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ORIGINAL RESEARCH

Comparing Cost Efficiency Between Financial and Non-financial Holding Banks and Insurers in Taiwan Under the Framework of Copula Methods and Metafrontier

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Abstract

This paper examines the cost efficiency (CE), technology gap ratio (TGR), and overall cost efficiency (OCE) of 43 banks and 27 life insurance companies operating in Taiwan. The use of the copula method to derive the joint probability density function for the cost functions of financial holding banks (FHBs) and financial holding life insurers (FHLIs) allows us to take into account the operational synergies enjoyed by the financial holding companies. Our empirical results are as follows. (1) A significant, positive correlation exists between the cost efficiencies of FHBs and FHLIs, supporting that both types of firms benefit from the synergy effect. (2) The omission of synergy effects leads to underestimated measures of CE and OCE for FHBs, but leaves the measure of TGR intact. (3) The absence of synergies results in underestimating the CE scores for FHLIs, but the TGRs of FHLIs and non-FHLIs are overestimated, exaggerating the OCE scores.

Keywords Copula method · Financial holding banks · Financial holding life insurers · Stochastic metafrontier cost function · Synergy effects · CE · TGR · OCE

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1 Introduction

There has been a wave of financial liberalization and internationalization worldwide ever since 1999. The United States first passed the Financial Services Modernization Act in 1999, which repealed the Banking Act of 1933 (Glass-Steagall Act) and Bank Holding Company Act of 1956. The new law permits firms working in the financial sector to combine their various operations and invest in each other's businesses, such as insurance companies, brokerage firms, investment dealers, and commercial banks. Banks could set up financial holding companies (FHCs) that are able to include a number of divisions to conduct non-banking activities, thus becoming capable of providing one-stop shopping to customers. Filson and Olfati (2014) sustain that diversification into a set of financial activities creates value for banks.

In Europe the Second Banking Directive in 1989 deleted the obstacles between different financial service sectors. Hence, a financial institution can serve as a distribution channel of financial and insurance products [see, for example, Starita et al. (2012)]. Universal banks can form financial conglomerates, leading to gains from economies of scale and scope, as well as improvements in profit and cost efficiencies due to diversified financial institutions. The above statements are confirmed by, e.g., Lang and Welzel (1996), Vander Vennet (2002), and Rime and Stiroh (2003).

With the trend of globalization and the pressure of competition, the Taiwan government has taken steps to deregulate its financial sector. Specifically, the government enacted The Financial Institutions Merger Act and the Financial Holding Company Act in 2000 and 2001, successively. The latter act encourages domestic financial institutions to transform into financial holding companies that are able to integrate with heterogeneous financial activities, such as commercial banks, life and non-life insurance companies, securities firms, investment trust companies, etc.

There are currently 16 FHCs running in Taiwan, and most of them have banks as one of their subsidiaries, except for one of them. In addition, one of them is state-owned and is thus not publicly listed. The establishment of FHCs aims to benefit from economies of scale and scope, product diversification, cost savings, and information sharing, in such a way as to enhance overall business performance. These benefits can be dubbed as synergies. Performance comparisons between FHCs and non-FHCs have drawn much attention of academic researchers specific to financial holding banks (FHBs), which are commercial banks affiliated with FHCs, and non-FHBs. However, almost all previous studies that compare the performances between FHBs and non-FHBs do not consider the synergy effect in their theoretical or econometric models. See, for example, Kohers et al. (2000), Yamori et al. (2003), Wu (2015), and Peng et al. (2017). This makes such comparisons unfair for FHBs, since the advantageous, synergistic effects on FHBs are overlooked.

Previous research works tend to verify that the benefits of consolidation exceed its costs. Kohers et al. (2000) argue that bank consolidation in the United States prompts the efficiency of bank operations, which is estimated by both stochastic frontier approach (SFA) and data envelopment analysis (DEA). Two synergies arise from the conduct of consolidation: cost synergies and revenue synergies. If banks involved in consolidation (or mergers and acquisitions) are able to reduce their production costs, then cost synergies exist. Revenue synergies are said to prevail if the conduct of consolidation raises a bank's revenues. This article attempts to examine the issue of (cost) efficiency synergies by inspecting whether the formation of FHCs helps stimulate the cost efficiency of their subsidiaries (FHBs).

To fill the gap in the literature, this paper specifically proposes a joint estimation procedure with respect to the cost frontiers of FHBs and financial holding life insurers (FHLIs) affiliated with the same FHCs. The required econometric model can be derived using copula methods. We claim that this joint estimation approach is able to recognize the joint decision-making process within FHBs and FHLIs and thus can at least implicitly embody synergies brought by the formation of FHCs as a result. Of course, an FHC may contain quite a few types of financial institutions as mentioned above. We suggest jointly estimating the cost frontiers of FHBs and FHLIs due to two reasons as follows.

First, the scale of both types of firms is close to each other, as opposed to, e.g., the scale of a commercial bank and a securities firm, where their production scales are quite dissimilar. Our issue of synergies is thus easily highlighted. Second, we can certainly simultaneously estimate three cost frontiers of, e.g., an FHB, an FHLI, and a securities firm, which belong to the same FHC. This makes the econometric model very difficult to be estimated, on the one hand, and the size of a securities firm is usually much smaller than a commercial bank and a life insurer, on the other hand. The unbalanced operational scale among different types of sample firms under consideration is likely to hinder synergistic gains from being detected. As for non-FHBs and non-FHLIs, their cost frontiers are estimated separately, instead of jointly estimated, because their decision-making is independent of one another.

Previous researchers who assess operational efficiencies of FHBs and non-FHBs or FHLIs and non-FHLIs usually by constrast estimate those firms' individual cost frontiers and then judge their cost efficiencies, either with or without using the metafrontier framework. In this context, the synergy effect appears to play no role at all. We recommend that any comparisons between FHBs and non-FHBs and between FHLIs and non-FHLIs be executed on the basis of the stochastic metafrontier cost functions, proposed by Huang et al. (2014), in addition to the use of joint estimation for both FHBs and FHLIs. This can be defended by the fact that the metafrontier model allows firms of different groups to undertake heterogeneous technologies and enables the calculation of comparable technical efficiencies for those firms.

In summary, this article mainly proposes a joint estimation procedure for FHBs and FHLIs, which demands the use of copula methods in order to derive the required joint probability density functions (pdfs). The procedure enables us to incorporate synergy effects, generated by the formation of FHCs, in our econometric model. Our procedure, together with the metafrontier model, reflects the true performance of an FHB and an FHLI and avoids possible underestimation of cost efficiencies. The novelty of the current paper is that it is the first research work in the literature to target the joint estimation of the cost frontiers of both FHBs and FHLIs in an attempt to somehow take synergy effects into account.

The rest of this paper is organized as follows. Section 2 briefly reviews the relevant literature, including both banks and insurance companies in the context of DEA and SFA. Section 3 introduces methodologies. Section 4 states the data source and presents sample statistics. Section 5 performs empirical studies and analyzes the outcomes. The last section concludes the paper.

2 Literature Review

There are two primary approaches to evaluate the technical efficiency of firms: DEA and SFA. Both methods have their own advantages and disadvantages. Färe et al. (1994) deliver a complete discussion of DEA, which relies on the use of programming techniques such that there is no need to stipulate a functional form for the border of the production technology. We note that DEA estimates a deterministic frontier and attributes all deviations from the frontier as being inefficient. The resulting efficiency measure tends to be susceptible to the effects of random shocks. Numerous studies use DEA to estimate and compare banks' (and other firm types') efficiencies and productivity changes, e.g., Bauer et al. (1998), Weill (2004), Delis et al. (2011), Holod and Lewis (2011), Chang et al. (2012), Curi et al. (2013), Fukuyama and Weber (2015), O'Donnell et al. (2017), and Spokeviciute et al. (2019), to mention a few.

In the context of DEA, Li (2009) finds no significant difference in operational performance between FHBs and non-FHBs in Taiwan during the period 1999–2007, while Wu (2015) validates that FHBs are more efficient than non-FHBs in Taiwan using data spanning 1996–2013. On the contrary, Li et al. (2019) develop an Epsilou-based measure meta-DEA approach to estimate and compare technical efficiencies of Taiwan's banks and conclude that non-FHBs outperform FHBs in terms of the average efficiency and technology gaps. Using a two-stage DEA model, Wang et al. (2014) study the correlation between the performance of BHCs and their intellectual capital in the U.S. and find a positive relationship between them by means of the truncated-regression model.

Chronopoulos et al. (2011) provide insight into the subject of product diversification for financial conglomerates running in the accession countries over the period 2001–2007. The results advocate that banks experience relatively high cost and profit inefficiencies and that more diversified institutions are more likely to be cost-efficient and profit-efficient.

There are also numerous papers concerning the performance of insurance companies. Cummins et al. (1999) estimate cost and revenue efficiencies over the period 1988–1995 by relying on DEA and investigate the nexus between mergers and acquisitions, efficiency, and scale economies in the U.S. life insurance industry. They conclude that acquired firms enjoy greater efficiency improvements than firms not engaged in mergers or acquisitions. Cummins et al. (2010) further examine economies of scope in the U.S. insurance industry over the period 1993–2006 and attain that property-liability insurers achieve cost scope economies and revenue scope diseconomies, while life-health insurers fulfill both cost and revenue scope diseconomies.

Huang et al. (2011a) probe the relationship between corporate governance and the efficiency of the U.S. property–liability insurance industry during the period 2000–2007 and confirm the presence of the relationship between corporate governance and efficiency. Biener and Eling (2012) exploit a new cross-frontier analysis to shed some light on the association between organization and efficiency in international insurance markets with a dataset containing 23,807 firm-year observations from 21 countries. Their results verify the efficient structure hypothesis, but fail to support the expense preference hypothesis. Reyna and Fuentes (2018) fail to show significant productivity gains in the Mexico insurance market. Mirdehghan and Fukuyama (2016) propose a two-phase network DEA approach and apply the method, as well as other approaches, to the dataset of Kao and Hwang (2010) who examine 24 non-life insurers in Taiwan for the period 2001–2002. Mirdehghan and Fukuyama (2016) support the use of network DEA particularly when managers want to enhance firms' overall operational efficiency and divisional efficiency.

The topic of the deterministic frontier can be disentangled by SFA, dating back to Aigner et al. (1977) and Meeusen and van den Broeck (1977). SFA contains two error terms: first, a one-sided error term signifying technical inefficiency, and, second, a two-sided error accounting for noise. This approach requires specifying a valid functional form for the deterministic part of the frontier and valid distributional forms for the composed errors. Maximum likelihood (ML) methods are suggested for estimating the unknown parameters of the frontier. Since we plan to jointly estimate the unknown parameters of cost frontiers for both FHBs and FHLIs, SFA appears to be a preferable choice to DEA.

Using SFA, Yamori et al. (2003) probe the differences in efficiency and profitability between Japanese banks affiliated with BHCs and independent banks using data in 2002. They conclude that the former is not more cost-efficient than the latter, due possibly to the short history of Japan's regional BHCs, while the former is more profit-efficient than the latter, arising from the increase in market power in regional markets incurred by the establishment of BHCs. Akhigbe and Stevenson (2010) focus on profit efficiency and its correlation with non-interest income for BHCs using data from the U.S. covering 2003–2006 and reach a negative relationship between profit efficiency and multi-non-interest income types.

Lee et al. (2013) suggest that the Taiwan government encourages FHCs and mergers among large banks due to the subsequent cost savings. Akhigbe et al. (2017) investigate the association of ownership type with the profit efficiency of BHCs in the U.S. They assert that the difference in profit efficiency between privately held and publicly traded BHCs is small during the global financial crisis period, while no statistically significant difference prevails during the crisis period.

Peng et al. (2017) explore whether the engagement in bancassurance business is capable of enhancing efficiency and profitability of banks in Taiwan between 2004 and 2012.[1]Their empirical outcomes confirm that bancassurance business benefits bank performance (measured by efficiency and profitability) and

[1] Peng et al. (2017) define banassurance as the use of banks by insurance companies as an additional distribution channel for their products.

shareholders. Feng et al. (2017) estimate a translog stochastic distance frontier (SDF) model with time-varying heterogeneity using data on large BHCs in the U.S. over the period 2004–2013. Their empirical findings uncover that the majority of large BHCs in the U.S. exhibit increasing returns to scale and that the sample BHCs undergo small positive or even negative technical change and productivity gains.

Fenn et al. (2008) apply SFA to estimate flexible Fourier cost functions for European insurance companies, including life, non-life, and composite companies, in 14 major European countries spanning 1995–2001. They conclude that larger firms and those with high market shares are apt to have higher cost inefficiency measures. Eling and Luhnen (2010) compile data on 6462 insurers, encompassing life and non-life ones for the period 2002–2006, from 36 countries and employ both DEA and SFA to provide some empirical evidence on frontier efficiency measurement in the international insurance industry.

Gaganis et al. (2013) inspect if profit (cost) efficiency, obtained by SFA, is responsive to stock returns, using 399 listed insurance firms across 52 countries during the period 2002–2008. They discover a positive and statistically significant relationship only between profit efficiency change and market adjusted stock return. Huang et al. (2019b) compile data from 26 Taiwanese life insurers and apply a copula-based network stochastic frontier approach to investigate those insurers' technical efficiency. They attain that domestic insurers, FHLIs, and new insurers respectively outperform foreign insurers, non-FHLIs, and old insurers in Taiwan over the sample period 2000–2012.

Battese et al. (2004) are perhaps the first work systematically presenting a metafrontier production function model for firms in different groups, which permits the estimation and calculation of comparable technical efficiencies for firms running under different technologies. Later, this model has been adopted by many researchers to contrast a firm's performance in different industries, such as banks and farms, e.g., Bos and Schmiedel (2007), O'Donnell et al. (2008), Moreira and Bravo-Ureta (2010), Huang et al. (2011b), Chen (2012), and Huang and Fu (2013). The second step of this mixed approach utilizes mathematical programming techniques to estimate the metafrontier, where the potential difficulty comes from its lack of statistical properties of the metafrontier estimator results. Huang et al. (2014) propose a new approach for estimating a metafrontier production function, in which the second step is altered to estimate a stochastic metafrontier production function in the context of an econometric approach. Several empirical scholars undertake this new approach, such as Chang et al. (2015), Jiang and Sharp (2015), Lee and Huang (2017), Melo-Becerra and Orozco-Gallo (2017), Chaffai and Hassan (2019), Huang et al. (2019a), Bravo-Ureta et al. (2020), and Safiullah and Shamsuddin (2021).

Copula methods have recently been utilized to derive the joint distribution of the composite errors, whose marginal distributions are uniform. Some example studies include Park and Gupta (2012), Amsler et al. (2014), Lai and Huang (2013), Huang et al. (2019b), to mention a few. This method is particularly useful when a part or all of the individual errors have, e.g., skewed normal distributions, such that their joint distribution is very barely derivable.

3 Econometric Models

Our research aims to estimate and compare the performance between FHBs and non-FHBs and between FHLIs and non-FHLIs, where the synergistic effects, accompanied by the establishment of FHCs, are exemplified through the joint estimation of FHBs with FHLIs under copula methods. As for non-FHBs and non-FHLIs, we estimate their cost frontiers separately. Finally, we use the stochastic metafrontier model of Huang et al. (2014) to compare efficiency scores among different groups. Below we illustrate our estimation procedure.

3.1 Stochastic Cost Frontiers

We assume that banks hire three inputs $x = \left(x_1 x_2 x_3\right)'$ with input prices $w = \left(w_1 w_2 w_3\right)'$ to produce three outputs $y = \left(y_1 y_2 y_3\right)'$. Let $C(w, y)$ be the cost function, which is specified as having a translog form:

$$\ln\left(\frac{E}{w_1}\right) = \ln C\left(\frac{w}{w_1}, y\right) + v + u = \alpha_0 + \sum_{k=2}^{3} \alpha_k \ln\frac{w_k}{w_1} + \frac{1}{2}\sum_{k=2}^{3}\sum_{j=2}^{3} \alpha_{kj} \ln\frac{w_k}{w_1} \ln\frac{w_j}{w_1} + \sum_{m=1}^{3} \beta_m \ln y_m + \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3} \beta_{mn} \ln y_m \ln y_n$$
$$+ \sum_{k=2}^{3}\sum_{m=1}^{3} \gamma_{km} \ln\frac{w_k}{w_1} \ln y_m + \sum_{k=1}^{2} \frac{1}{k}\delta_k t^k + \sum_{j=2}^{3} \delta_{j+1} t \ln\frac{w_j}{w_1} + \sum_{m=1}^{3} \delta_{m+4} t \ln y_m + v + u, \tag{1}$$

where E denotes the observed expenditure, α, β, γ, and δ are unknown parameters, $v \sim N\left(0, \sigma_v^2\right)$ is the error term, and $u \sim N^+\left(0, \sigma_u^2\right)$ signifies technical inefficiency independent of v. The presence of u is to capture the input-oriented technical inefficiency that pushes the actual cost E in excess of the optimal cost. Note that the homogeneity constraint has been imposed on (1).[2] The symmetry restrictions must be imposed before estimating (1), i.e., $\alpha_{kj} = \alpha_{jk}, i \neq j$, and $\beta_{mn} = \beta_{nm}, m \neq n$.

Let $\varepsilon_i = v_i + u_i$ be the composed error of the i^{th} observation, whose probability density function (pdf) is known as:

$$f\left(\varepsilon_i\right) = \frac{2}{\sigma}\phi\left(\frac{\varepsilon_i}{\sigma}\right)\Phi\left(\frac{\varepsilon_i \lambda}{\sigma}\right), \tag{2}$$

where $\phi(\bullet)$ and $\Phi(\bullet)$ denote the pdf and cumulative distribution function (CDF) of the standard normal distribution, respectively, $\lambda = \sigma_u / \sigma_v$, and $\sigma^2 = \sigma_v^2 + \sigma_u^2$. The following conditional mean can serve as a point estimator of u_i:

$$CI_i = E\left(u_i | \varepsilon_i\right) = \mu_{*i} + \sigma_* \left[\frac{\phi\left(\frac{-\mu_{*i}}{\sigma_*}\right)}{1 - \Phi\left(\frac{-\mu_{*i}}{\sigma_*}\right)}\right], \tag{3}$$

[2] This is done by dividing E and w by w_1, which is arbitrarily selected and can be replaced by either w_2 or w_3.

where $\mu_{*i} = \varepsilon_i \sigma_u^2 / \sigma^2$ and $\sigma_*^2 = \sigma_v^2 \sigma_u^2 / \sigma^2$. The i^{th} bank's point estimator of cost efficiency (CE) can be calculated as:

$$CE_i = \exp\left(-CI_i\right). \tag{4}$$

Since CI_i is expected to be non-negative, the cost efficiency measure of CE_i ranges between zero and unity. The closer is the value of CE_i to unity, the more technically efficient is the bank, and the reverse is true when CE_i is close to zero.

3.2 Stochastic Metafrontier Cost Function

Readers are suggested to refer to Huang et al. (2014) for details about the model of the stochastic metafrontier production function. Here, we extend it to a cost function. Assume that there are J groups in the sample and that each group is composed of N_j observations. For example, this study compares efficiencies between FHBs and non-FHBs and between FHLIs and non-FHLIs. Hence, $J=2$. It is worth mentioning for the groups of non-FHBs and non-FHLIs that their cost frontiers are formulated similar to (1) and are estimated separately.[3] For the groups of FHBs and FHLIs, both cost frontiers should be estimated simultaneously to exemplify the synergy effect. The estimation procedure will be illustrated in the next subsection.

Given the SFA estimates of the group-specific cost frontiers $\widehat{C}_i^j\left(w_{ji}, y_{ji}\right)$ for all $i=1,\ldots,N_j$ and $j=1,\ldots, J$ groups from (1), the estimation error of the group-specific frontier is then:

$$\ln\widehat{C}_i^j\left(w_{ji}, y_{ji}\right) - \ln C_i^j\left(w_{ji}, y_{ji}\right) = \varepsilon_{ji} - \widehat{\varepsilon}_{ji}, \tag{5}$$

where $\widehat{\varepsilon}_{ji}$ denotes the residual. The relation between the group-specific cost frontier and the metafrontier cost functions is given by:

$$\ln C_i^j\left(w_{ji}, y_{ji}\right) = \ln C_i^M\left(w_{ji}, y_{ji}\right) + U_{ji}^M, \forall i, j. \tag{6}$$

The metafrontier cost function of $\ln C_i^M\left(w_{ji}, y_{ji}\right)$ by definition envelops all individual groups' cost frontiers from below and hence $U_{ji}^M \geq 0$, which reflects the gap between the group-specific frontiers and the metafrontier and will be specified as a one-sided error later. Defining the estimation error in (5) as $V_{ji}^M = \varepsilon_{ji} - \widehat{\varepsilon}_{ji}$, the metafrontier relation in (6) can be rewritten by replacing the unobserved group-specific frontiers $C_i^j\left(w_{ji}, y_{ji}\right)$ on the left-hand side with the estimates $\widehat{C}_i^j\left(w_{ji}, y_{ji}\right)$, i.e.:

$$\ln\widehat{C}_i^j\left(w_{ji}, y_{ji}\right) = \ln C_i^M\left(w_{ji}, y_{ji}\right) + V_{ji}^M + U_{ji}^M. \tag{7}$$

[3] Note that the numbers of inputs and outputs may differ in both industries. For details, please see section IV.

Equation (7) is similar to the conventional stochastic frontier regression and is therefore called the stochastic metafrontier (SMF) regression by Huang et al. (2014).[4] We estimate the SMF of banks using the observations from both FHBs and non-FHBs and the SMF of insurers using the observations from both FHLIs and non-FHLIs. In other words, we estimate two SMFs separately. One of them represents the banking industry and the other the insurance industry.

The ratio of the metafrontier cost function to the j^{th} group's cost frontier is labeled as the technology gap ratio (TGR), i.e.:

$$TGR_i^j = \frac{C_i^M\left(w_{ji}, y_{ji}\right)}{C_i^j\left(w_{ji}, y_{ji}\right)} = exp\left(-U_{ji}^M\right) \leq 1. \tag{8}$$

The presence of the technology gap accounts for the choice of a particular technology that rests on the production environments. The technology gap component U_{ji}^M in (7) thus varies across group and firm, which is subject to the accessibility and extent of undertaking the obtainable metafrontier production technology. The larger is the gap component U_{ji}^M, the less advanced technology the firm adopts, and hence the smaller is the TGR score. The reverse is true when U_{ji}^M is smaller.

Following Battese et al. (2004) and Huang et al. (2014), we define the overall cost efficiency score (OCE) as:

$$OCE_{ji} = \frac{C_i^M\left(w_{ji}, y_{ji}\right)e^{v_{ji}}}{E_{ji}} = CE_i^j \bullet TGR_i^j, \tag{9}$$

where CE_i^j is calculated from (4), TGR_i^j comes from (6), and the term $e^{v_{ji}}$ is treated like an error term arising from the substitution of $\widehat{C}_i^j\left(w_{ji}, y_{ji}\right)$ for $C_i^j\left(w_{ji}, y_{ji}\right)$, since $C_i^j\left(w_{ji}, y_{ji}\right)$ is in fact unobservable and has to be replaced by its estimated value, i.e., $\widehat{C}_i^j\left(w_{ji}, y_{ji}\right)$. The measure of OCE is then decomposed into two items, CE_i^j and TGR_i^j, where the first item is derived from the group-specific cost frontier, representing the managerial abilities of the firm, and the latter is from the metafrontier.

3.3 Copula Methods

To account for synergy effects in our econometric model for the groups of FHBs and FHLIs we propose a simultaneous estimation procedure that is able to characterize, to some extent, the joint decision process inherent to an FHC. Recall that both groups' cost frontiers contain a composed error with a skewed normal distribution. The copula methods appear to be a suitable choice to derive the joint pdf for the two error components, as having been employed by, e.g., Lai and Huang (2013), Huang et al. (2019b).

[4] The distinction between the SMF and the model proposed by Battese et al. (2004) and O'Donnell et al. (2008) is the emergence of the term ofV_{ji}^M in (7), which makes (7) a regression equation, instead of a deterministic regression such that linear programming techniques are required to find the cost boundary.

Let $F_1(\varepsilon_{1i})$ and $F_2(\varepsilon_{2i})$ be the marginal CDFs of ε_{1i} (for FHBs) and ε_{2i} (for FHLIs), respectively, and their correlation coefficient is denoted by ρ. According to the theory of Sklar (1959), we specify the joint CDF ofε_{1i} and ε_{2i}, $F(\varepsilon_{1i}, \varepsilon_{2i})$ as:

$$F(\varepsilon_{1i}, \varepsilon_{2i}) = C(F_1(\varepsilon_{1i}), F_2(\varepsilon_{2i});\rho), \tag{10}$$

where $C(\bullet)$ is the copula function of $F_1(\varepsilon_{1i})$ and $F_2(\varepsilon_{2i})$. If $F_1(\varepsilon_{1i})$ and $F_2(\varepsilon_{2i})$ are continuous functions, then a unique copula function can be identified. After taking the second-order partial derivative of $F(\varepsilon_{1i}, \varepsilon_{2i})$ with respect to ε_{1i} and ε_{2i}, the joint pdf of ε_{1i} and ε_{2i} can then be expressed as:

$$f(\varepsilon_{1i}, \varepsilon_{2i}) = c(F_1(\varepsilon_{1i}), F_2(\varepsilon_{2i});\rho) \cdot f_1(\varepsilon_{1i}) \cdot f(\varepsilon_{2i}), \tag{11}$$

where $c(F_1(\varepsilon_{1i}), F_2(\varepsilon_{2i});\rho) = \partial^2 C(F_1(\varepsilon_{1i}), F_2(\varepsilon_{2i});\rho)/\partial F_1(\varepsilon_{1i})\partial F_2(\varepsilon_{2i})$ is the copula density function, and $f_j(\varepsilon_{ji}), j = 1, 2$, is the marginal pdf of ε_{ji}, similar to (2).

There are many different copula functions being developed in the literature, such as multivariate Student's *t* copula, Archimedean copula, Gumble *n*-copula, Clayton *n*-copula, and so on, with different dependence structures. Readers are suggested to refer to Cherubini et al. (2004) for a thorough review of the copula functions. Following Lai and Huang (2013), Huang et al. (2017), and Amsler et al. (2016, 2017), we choose the Gaussian copula to derive the bi-variate distribution function of (10), which takes the form[5]:

$$\begin{aligned} C(F_1(\varepsilon_{1i}), F_2(\varepsilon_{2i});\Omega) &= \Phi_2(\Phi^{-1}(F_1(\varepsilon_{1i})), \Phi^{-1}(F_2(\varepsilon_{2i}));\Omega) \\ &= \int_{-\infty}^{\Phi^{-1}(F_1(\varepsilon_{1i}))} \int_{-\infty}^{\Phi^{-1}(F_2(\varepsilon_{2i}))} \frac{1}{2\pi|\Omega|^{1/2}} exp\left\{ \frac{-1}{2} Z'\Omega^{-1}Z \right\} dZ_1 dZ_2, \end{aligned} \tag{12}$$

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

$$\Omega = \begin{pmatrix} 1 & \Omega_{12} \\ \Omega_{12} & 1 \end{pmatrix}, \tag{13}$$

where the off-diagonal elements of Ω_{12} denotes the correlation coefficients between the two variables. The corresponding Gaussian copula density of (11) is written as:

$$c(F_1(\varepsilon_{1i}), F_2(\varepsilon_{2i});\Omega) = \frac{1}{|\Omega|^{1/2}} exp\left\{ -\frac{1}{2}\xi_i'(\Omega^{-1} - I_2)\xi_i \right\}, \tag{14}$$

where $\xi_i = [\Phi^{-1}(F_1(\varepsilon_{1i})), \Phi^{-1}(F_2(\varepsilon_{2i}))]'$, and I_2 is a 2×2 identity matrix.

[5] See chapter 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 ranges 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.

Plugging (14) into (11), we obtain the joint pdf of the composite errors in (11):

$$\begin{aligned} f(\varepsilon_{1i},\varepsilon_{2i}) &= c(F_1(\varepsilon_{1i}),F_2(\varepsilon_{2i});\Omega)\cdot f_1(\varepsilon_{1i})\cdot f(\varepsilon_{2i}) \\ &= \frac{1}{|\Omega|^{1/2}} exp\left\{-\frac{1}{2}\xi_i'(\Omega^{-1}-I_2)\xi_i\right\}\cdot f_1(\varepsilon_{1i})\cdot f(\varepsilon_{2i}). \end{aligned} \tag{15}$$

Finally, the implied log-likelihood function takes the following form:

$$\begin{aligned} \ln L(\theta) &= \sum_{i=1}^{N} \ln f(\varepsilon_{1i},\varepsilon_{2i}) = \sum_{i=1}^{N} \ln c(F_1(\varepsilon_{1i}),F_2(\varepsilon_{2i});\Omega) + \sum_{i=1}^{N}\sum_{j=1}^{2} \ln f_j(\varepsilon_{ji}) \\ &= -\frac{N}{2}\ln|\Omega| - \frac{1}{2}\sum_{i=1}^{N}\xi_i'(\Omega^{-1}-I_2)\xi_i + \sum_{i=1}^{N}\sum_{j=1}^{2}\ln f_j(\varepsilon_{ji}). \end{aligned} \tag{16}$$

Here, θ represents all of the unknown parameters in the cost frontiers of FHBs and FHLIs, as well as Ω_{12}. The first two terms on the right-hand side of (16) describe the correlations between the two cost frontiers, and the last term corresponds to the log-likelihood function derived from a separate regression. Although the separate regression may give consistent estimates and suitable standard errors under correctly specified marginal densities, the standard errors are less efficient than those yielded by maximizing (16), provided that the correct copula density is incorporated.

Lai and Huang (2013) suggest conducting the Hausman (1987) test by comparing the difference in the estimators of the separate and joint estimation of (16). If the copula function is misspecified, then the two sets of estimators will have different probability limits. The test statistic can be shown to have a Chi-squared distribution with K degrees of freedom, i.e.:

$$H = \left(\hat{\theta}_S - \hat{\theta}_J\right)'\left[C\hat{o}v\left(\hat{\theta}_S\right) - C\hat{o}v\left(\hat{\theta}_J\right)\right]^{-1}\left(\hat{\theta}_S - \hat{\theta}_J\right) \sim \chi^2_K, \tag{17}$$

where subscripts S and J denote separate and joint estimation, $\hat{\theta}$ is the estimated vector of parameters, and K is the number of common parameters in the separate and joint estimation. The rejection of the H statistic supports the use of the Gaussian copula, and hence of (16), to implement the empirical study.

It can be seen from (2) that the pdfs of the composite errors of ε_{1i} and ε_{2i} involve a CDF of the standard normal distribution that has no closed functional form. Unfortunately, (15) requires researchers to offer both functional forms of $F_1(\varepsilon_{1i})$ and $F_2(\varepsilon_{2i})$. Greene (2003) suggests using the simulated ML method, and Amsler et al. (2014) apply the numerical integration procedure to approximate the integration in calculating$F_j(\bullet)$, j= 1, 2. Here, we follow Tsay et al. (2013) to derive the approximate function of$F_j(\bullet)$, denoted by $F_j^{app}(\bullet)$, which has been utilized by, e.g., Lai and Huang (2013), Huang et al. (2017, 2018, 2019b).

From now on we omit the subscripts of j and i for notational conciseness. The CDF of ε, $F(Q)$, evaluated at a point Q can be written as:

$$P(\varepsilon \le Q) = F(Q) = \frac{2}{\sigma} I(Q),$$

where:

$$I(Q) = \int_{-\infty}^{Q} \left(\int_{-\infty}^{\frac{\varepsilon\lambda}{\sigma}} \phi(\omega) d\omega \right) \phi\left(\frac{\varepsilon}{\sigma} \right) d\varepsilon. \tag{18}$$

The integration of (18) can at most be done approximately by $I^{app}(\bullet)$, i.e.:

$$\begin{aligned} I(Q) \approx I^{app}(Q) = \frac{1}{4\sqrt{\mathrm{b}^2 - \mathrm{a}^2\mathrm{c}_2}} \exp\left\{ \frac{a^2 c_1^2}{4\left(b^2 - a^2 c_2\right)} \right\} \\ \left\{ 1 - erf\left(\frac{-ac_1 + \sqrt{2}Q\left(b^2 - a^2 c_2\right) sign(Q)}{2\sqrt{b^2 - a^2 C_2}} \right) \right\} + \frac{erf\left(\frac{bQ}{\sqrt{2}}\right)}{2b} \left(\frac{1 + \mathrm{sign}(Q)}{2} \right), \end{aligned} \tag{19}$$

where $c_1 = -1.0950081470333$ and $c_2 = -0.75651138383854$are two constants that can make the approximation function quite close to the true value, as claimed by Tsay et al. (2013).[6] Moreover, $a = \lambda/\sigma$, $b = 1/\sigma$, $sign(Q) = 1, 0$, and -1, corresponding to $Q > 0, = 0$, and < 0, respectively, and the error function is defined as:

$$erf(\omega) = 2\int_0^{\sqrt{2}\omega} \phi(t)dt = 2\Phi\left(\sqrt{2}\omega\right) - 1 \approx 1 - \exp\left(c_1\omega + c_2\omega^2\right).$$

4 The Data

4.1 Data Sources

We collect banking data mainly from the Taiwan Economic Journal (TEJ) databank covering 2002–2017. Recall that this paper focuses on the performance comparisons between FHBs and non-FHBs and between FHLIs and non-FHLIs operating in Taiwan. Therefore, only domestic commercial banks and life insurers are selected without considering foreign banks and non-commercial banks. After deleting missing data, we have 43 banks with 483 bank-year observations, where some of them have been acquired. The sample banks can be classified as 7 FHBs with 83 observations and 36 non-FHBs with 403 observations.[7]

We are able to compile 27 insurance companies running in Taiwan also spanning the period 2002–2017, after removing five insurers whose data are either not accessible entirely or a few variables are not available, while acquired insurers are kept in the data. The main source of data is from TEJ, along with "The Annual Report

[6] Tsay et al. (2013) prove that the approximation error is within10^{-5}.

[7] Some FHCs contain either no commercial bank or no insurance company. Their affiliated insurers or banks are therefore identified as non-FHLIs or non-FHBs.

Table 1 Sample statistics for banks

	Mean	Standard Dev.	Mean	Standard Dev.
Non-FHBs			FHBs	
TC_b	13,823,181.41	11,846,624.14	28,361,358.17	19,730,463.75
y_1 *	135,304,292.54	146,665,677.36	391,342,317.90	396,993,447.35
y_2 *	440,956,816.72	461,938,921.20	869,011,035.00	682,931,900.73
y_3 *	3,149,174.77	3,398,967.43	7,332,405.48	6,898,879.49
x_1 **	2,978.38	2,057.54	5,408.12	2,634.88
x_2 *	8,682,992.89	8,377,021.66	28,193,339.83	31,091,600.57
x_3 *	553,040,677.39	546,820,956.38	1,252,756,802.78	1,069,762,670.54
w_1 *	1,229.81	373.99	1,285.34	289.02
w_2	0.7062	2.4156	0.3773	0.1936
w_3	0.0141	0.0077	0.0133	0.0069
# of observations	403		83	

*Measured by thousands of NTD and deflated by Taiwan's CPI with the base year of 2016

**Measured by number of persons

of Life Insurance in Taiwan". There are 283 insurer-year observations, including 7 FHLIs with 83 observations and 20 non-FHLIs with 200 observations. It is pivotal to note that the number of observations and sample periods for the seven pairs of FHBs and FHLIs must be identical since their group-specific cost frontiers are suggested to be jointly estimated in order to account for synergy effects, arising from the establishment of FHCs. Their operational strategies are expected to be, more or less, interdependent, which may vary across different FHCs with distinct business culture and tradition. As for non-FHBs and non-FHLIs, their group-specific cost frontiers are separately estimated.

Once obtaining the parameter estimates for the four groups' cost frontiers, we can calculate their fitted values to be used as the dependent variable in (7). This allows us to estimate the SMF cost function for banks using the fitted costs of FHBs and non-FHBs as the dependent variable and to estimate the SMF cost function for insurers using the fitted costs of FHLIs and non-FHLIs as the dependent variable. The estimation of those SMF cost functions enables one to calculate TGR in accordance with (8) and then to compute OCE on the basis of (9) for both banks and insurers.

4.2 Variable Definitions and Sample Statistics

Following most of the previous works, we adopt the intermediation approach proposed by Sealey and Lindley (1977) to identify the input and output variables for banks. Specifically, we define three inputs and three outputs for banks, where the former are labor (x_1, number of full-time equivalent employees), capital (x_2, net fixed assets), and funds (x_3, various types of deposits) and the latter are investments (y_1, other earning assets including bonds and securities), loans (y_2, various loans), and non-interest income (y_3, fee income, commission, etc.). The input prices are

Table 2 Sample statistics for insurers

	Mean	Standard Dev.	Mean	Standard Dev.
Non-FHLIs			FHLIs	
*TC_in**	5,422,869.91	7,004,859.27	14,596,514.49	11,302,780.76
y_1 *	39,551,906.63	53,447,186.20	198,369,353.32	165,448,720.70
y_2 *	8,687,434.62	15,146,206.49	53,523,011.63	51,333,956.93
x_1 **	823.86	968.41	2,086.30	1,538.75
x_2 *	2,304,908.83	3,454,049.64	9,045,610.66	8,311,578.83
x_3 **	5,417.73	8,709.59	19,719.99	19,800.93
w_1 *	1,494.10	2,064.73	1,717.78	1,484.54
w_2	0.4037	0.9201	0.1466	0.2220
w_3 *	2,303.64	3,669.10	2,074.42	3,824.11
# of observations	200		83	

*Measured by thousands of NTD and deflated by Taiwan's CPI with the base year of 2016

**Measured by number of persons

computed by dividing the corresponding expenditure by the input quantity. Specifically, the price of labor (w_1) is calculated as the ratio of personnel expenses to the number of employees, the price of capital (w_2) is equal to the ratio of operational expense net of personnel expenses to capital, and the price of funds (w_3) is equal to the ratio of interest expenses to funds. The sum of expenditures on labor, capital, and funds is defined as total costs (TC_b). Note that TC_b and w_1 are measured in terms of thousands of New Taiwan dollar (NTD), which are further deflated by the consumer price index (CPI) of Taiwan with the base year of 2016.

Table 1 presents descriptive statistics for the relevant variables and classify them into non-FHBs and FHBs. It is apparent that the magnitudes of FHBs are, on average, much larger than those of non-FHBs in terms of TC_b and the quantities of inputs and outputs. Moreover, those differences attain statistical significance. FHBs compensate their employees with higher wages than non-FHBs, while they pay lower input prices to capital and funds.

Following Fecher et al. (1993), Cummins et al. (1999), and others, we define three inputs and two outputs for insurers, where the former are the number of internal staffs (x_1), capital (x_2, measured by net fixed assets), and the number of field staffs (x_3), and the latter are premium income (y_1)and investment income (y_2). The price of internal staffs (w_1) is calculated as the ratio of personnel expenses to the number of internal staffs, the price of capital (w_2) is equal to the ratio of the sum of depreciation, bad debts, and amortization expenses to capital, and the price of external staffs (w_3) is identified as the ratio of underwriting and commission expenses to the number of external staffs. The sum of the above three types of expenditure constructs the insurer's total costs (TC_in). Variables w_1, w_3, and TC_in are measured in terms of thousands of NTD, which are further deflated by the CPI of Taiwan with the base year of 2016.

Table 2 presents sample statistics for the variables of interest and divides them into two groups: non-FHLIs and FHLIs. It can be seen that the sizes of FHLIs are, on average, much larger than those of non-FHLIs in terms of TC_in and the quantities of inputs and outputs. Those differences also achieve statistical significance. FHLIs compensate their internal staffs with a higher wage than non-FHLIs, while they pay lower input prices to capital and field staffs.

5 Empirical Results

5.1 Parameter Estimates of the Group-Specific Frontier

Our estimation procedure is composed of two steps. In the first step we jointly estimate the cost frontiers of FHBs and FHLIs by means of copula methods and then estimate the cost frontiers of non-FHBs and non-FHLIs separately. All estimations are executed by ML. We claim that the joint estimation procedure enables us to take synergy effects into account for banks and insurers under FHCs, which adopt different technologies from those same types of firms under non-FHCs. In the second step, the parameter estimates of the above four groups are applied to calculate the fitted cost values that will be treated as the dependent variable in (7) such that the two stochastic metafrontier cost functions for banks and insurers can be respectively estimated, according to the model developed by Huang et al. (2014). The values of TGR can then be computed.

Table 3 lists the joint estimation results of (16) for both FHBs and FHLIs under the framework of the copula method. More than a half of the parameter estimates are significantly estimated at least at the 10% level for the group-specific cost frontier of banks; nonetheless, the estimates for FHLIs are less satisfactory. There are merely 9 out of 23 estimates that attain statistical significance at least at the 10% level. The estimated dependence parameter of Ω_{12} is equal to 0.2432 and is significant at the 10% level. This reflects that both cost frontiers of FHBs and FHLIs are positively correlated, due possibly to the correlation between statistical noises and/or inefficiency of the two composed errors. This may signify the presence of the joint decision-making process under an FHC and the presence of possible synergy effects due to the creation of FHCs. The H test statistic of (17) is equal to 8407.7, which justifies the use of the Gaussian copula.

To highlight the importance of using the copula method to characterize the joint decision-making process between FHBs and FHLIs, we estimate the individual cost frontiers of FHBs and FHLIs without relying on the copula method; i.e., those two cost frontiers are estimated separately such that synergy effects are overlooked. We also distinctly estimate the cost frontiers of non-FHBs and non-FHLIs and the estimation results are shown in Tables 4 and 5. More than a half of the parameter estimates achieve statistical significance at least at the 10% level. It is interesting to note that the magnitudes and signs of those parameter estimates for FHBs and FHLIs in Tables 4 and 5 are somewhat close to those in Table 3. This reveals that those estimates appear to be acceptable and somewhat robust. Note that this does not necessarily imply that the subsequent calculation (e.g., CE, TGR, and OCE) from using those estimates in Tables 3, 4, 5 is close to one another. We now are capable

Table 3 Parameter estimates of FHBs and FHLIs using the Copula method

Explanatory variable	FHBs		FHLIs	
	Estimate	Std. Error	Estimate	Std. Error
Ω_{12}	0.2432*	0.1345		
λ	1.0825	1.9091	0.6257**	0.3040
σ	0.1051**	0.0454	0.2408***	0.0297
Constant	37.3692***	3.9473	5.8628	15.1132
$\ln y_1$	1.0312***	0.2397	6.5867***	2.3597
$\ln y_2$	− 2.8609***	0.2049	− 6.1363***	1.7532
$\ln y_3$	2.0318***	0.3559		
$\ln(w_2/w_1)$	0.6701	0.5855	2.6324**	1.1283
$\ln(w_3/w_1)$	4.1490***	0.4267	− 0.8672	1.7655
$0.5 \times (lny_1)^2$	0.1170***	0.0148	− 0.8035***	0.2764
$0.5 \times (lny_2)^2$	0.4413***	0.0140	0.0979	0.2497
$0.5 \times (lny_3)^2$	− 0.0751**	0.0364		
$\ln y_1 \times \ln y_2$	− 0.2211***	0.0082	0.3537	0.2306
$\ln y_1 \times \ln y_3$	0.1278***	0.0162		
$\ln y_2 \times \ln y_3$	− 0.1415***	0.0147		
$0.5 \times [\ln(w_2/w_1)]^2$	0.0256	0.0551	0.0561	0.0499
$0.5 \times [\ln(w_3/w_1)]^2$	0.4619***	0.0697	− 0.3541***	0.0932
$\ln(w_2/w_1)\ln(w_3/w_1)$	− 0.0524	0.0443	− 0.0880	0.0577
$\ln(w_2/w_1) \times \ln y_1$	− 0.0628***	0.0241	− 0.2330*	0.1214
$\ln(w_2/w_1) \times \ln y_2$	− 0.1377***	0.0252	0.1280	0.1076
$\ln(w_2/w_1) \times \ln y_3$	0.1942***	0.0279		
$\ln(w_3/w_1) \times \ln y_1$	0.1086***	0.0233	− 0.0609	0.1294
$\ln(w_3/w_1) \times \ln y_2$	0.0477**	0.0230	0.0473	0.0876
$\ln(w_3/w_1) \times \ln y_3$	− 0.1225***	0.0346		
t	− 0.1765	0.1263	− 0.0684	0.5463
$0.5t^2$	− 0.0049*	0.0029	− 0.0007	0.0083
$t \times \ln y_1$	0.0085	0.0076	0.0302	0.0522
$t \times \ln y_2$	0.0087	0.0117	− 0.0258	0.0380
$t \times \ln y_3$	0.0006	0.0098		
$t \times \ln(w_2/w_1)$	− 3.4229E− 05	0.0095	0.0067	0.0138
$t \times \ln(w_3/w_1)$	0.0111	0.0133	0.0442*	0.0237
Log-likelihood value	79.6314		#of observations	83

*, **, and ***Denote significance at the 10%, 5%, and 1% levels, respectively

$\lambda = \sigma_u/\sigma_v$ and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$

of calculating the fitted cost values for each bank and insurer and ready to proceed to the second step, which aims to estimate the SMF cost functions for banks and insurers.

Table 4 Parameter estimates of FHBs and Non-FHBs without synergy effects

Explanatory variable	FHBs		Non-FHBs	
	Estimate	Std. Error	Estimate	Std. Error
Constant	37.9988***	8.7351	4.6249	6.5292
$\ln y_1$	1.0517*	0.5448	− 0.9989**	0.4866
$\ln y_2$	− 3.3953***	1.0608	2.9780***	0.8173
$\ln y_3$	1.8073	1.1298	− 0.4532	0.7075
$\ln(w_2/w_1)$	0.6776	0.6083	1.1794**	0.5032
$\ln(w_3/w_1)$	3.1179**	1.4200	2.3185**	0.9887
$0.5 \times (lny_1)^2$	0.0812**	0.0385	− 0.0583	0.0361
$0.5 \times (lny_2)^2$	0.4107**	0.1652	− 0.2816***	0.0871
$0.5 \times (lny_3)^2$	0.0028	0.0854	0.0254	0.0554
$\ln y_1 \times \ln y_2$	− 0.1333**	0.0598	0.1315***	0.0475
$\ln y_1 \times \ln y_3$	0.0588	0.0368	0.0091	0.0287
$\ln y_2 \times \ln y_3$	− 0.1635	0.1230	− 0.0032	0.0654
$0.5 \times [\ln(w_2/w_1)]^2$	− 0.0892	0.0576	− 0.2070***	0.0358
$0.5 \times [\ln(w_3/w_1)]^2$	0.3878***	0.1235	0.2201***	0.0819
$\ln(w_2/w_1)\ln(w_3/w_1)$	− 0.0441	0.0481	0.0416	0.0356
$\ln(w_2/w_1) \times \ln y_1$	− 0.0265	0.0224	0.0809***	0.0236
$\ln(w_2/w_1) \times \ln y_2$	− 0.1668**	0.0714	− 0.3276***	0.0531
$\ln(w_2/w_1) \times \ln y_3$	0.1268**	0.0639	0.1893***	0.0446
$\ln(w_3/w_1) \times \ln y_1$	0.0856**	0.0338	0.0054	0.0419
$\ln(w_3/w_1) \times \ln y_2$	0.0804	0.0850	0.1591**	0.0642
$\ln(w_3/w_1) \times \ln y_3$	− 0.1282*	0.0688	− 0.1604***	0.0542
t	− 0.1304	0.1688	0.2042*	0.1136
$0.5t^2$	− 0.0043**	0.0022	0.0021	0.0018
$t \times \ln y_1$	0.0067	0.0054	0.0091	0.0058
$t \times \ln y_2$	0.0132	0.0118	0.0024	0.0088
$t \times \ln y_3$	0.0090	0.0090	− 0.0150**	0.0066
$t \times \ln(w_2/w_1)$	0.0074	0.0065	− 0.0093*	0.0053
$t \times \ln(w_3/w_1)$	0.0261*	0.0149	0.0259***	0.0095
σ	0.0967***	0.0066	0.3439***	0.0170
λ	137.9910	315,054.0	689.3890	434,087.0
Log-likelihood	− 113.847		− 626.092	
#of observations	83		403	

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

$\lambda = \sigma_u/\sigma_v$ and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$

5.2 Parameter Estimates of the SMF Cost Functions

Following Huang et al. (2014), we regard the fitted cost values, obtained from Subsection5.1, as the dependent variables to estimate the stochastic metafrontier of (7)

Table 5 Parameter estimates of FHLIs and Non-FHLIs without synergy effects

Explanatory variable	FHLIs		Non-FHLIs	
	Estimate	Std. Error	Estimate	Std. Error
Constant	− 16.0793***	4.9351	36.2437***	3.0904
$\ln y_1$	9.7668***	2.1657	− 2.3478*	1.3748
$\ln y_2$	− 5.4529**	2.1796	− 2.4453*	1.2871
$\ln(w_2/w_1)$	5.1181***	0.8761	− 0.5019**	0.2275
$\ln(w_3/w_1)$	− 1.9074**	0.9595	− 0.2079	0.7831
$0.5 \times (lny_1)^2$	− 0.6299**	0.2811	0.1907	0.1799
$0.5 \times (lny_2)^2$	0.4677***	0.1771	0.0063	0.0412
$\ln y_1 \times \ln y_2$	− 0.0521	0.2095	0.0737	0.1141
$0.5 \times [\ln(w_2/w_1)]^2$	0.2183***	0.0354	− 0.0123*	0.0065
$0.5 \times [\ln(w_3/w_1)]^2$	− 0.1951***	0.0522	− 0.1058***	0.0405
$\ln(w_2/w_1)\ln(w_3/w_1)$	− 0.2727***	0.0450	− 0.0339**	0.0152
$\ln(w_2/w_1) \times \ln y_1$	− 0.1675*	0.0978	0.1553***	0.0211
$\ln(w_2/w_1) \times \ln y_2$	− 0.0198	0.0891	− 0.1587***	0.0281
$\ln(w_3/w_1) \times \ln y_1$	− 0.1295***	0.0460	− 0.0370	0.0876
$\ln(w_3/w_1) \times \ln y_2$	0.0991	0.0611	0.0694*	0.0420
t	− 0.5021**	0.2227	0.2403	0.1501
$0.5t^2$	0.0026	0.0031	0.0196***	0.0034
$t \times \ln y_1$	0.1173***	0.0191	− 0.0031	0.0131
$t \times \ln y_2$	− 0.0800***	0.0217	− 0.0172***	0.0054
$t \times \ln(w_2/w_1)$	0.0385***	0.0129	0.0184***	0.0040
$t \times \ln(w_3/w_1)$	0.0164	0.0130	− 0.0170***	0.0043
σ	0.4038***	0.0444	0.8269***	0.0591
λ	75.9884	2251.5800	235.2530	4499.7800
Log-likelihood	− 46.1465		− 246.793	
#of observations	83		200	

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

$\lambda = \sigma_u/\sigma_v$ and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$

for banks and insurers by ML. Tables 6 and 7 display the outcomes, which incorporate both sets of parameter estimates with and without reflecting synergy effects. If the dependent variables of FHBs and FHLIs are calculated from the joint estimation of (16), whose coefficient estimates are shown in Table 3, together with the dependent variables of non-FHBs and non-FHLIs calculated from both right halves of Tables 4 and 5, then the estimation results are shown in the left halves of Tables 6 and 7 under the title of "With Synergy Effects". If the dependent variables of FHBs, non-FHBs, FHLIs, and non-FHLIs are acquired from a separate estimation, using the coefficient estimates in Tables 4 and 5, then the estimation results are displayed in the right halves of Tables 6 and 7 under the title of "Without Synergy Effects".

Table 6 Parameter estimates of the SMF cost function for banks

Explanatory variable	With synergy effects		Without synergy effects	
	Estimate	Std. Error	Estimate	Std. Error
Constant	4.0285	4.8186	4.5046***	1.5970
$\ln y_1$	− 1.0224***	0.2250	− 1.0103***	0.1488
$\ln y_2$	3.0096***	0.3135	3.0016***	0.3035
$\ln y_3$	− 0.4216	0.2931	− 0.4559***	0.0734
$\ln(w_2/w_1)$	1.1761***	0.1631	1.1814***	0.0495
$\ln(w_3/w_1)$	2.2735***	0.4036	2.3156***	0.0852
$0.5 \times (lny_1)^2$	− 0.0603***	0.0181	− 0.0590***	0.0094
$0.5 \times (lny_2)^2$	− 0.2884***	0.0563	− 0.2851***	0.0440
$0.5 \times (lny_3)^2$	0.0260	0.0162	0.0240	0.0189
$\ln y_1 \times \ln y_2$	0.1362***	0.0376	0.1332***	0.0212
$\ln y_1 \times \ln y_3$	0.0067	0.0205	0.0087	0.0060
$\ln y_2 \times \ln y_3$	− 0.0025	0.0172	− 0.0019	0.0176
$0.5 \times [\ln(w_2/w_1)]^2$	− 0.2101***	0.0263	− 0.2066***	0.0054
$0.5 \times [\ln(w_3/w_1)]^2$	0.2159***	0.0388	0.2197***	0.0090
$\ln(w_2/w_1)\ln(w_3/w_1)$	0.0421***	0.0130	0.0420***	0.0062
$\ln(w_2/w_1) \times \ln y_1$	0.0823***	0.0131	0.0807***	0.0027
$\ln(w_2/w_1) \times \ln y_2$	− 0.3294***	0.0197	− 0.3278***	0.0056
$\ln(w_2/w_1) \times \ln y_3$	0.1887***	0.0125	0.1900***	0.0101
$\ln(w_3/w_1) \times \ln y_1$	0.0035	0.0183	0.0058	0.0052
$\ln(w_3/w_1) \times \ln y_2$	0.1601***	0.0184	0.1598***	0.0098
$\ln(w_3/w_1) \times \ln y_3$	− 0.1588***	0.0189	− 0.1615***	0.0148
t	0.2011***	0.0334	0.2041***	0.0097
$0.5t^2$	0.0021***	0.0004	0.0021***	0.0003
$t \times \ln y_1$	0.0085*	0.0048	0.0091***	0.0005
$t \times \ln y_2$	0.0028	0.0040	0.0024***	0.0009
$t \times \ln y_3$	− 0.0149***	0.0020	− 0.0151***	0.0009
$t \times \ln(w_2/w_1)$	− 0.0091***	0.0017	− 0.0092***	0.0007
$t \times \ln(w_3/w_1)$	0.0255***	0.0039	0.0259***	0.0011
σ	0.7240***	0.1653	0.3542***	0.0308
λ	38.8577	287.0120	44.2054	538.9360
Log-likelihood	− 461.455		− 199.410	
#of observations	486		486	

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

$\lambda = \sigma_u/\sigma_v$ and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$

Table 6 presents the outcomes specific to banks. The estimated parameters for both models of "with and without synergy effects" are close to one another to some extent, and most of those estimates achieve at least the 10% significance level. However, their log-likelihood values differ substantially.

Table 7 Parameter estimates of the SMF cost function for insurers

Explanatory variable	With synergy effects		Without synergy effects	
	Estimate	Std. Error	Estimate	Std. Error
Constant	25.7220***	2.5408	24.0553***	2.4152
$\ln y_1$	– 0.7028	0.5108	– 0.3907	0.5207
$\ln y_2$	– 2.6263***	0.4672	– 2.6590***	0.5025
$\ln(w_2/w_1)$	0.0242	0.1728	0.1065	0.1694
$\ln(w_3/w_1)$	– 0.5313***	0.1798	– 0.4277**	0.1852
$0.5 \times (lny_1)^2$	0.0388	0.0930	0.0873	0.0944
$0.5 \times (lny_2)^2$	0.0231	0.0703	0.0976	0.0696
$\ln y_1 \times \ln y_2$	0.0964	0.0811	0.0249	0.0822
$0.5 \times [\ln(w_2/w_1)]^2$	– 0.0061	0.0110	0.0066	0.0111
$0.5 \times [\ln(w_3/w_1)]^2$	– 0.1392***	0.0177	– 0.1064***	0.0201
$\ln(w_2/w_1)\ln(w_3/w_1)$	– 0.0391***	0.0133	– 0.0742***	0.0139
$\ln(w_2/w_1) \times \ln y_1$	0.0703**	0.0338	0.0888***	0.0337
$\ln(w_2/w_1) \times \ln y_2$	– 0.0897***	0.0308	– 0.1108***	0.0315
$\ln(w_3/w_1) \times \ln y_1$	0.0733***	0.0229	0.0405*	0.0226
$\ln(w_3/w_1) \times \ln y_2$	– 0.0498**	0.0210	– 0.0334	0.0212
t	0.2824***	0.0592	0.2535***	0.0621
$0.5t^2$	0.0154***	0.0018	0.0158***	0.0016
$t \times \ln y_1$	– 0.0175*	0.0097	– 0.0109	0.0101
$t \times \ln y_2$	– 0.0054	0.0086	– 0.0090	0.0091
$t \times \ln(w_2/w_1)$	0.0103***	0.0033	0.0145***	0.0035
$t \times \ln(w_3/w_1)$	– 0.0003	0.0037	– 0.0131***	0.0037
σ	0.2476***	0.0146	0.1850***	0.0286
λ	2.2847***	0.3497	0.6131	0.5861
Log-likelihood	– 87.7492		– 93.1738	
#of observations	283		283	

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

$\lambda = \sigma_u/\sigma_v$ and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$

Table 7 presents the outcomes specific to insurers. Likewise, the estimated coefficients for both models of "with and without synergy effects" are near to one another, and most of those estimates achieve at least the 10% significance level. Their log-likelihood values are close to each other, due potentially to fewer observations involved. Although the parameter estimates shown in Tables 6 and 7 are not quite different between the respective two models, whether their implied efficiency scores and various measures, such as scale economies and technical change, are similar is worth a deeper investigation.

Table 8 Various performance measures of banks based on group frontiers

	Mean	Standard Dev.	Mean	Standard Dev.
With synergy effects			Without synergy effects	
FHBs			FHBs	
SE	0.7372	0.1027	0.7621	0.1648
TC	− 0.0135	0.0257	− 0.0090	0.0295
CE	0.9390	0.0249	0.8100	0.0650
#of observations	83		83	
			Non-FHBs	
SE			0.8541	0.0735
TC			− 0.0019	0.0193
CE			0.5504	0.0953
#of observations			403	

5.3 Measures of CE and Scale Economies (SE) for Banks

The coefficient estimates of the foregoing group-specific cost frontier can be applied to gauge cost efficiency scores (CE), scale economies (SE), and the rate of technical change (TC) for each bank and insurer. Table 8 shows the average values of relevant measures for banks, where the figures in the left two columns are derived in the context of copula methods for FHBs, while those in the right two columns are obtained without using copula methods for both FHBs and non-FHBs. It is crucial to note that the model using copula methods leads to a higher average efficiency score (0.939) than that of the non-copula model (0.810). If an average FHB is producing on the boundary of the production technology, then it can save respectively 6.1% and 19% of its current expenditure to produce the same level of output. This implies that the omission of synergy effects tends to underestimate cost efficiency on average and hence confirms that the use of copula methods may help discover the true cost efficiency of FHBs and FHLIs affiliated with FHCs. The average cost efficiency score of non-FHBs is found to be equal to 0.5504. Although this value is much lower than those of FHBs, they are not directly comparable, because they are measured against different benchmarks (cost boundaries).

Since all three average values of SE are less than unity, increasing returns to scale technology prevail in both forms of banks.[8] FHBs and non-FHBs are suggested to expand their production scale to lower their long-run average costs. In addition, all three average values of TC are negative, indicating the presence of technical progress during the sample period.[9] Their cost frontiers shift down with time at the rates of 1.35%, 0.9%, and 0.19% per annum. Again, the model that takes synergy

[8] The measure of SE is calculated as $SE = \sum_{i=1}^{3} \partial \ln C / \partial \ln y_i$.

[9] The measure of TC is formulated as $TC = \partial \ln C / \partial t$.

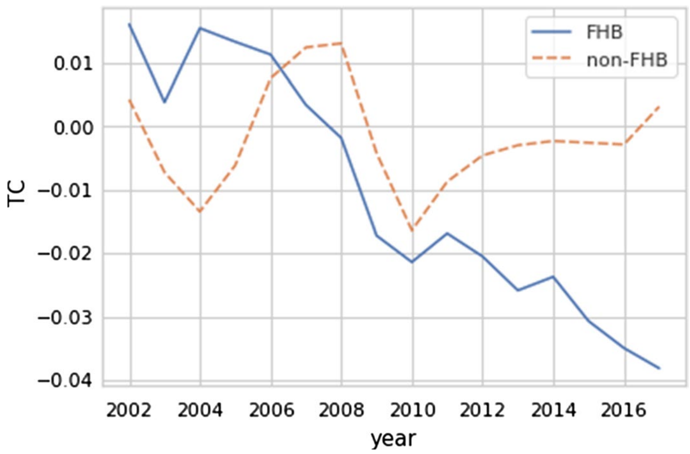

Fig. 1 Trends of average TC for FHBs (with synergies) and non-FHBs

Table 9 The average values of CE, TGR, and OCE for banks with synergies

	#of observations	Mean	Standard Err.
CE			
FHBs	83	0.9390	0.0249
Non-FHBs	403	0.5504	0.0953
TGR			
FHBs	83	0.4590	0.0797
Non-FHBs	403	0.5440	0.0940
t-statistic	− 8.5676***		
OCE			
FHBs	83	0.4318	0.0808
Non-FHBs	403	0.3084	0.1135
t-statistic	11.7329***		

***Denotes significance at the 1% level

effects into account gives the fastest rate of technical advancement at 1.35%, validating the usefulness of copula methods in reflecting the advantages of FHCs.

We also draw the diagrams for the above three measures, but choose to show the one for TC only to save space, and because it is the most heuristic.[10] Figure 1 illustrates that before 2007 the average TC measures of FHBs are positive, implying the existence of technical regression. This measure turns negative thereafter, supporting the occurrence of technical improvement. Recall that Taiwan's Financial Holding

[10] Both diagrams of CE for FHBs and non-FHBs are found to peak in 2007 and achieve a trough in 2009 after the subprime crisis. The measure of SE for non-FHBs slightly fluctuates around 0.85 during the sample period, while the same measure for FHBs increases over time from around 0.58 in 2002 to 0.87 in 2017, except for the years of 2007 and 2009.

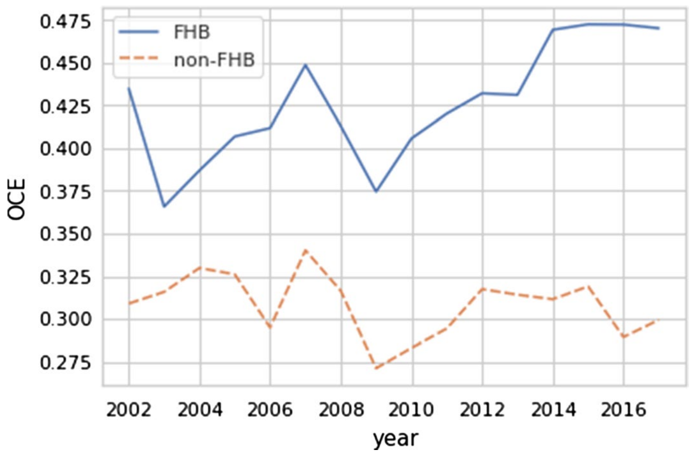

Fig. 2 Trends of average OCE for FHBs and non-FHBs

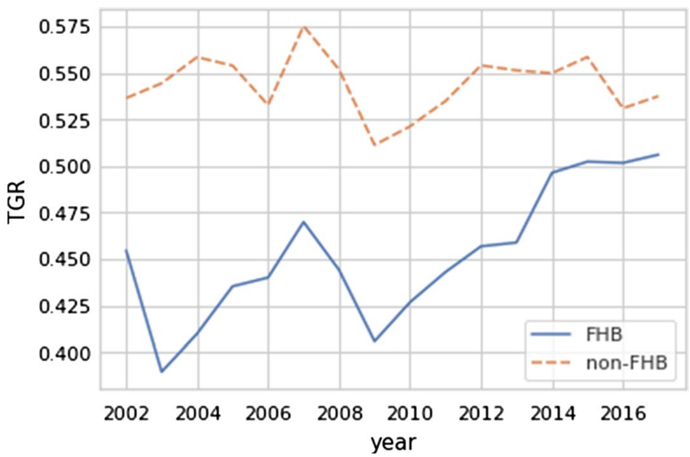

Fig. 3 Trends of average TGR for FHBs and non-FHBs

Company Act was passed in 2001. The period 2002–2007 can be viewed as the early stage of the formation of FHCs or a run-in period, such that the beneficiary effects of FHCs are either off-set or unable to come into play. It is not until 2008 and later that the gains of FHCs are unleashed, making the absolute value of the mean TC of FHBs to grow swiftly from about 0 to 3.8% per year. Conversely, the average TC values of non-FHBs fluctuate up and down with positive values during most of the sample years, except for 2 years, i.e., 2004 and 2010.

Table 10 Various performance measures of insurers based on group frontiers

	Mean	Standard Dev.	Mean	Standard Dev.
With synergy effects			Without synergy effects	
FHLIs				
SE	0.8933	0.2443	0.9867	0.4007
TC	− 0.0441	0.0664	− 0.0409	0.0710
CE	0.8976	0.0321	0.7792	0.1805
#of observations	83		83	
			Non-FHLIs	
SE			0.7006	0.4014
TC			− 0.0532	0.0826
CE			0.5955	0.2544
#of observations			200	

5.4 Measures of TGR and OCE for Banks

Employing the parameter estimates of Table 6, we can compute the measures of TGR and OCE for each bank, which allows one to compare the performance between FHBs and non-FHBs under the framework of the SMF cost function. According to Table 9, we see that FHBs outperform non-FHBs in the sense that the former's average OCE (0.432) is higher than that of the latter (0.308). This difference achieves statistical significance at the 1% level and becomes larger particularly after 2009, which corresponds to the turning points for FHBs and non-FHBs, as depicted in Fig. 2. FHBs are producing closer to the cost metafrontier than non-FHBs. The superiority of FHBs comes primarily from their higher average CE measures instead of average TGR. Although Table 9 displays that the difference in average TGR between both types of banks is significant at the 1% level, Fig. 3shows that their gaps shrink after 2009, implying that the technology adopted by FHBs catches up with non-FHBs over time. The foregoing findings are consistent with Wu (2015), Lee et al. (2013), and Yamori et al. (2003), while they deviate from Li et al. (2019), whose empirical results bolster the dominance of non-FHBs over FHBs.

5.5 Measures of CE and SE for Insurers

Table 10 presents the average values of CE, SE, and TC for insurers. Similar to Table 8 for banks, the model using copula methods leads to a higher average cost efficiency score (0.898) than that of the non-copula model (0.779). If an insurer is producing on the frontier of the production technology, then it can cut respectively 10.2% and 22.1% of its current expenditure to produce the same level of output. This implies that ignoring synergy effects is apt to undervalue CE on average and hence explains that the use of copula methods helps uncover the true CE of FHBs and FHLIs affiliated with FHCs. The average CE score of non-FHLIs is equal to 0.596, implying a potential 40.4% in cost savings can be achieved. It is interesting to note

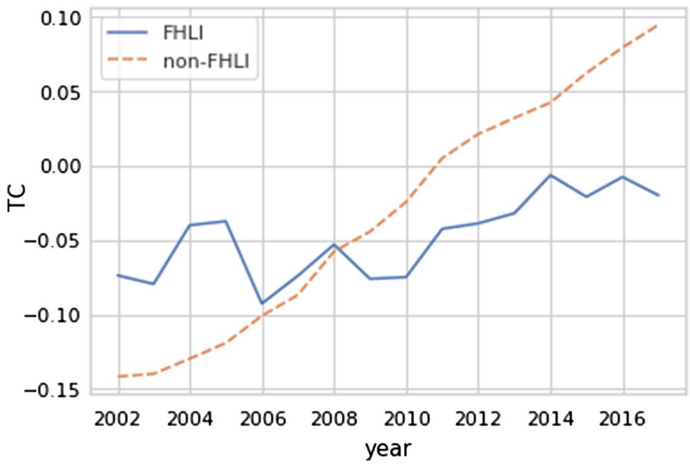

Fig. 4 Trends of average TC for FHLIs (with synergies) and non-FHLIs

Table 11 The average values of CE, TGR, and OCE for insurers with synergies

	#of observations	Mean	Standard Dev.
CE			
FHLIs	83	0.8976	0.0321
Non-FHLIs	200	0.5955	0.2544
TGR			
FHLIs	83	0.7137	0.1448
Non-FHLIs	200	0.5638	0.2010
t-statistic	7.0289***		
OCE			
FHLIs	83	0.6432	0.1419
Non-FHLIs	200	0.3853	0.2647
t-statistic	10.5919***		

***Denotes significance at the 1% level

that Pearson and Spearman rank correlation coefficients between FHBs and FHLIs are equal to 0.2590 and 0.2595, respectively, and both of them are significantly different from zero at the 1% level. This positive correlation verifies that the existence of the joint decision-making procedure between FHBs and FHLIs is affiliated with FHCs and the necessity of applying copula methods.

Since all three average values of SE are less than unity, increasing returns to scale technology prevail in both forms of insurers.[11] FHLIs and non-FHLIs are recommended to keep raising their production scale so as to lower their long-run average

[11] The SE measure of FHLIs excluding the synergy effects is equal to 0.987, which is quite close to unity and corresponds to constant returns to scale.

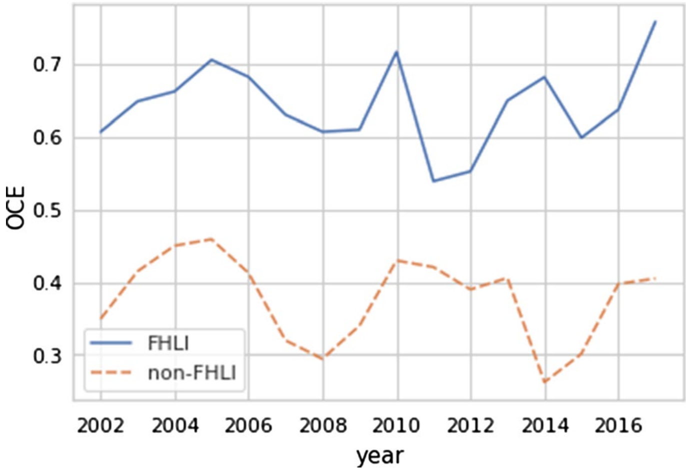

Fig. 5 Trends of average OCE for FHLIs and non-FHLIs

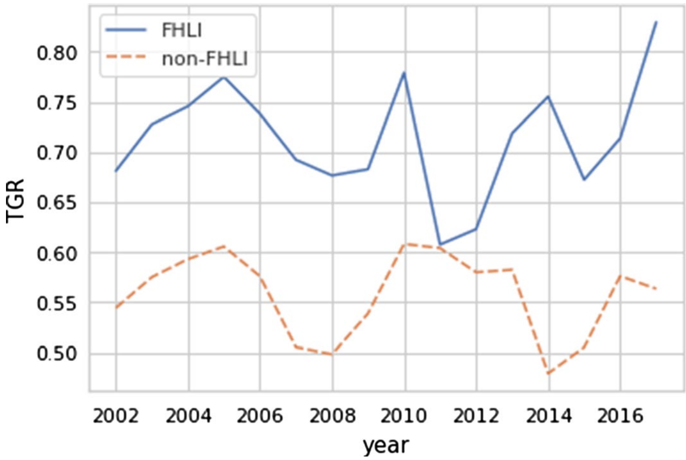

Fig. 6 Trends of average TGR for FHLIs and non-FHLIs

cost. All three average values of TC are negative, revealing the occurrence of technical progress during the sample period. Their cost frontiers shift down with time at the rates of 4.41%, 4.09%, and 5.32% per annum. For this case, non-FHLIs have the fastest rate of technical advancement, while the difference between both forms of insurers is around one percentage point.

Similar to banks, we choose to display the diagram of TC only. Figure 4 exhibits that the average TC measures of FHLIs across time are all negative, but slightly decreasing in absolute value, indicating the prevalence of technical progress during the sample period at a decreasing rate. The average TC values of non-FHLIs monotonically deteriorate over time and turn positive after 2010, supporting technical regression since then.

Table 12 Efficiency comparisons for banks without synergy effects

	#of observations	Mean	Standard Dev.
CE			
FHBs	83	0.8100	0.0650
Non-FHBs	403	0.5504	0.0953
TGR			
FHBs	83	0.4619	0.0798
Non-FHBs	403	0.5482	0.0948
t-statistic	− 8.6666***		
OCE			
FHBs	83	0.3766	0.0857
Non-FHBs	403	0.3107	0.1146
t-statistic	5.9847***		

***Denotes significance at the 1% level

Table 13 Efficiency comparisons for insurers without synergy effects

	# of observations	Mean	Standard Dev.
CE			
FHLIs	83	0.7792	0.1805
Non-FHLIs	200	0.5955	0.2544
TGR			
FHLIs	83	0.8821	0.0503
Non-FHLIs	200	0.8192	0.0936
t-statistic	7.3042**		
OCE			
FHLIs	83	0.6923	0.1811
Non-FHLIs	200	0.5102	0.2568
t-statistic	6.7623***		

***Denotes significance at the 1% level

5.6 Measures of TGR and OCE for Insurers

Using the parameter estimates shown in Table 7, we can calculate the measures of TGR and OCE for insurers with and without taking synergy effects into account. This permits us to compare the production performance between FHLIs and non-FHLIs under the framework of the SMF cost function. Table 11 presents that FHLIs outperform non-FHLIs in the sense that the former's average OCE (0.643) is significantly higher than that of the latter (0.385) at the 1% level. This divergence is mainly attributed to the component of CE, where the average CE of FHLIs (0.898) is much higher than that of non-FHLIs (0.596), rather than the average TGR (0.714 vs. 0.564). FHLIs are producing nearer to the cost metafrontier than non-FHLIs.

Figures 5 and 6depict that the largest gaps of OCE and TGR between both types of insurers take place in 2008 and 2014, which may arise respectively from the occasion of the subprime crisis in the U.S. and from two severe accidents incurring large amounts of insurance claims. One of the accidents was the air crash of a plane of TransAsia Airways (an airline in Taiwan), resulting in 43 deaths and 15 injured, and the other was the explosion due to a propylene leakage in Kaohsiung City, causing 32 deaths and 321 injured. Both accidents tended to adversely impact the smaller-sized non-FHLIs greater than they did to larger-sized FHLIs. Our empirical results support the advantage of FHLIs over non-FHLIs and justify the formation of FHCs in terms of CE, TGR, and OCE. The foregoing is congruent with Fenn et al. (2008) and Huang et al. (2019b), whose data include insurance companies only.

5.7 Results Excluding Synergy Effects

To illustrate the consequence of ruling out synergy effects from the model of SMF cost functions, we also compute the relevant measures similar to the above four subsections and draw diagrams analogous to the above six figures. However, we choose to focus our attention on the comparisons between Tables 9 and 12 for banks and between Tables 11 and 13 for insurers to save space. Generally speaking, both Tables 9 and 12 uncover that FHBs perform better than non-FHBs in terms of CE and OCE, but not for TGR. In addition, both Tables 11 and 13 imply that FHLIs perform better than non-FHLIs in terms of CE, TGR, and OCE.

It is clear that the omission of synergy effects tends to underestimate the average CE scores of FHBs, as shown in Table 9 (0.939) versus Table 12 (0.810), while this omission appears to have negligible impacts on the average TGR values (0.459 vs. 0.462). The outcomes validate the use of copula methods to take account of synergy effects; otherwise, the measures of CE and OCE are inclined to be biased downward, hence leading to false policy suggestions. Both tables show that the main source of contribution to OCE comes from CE, instead of TGR, suggesting that both forms of banks are devoted to enhancing their production technologies and to have access to the array of the potential technology set. Although both Tables 9 and 12 support the outperformance of FHBs over non-FHBs in terms of OCE, the gap between both types of banks is greater in Table 9 than in Table 12.

Tables 11 and 13 indicate that the exclusion of synergy effects also tends to underestimate the average CE scores of FHLIs (0.898 vs. 0.779). Differing from the banking industry, this exclusion leads to overestimating the average TGR values for FHLIs and non-FHLIs—that is, (0.714 and 0.564) vs. (0.882 and 0.819). Even though FHLIs still have a higher OCE value than non-FHLIs, the major source of contribution to OCE changes from CE to TGR, and the difference in OCE between FHLIs and non-FHLIs shrinks from about 0.258 (=0.643–0.385) to 0.182 (=0.692–0.510). Similar to the banking industry, Table 11 recommends that both forms of insurers improve their production technologies and get access to the array of the potential technology set. However, Table 13 gives a reverse recommendation: both forms of insurers should raise their managerial abilities (CE) in such a way as to decrease input quantities in order to produce the given output levels.

6 Concluding Remarks

To compare and/or support the formation of FHCs, most previous works in the literature collect data that simply include both FHBs and non-FHBs to estimate the production or cost frontiers for both types of banks either separately or together. The resulting performance measures are then used to judge the superiority of both types of banks. This procedure entirely excludes other types of subsidiary companies in a FHC and hence is apt to ignore the potential synergy effects generated by FHCs. Our current paper takes the synergy effects into account by means of the joint estimation of the cost frontier for FHBs and FHLIs affiliated with FHCs using copula methods. We argue that this can at least implicitly capture the joint decision-making process between FHBs and FHLIs under FHCs. The SMF cost functions are next estimated, which allows us to conduct performance comparisons between different groups adopting distinct technologies. We present evidence that scale economies and technical progress prevail in both banking and insurance sectors, whether or not synergies are considered.

Our empirical results from the use of our proposed approach can be summarized as follows. First, the correlation coefficient of CE between FHBs and FHLIs is significantly positive, verifying the presence of synergies. Second, the omission of synergy effects leads to underestimating the CE measure and OCE for FHBs, while the measure of TGR is intact. Third, the absence of synergies also results in underestimating the CE score for FHLIs. Conversely, the measures of TGR for FHLIs and non-FHLIs are overestimated, thus overvaluing the measures of OCE for both forms of insurers. Fourth, the average OCE values of FHBs and FHLIs exceed the respective non-FHBs and non-FHLIs, irrespective of whether or not we account for synergies. Fifth, the sample banks are advised to promote their production technologies due to the average TGR values of FHBs and non-FHBs falling short of the average CE scores, again irrespective of whether or not we consider synergies. Sixth, the sample insurers should boost their production technologies when synergies are included.

This paper does not focus on the inclusion of exogenous variables, which are neither inputs nor outputs of the production process, but which do have an impact on producer performance due to the following three reasons. (i) If the inefficiency term of u in (1) is related to a set of environmental variables, as suggested by Battese and Coelli (1995), then the approximated function of $I^{app}(Q)$ in (18) has to be re-derived, which has not yet been done in the literature. (ii) The log-likelihood function of (16) is highly non-linear such that it is challenging to make (16) achieve convergence. Once u is associated with several environmental variables, the task becomes even more difficult. (iii) The included environmental variables are likely to be endogenous due to their correlation with the statistical noise of v in (1), as discussed by Amsler et al. (2017). This may lead the econometric model to be very complicated and intractable. We leave this topic for future research.

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