration.

[7] Note that Aghion et al. (2005), Nickell (1996), Bos et al. (2013), and Bos et al. (2010) computed the measure of price cost margin (PCM) to reflect the degree of market competition. Boone (2008) proposed the measure of profit elasticity to indicate market competition, which has been applied by several papers, such as van Leuvensteijn, Bikker, van Rixtel, and Sorensen (2011), Delis (2012), Bérubé, Duhamel, and Ershov (2012), Peroni and Ferreira (2012), Tabak, Fazio, and Cajueiro (2012), and van Leuvensteijn, Sorensen, Bikker, and van Rixtel (2013).

at the bank level, where the financial sector is facing a changing environment in all aspects during the sample period.

The rest of the paper is organized as follows. Section 2 briefly describes the banking industry in Taiwan. Section 3 mainly establishes the econometric model suitable for simultaneously estimating the cost and the price frontiers by means of copula methods and introduces the new metafrontier model suitable for evaluating financial innovation. Section 4 proposes several hypotheses to be tested later in the empirical study. Section 5 briefly describes the data source and presents descriptive statistics of all relevant variables. Section 6 shows all empirical results and their implications, while the last section concludes the paper.

2. Overview of the banking industry in Taiwan

The banking sector in Taiwan is strictly regulated by the government and the sector is governed by state-owned banks, particularly prior to 1989. The government started to privatize public banks and liberalize the financial market by allowing for new entry of private and foreign banks since 1989 when the New Banking Law was passed by the Legislation Yuan. Since then, the sector's degree of competition has increased substantially. The number of domestic, commercial banks went from 48 in 1997 to 53 in 2002, and then dropped to 39 in 2011 due to mergers and acquisitions. However, the condition of over-banking incurs keen competition and lowers interest margins below 1.5%, such that the existing banks suffer from a low level of profits and worse quality of loans.

To improve the banking industry performance and restructure the financial system, Taiwanese authorities launched a series of financial reforms. The "First Financial Restructuring (henceforth, FFR)," starting from 2002 to 2003, aimed to write off non-performing loans (NPLs) of financial institutions, mainly incurred by the Asian financial crisis in 1997. Many important laws on deregulating financial institutions were legislated and revised at the same time, such that financial holding companies (FHCs) were permitted to be established, attempting to spur the performance of banks. The first financial holding company—Hua-Nan Financial Holding Company—was founded in 2001. There are now 16 FHCs and most of them own a commercial bank. In 2012, the banking industry in Taiwan included 37 commercial banks, 2 industrial banks, and 28 foreign banks.[8] The banking market can still be characterized as over-banking.

3. Methodology

3.1. Measuring competition

LI reflects the mark-up of an output price over MC and is a sign of the degree of market power, which can be viewed as the inverse of market competition. The greater the value of the index is, the larger (less) the market power (competition) is in which the firm is more able to set a higher price. Under this condition, the firm is facing a lower degree of competition in the market.

The traditional (old) LI (L) is defined by:

$$L_{it} = (P_{it} - MC_{it})/P_{it}, \tag{1}$$

where P_{it} is bank i's output price at time t, calculated by the ratio of total revenues to total assets, and MC is the marginal cost of producing an additional unit of output, proxied by total assets. MC is indirectly derived from the following translog cost function with a single output (e.g., Angelini & Ceterolli, 2003; Berg & Kim, 1994; Berger et al., 2009; Turk-Ariss, 2010):

$$\begin{aligned}\ln TC_{it} &= \alpha_0 + \alpha_1 \ln Y_{it} + \frac{1}{2}\alpha_2 (\ln Y_{it})^2 + \sum_{k=1}^{3}\lambda_k \ln W_{k,it} \\ &+ \frac{1}{2}\sum_{k=1}^{3}\sum_{h=1}^{3}\beta_{kh}\ln W_{k,it}\ln W_{h,it} + \sum_{k=1}^{3}\gamma_k \ln Y_{it}\ln W_{k,it} + \omega_1 Trend\,, \\ &+ \frac{1}{2}\omega_2 Trend^2 + \omega_3 Trend \times \ln Y_{it} + \sum_{k=1}^{3}\varphi_k Trend \times \ln W_{k,it} + \varepsilon_{1it}\end{aligned} \tag{2}$$

where TC denotes total costs, Y stands for the single output (total assets), W_k (k = 1–3) corresponds to the input prices of labor, capital, and funds, respectively, $Trend$ is the time trend reflecting technical change over time, and $\varepsilon_1 = v_1 + u_1$ is the composed errors with $v_1 \sim N(0, \sigma_{v1}^2)$ and $u_1 \sim |N(0, \sigma_{u1}^2)|$. Random variable v_1 is assumed to be independent of the half-normal random variable, u_1, which signifies the increase in production costs arising from managerial inefficiency. Notations α, β, λ, γ, ω, φ, σ_{v1}^2, and σ_{u1}^2 are the corresponding unknown parameters to be estimated. It is worth mentioning that some restrictions on the cost function required by the microeconomic theory, such as symmetry and homogeneity of degree one in input prices, have to be imposed before estimating (Eq. (2)).

After obtaining the unknown parameters, one can use them to figure out the measure of technical inefficiency, according to the formula of conditional expectation $E(u_{1it}|\varepsilon_{1it})$.[9] The implied MC function by Eq. (2) can be deduced by taking the partial derivative of the cost function with respect to the output, i.e.:

$$MC_{it} = \frac{\partial TC_{it}}{\partial Y_{it}} = \frac{TC_{it}}{Y_{it}}\left[\alpha_1 + \alpha_2 \ln Y_{it} + \sum_{k=1}^{3}\gamma_k \ln W_{k,it} + \omega_3 Trend\right], \tag{3}$$

where terms in the brackets are yielded by $\partial \ln TC/\partial \ln Y$. Formula (1) requires information on output price and MC. Since both variables come from separate procedures and are subject to the impact of random shocks, the computed LIs are likely to be negative for some observations subject to substantial adverse shocks and vary relatively large — that is, the old LI is apt to be confounded by shocks uncontrollable by managers. A negative value of L_{it} implies that the firm is setting its output price below MC, which is a contradiction to the behavior of a profit-maximizing firm that seeks to equate marginal revenue (MR) to MC.

It is necessary to split random shocks from the measure of Lerner margins. This can be accomplished in the context of the stochastic frontier approach (SFA). We start with the following inequality under an imperfectly competitive market:

$$P_{it} \geq MR_{it} = MC_{it}. \tag{4}$$

To transform the inequality sign into equality we add a non-negative random variable $u_2 \sim |N(0, \sigma_{u2}^2)|$. After appending a disturbance term of $v_2 \sim N(0, \sigma_{v2}^2)$, we yield a price frontier, i.e.:

$$P_{it} = MC_{it} + v_{2it} + u_{2it}, \tag{5}$$

where u_{2it} and v_{2it} are independent of each other. The presence of the error term v_{2it} is to capture statistical noise, as well as it

[8] The 28 foreign banks are excluded from our sample due to their small scale relative to those domestic banks.

[9] This conditional expectation can be readily shown to be equal to: $E(u_{1it}|\varepsilon_{1it}) = \mu_{1*it} + \sigma_{1*}\frac{\phi(-\mu_{1*it}/\sigma_{1*})}{1-\Phi(-\mu_{1*it}/\sigma_{1*})}$, where $\sigma_{1*}^2 = \sigma_{u1}^2\sigma_{v1}^2/\sigma_1^2$, $\sigma_1^2 = \sigma_{u1}^2 + \sigma_{v1}^2$, $\mu_{1*it} = -\sigma_{u1}^2\varepsilon_{1it}/\sigma_1^2$, and $\phi(.)$ and $\Phi(.)$ are respectively the pdf and CDF of the standard normal random variable. Please see Kumbhakar and Lovell (2000) for details.

makes Eq. (5) a regression equation. Let $\varepsilon_2 = v_2 + u_2$ be a composed error term possibly correlated with ε_1 of Eq. (2). The one-sided error u_2 measures the extent to which the price deviates from MC and is estimated by the conditional expectation $E(u_{2it}|\varepsilon_{2it})$, as in the SFA literature. The implied LI (henceforth, the new LI) is then derived by taking the ratio of the conditional expectation to P_{it}, i.e., $E(u_{2it}|\varepsilon_{2it})/P_{it}$. In this manner, the variation of the new LI can be largely reduced, as the conditional expectation enables us to average out u_{2it}. As a result, the resulting new LI measure is expected to have less variation (smaller variance) than the old LI measure.

Composed errors ε_1 and ε_2 in Eqs. (2) and (5) are both permitted to be correlated in that banks with higher market power may set favorable prices in response to higher costs possibly arising from technical inefficiencies. In contrast, if the market is contestable, then its constituent banks tend to charge competitive prices even though they have more or less market power. Hence, composite errors in the two equations are better to allow for correlation, and this assumption can be readily tested.[10] In this context, Eqs. (2) and (5) are suggested to be simultaneously estimated, where both TC and Y are treated as endogenous variables, in order to take advantage of efficiency gains and, more importantly, to avoid the potential biased estimates on technical efficiency scores (and LI), as mentioned by Lai and Huang (2013). The estimation results are thus preferable to those obtained from estimating the single Eq. (2) without regard to the dependence of ε_1 and ε_2. We recommend estimating the system model under the seemingly unrelated stochastic frontier regression framework with dependent composite errors.

The new LI differs from the old one in several aspects. First, Eqs. (2) and (5) are jointly estimated by ML, such that the resulting parameter estimates are consistent and more efficiently estimated. This procedure explicitly recognizes the dependence between a firm's production costs and pricing strategy. Second, the computed measure of the new LI is non-negative, as opposed to the conventional one that could be negative for some observations in the sample, which may purely result from huge shocks. Third, the new index is subject to less impact from random shocks than the traditional one due to the fact that the former is inferred on the basis of Eq. (5), which allows for the presence of v_2 in the separation of term MC, and the calculation of the conditional expectation $E(u_{2it}|\varepsilon_{2it})$ averages out u_{2it}. Conversely, the latter tends to be confounded by random shocks as the computed index is indistinguishable from possible shocks.[11]

3.2. Copula-based joint probability density function (pdf)

A copula, dating back to Sklar (1959), is a multivariate joint distribution function on a group of random variables given the univariate margins. It is especially useful in the case of non-normal margins of composite errors and has been applied to some major issues such as asset pricing, risk management, and credit risk analysis. Sklar's theorem provides the theoretical underpinnings to derive the joint CDF for a set of random variables, which can be formulated as a function of their own one-dimensional margins.[12] Since the marginal distributions range from 0 to 1, the copula function can be regarded as a multivariate distribution of uniform variables with the dependence parameter, ρ, say. The merits of copulas are that they separate the modeling of marginal and dependence structure and capture both linear and non-linear relationships. The copula method has been widely employed in the area of finance and recently has been gathering more and more popularity among applied researchers in the field of efficiency and productivity analysis, mainly because of its capacity to handling the dependence structure of the error components. See, for example, Smith (2008), Carta and Steel (2012), Shi and Zhang (2011), Amsler, Prokhorov, and Schmidt (2014), and Lai and Huang (2013).

In the following, we focus only on the bivariate case that will be utilized to perform our empirical study later. The analysis can be readily generalized to cases with dimensions exceeding 2, which are somewhat complicated and require more elaboration, as discussed by Aas, Czado, Frigessi, and Bakken (2009). Let $F_1(\varepsilon_{1it})$ and $F_2(\varepsilon_{2it})$ be the respective marginal CDFs of the composite errors in Eqs. (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:

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

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, which is a 2×2 matrix, measures dependence between the marginal CDFs.

The corresponding joint pdf to (6) can be shown to be:

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

where $c(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \rho) = \partial^2 C(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \rho)/\partial F_1(\varepsilon_{1it})\partial F_2(\varepsilon_{2it})$ is the copula density and $f_j(\varepsilon_{jit})$ is the marginal pdf of $F_j(\varepsilon_{jit})$. Following Lai and Huang (2013), this paper selects the Gaussian copula to deduce the bivariate distribution and density functions of Eqs. (6) and (7). After obtaining the pdf of Eq. (7), the likelihood function is not difficult to be deduced, which is highly non-linear and can be used to estimate the unknown parameters by ML. The estimation job involves much elaboration to make this likelihood function converge.

The bi-variate Gaussian distribution function of Eq. (6) is written as:[13]

$$\begin{aligned} C(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \rho) &= \Phi_2\left(\Phi^{-1}(F_1(\varepsilon_{1it})), \Phi^{-1}(F_2(\varepsilon_{2it})); \rho\right) \\ &= \frac{1}{2\pi|\rho|^{1/2}} \exp\left[\frac{-1}{2}\zeta'_{it}\rho^{-1}\zeta_{it}\right] \end{aligned} \tag{8}$$

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 ρ that is specified by:

$$\rho = \begin{pmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{pmatrix}, \tag{9}$$

where the off-diagonal elements of ρ are the correlation coefficients between the two variables, $\zeta_{it} = \left[\Phi^{-1}(F_1(\varepsilon_{1it})) \quad \Phi^{-1}(F_2(\varepsilon_{2it}))\right]'$. The corresponding Gaussian copula density of Eq. (8) is:

$$c(F_1(\varepsilon_{1it}), F_2(\varepsilon_{2it}); \rho) = \frac{1}{|\rho|^{1/2}} \exp\left(-\frac{1}{2}\zeta'_{it}\left(\rho^{-1} - I_2\right)\zeta_{it}\right), \tag{10}$$

where I_2 is a 2×2 identity matrix.

[10] The correlation may stem from the correlation between both statistical noises possibly arising from the common stochastic shocks to some banks, or the correlation between the inefficiency term and the gap, i.e., u_1 and u_2, or both.

[11] The conventional LI is, in fact, measured by $[P_{it} - (MC_{it} + v_{2it})]/P_{it}$, which includes the random error v_{2it}.

[12] For detailed presentations of copula functions, readers are suggested to refer to Sklar (1959), Joe (1997), Frees and Valdez (1998), Cherubini, Luciano, and Vecchiato (2004), and Nelsen (2006).

[13] See chapter 4.8.1 of Cherubini et al. (2004) for a detailed description on the Gaussian copula.

The joint pdf of the composite errors in Eq. (7) is thus:

$$\begin{aligned} f(\varepsilon_{1it},\varepsilon_{2it}) &= c\left(F_1(\varepsilon_{1it}),F_2(\varepsilon_{2it});\rho\right)\times\prod_{j=1}^{2} f_j(\varepsilon_{jit}) \\ &= \frac{1}{|\rho|^{1/2}}\exp\left(-\frac{1}{2}\zeta'_{it}\left(\rho^{-1}-I_2\right)\zeta_{it}\right)\times\prod_{j=1}^{2} f_j(\varepsilon_{jit}) \end{aligned}, \tag{11}$$

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

$$\begin{aligned} \ln L(\theta) &= \sum_{i=1}^{N}\sum_{t=1}^{T} f\left(\varepsilon_{1it},\varepsilon_{2it}\right) \\ &= \sum_{i=1}^{N}\sum_{t=1}^{T}\ln c\left(F_1\left(\varepsilon_{1it}\right),F_2\left(\varepsilon_{2it}\right);\rho\right)+\sum_{j=1}^{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\ln f_j\left(\varepsilon_{jit}\right) \\ &= \frac{-NT}{2}\ln|\rho|-\frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T}\zeta'_{it}\left(\rho^{-1}-I_2\right)\zeta_{it}+\sum_{i=1}^{N}\sum_{t=1}^{T}\left[\ln f_1\left(\varepsilon_{1it}\right)+\ln f_2\left(\varepsilon_{2it}\right)\right] \end{aligned}, \tag{12}$$

where $\theta=\left(\theta_1,\theta_2;\rho\right)$, and θ_1 and θ_2 are the vectors of unknown parameters of the stochastic frontier regressions in Eqs. (2) and (5), respectively.

The ML estimation requires the evaluation of the pdf, $f_j(\varepsilon_{jit})$, $j=1$, 2, and the inverse of the distribution function $F_j(\varepsilon_{jit})$. The form of the pdf $f_j(\varepsilon_{jit})$ is already known in the literature, while the computation of the CDF, $F_j(\varepsilon_{jit})$, is intractable due to the pdf $f_j(\varepsilon_{jit})$ failing to have a closed form.[14] Greene (2003, 2010) suggested using a simulated ML estimation and Amsler et al. (2014) applied a numerical integration procedure to approximate the integration in computing $F_j(\cdot)$. We adopt the approach of Tsay et al. (2013), who showed that the approximation is quite accurate, to get the CDF $F_j(\cdot)$.

Given the pdf $f(\varepsilon_{it})$ and ignoring the subscript j temporarily, the corresponding CDF $F(Q_{it})$ of ε_{it} at point Q_{it} is written as:

$$F\left(Q_{it}\right)=\int_{-\infty}^{Q_{it}} f\left(\varepsilon_{it}\right)d\varepsilon_{it}=\frac{2}{\sigma}I(Q_{it}), \tag{13}$$

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

$$\begin{aligned} I(Q_{it}) &= \int_{-\infty}^{Q_{it}}\left[\int_{-\infty}^{\frac{\lambda\varepsilon_{it}}{\sigma}}\phi\left(\xi\right)d\xi\right]\phi\left(\frac{\varepsilon_{it}}{\sigma}\right)d\varepsilon_{it} \\ &= \int_{-\infty}^{Q_{it}}\left[\int_{-\infty}^{a\varepsilon_{it}}\phi\left(\xi\right)d\xi\right]\phi\left(b\varepsilon_{it}\right)d\varepsilon_{it}, \end{aligned} \tag{14}$$

with $a=\lambda/\sigma>0$ and $b=1/\sigma>0$. The derivation of $I\left(Q_{it}\right)$ is tedious and time consuming since the integration of (14) cannot be performed analytically. Following Tsay et al. (2013), it can be approximated by $I_{app}(Q_{it})$[15]:

$$\begin{aligned} I_{app}(Q_{it}) &= \frac{1}{2b}erf\left(\frac{bQ_{it}}{\sqrt{2}}\right)\left(\frac{1+sign(Q_{it})}{2}\right)+\frac{1}{4\sqrt{b^2-a^2c_2}}\exp\left(\frac{a^2c_1^2}{4(b^2-a^2c_2)}\right) \\ &\left\{1-erf\left[\frac{-ac_1+\sqrt{2}Q_{it}(b^2-a^2c_2)sign(Q_{it})}{2\sqrt{b^2-a^2c_2}}\right]\right\} \end{aligned}, \tag{15}$$

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

$$\begin{aligned} erf(z) &= \frac{2}{\sqrt{\pi}}\int_0^z e^{-t^2}dt=2\int_0^{\sqrt{2}z}\phi(t)dt=2\Phi\left(\sqrt{2}z\right)-1 \\ &\approx 1-\exp\left(c_1z+c_2z^2\right)=g(z) \end{aligned}. \tag{16}$$

Tsay et al. (2013) presented that the choice of constants c_1 and c_2 is to ensure that the error function $erf(z)$ can be well approximated by $g(z)$, for $z\geq 0$. The introduction of the error function and $g(z)$ into (15) and (16) is novel, and the integration of $I(Q_{it})$ in (14) can then be analytically approximated by $I_{app}(Q_{it})$. Substituting $I_{app}(Q_{it})$ into (13), the CDF of $F(.)$ is approximated by:

$$F_{app}\left(Q_{it}\right)=\frac{2}{\sigma}I_{app}\left(Q_{it}\right). \tag{17}$$

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

3.3. Financial innovation

Financial innovation can be referred to as the act of creating and popularizing new financial instruments as well as new financial technologies, institutions, and markets (Tufano, 2003), or as something under which a bank internally reduces costs and risks or externally provides some improved products and services that better satisfy the convenience and needs of clients (Frame & White, 2004). To study the relationship between competition and innovation at the bank level, we need a valid bank-specific measure of innovation. One suggestion is using an ordinal measure to discriminate the most innovative banks from the least innovative banks, which should be gauged under a uniform benchmark for each decision making unit. Previous indicators, such as the number of patents and R&D expenditures, are only appropriate for manufacturing firms, but not for banks.

Following Bos et al. (2013) and Bos, van Lamoen, and Eonomidou (2010), we employ the estimated technology gap ratio (TGR) of banks as a measure of innovation. This requires estimating individual annual cost frontiers, as well as the metafrontier that envelops these annual cost frontiers. TGR is then calculated as the ratio of the difference between the annual cost frontiers and the metafrontier to the annual cost frontiers. An increase in a bank's TGR means that the annual cost frontiers are approaching the metafrontier, due to its improvement in technology undertaken, which may be stimulated by financial innovations. The forgoing two papers adopt mathematical programming techniques to calculate each bank's TGR, which are in line with Battese et al. (2004), O'Donnell et al. (2008), and Bos and Schmiedel (2007). Huang et al. (2014) pointed out that the estimators from programming techniques lack statistical properties, are unable to take account of differences in production environments facing banks, and are incapable of being insulated from idiosyncratic shocks. They instead proposed a new two-step stochastic frontier approach to estimate the TGRs in the second step, which avoids the foregoing difficulties. We therefore adopt this new TGR measure to represent innovation. The original TGR measure of Battese et al. (2004) (henceforth, old TGR) is also calculated for the purpose of comparison. Below, the new TGR measure is briefly summarized.

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[14] The pdf is known as $f_j(\varepsilon_{jit})=\frac{2}{\sigma_j}\phi\left(\frac{\varepsilon_{jit}}{\sigma_j}\right)\Phi\left(\frac{\lambda_j\varepsilon_{jit}}{\sigma_j}\right)$, $j=1,2$, where $\lambda_j=\sigma_{uj}/\sigma_{vj}$ and $\sigma_j^2=\sigma_{vj}^2+\sigma_{uj}^2$.

[15] Readers are suggested to refer to the Appendix of Tsay et al. (2013) for a detailed derivation of $I_{app}(Q_{it})$. Note that their composite error is defined as $\varepsilon_{it}=v_{it}-u_{it}$, rather than $\varepsilon_{it}=v_{it}+u_{it}$.

In this paper we divide the sample into five groups. Each group covers three consecutive years of the sample periods in order to have enough observations in each group.[16] Rewrite Eq. (2) as:

$$\ln TC_{jit} = \ln f_{it}^{j} + \varepsilon_{1jit}, \quad j = 1, \ldots, 5 \tag{18}$$

where j signifies the j^{th} group. The group-specific frontier of $\ln f_{it}^{j}$ is associated with the metafrontier of $\ln f_{it}^{M}$ as follows:

$$\ln f_{it}^{j} = \ln f_{it}^{M} - U_{jit}^{M}, \tag{19}$$

where U_{jit}^{M} denotes the gap between the metafrontier and the group frontier, which must be non-negative by construction and is specified as a half-normal random variable, similar to u_{1it} in Eq. (2). In this manner, the metafrontier forms the envelop curve over all group frontiers. Each group's cost frontier, such as Eq. (18), is first estimated to obtain the fitted values of $\ln f_{it}^{j}$, $\ln \hat{f}_{it}^{j}$. Eq. (18) can now be expressed as:

$$\begin{aligned} \ln TC_{jit} &= \ln f_{it}^{j} + \varepsilon_{1jit}, \\ &= \ln \hat{f}_{it}^{j} + \hat{\varepsilon}_{1jit} \end{aligned} \tag{20}$$

which implies:

$$\ln \hat{f}_{it}^{j} - \ln f_{it}^{j} = \varepsilon_{1jit} - \hat{\varepsilon}_{1jit} = V_{jit}^{M}, \tag{21}$$

and V_{jit}^{M} is the estimation error. The metafrontier relation in Eq. (19) can be rewritten by replacing the unobserved group-specific frontiers f_{it}^{j} on the left-hand side with the estimates $\hat{f}_{it}^{j}$, i.e.:

$$\ln \hat{f}_{it}^{j} = \ln f_{it}^{M} - U_{jit}^{M} + V_{jit}^{M} \quad \forall i, t, j = 1, 2, \ldots, J. \tag{22}$$

Eq. (23) resembles the conventional stochastic frontier regression and can be estimated by ML. The estimated TGR must be less than or equal to unity, i.e.:

$$T\hat{G}R_{it}^{j} = \hat{E}\left(e^{-U_{jit}^{M}} | \hat{\varepsilon}_{jit}^{M}\right) \leq 1, \tag{23}$$

where $\hat{\varepsilon}_{jit}^{M} = \ln \hat{f}_{it}^{j} - \ln \hat{f}_{it}^{M}$ are the estimated composite residuals of Eq. (22). It is crucial to note that the so-derived TGR score suffers less impacts from shocks than those obtained by programming techniques.

4. The hypotheses: QLH, SH, and ECH

This subsection introduces two hypotheses to be tested.

$H1^0$: Banks with market power incur inefficiencies.

This QLH asserts that banks with market power prefer to operate inefficiently rather than reap all potential rents. Bertrand and Mullainathan (2003) pointed out that this possible negative association between efficiency and market power has prompted liberalization in some sectors of developed and developing countries in the past decades.

SH: $H2^0$: There is a negative (positive) effect of competition (market power) on innovation.

ECH: $H2^A$: There is a positive (negative) effect of competition (market power) on innovation.

Bos et al. (2013) extended the model of Aghion et al. (2005) to the banking industry, which is able to deduce both SH and ECH. The balance between the Schumpeterian and escape competition effects generates an inverted-U relationship.

The following regression equation is used to investigate the relationship between financial innovation and market competition, i.e., SH and ECH hypotheses:

$$TGR_{it} = a_i + b_1 C_{it} + b_2 C_{it}^2 + \gamma' Z_{it} + \eta_{it}, \tag{24}$$

where C denotes an index of market competition, Z is a set of control variables, η is the random disturbance, a_i signifies the fixed (random) effects, and b and γ are unknown parameters. The inclusion of the squared term of C is to account for the inverted-U pattern between competition and innovation (e.g., Aghion et al., 2005; Bos et al., 2013; , 2010; Mowrey 1985; Scherer, 1967). If C positively affects TGR, then the ECH hypothesis is supported, while a negative association between TGR and C validates the SH hypothesis. Since a larger value of C = LI reflects a lower degree of competition, and vice-versa, a negative estimate of b_1 and a positive estimate of b_2 imply the existence of the U-shape relationship between market power and innovation. This tells that the initial increase in market power hinders innovation when the monopoly rent is small, until reaching a turning point. After then, an increase in market power starts to induce innovation, driven possibly by growing monopoly rents. Conversely, if C is replaced by a competition index, such as the DC defined in footnote 18, then a positive estimate of b_1 and a negative estimate of b_2 confirm the existence of the inverted-U conjecture, since it is a direct measure of market competition.

Following Aghion et al. (2005) and Bos et al. (2013), the control variables consist of total assets, equity to total assets ratio, and average production of a full-time equivalent employee. A larger bank may be more capable of conducting the activities of research and development and diversifying various risks (Kamien & Schwartz, 1982). Hence, this variable is expected to be positively correlated with TGR. The equity to total assets ratio can be viewed as an inverse measure of debt pressure. Debt pressure may stimulate a firm's innovations to reduce the risk of bankruptcy, as Aghion et al. (2005) argued. Finally, the variable of average production per full-time employee is used to proxy for labor productivity, which is likely to be positively related to innovation.[17] Eq. (24) is further transformed, by taking the first difference to remove the unobserved heterogeneity a_i, into:

$$\Delta TGR_{it} = b_1 \Delta C_{it} + b_2 \Delta C_{it}^2 + \gamma' \Delta Z_{it} + \Delta \eta_{it}. \tag{25}$$

It is noteworthy that innovation may lower competition; or equivalently, the competition variable is likely to be endogenous due to the possible reverse causality from innovation to competition, resulting in biased parameter estimates for b_1 and b_2. This justifies the use of the generalized method of moment approach that requires collecting additional instrumental variables to solve the problem of the endogenous competition variable. We choose lags of these endogenous variables in levels and lags of control variables both in levels and in first difference as instruments for ΔC_{it} and ΔC_{it}^2.

5. Data description

We utilize the above model to investigate the competitive conditions of Taiwan's banking industry and related issues of interest. Relevant variables are compiled from the balance sheets and income statements of each sample bank, provided by the Taiwan Economic Journal (TEJ) database. Starting from 2011, some banks in Taiwan began to provide their accounting reports according to International Financial Reporting Standards (IFRS). In order to compile variables that are consistently defined over the entire sample

[16] This is mainly because our sample contains at most 48 banks in a single year.

[17] We also attempt to utilize the variable of average wage per full-time equivalent employee, as suggested by Bos et al. (2013). However, its coefficient estimate is insignificant and hence ignored.

Table 1
Descriptive statistics.

	Entire sample	Financial holding banks	Non-financial holding banks
Total revenues (TR)[a]	2.45874×10^7 (2.51191×10^7)	3.84441×10^7 (2.80792×10^7)	1.76922×10^7 2.02703×10^7
Total assets (Y)[a]	5.85774×10^8 (6.49869×10^8)	9.30391×10^8 (7.56094×10^8)	4.14291×10^8 5.10383×10^8
Total costs (TC)[a]	1.78910×10^7 (1.89923×10^7)	2.66878×10^7 (2.10901×10^7)	1.35137×10^7 (1.61872×10^7)
Price of labor (W_1)[a]	1053.2279 (337.0641)	1178.6227 (368.2333)	990.8305 (302.0366)
Price of capital (W_2)	0.3919 (0.3268)	0.3634 (0.1646)	0.40607 (0.3821)
Price of funds (W_3)	0.0303 (0.0198)	0.0291 (0.0188)	0.0309 (0.0202)
Output price (P)	0.0486 (0.0200)	0.0487 (0.0207)	0.0484 (0.0196)
Equity/total assets	0.0836 (0.0901)	0.0990 (0.1268)	0.0759 (0.0634)
Output per worker	178,476.46 (89,028.40)	211,767.63 (93,906.57)	161,910.52 (81,695.59)
DC	0.6990 (0.7205)	0.5603 (0.1493)	0.7680 (0.8675)
No. of banks	50	14	36
No. of observations	626	208	418

Note: 1. Numbers in parentheses are standard deviations.
[a] Thousands of real New Taiwan dollars with base year 2006.

period, we choose the sample period spanning from 1997 to 2011. All sample banks are domestic commercial banks and more than one half of them are listed in Taiwan's stock market. Cooperative banks, industrial banks, and branches of all foreign banks are excluded. The unbalanced panel data include 50 banks, and the total number of bank-year observations is 626. All nominal variables are deflated by the consumer price index of Taiwan with base year 2006.

Following the intermediation approach, we identify three inputs, i.e., labor (number of full-time employees, X_1), capital (total fixed assets, X_2), and borrowed funds (all types of deposits, X_3). Their corresponding prices are calculated as the ratio of personnel expenses to X_1 (W_1), the ratio of other operating expenses to $X_2(W_2)$, and the ratio of interest expenses to $X_3(W_3)$, respectively. Following the previous literature, total assets are used as the proxy for the single output (Y), and its price (P) is defined as the ratio of total revenue to output. Total cost is equal to the sum of the three input expenses.

Taiwan entered the World Trade Organization in 2001, and since then its banking industry has been facing worldwide competition in the financial markets. To promote the performance of Taiwan's banks, the government promulgated the Financial Holding Company Act in 2001, which attempts to enlarge the operating scale of banks and encourages mergers among banks and/or non-bank financial institutions, such as life and non-life insurance companies and financial securities firms, in order to achieve synergic gains from scale and scope economies and through product diversification. Therefore, we split the entire sample into two groups, i.e., financial holding banks (FHBs) and non-financial holding banks (NHBs), in an attempt to estimate and compare their performances.

Table 1 summarizes the descriptive statistics of the relevant variables, where the entire sample is split into two groups, i.e., FHBs and NHBs. The former group includes 14 banks, and the latter group contains 36 banks. It is seen that FHBs are roughly twice as large as NHBs in terms of average TC, TR, and Y, while the former charge a slightly higher output price than the latter. FHBs give higher salaries than NHBs, but pay lower prices to X_2 and X_3 than NHBs do.

If we divide the whole sample period into three sub-periods, i.e., 1997–2001, 2002–2004, and 2005–2011, then the corresponding average output prices are declining over time at 0.0673, 0.0436, and 0.0339, respectively. The average prices in the groups of FHBs and NHBs have analogous trends, which likely result from keen competition in the market, a sign of over-banking. An interesting question can be immediately raised: Does the diminishing output price imply a more competitive market and its member banks' market power fades out? This can be answered by an empirical study in the next section. Finally, the average competition index, DC, of those NHBs is greater than that of FHBs, meaning that the degree of competition among the former is fiercer than among the latter.[18] Although the average value of DC fluctuates across the three sub-periods, i.e., 0.814, 0.584, and 0.656, it shows a declining trend and is somewhat congruent with the trend of average output prices. The remaining average values across the three sub-periods are ignored to save space, but are available upon request to the authors.

6. Empirical results

6.1. Parameter estimates

Table 2 presents the joint coefficient estimates of the cost frontier and price frontier for the copula method. We also estimate the single cost frontier without considering the price equation simultaneously, and the results are shown in the last two columns of Table 2. All of the estimates of the copula method attain the 1% level of significance, while 3 estimates fail to be significant in the single equation model. The efficiency gain from using the copula method, arising from the simultaneous estimation procedure, is confirmed. These parameter estimates appear to be acceptable as the partial derivatives of the cost function with respect to the three input prices as well as the output quantity are all positive on average, which is consistent with the requirement of the microeconomic theory. It is crucial to note that the dependence parameter ρ is significantly negative, indicating that the simultaneous equation models of Eqs. (2) and (5) are preferable to the single equation model, that the omission of ρ may lead to inconsistent parameter estimates, and that the subsequent technical efficiency and LI measures may be misleading.

[18] Following Aghion et al. (2005) and Bos et al. (2013), we calculate the competition index of DC as (1–PCM), and the measure of price cost margin (PCM) is defined as $PCM_{it} = (\pi_{it} + Fix_{it})/TR_{it}$, where π_{it} is the profit of bank i at time t, Fix denotes fixed costs, and TR is total revenues. In other words, PCM is calculated by dividing the net income after taxes and extraordinary items plus expenses of premises and fixed assets by total non-interest income plus total interest income. A larger DC value denotes a higher degree of competition within the market, and vice-versa. This measure is used for the purpose of comparison to the Lerner index in testing for QLH and examining the nexus between competition and financial innovation.

Table 2
Parameter estimates of the cost function.

Variables	Copula method		Single equation	
	Cost function		Cost function	
	Parameter estimates	Standard errors	Parameter estimates	Standard errors
Constant	−8.7096***	0.0280	25.7963***	7.2682
$\ln Y$	2.1301***	0.0035	−0.4716	0.5406
$\ln Y \times \ln Y$	0.1997***	0.0003	0.1311***	0.0306
$\ln W_2$	3.8301***	0.0170	−1.5244***	0.5113
$\ln W_3$	−1.3541***	0.0047	4.6501***	0.9038
$\ln W_2 \times \ln W_2$	0.3094***	0.0011	0.0128	0.0324
$\ln W_3 \times \ln W_3$	−0.5866***	0.0025	0.3281***	0.0733
$\ln W_2 \times \ln W_3$	0.8899***	0.0023	0.0809*	0.0435
$\ln Y \times \ln W_2$	0.3342***	0.0007	0.1283***	0.0296
$\ln Y \times \ln W_3$	0.2257***	0.0004	0.0010	0.0291
t	−0.1528***	0.0005	0.6305***	0.1556
t^2	−0.0447***	0.0004	0.0049*	0.0030
$t \times \ln Y$	0.0113***	0.0003	−0.0101*	0.0054
$t \times \ln W_2$	0.2358***	0.0007	0.0254***	0.0081
$t \times \ln W_3$	−0.2028***	0.0006	0.0249**	0.0108
ρ	−0.1607***	0.0304	NA	NA
λ_1	1.1243***	0.0036	1.2577***	0.1836
λ_2	0.6140***	0.0517	NA	NA
σ_1	0.6801***	0.0023	0.3994***	0.0301
σ_2	0.0114***	0.0001	NA	NA
Log-likelihood	1166.76		−131.65	
# of observations	626		626	

Note: 1. Numbers in parentheses are standard errors.
2. W_1 is arbitrarily selected as the numeraire to satisfy the homogeneity restriction in input prices.
3. $\lambda_j = \sigma_{uj}/\sigma_{vj}$ and $\sigma_j = \sqrt{\sigma_{vj}^2 + \sigma_{uj}^2}$, where $j = 1, 2$.
* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at 1% level.

6.2. Various measures of interest

The parameter estimates in Table 2 are next applied to calculate a set of relevant measures, such as LI, cost efficiency, and scale economies (SC).[19] Table 3 summarizes the outcomes. On the basis of the copula model, the average LI is equal to 0.1362 for the entire sample period and grows over the three sub-periods, which is in line with the decreasing number of banks and is somewhat consistent with the finding of DC (see the last paragraph of Section 3). Since the estimated index is quite low, one may conclude that the market power of an average bank in Taiwan's banking sector is small, and that the market can be classified as monopolistic competition. If the conventional, single equation model is employed, then the average LI is equal to 0.1912, which is much higher than the one obtained from the copula model and shows no clear trending over the three sub-periods. These mean values are even higher, should all negative LIs be forced to be equal to zero, as shown in the brackets of Table 3. Conversely, there is no negative estimate of LI from the copula model, as the inequality relationship between output price and MC of Eq. (4) is explicitly built in by Eq. (5).

As mentioned previously, Taiwan's banking industry contains too many banks and most of them are not large. Table 3 reveals that the degrees of market competition for both FHBs and NHBs do not differ substantially from each other under the copula model. This is consistent with the reality. On the contrary, the single equation method reflects that FHBs have much higher market power than NHBs.

The mean cost efficiency measure deduced from our copula model is equal to 0.777, which lies in the range of the past literature and does not largely vary across the three sub-periods.[20] The single equation model leads to quite a high average efficiency of 0.9296. Both models find similar mean cost efficiency scores between respective FHBs and NHBs.[21] It is noteworthy that the mean efficiency score of the copula method is closer to the previous works on Taiwan's banking, e.g., Huang and Kao (2006) and Chen (2012), than the one from the single equation model, which lies on the upper end of the range of 0.31–0.97, as found by Berger and Humphrey (1997) who reviewed the outcomes of 130 financial institution efficiency works. Finally, the copula model suggests that a representative bank in Taiwan is operating under a production scale slightly in excess of the optimal scale. Among them, NHBs enjoy some extent of scale economies in the latter two sub-periods, while FHBs do not throughout the sample period. The single equation model gives similar outcomes. This finding appears to be acceptable since an average FHB is much larger than an average NHB as far as TC, TR, and Y are concerned. See Table 1.

To test for the QLH we regress the cost efficiency score over an intercept and the LI measure under the fixed effects model, as suggested by the Hausman's test. Table 4 summarizes the regression results. For the whole sample period, both the copula and single equation models validate the hypothesis, since the coefficient estimates of LI are all negative and significant at the 1% level. However, the copula model verifies the hypothesis only in the first sub-period, while in the remaining two sub-periods the coefficient estimates are either significantly positive (2002–2004)

[19] The measure of scale economies is defined as $SC = \partial \ln TC/\partial \ln Y$. A bank is producing under increasing, constant, or decreasing returns to scale if the value of SC is less than, equal to, or greater than unity.

[20] Note that this mean cost efficiency score is close to Mohanty, Lin, and Lin (2013) who assessed the cost efficiency in Taiwan's banking industry for the 1996–2011 period.

[21] However, the null hypothesis that the FHBs and NHBs are equally efficient on average, on the basis of the copula method, is rejected by the t-test statistics at least at the 10% level, except for the second sub-period of 2002–2004, i.e., the average efficiency scores of FHBs are found to be greater than those of NHBs.

Table 3
Summary statistics of the Lerner index, cost efficiency, and scale economies.

	Copula model				Single equation			
Lerner Index	1997–2011 (N = 626)	1997–2001 (N = 234)	2002–2004 (N = 140)	2005–2011 (N = 252)	1997–2011 (N = 626)	1997–2001 (N = 234)	2002–2004 n(N = 140)	2005–2011 (N = 252)
Mean	0.1362	0.0803	0.1543	0.1780	0.1912 [0.2666] {0.6990}	0.0970 [0.1833] {0.8139}	0.3020 [0.3546] {0.5840}	0.2171 [0.2950] {0.6561}
Standard Dev.	0.0868	0.0671	0.0503	0.0912	0.6350 {0.7205}	0.7645 {0.8649}	0.4575 {0.1463}	0.5745 {0.6550}
Min.	0.0266	0.0266	0.0567	0.0580	−9.5259	−9.5259	−3.7905	−5.7147
Max.	1.0000	0.8661	0.3686	1.0000	0.8390	0.7983	0.7897	0.8390
FHBs	(N = 208)	(N = 68)	(N = 42)	(N = 98)	(N = 208)	(N = 68)	(N = 42)	(N = 98)
Mean	0.1325	0.0784	0.1516	0.1619	0.2720 {0.5603}	0.2021 {0.6677}	0.3758 {0.4586}	0.2760 {0.5293}
Standard Dev.	0.0602	0.0363	0.0389	0.0557	0.1588 {0.1493}	0.1430 {0.1224}	0.1273 {0.1129}	0.1572 {0.1287}
NHBs	(N = 418)	(N = 166)	(N = 98)	(N = 154)	(N = 418)	(N = 166)	(N = 98)	(N = 154)
Mean	0.1380	0.0811	0.1554	0.1884	0.1510 {0.7680}	0.0540 {0.8739}	0.2703 {0.6378}	0.1796 {0.7368}
Standard Dev.	0.0973	0.0763	0.0546	0.1068	0.7662 {0.8675}	0.9003 {1.0187}	0.5382 {0.6042}	0.7226 {0.8225}
Cost Efficiency	(N = 626)	(N = 234)	(N = 140)	(N = 252)	(N = 626)	(N = 234)	(N = 140)	(N = 252)
Mean	0.7770	0.7792	0.7843	0.7710	0.9296	0.9335	0.9262	0.9280
Standard Dev.	0.0799	0.0821	0.0479	0.0911	0.0161	0.0133	0.0160	0.0177
FHBs	(N = 208)	(N = 68)	(N = 42)	(N = 98)	(N = 208)	(N = 68)	(N = 42)	(N = 98)
Mean	0.7902	0.8012	0.7857	0.7845	0.9322	0.9351	0.9291	0.9315
Standard Dev.	0.0758	0.0499	0.0546	0.0956	0.0170	0.0097	0.0191	0.0196
NHBs	(N = 418)	(N = 166)	(N = 98)	(N = 154)	(N = 418)	(N = 166)	(N = 98)	(N = 154)
Mean	0.7705	0.7702	0.7836	0.7624	0.9284	0.9329	0.9249	0.9257
Standard Dev.	0.0811	0.0907	0.0449	0.0873	0.0155	0.0145	0.0144	0.0161
Scale Economies	(N = 626)	(N = 234)	(N = 140)	(N = 252)	(N = 626)	(N = 234)	(N = 140)	(N = 252)
Mean	1.0406	1.1275	0.9547	1.0077	0.9843	0.9994	0.9733	0.9765
Standard Dev.	0.2775	0.2502	0.2678	0.5773	0.1273	0.1135	0.1266	0.1384
FHBs	(N = 208)	(N = 68)	(N = 42)	(N = 98)	(N = 208)	(N = 68)	(N = 42)	(N = 98)
Mean	1.1085	1.1498	1.0099	1.1221	1.0507	1.0448	1.0450	1.0572
Standard Dev.	0.1967	0.1597	0.1892	0.2103	0.0756	0.0649	0.0680	0.0851
NHBs	(N = 418)	(N = 166)	(N = 98)	(N = 154)	(N = 418)	(N = 166)	(N = 98)	(N = 154)
Mean	1.0068	1.1184	0.9310	0.9349	0.9513	0.9808	0.9426	0.9251
Standard Dev.	0.3046	0. 7882	0.2929	0.3039	0.1347	0.1236	0.1335	0.1414

Note: 1. Numbers in brackets are mean values after setting all negative values to be equal to zero.
2. Numbers in curled brackets are mean values of the DC measure.

Table 4
Testing results for the quiet life hypothesis using the fixed effects model.

Variables	Copula model Parameter estimates (standard errors)	Single equation Parameter estimates (standard errors)
1997–2011		
Lerner index	−0.2172*** (0.0400)	−0.0043*** (0.0012)
Adj. R^2	0.2426	0.5770
Number of observations	626	626
1997–2001		
Lerner index	−0.7257*** (0.0683)	−0.0024 (0.0021)
Adj. R^2	0.5315	0.3460
Number of observations	234	234
2002–2004		
Lerner index	0.1886* (0.1045)	−0.0038 (0.0028)
Adj. R^2	0.7073	0.8692
Number of observations	140	140
2005–2011		
Lerner index	0.0481 (0.0511)	−0.0041** (0.0019)
Adj. R^2	0.6537	0.8468
Number of observations	252	252

* Denotes significance at the 10% level.
** Denotes significance at the 5% level.
*** Denotes significance at the 1% level.

Table 5
Summary statistics of the TGRs.

	New metafrontier				Old metafrontier			
TGR	1997–2011 (N = 626)	1997–2001 (N = 234)	2002–2004 (N = 140)	2005–2011 (N = 252)	1997–2011 (N = 626)	1997–2001 (N = 234)	2002–2004 (N = 140)	2005–2011 (N = 252)
Mean	0.8655	0.8623	0.8767	0.8624	0.7433	0.7781	0.7088	0.7301
Standard Dev.	0.0703	0.0808	0.0544	0.0672	0.1420	0.1514	0.1266	0.1346
Min.	0.1801	0.1801	0.6780	0.5235	0.0466	0.0466	0.4021	0.3037
Max.	0.9754	0.9754	0.9629	0.9741	1.00	1.00	1.00	1.00
FHBs	(N = 208)	(N = 68)	(N = 42)	(N = 98)	(N = 208)	(N = 68)	(N = 42)	(N = 98)
Mean	0.8596	0.8591	0.8792	0.8517	0.7612	0.7843	0.7394	0.7546
Standard Dev.	0.0707	0.0699	0.0464	0.0783	0.1316	0.1543	0.1152	0.1194
NHBs	(N = 418)	(N = 166)	(N = 98)	(N = 154)	(N = 418)	(N = 166)	(N = 98)	(N = 154)
Mean	0.8685	0.8636	0.8756	0.8692	0.7343	0.7755	0.6957	0.7145
Standard Dev.	0.0700	0.0851	0.0576	0.0582	0.1463	0.1506	0.1296	0.1416

or insignificantly positive (2005–2011). In other words, the latter two sub-periods fail to confirm the hypothesis. The enforcement of the FFR policy is likely to stimulate cost efficiency when the market becomes more concentrated with larger Lerner margins. The single equation model appears to bolster the hypothesis, particularly in the last sub-periods, implying that an increase in market power prompts cost inefficiency.

We now turn to the estimation of the metafrontier cost function. Recall that we divide the sample into five groups with each group covering three consecutive years of the sample periods. These five groups' cost frontiers are first estimated according to Eq. (18), followed by the metafrontier of Eq. (22). Both the new and the old metafrontiers are estimated. Their parameter estimates are not shown to save space, but are available upon request to the authors.

Table 5 presents descriptive statistics of the TGRs from the new and the old metafrontiers. The average TGR of the new metafrontier is found to be larger than that of the old metafrontier. The former varies slightly over the three sub-periods without a clear trend, while the latter fluctuates relatively large with a downward trend. This is as expected since the old metafrontier is subject to more impact from noises than the new one, and their standard deviations confirm this. The FHBs appear to adopt similar technology to the NHBs as their average TGRs are quite close to each over time, on the basis of the new metafrontier.[22]

Table 6 shows the regression results for the nexus between financial innovation and market competition, where the former is derived from the new TGR measure. Three different regression models are estimated, and they all pass the overidentifying restriction test. Using the new TGR measure as the dependent variable, we find from Model I a U-shape relationship between innovation and market power (measured by the new LI). The implied critical value of LI is around 0.3366 (=0.2801/(2 × 0.4161)), meaning that an increase in market power initially reduces financial innovation until 0.3366, and innovation turns up after LI exceeds 0.3366. This finding partially accepts ECH when LI is small (below 0.3366), where the market is relatively competitive. The constituent banks are mostly small in size and hence may not be able to actively conduct research and development (R&D) to innovate production processes and design new financial products. This finding also partially agrees with SH once LI is large (exceeding 0.3366), where the existing banks can exert market power to enjoy large monopoly rent and are more able and willing to perform R&D activity.

Model II confirms ECH as both estimates of b_1 and b_2 are significantly negative, indicating that a decrease in LI, i.e., an increase in market competition, stimulates financial innovation. Model III supports the inverted-U conjecture when the DC variable is applied, which is consistent with Bos et al. (2013) and Bos et al. (2010).

[22] The null hypothesis that the FHBs and NHBs have equal average TGR values cannot be rejected by t-test statistics. However, on the basis of old TGRs, the FHBs tend to undertake more advanced technology to offer financial services than the NHBs do in the sample period, except for the first sub-period of 1997–2001, according to t-test statistics.

Table 6
GMM regression results for new ΔTGR.

Variables		Model I Parameter estimates (standard errors)	Model II Parameter estimates (standard errors)	Model III Parameter estimates (standard errors)
Constant		0.0031	0.0027	0.0023
		(0.0021)	(0.0019)	(0.0019)
ΔLI	(new)	-0.2801^{**}		
		(0.1307)		
ΔLI^2	(new)	0.4161^{**}		
		(0.1832)		
ΔLI	(old)		-0.1307^{***}	
			(0.0441)	
ΔLI^2	(old)		-0.0111^{**}	
			(0.0046)	
ΔDC				0.1385^{***}
				(0.0424)
ΔDC^2				-0.0091^{***}
				(0.0034)
ΔTA		$6.8885 \times 10^{-11**}$	$7.9802 \times 10^{-11***}$	$9.4738 \times 10^{-11***}$
		(2.8769×10^{-11})	(2.8370×10^{-11})	(2.8249×10^{-11})
ΔEquity/assets		-0.3021^{**}	-0.1725^{*}	-0.1402
		(0.1454)	(0.0944)	
		(0.1454)	(0.0944)	(0.0964)
ΔLab_Prod		-1.7313×10^{-7}	-1.4792×10^{-7}	-1.7618×10^{-7}
		(1.4784×10^{-7})	(1.2248×10^{-7})	(1.2154×10^{-7})
p-Value of the overidentifying restrictions test		0.998	0.999	0.999
# of observations		526	526	526

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance 1% level.

Table 7
Ordinary least squares regression results for new ΔTGR.

Variables		Model I Parameter estimates (standard errors)	Model II Parameter estimates (standard errors)	Model III Parameter estimates (standard errors)
Constant		0.0069^{*}	3.5849×10^{-5}	-0.0004
		(0.0036)	(0.0037)	(0.0037)
ΔLI	(new)	-0.9949^{***}		
		(0.1382)		
ΔLI^2	(new)	0.8729^{***}		
		(0.1409)		
ΔLI	(old)		-0.0435^{*}	
			(0.0382)	
ΔLI^2	(old)		-0.0036	
			(0.0023)	
ΔDC				0.0024
				(0.0269)
ΔDC^2				2.2938×10^{-5}
				(0.0019)
ΔTA		7.1031×10^{-11}	6.6838×10^{-11}	6.1498×10^{-11}
		(4.8807×10^{-11})	(5.1180×10^{-11})	(5.1660×10^{-11})
ΔEquity/assets		-0.1663	-0.1732	-0.1776
		(0.8851)	(0.1939)	(0.1947)
ΔLab_Prod		1.7775×10^{-7}	-5.0912×10^{-8}	-5.9698×10^{-8}
		(1.3154×10^{-7})	(1.8833×10^{-7})	(1.8883×10^{-7})
R^2		0.0978	0.0107	0.0047
# of observations		526	526	526

**Significance at the 5% level.
* Significance at the 10% level.
*** Significance 1% level.

However, the implied critical value of DC is equal to an implausible number, 7.6099 (=0.1385/(2 × 0.0091)).

The parameter estimates of variable TA in the three models are all significantly positive, which are as expected and in line with Bos et al. (2013). Similarly, the variable of the ratio of equity to total assets has the expected negative signs in Models I and II at least at the 10% level, but is insignificant in Model III. The measure of labor productivity fails to be significant in all three models.

We also present results from OLS (ordinary least squares) in Table 7. Although the magnitudes of the coefficient estimates of competition measures differ from those of Table 6, their signs are the same, except for ΔC^2 of Model III. Moreover, all control variables have no significant effects on innovations. Recall that those parameter estimates and standard errors may not be consistently estimated due to the failure of properly dealing with the endogeneity problem for competition measures. For the purpose of comparison, we also present the estimation results when innovations are measured by old TGR in Tables 8 and 9. Models I and III still confirm the presence of the U-shape and inverted-U relationships between innovations and competition, respectively, while Model II validates ECH.

Table 8
GMM regression results for old ΔTGR.

Variables		Parameter estimates (standard errors)	Parameter estimates (standard errors)	Parameter estimates (standard errors)
Constant		-6.6493×10^{-4}	-0.0092^{**}	-0.0069^{*}
		(0.0042)	(0.0041)	(0.0037)
ΔLI	(new)	-1.8453^{***}		
		(0.3000)		
ΔLI^2	(new)	1.7061^{***}		
		(0.3724)		
ΔLI	(old)		-0.2556^{***}	
			(0.0909)	
ΔLI^2	(old)		-0.0159	
			(0.0099)	
ΔDC				0.479^{***}
				(0.0904)
ΔDC^2				-0.0288^{***}
				(0.0077)
ΔTA		5.3657×10^{-11}	5.5963×10^{-11}	$1.1007 \times 10^{-10**}$
		(5.1316×10^{-11})	(5.8960×10^{-11})	(5.4330×10^{-11})
ΔEquity/assets		-0.7635^{***}	-0.7204^{***}	-0.5385^{**}
		(0.2476)	(0.2237)	(0.2294)
ΔLab_Prod		-3.8862×10^{-7}	$-7.4419 \times 10^{-7***}$	$-8.1327 \times 10^{-7***}$
		(2.6607×10^{-7})	(2.3700×10^{-7})	(2.2607×10^{-7})
p-Value of the overidentifying restrictions test		0.610	0.655	0.899
# of observations		526	526	526

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance 1% level.

Table 9
Ordinary least squares regression results for old ΔTGR.

Variables		Parameter estimates (standard errors)	Parameter estimates (standard errors)	Parameter estimates (standard errors)
Constant		0.0132^{**}	-0.0043	-0.0053
		(0.0053)	(0.0058)	(0.0058)
ΔLI	(new)	-2.7475^{***}		
		(0.1995)		
ΔLI^2	(new)	2.4821^{***}		
		(0.0324)		
ΔLI	(old)		-0.2131^{***}	
			(0.0382)	
ΔLI^2	(old)		-0.0180^{***}	
			(0.0036)	
ΔDC				0.1979^{***}
				(0.0424)
ΔDC^2				-0.0127^{***}
				(0.0030)
ΔTA		-3.4341×10^{-12}	-1.5421×10^{-13}	2.0080×10^{-11}
		(7.0454×10^{-11})	(8.0206×10^{-11})	(8.1396×10^{-11})
ΔEquity/assets		-0.5276^{*}	-0.4864	-0.4428
		(0.2721)	(0.3039)	(0.3068)
ΔLab_Prod		-1.0263×10^{-7}	$-6.8886 \times 10^{-7**}$	$-7.2953 \times 10^{-7**}$
		(2.6438×10^{-7})	(2.9514×10^{-7})	(2.9752×10^{-7})
R^2		0.2742	0.0620	0.0553
# of observations		526	526	526

* Significance at the 10% level.
** Significance at the 5% level.
*** Significance 1% level.

7. Conclusion

The main purpose of this article is proposing a new method for estimating TGRs that may mostly be immune from shocks, as well as offering the new LI under the framework of simultaneous equations that is able to impose the inequality constraint between output price and marginal cost. This inequality constraint is further transformed into a stochastic frontier regression equation with composed errors. The difficulty is how to derive the joint distribution of the maintained model that contains two error components. One contribution of this paper is that it introduces the use of the copula method, together with the approximation technique of Tsay et al. (2013). Our method is applied to estimate the market power in Taiwan's banking sector, which is then compared to the results from the conventional, single equation model. The estimated value of LI by the copula method is not large and grows with time. This is consistent with the declining number of banks in Taiwan's market, which is characterized by over-banking, while the single equation model fails to capture this trend and its LI measure tends to be over-estimated. This would mislead one to conclude that the sample banks have somewhat degrees of market power.

The average value of TGR, based on the new metafrontier, is greater than that of the old TGR and is less volatile. The copula method shows an average cost efficiency score of 0.78, well within the interval of 0.31–0.97 that is summarized by Berger and Humphrey (1997), while the same score yielded from the single equation model tends to be much larger than the related literature on the study of Taiwan's banking efficiency. The FFR policy appears to be more effective in raising banks' market power rather than enhancing their managerial ability. FHBs are on average larger in size and hence produce under decreasing returns to scale technology, while NHBs are relatively small-scaled and operate under increasing returns to scale. Evidence is found that the relationship between financial innovation and market power, measured by the new LI, is U-shaped, while ECH is supported by the old LI. The inverted-U relationship between innovation and market competition, measured by DC, is found by the data, which compromises ECH and SH. Our finding is robust over different specifications and is in line with the theoretical and empirical work of Aghion et al. (2005). The SH alone is not supported by the data.

To sum up, our empirical study finds that an increase in market power may stimulate efficiency, on the one hand, because the quiet life hypothesis is rejected by the data. On the other hand, the increase in market power helps innovation, particularly when LI is in excess of 0.3366. One is therefore led to conclude that Taiwan's financial consolidation may be a correct choice to enhance this industry's future efficiency and productivity.

An extension from the current single output setting to a multi-output one may be considered as a future research direction. Furthermore, some environmental variables can be linked with the inefficiency term of u_1 and the gap of u_2 that evaluates the distance from output price to MC. These extensions are anticipated to make the corresponding likelihood function highly non-linear and thus quite difficult to be estimated.

References

Aas, K., Czado, C., Frigessi, A., & Bakken, H. (2009). Pair-copula constructions of multiple dependence. *Insurance: Mathematics and Economics*, *44*, 182–198.

Aghion, P. C., & Griffith, R. (2005). *Competition and growth: Reconciling theory and evidence*. Cambridge, Mass.; London: MIT Press.

Aghion, P., Harris, C., Howitt, P., & Vickers, J. (2001). Competition imitation and growth with step-by-step innovation. *Review of Economic Studies*, *68*(3), 467–492.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics*, *120*(2), 701–728.

Agoraki, M. K., Delis, M. D., & Pasiouras, F. (2011). Regulations, competition and bank risk-taking in transition countries. *Journal of Financial Stability*, *7*, 38–48.

Ai-Muharrami, S., Matthews, K., & Khabari, Y. (2006). Market structure and competitive conditions in the Arab GCC banking system. *Journal of Banking and Finance*, *30*, 3487–3501.

Alegria, C., & Schaeck, K. (2008). On measuring concentration in banking systems. *Finance Research Letters*, *5*, 59–67.

Amsler, C., Prokhorov, A., & Schmidt, P. (2014). Using copulas to model time dependence in stochastic frontier models. *Econometric Reviews*, *33*, 497–522.

Angelini, P., & Cetorelli, N. (2003). The effects of regulatory reform on competition in the banking industry. *Journal of Money, Credit, and Banking*, *35*, 663–684.

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

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2006). Bank concentration, competition, and crisis: First results. *Journal of Banking and Finance*, *30*, 1581–1603.

Berg, S. A., & Kim, M. (1994). Oligopolistic interdependence and the structure of production in banking: An empirical evaluation. *Journal of Money, Credit, and Banking*, *26*, 309–322.

Berg, S. A., & Kim, M. (1998). Bank as multioutput oligopolies: An empirical evaluation of the retail and corporate banking markets. *Journal of Money, Credit, and Banking*, *30*, 135–153.

Berger, A. N., Demirgüç-Kunt, A., Levine, R., & Haubrich, J. G. (2004). Bank concentration and competition: An evolution in the making. *Journal of Money, Credit, and Banking*, *36*, 433–451.

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

Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank competition and financial stability. *Journal of Financial Services Research*, *35*, 99–118.

Bertrand, M., & Mullainathan, S. (2003). Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy*, *111*(5), 1043–1075.

Bérubé, C., Duhamel, M., & Ershov, D. (2012). Market incentives for business innovation: Results from Canada. *Journal of Industrial Competitive Trade*, *12*, 47–65.

Bikker, J. A., & Groeneveld, J. M. (2000). Competition and concentration in the EU banking industry. *Kredit and Kapital*, *33*, 62–98.

Bikker, J. A., & Haaf, K. (2002). Competition, concentration and their relationship: An empirical analysis of the banking industry. *Journal of Banking and Finance*, *26*, 2191–2214.

Bikker, J. A., Shaffer, S., & Spierdijk, L. (2012). Assessing competition with the Panzar–Rosse model: The role of scale, costs, and equilibrium. *Review of Economics and Statistics*, *94*, 1025–1044.

Boone, J. (2008). A new way to measure competition. *Economic Journal*, *118*, 1245–1261.

Bos, J. W. B., van Lamoen, R., & Eonomidou, C. (2010). Too big to innovate? Scale (dis)economies and the competition–innovation relationship in U.S. banking. *Maastricht Research School of Economics of Technology and Organization*, *54*.

Bos, J. W. B., Kolari, J. W., & van Lamoen, R. (2013). Competition and innovation: Evidence from financial services. *Journal of Banking and Finance*, *37*, 1590–1601.

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

Carbó, S., Humphrey, D., & Rodríguez, F. (2003). Deregulation, bank competition and regional growth. *Regional Studies*, *37*, 227–237.

Carbó, S., Humphrey, D., Maudos, J., & Molyneux, P. (2009). Cross-country comparisons of competition and pricing power in European banking. *Journal of International Money and Finance*, *28*, 115–134.

Carta, A., & Steel, M. F. J. (2012). Modelling multi-output stochastic frontiers using copulas. *Computational Statistics and Data Analysis*, *56*, 3757–3773.

Casu, B., & Girardone, C. (2006). Bank competition, concentration and efficiency in the single European market. *The Manchester School*, *74*, 441–468.

Chen, K. H. (2012). Incorporating risk input into the analysis of bank productivity: Application to the Taiwanese banking industry. *Journal of Banking and Finance*, *36*, 1911–1927.

Cherubini, U., Luciano, E., & Vecchiato, W. (2004). *Copula methods in finance*. New York: John Wiley.

Claessens, S., & Laeven, L. (2004). What drives bank competition? Some international evidence. *Journal of Money, Credit, and Banking*, *36*, 563–583.

De Bandt, O., & Davis, E. P. (2000). Competition, contestability and market structure in European banking sectors on the eve of EMU. *Journal of Banking and Finance*, *24*, 1045–1066.

Delis, M. D., & Tsionas, E. G. (2009). The joint estimation of bank-level market power and efficiency. *Journal of Banking and Finance*, *33*, 1842–1850.

Delis, M. D. (2010). Competitive conditions in the Central and Eastern European banking systems. *Omega*, *38*, 268–274.

Delis, M. D. (2012). Bank competition, financial reform, and institutions: The importance of being developed. *Journal of Development Economics*, *97*, 450–465.

Fernández de Guevara, J., Maudos, J., & Pérez, F. (2005). Market power in European banking sectors. *Journal of Financial Services Research*, *27*, 109–137.

Fernández de Guevara, J., Maudos, J., & Pérez, F. (2007). Integration and competition in the European financial markets. *Journal of International Money and Finance*, *26*, 26–45.

Frame, W. S., & White, L. J. (2004). Empirical studies of financial innovation: Lots of talk little action? *Journal of Economic Literature*, *42*(1), 116–144.

Frees, E. W., & Valdez, E. A. (1998). Understanding relationships using copulas. *North American Actuarial Journal*, *2*, 1–25.

Gelos, R. G., & Roldós, J. (2004). Consolidation and market structure in emerging market banking systems. *Emerging Markets Review*, *5*, 39–59.

Greene, W. H. (2003). Simulated likelihood estimation of the normal–gamma stochastic frontier function. *Journal of Productivity Analysis*, *19*, 179–190.

Greene, W. H. (2010). A stochastic frontier model with correction for sample selection. *Journal of Productivity Analysis*, *34*, 15–24.

Huang, T. H., Chiang, D. L., & Chao, S. W. (2017). A new approach to jointly estimating the Lerner index and cost efficiency for multi-output banks under a stochastic meta-frontier framework. *Quarterly Review of Economics and Finance*, in press.

Huang, C. J., Huang, T. H., & Liu, N. H. (2014). A new approach to estimating the metafrontier production function based on a stochastic frontier framework. *Journal of Productivity Analysis*, *42*, 241–254.

Huang, T. H., & Kao, T. L. (2006). Joint estimation of technical efficiency and production risk for multi-output banks under a panel data cost frontier model. *Journal of Productivity Analysis*, *26*, 87–102.

Huang, T. H., Liu, N. H., & Kumbhakar, S. C. (2016). Joint estimation of the Lerner index and cost efficiency using copula methods. *Empirical Economics*, in press.

Joe, H. (1997). *Multivariate models and dependence concepts*. London: Chapman and Hall.

Kamien, M. I., & Schwartz, N. L. (1982). *Market structure and innovation*. New York, NY: Cambridge University Press.

Koetter, M., Kolari, J., & Spierdijk, L. (2012). Enjoying the quiet life under deregulation? Evidence from adjusted lerner indices for U.S. banks. *Review of Economics and Statistics*, *94*, 462–480.

Koetter, M., & Poghosyan, T. (2009). The identification of technology regimes in banking: Implications for the marker power-fragility nexus. *Journal of Banking and Finance*, *33*, 1413–1422.

Kumbhakar, S. C., & Lovell, C. A. K. (2000). *Stochastic frontier analysis*. Cambridge: Cambridge University Press.

Lai, H. P., & Huang, C. J. (2013). Maximum likelihood estimation of seemingly unrelated stochastic frontier regressions. *Journal of Productivity Analysis*, *40*, 1–14.
Lerner, A. P. (1934). The concept of monopoly and the measurement of monopoly power. *The Review of Economic Studies*, *1*, 157–175.
Levin, R. C., & Mowrey, D. C. (1985). R&D appropriability opportunity, and market structure: New evidence on some Schumpeterian hypotheses. *American Economic Review*, *75*(2), 20–24.
Maudos, J., & Fernández de Guevara, J. (2004). Factors explaining the interest margin in the banking sectors of the European Union. *Journal of Banking and Finance*, *28*, 2259–2281.
Maudos, J., & Fernández de Guevara, J. (2007). The cost of market power in banking: Social welfare loss vs. cost inefficiency. *Journal of Banking and Finance*, *31*, 2103–2125.
Maudos, J., & Pérez, F. (2003). Factors explaining the interest margin in the banking sectors of the European Union. *Journal of Banking and Finance*, *28*, 2259–2281.
Mohanty, S. K., Lin, W. T., & Lin, H. J. (2013). Measuring cost efficiency in presence of heteroskedasticity: The case of the banking industry in Taiwan. *Journal of International Financial Markets, Institutions and Money*, *26*, 77–90.
Nelsen, R. B. (2006). *An introduction to copulas* (2nd ed.). New York: Springer-Verlag.
Nickell, S. (1996). Competition and corporate performance. *Journal of Political Economy*, *104*, 724–746.
O'Donnell, C. J., Rao, D. S. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics*, *34*, 231–255.
Panzar, J. C., & Rosse, J. N. (1987). Testing for monopoly equilibrium. *Journal of Industrial Economics*, *35*, 443–456.
Peroni, C., & Ferreira, I. S. G. (2012). Competition and innovation in Luxembourg. *Journal of Industrial Competitive Trade*, *12*, 93–117.
Prescott, H., & McCall, A. (1975). Market power and structure and commercial mank instalment lending. *Journal of Money, Credit, and Banking*, *7*, 449–467.
Scherer, F. M. (1967). Market structure and the employment of scientists and engineers. *The American Economic Review*, *57*(3), 524–531.
Schumpeter, J. A. (1942). *Capitalism, socialism and democracy*. New York, NY: Harper and Row.
Shaffer, S. (1993). A test of competition in canadian banking. *Journal of Money, Credit, and Banking*, *25*, 49–61.
Shi, P., & Zhang, W. (2011). A copula regression model for estimating firm efficiency in the insurance industry. *Journal of Applied Statistics*, *38*, 2271–2287.
Sklar, A. (1959). Functions de Répartition àn Dimensions et Leurs Marges. *Publications de l'Institut de Statistique de L'Université de Paris*, *8*, 229–231.
Smith, M. D. (2008). Stochastic frontier models with dependent error components. *Econometrics Journal*, *11*, 172–192.
Staikouras, C., & Koutsomanoli-Fillipaki, A. (2006). Competition and concentration in the new European banking landscape. *European Financial Management*, *12*, 443–482.
Tabak, B. M., Fazio, D. M., & Cajueiro, D. O. (2012). The relationship between banking market competition and risk-taking: Do size and capitalization matter? *Journal of Banking and Finance*, *36*, 3366–3381.
Tsay, W. J., Huang, C. J., Fu, T. T., & Ho, I. L. (2013). A simple closed-form approximation for the cumulative distribution function of the composite error of stochastic frontier models. *Journal of Productivity Analysis*, *39*, 259–269.
Tufano, P. (2003). *Chapter 6 Financial innovation*. pp. 307–335. *The handbook of the economics of finance* (vol. 1, Part 1) Elsevier.
Turk-Ariss, R. (2009). Competitive behavior in Middle East and North Africa banking systems. *The Quarterly Review of Economics and Finance*, *49*, 693–710.
Turk-Ariss, R. (2010). On the implications of market power in banking: Evidence from developing countries. *Journal of Banking and Finance*, *34*, 765–775.
van Leuvensteijn, M., Bikker, J. A., van Rixtel, Adrian A. R. J. M., & Sorensen, C. K. (2011). A new approach to measuring competition in the loan markets of the euro area. *Applied Economics*, *43*, 3155–3167.
van Leuvensteijn, M., Sorensen, C. K., Bikker, J. A., & van Rixtel, Adrian A. R. J. M. (2013). Impact of bank competition on the interest rate pass-through in the euro area. *Applied Economics*, *45*, 1359–1380.
Yeyati, & Micco, A. (2007). Concentration and foreign penetration in Latin American banking sectors: Impact on competition and risk. *Journal of Banking and Finance*, *31*, 1633–1647.