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Authors: Tai-Hsin Huang, Chung-I Lin, Ruei-Cian Wu

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Assessing the Marketing and Investment Efficiency of Taiwan's Life Insurance Firms under Network Structures

Tai-Hsin Huang

Department of Money and Banking
National Chengchi University
Taipei, Taiwan
Email: thuang@nccu.edu.tw

Chung-I Lin
Department of International Business
Providence University
Taichung, Taiwan
Email: cilin2@pu.edu.tw

Ruei-Cian Wu
Department of Money and Banking
National Chengchi University
Taipei, Taiwan
Email: 101352021@nccu.edu.tw

Highlights

- ・This paper proposes the network stochastic frontier approach (SFA).
- ・The production process is split into marketing and investment stages.
- ・The model consists of a production and a cost frontiers with two share equations.
- ・A copula-based econometric model is used to identify structural parameters.
- ・Scale economies and technical progress prevail in the two production stages.
- ・Domestic, FHC, and new insurers outperform foreign, non-FHC, and old insurers.

Abstract

This paper proposes the network stochastic frontier approach (SFA) to fill the gap in the efficiency measurement literature, splitting the entire production process of life insurers into two stages: marketing and investment. A salient feature of the method is that it can characterize technologies undertaken by a series of stages without requiring disaggregate data for individual sectors of insurers. In the context of copula methods, the simultaneous equations can be estimated by the maximum likelihood, and the parameter estimates are used to compute measures of the technical efficiency score, technical change, and scale economies in the two production stages. We find that twenty-six of Taiwan's life insurers have a higher average technical efficiency score in the investment stage than that in the marketing stage. Scale economies and technical advancements prevail in the two production stages over the sample period 2000-2012. Findings also show that domestic, FHC (financial holding company), and new insurers outperform foreign, non-FHC, and old insurers, respectively. The traditional single production stage model neither accurately describes an insurer's production technology nor correctly evaluates its performance.

Key Words: Taiwan's life insurers; network SFA; copula methods; disaggregate data; simultaneous equations; the maximum likelihood; technical efficiency score; technical change; scale economies

JEL Classification: C51; D24;

1. Introduction

As complementary financial institutions, banks and insurance companies are different in several aspects. Genetay and Molyneux (1998) assert that banks engage in various activities of payments, pool short-term funds, and transform them into medium-term portfolios. These deposit-taking institutions establish necessary procedures to prevent any contingent risks, whereas insurance companies provide channels to their clients and policy holders that enable them to bear the risk of contingency and to perform the activities of long-term fund management.

This paper studies the performance of life insurance firms in Taiwan. It is widely known that life insurance essentially insures human life, covers a certain risk, which is the death of the insured, is not renewed annually, and expires only upon the death of the insured or in the case of a lapse (in most cases). In life insurance, the beneficiaries receive the payable benefit following the death of the insured. Once this transaction occurs, the policy is terminated. For insurance penetration (the ratio of insurance premiums to GDP), Taiwan was first globally in 2006, 2008, 2009, 2012, and 2015, thus revealing the pivotal role of the insurance sector in Taiwan's financial market.

With declining interest rates in Taiwan for the past 15 years, many life insurance firms there have offered different kinds of high-interest policies in an attempt to gain market share at the expense of higher default risk. To protect the rights of customers and to stabilize the domestic financial environment, Taiwan's authorities prohibited these products in 2001. In response to the pressure from Taiwan's rising aging population, Lee et al. (2017) note that life insurance product have developed towards long-term annuity policies.

Taiwan's life insurance industry was highly regulated until the end of the 1980s, with just eight insurance companies operating on the island in 1987. Following rapid economic growth and wealth accumulation in the 1970s and 1980s, Taiwan's government opened up and allowed newly-established and foreign life insurance companies to enter the domestic market. By end-1994, 16 domestic and 18 foreign life insurers had been set up. Thus, the market structure of Taiwan's life insurance sector changed dramatically.

Fierce competition among existing companies soon occurred, forcing some newly-established life insurance companies to enter the market through strategic mergers and acquisitions rather than as new firms. By the end of 2012, Taiwan's life insurance market consisted of 24 domestic and 6 foreign insurers with total assets of the industry amounting to 14.7 trillion New Taiwan dollars (NTD), or about six times larger than in 2000 (2.5 trillion NTD).[1] After the global financial tsunami of 2008 a huge amount of bank deposits flocked over to domestic life insurance firms to buy investment-type, pension-type, and medical-type insurance policies, further expanding the scale of domestic insurers. By 2012 the ratio of total assets in the life insurance industry to that of the entire financial sector was equal to 20.7%, just behind 40.7% for the banking industry.

The life insurance sector in Taiwan has faced structural changes and become highly competitive due to the enforcement of the deregulation policy in the 1980s, and its importance is growing with increasing total assets. The performance of Taiwan's insurers is worth a more thorough investigation, because their production efficiency is likely the main driver of profitability and earnings, which in turn determine the viability of those firms. Each insurer provides fairly homogeneous products and services due to the fact that most innovations are imitated soon after their launch and few financial inventions can be patented. Inefficiency entails actual levels of earnings and cash flows that are below those potentially feasible under optimal operations. The adverse effects on earnings and cash flows reduce firm value either through lower after-tax profits or lower investments that slow a firm's growth towards its optimal size. As a result, success in this industry relies on the life insurer's managerial ability to control production/costs and on other factors, such as client relationships, risk attitudes, marketing skills, and perceived quality of service. Hence, we expect that production/cost inefficiency significantly impacts the profitability and viability of life insurance companies.

[1] The statistics are taken from the Life Insurance Association of the Republic of China, Taiwan.

There are many approaches to evaluating the performance of a decision-making unit (DMU); for example, standard financial ratios like returns on assets or the cost/revenue ratio from accounting statements are commonly used by regulators, financial institution managers, and industry consultants. Frontier efficiency measures firms' deviations in performance from that of best-practice firms on the efficient frontier, keeping a set of exogenous market factors constant. The measures use either mathematical programming (e.g., data envelopment analysis, DEA) or econometric techniques (e.g., stochastic frontier approach, SFA) to try to purge the effects of the differences in prices and other market factors that are influencing the standard financial ratios. Frontier efficiency is able to in this manner give better estimates of the firm's underlying performance for managers and is superior for regulatory and managerial purposes versus the standard financial ratios. Moreover, frontier efficiency allows one to target the quantitative impacts on profits, costs, and input-output relationships, which may be induced by mergers and acquisitions, capital regulations, deregulation of deposit rates, entry of foreign banks, removal of geographic restrictions on branching, holding company acquisitions, etc. There is no consensus on the best method or the set of methods for assessing frontier efficiency, and the selection of a method may affect the conclusions drawn from the analyses.

DEA is known to be function free with the drawback that it estimates a deterministic frontier such that all deviations from the frontier are implicitly attributed to inefficiency. This implies that the method is especially vulnerable to the impacts of data noise, which can result in biased estimates of the shape and location of the frontier surface. SFA can address the topic of data noise, because it relies on a suitable functional form for the deterministic part of the frontier and suitable distributional forms for the composed error terms. The flexible functional form of the translog is widely utilized by numerous empirical researchers. This function can provide a second-order approximation to an arbitrary, unknown functional form and can be reduced to the commonly used Cobb-Douglas and CES (constant elasticity of substitution) functions. As far as the distributional forms are concerned, some evidence, e.g., Greene (1990), shows that the efficiency measures are insensitive to distributional assumptions on the one-sided error. Ritter and Simar (1997) suggest employing a comparatively simple distribution, such as half normal or exponential, rather than a more flexible distribution like truncated normal or gamma.

Previous studies on performance evaluation in life insurance and banking industries usually assume a single production stage, through which input factors transform into a variety of goods and services. Most traditional DEA and SFA models treat their reference technologies as black boxes in the sense that internal structures are ignored, as noted by Färe and Grosskopf (2000), Kao and Hwang (2008), and

Cook et al. (2010). In this context a DMU's performance is assumed to be a function of the input mix and the output quantities. Managers and business consultants are unable to know the weaknesses in different production stages of a firm and hence cannot target those inefficient stages of the production process. Network DEA (two-stage DEA) splits a DMU into sub-DMUs connected in series and evaluates individual sub-DMUs' efficiency score. Such an approach provides insight regarding the locations of inefficiency and offers specific guidance to DMU managers for helping them improve a DMU's efficiency.

Academic research on the performance of financial institutions in recent years has increasingly stressed network DEA, because it can gauge divisional efficiencies as well as the overall efficiency of DMUs. When some inputs, such as labor and capital, are used in different stages, network DEA requires the availability of the amounts of labor and capital hired in different stages; otherwise, the efficiency scores of sub-DMUs cannot be evaluated separately. The requirement of disaggregate data for some inputs (or outputs) is usually not met, implying researchers have to make a specific assumption on the distribution of those inputs between stages.

This paper extends network DEA to network SFA so as to enable one to estimate efficiencies of individual sub-units based on aggregate data, because disaggregate data of different sub-sectors are usually not available from accounting data. The ratios of inputs utilized in different stages are viewed as unknown parameters and can be estimated under the framework of simultaneous equations, which consist of a production frontier, cost frontier, and cost share equations. The presence of cost share equations helps identify the unknown ratios. Specifically, we shall develop an economic model that splits a life insurer's production activities into two stages by its unique characteristics. In the first production stage, called the marketing activity stage, the firm is assumed to employ parts of labor and capital, say, to collect (produce) premiums by selling various types of insurance policies to customers. In the second stage, called the investment activity stage, the firm seeks to minimize production costs incurred by employing premiums (the single output in the first stage) and the remaining inputs of labor and capital in order to generate investment revenues, which make up the final output. Here, we treat premiums as an intermediate output in the first production stage, which in turn is regarded as one of the inputs in the second production stage. By doing so, premiums are not viewed as an output, like in conventional DEA and SFA, but rather as an intermediate output that plays dual roles to connect both production stages. This intermediate output is further used, along with other inputs, to produce final outputs, i.e., investment revenues. Note that labor and capital are used in both stages and the ratios distributed between stages are not required to be observed, but instead can be estimated. The identification of those ratios counts on the employment of cost share equations. Our network SFA is therefore applicable under weaker conditions than required by network DEA.

The rest of the paper is organized as follows. Section 2 briefly reviews relevant works. Section 3 develops an economic model to describe the multi-stage production process of a life insurer and builds a copula-based econometric model to be used to conduct the empirical study. Section 4 introduces data source and variable definitions. Section 5 analyzes empirical results. The last section concludes the paper.

2. Literature Review

There are three comprehensive survey articles pertaining to efficiency measurement in the insurance industry. Berger and Humphrey (1997) cover eight works, Cummins and Weiss (2000, 2013) review 21 and 95 related papers, respectively, while Eling and Luhnen (2010) provide quick and clear ways for understanding frontier techniques when analyzing insurance firms. Most of the earlier research works investigate the performance of insurance firms in developed countries. For example, Fecher et al. (1993) apply standard DEA and SFA to examine the performance of French life and non-life insurance companies in the period 1984-1989, finding that both methods produce highly correlated efficiency scores that are attributable to the characteristics of the sample companies. Hardwick (1997) applies SFA to estimate the technical efficiency scores of 54 British life insurers in the period 1992-1996, focusing particularly on the effect of an increase in competitiveness on cost efficiency. Cummins and Zi (1998) examine the performance of various efficiency estimation methods, including a variety of econometric and mathematical programming techniques, with respect to 445 U.S. life insurers during the period 1988-1992. The efficiency rankings are well-preserved among the econometric methods, while the rankings are less consistent between the econometric and programming methods and between the DEA and free disposal hull techniques. They thus conclude that the choice of estimation method has a significant effect on the conclusions of an efficiency study.

Cummins et al. (1999) apply DEA to analyze the relationship among merger and acquisition (M&A), efficiency, and scale for the U.S. life insurance industry for the period 1988-1995, along with productivity changes measured by the Malmquist index. Greene and Segal (2004) estimate the management performance of 136 U.S. life insurance companies by SFA for the period 1995-1998 and find substantial cost inefficiency relative to earnings, and the inefficiency is negatively associated with profitability measures such as ROA. Also using SFA, Fenn et al. (2008) estimate flexible Fourier cost functions for European insurance companies for the period

1995-2001. The data contain life, non-life, and composite insurance businesses in 14 European countries. Most European insurers are found to operate under conditions of increasing returns to scale, and company size and domestic market share are significant factors determining X-inefficiency; moreover, larger and high market share firms tend to have higher levels of cost inefficiency. Barros et al. (2010) utilize the two-stage DEA procedure of Simar and Wilson (2007) to analyze the effects of deregulation on the efficiency of Greece's insurance industry for the period 1994-2003. The first-stage results indicate a decline in efficiency over the sample period, while the second-stage results confirm that the competition for market share is an important driver of efficiency in this industry.

The standard version of DEA has been extended to measure multi-stage efficiency of banks. Seiford and Zhu (1999) use a two-stage DEA model to study the performance of 55 U.S. commercial banks and verify that the performance evaluation under two consecutive production stages provides more information on operational management. Chen (2002) decomposes a bank's managerial ability into operational efficiency, marketing efficiency, and financial efficiency and exploits network DEA to investigate the efficiencies of Taiwan's banks. Avkiran (2009) applies the non-oriented network slacks-based measure to estimate the efficiency of domestic commercial banks in the United Arab Emirates. Holod and Lewis (2011) use network DEA to examine the efficiency of U.S. financial holding companies in the period 1986-2008 for which deposits are treated as an intermediate product in the first production stage and one of the inputs in the next production stage. This solves the difficulty regarding whether to define deposits as an input or output for banks.

Despotis et al. (2016) point out that a biased or non-unique result may arise in the two-stage network DEA model of additive and multiplicative decomposition methods. They propose a novel reverse approach to correct this problem. Others apply various methods of network DEA to examine bank efficiency in different countries, e.g., Yang and Liu (2012), Akther et al. (2013), Matthews (2013), Kao and Liu (2014), Wang et al. (2014), Wanke and Barros (2014), Avkiran (2015), Chao et al. (2015), Fukuyama and Weber (2015),and Zha et al. (2016).

Many papers employ network DEA to examine the efficiency of non-financial institutions, e.g., Löthgren and Tambour (1999), Färe and Grosskopf (2000), Zhu (2000), Sexton and Lewis (2003), Prieto and Zofío (2007), Yu and Lin (2008), Tone and Tsutsui (2009), Cook et al. (2010), Hsieh and Lin (2010), Chen and Yan (2011), and Herrera-Restrepo et al. (2016), to mention a few. Chen (2009) extends the network DEA model to incorporate the dynamic effect in production networks. Cook, Liang, and Zhu (2009) provide an excellent review and future perspectives about the subset of network DEA, where all the outputs from the first stage are the only inputs to the second stage.

Relatively fewer studies apply network DEA to evaluate insurers' performance. Yang (2006) conducts two-stage DEA by dividing the whole production process into two stages, i.e., operation and investment, to explore the performance of Canadian life and health insurance companies. Hwang and Kao (2006) use two-stage, i.e., marketability and profitability, DEA to evaluate the managerial performance of Taiwan's 24 non-life insurers. Using the same data as Hwang and Kao (2006), Kao and Hwang (2008) propose the relational two-stage DEA approach to measure the performance of the sample firms. They show that there is a considerable difference between marketing efficiency and investment efficiency, whereby the latter constitutes the major source of insurance companies' deficiencies. We note that the previous two papers do not allow the two production stages to employ common inputs such that both stages can be viewed as independent processes.

Kao (2009) builds a relational network DEA model to measure the efficiency of a system and those of individual processes. He exemplifies that the resultant system efficiency is more relevant and representative of the aggregate performance of the component processes, using data from Taiwan's non-life insurance industry. Shahroudi et al. (2012) employ both traditional and two-stage DEA to measure the efficiency levels of Iranian private insurance companies during the period 2007-2009 and conclude that traditional DEA fails to explain network systems properly. Some insurance firms are found to be technically efficient by traditional DEA, but lack efficiency in their sub-units, e.g., marketing and investment.

The performance evaluation of the insurance sector in emerging countries has drawn much attention in the past few years. Huang and Eling (2013) investigate the performance of non-life issuers in BRIC (Brazil, Russia, India, and China), using the multiple-stage bootstrap DEA approach in order to correct for environmental differences in those four countries. They find that Brazilian issuers perform the best in terms of technical efficiency, pure technical efficiency, and scale efficiency during the sample period 2000-2008. Lu et al. (2014) apply the dynamic SBM model to examine the operating efficiency of 34 Chinese life insurance companies over the period 2006-2010. They suggest that investment in intellectual capital, composed of human capital, structural capital, and financial capital, is beneficial for gaining higher overall operating efficiency scores. Gaganis et al. (2013) compile data consisting of 399 listed insurance companies from 52 nations and apply SFA to examine the effect of stock returns on their efficiency for the period 2002-2008. Evidence is found that the profit efficiency measure, instead of the cost efficiency measure, has a significantly positive impact on stock returns.

There are fewer research works analyzing the efficiency of Taiwan's life insurance industry. Hao and Chou (2005) find that the average cost efficiency score of Taiwan's life insurance sector is equal to 0.66 in the period 1977-1999. Market share is positively associated with profits, whereas product diversification is incapable of enhancing an insurer's efficiency. Conversely, Huang et al. (2007), Wang et al. (2007), and Jeng and Lai (2008) investigate the influence of deregulations and corporate governance on the efficiency of Taiwanese life insurers. Empirical evidence suggests that the age of insurers and family-controlled insurers have higher efficiency performance in Taiwan. Moreover, greater ownership, instead of the size of the insurer, has a negative impact on life insurers' performance. As for the issue of deregulation and liberalization, evidence supports that new insurers are technically more efficient initially, but are indifferent subsequently in terms of cost and revenue efficiencies. They suggest that new entrants in the insurance industry acquire existing firms instead of establishing new one.

Several recent papers re-examine the performance of Taiwan's life insurance industry from different angles, such as market structure, risk management, etc. Chuang and Tang (2015) claim that a non-linear relationship exists in the market share and efficiency of Taiwan's life insurance industry over the period 1976-2010 and assert that the pursuit of greater market power is not deterministic in creating better performance. In addition, domestic life insurers with larger market power are found to outperform foreign insurers with less market share. Hu and Yu (2015) employ the stochastic cost frontier to study the relationship among asset risk, product risk, capital, and operation performance for Taiwan's twenty-seven life insurance firms over the period 2004-2009. The average cost efficiency is equal to 0.67, less inefficient insurers tend to take higher product risk that is positively related to capital, more efficient insurers tend to maintain higher capital levels as the buffer, and asset risk has a negative effect on capital and operating inefficiency.

Lee et al. (2017) emphasize the important function of insurers' solvency, by incorporating insurance claims as one of the inputs, and classify investment into high- and low-risk types. Under the dynamic network slack-based measurement model, they view return on assets as the carryover variable so as to explore the efficiency of sample insurers over the period 2006-2013. Evidence is found that the overall efficiency of domestic insurers is superior to that of foreigner insurers. According to the performance of subsector production processes, foreign insurance firms outperform domestic firms in the production process of underwriting, fund management, and claims management. Insurers that have merged into financial holding companies exhibit greater efficiency improvement.

3. Methodology

3.1 Network SFA

Following Shahroudi et al. (2012), the entire production process of a life insurance company is divided into marketing and investment activities as shown in Figure 1. In the first marketing production stage an insurer is assumed to utilize all field staff members and some fractions of internal staff members and physical capital to produce a single output, i.e., premiums. Premiums are viewed as an intermediate output to be exploited as one of the inputs in the following production process. In the second investment stage the firm hires the other internal staff members and physical capital, together with the intermediate output, premiums, to create a single, final output, investment revenues.

[Insert Figure 1 Here]

Let $x = (x_1, x_2, x_3)'$ be a 3×1 vector of inputs, corresponding to the number of internal staff members, physical capital, and the number of field staff members, and $\alpha = (\alpha_1, \alpha_2, \alpha_3)'$ is the corresponding fractions of the three input factors being used in the first stage. Naturally, α lies between zero and unity. Since the insurance company under consideration is assumed to utilize its entire field staff to create premiums in the first stage, α_3 is set to be equal to unity. We apply the standard stochastic production frontier to characterize a single output production process in this stage as:

$$Z = f(\alpha x)e^{v_1 - u_1},$$

where Z is the quantity of the intermediate output, i.e., premiums, $f(\cdot)$ is the production function, $u_1 \sim N^+(0, \sigma_{u1}^2)$ is the one-sided error signifying output-oriented technical inefficiency of the firm, and $v_1 \sim N(0, \sigma_{v1}^2)$ is statistical noise uncontrollable by managers.[2] Terms u_1 and v_1 are conventionally assumed to be

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[2] Note that vector α differs from the measure of input-oriented technical inefficiency, say, B $(0 < B \le 1)$, as proposed by Atkinson and Cornwell (1993, 1994), who specify a production function with input-oriented technical inefficiency as $y = f(Bx)$. The higher the value of B is, the more technically efficient is the firm, and vice versa. Scalar B represents the degree of technical efficiency, while vector α represents the distribution of inputs between production stages.

mutually independent.

We assume the production function of $f(\cdot)$ takes the translog function form of:

$$\ln Z = a_0 + \sum_{1}^{3} a_i \ln(\alpha_i x_i) + \frac{1}{2}\sum_{i=1}^{3}\sum_{j=1}^{3} a_{ij} \ln(\alpha_i x_i)\ln(\alpha_j x_j) + a_t t + \frac{1}{2}a_{tt}t^2 + \sum_{i=1}^{3} a_{it} t \ln(\alpha_i x_i) + v_1 - u_1 \quad (1)$$

Here, a's are unknown parameters to be estimated, and variable t represents the time trend, capturing the technical change of the firm.

In the second production process, we presume an insurance company employs the remaining portions of internal staff members, $(1-\alpha_1)$, and capital stock, $(1-\alpha_2)$, in addition to the intermediate output, premiums (Z), to manufacture its final output, investment revenue (y). For a cost minimizing insurer, its cost function, $C^*(\cdot)$, in this stage can be formulated as:

$$\begin{aligned} C^*\left(y,\ \frac{W}{b}\right) &= \min_{b\tilde{\alpha}X}\left[\frac{W'}{b}(b\tilde{\alpha}X) \middle| F(y, b\tilde{\alpha}X) = 0\right] \\ &= \frac{1}{b}\min_{b\tilde{\alpha}X}\left[W'(b\tilde{\alpha}X) \middle| F(y, b\tilde{\alpha}X) = 0\right] \\ &= \frac{1}{b}C(y, W), \end{aligned} \quad (2)$$

where $\tilde{\alpha}X = (\tilde{\alpha}_1 x_1,\ \tilde{\alpha}_2 x_2,\ \tilde{\alpha}_3 Z)'$, $\tilde{\alpha}_1 = 1-\alpha_1$, $\tilde{\alpha}_2 = 1-\alpha_2$, $\tilde{\alpha}_3 = 1$, W is the corresponding 3×1 vector of input prices, and $F(\cdot)$ denotes the production transformation function that takes input-oriented technical inefficiency into account, i.e., b $(0 < b \leq 1)$.[3] Scalar b has the same economic implications as B in footnote 2. Equation (2) indicates that the presence of technical inefficiency raises a firm's optimal cost, $C^*(\cdot)$, by a factor of $1/b > 1$.

The demand function of the i^{th} input can be derived by Shephard's lemma:

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[3] Although we can equivalently specify a production frontier to describe the second-stage activity as in the first stage, the fractional parameter α cannot be identified by the two production frontiers without extra information. This difficulty is easily solved by specifying a cost frontier to represent the second-stage technology since the corresponding cost share equations can be deduced by applying Shephard's lemma. Those share equations provide additional information required to identify α.

$$\frac{\partial C^*}{\partial (W_i/b)} = b\tilde{\alpha}_i X_i\left(y, \frac{W}{b}\right) \\ = b\tilde{\alpha}_i X_i(y, W), \qquad i = 1,2,3 \tag{3}$$

$$\frac{\partial C^*}{\partial W_i} = \frac{\partial C^*}{\partial (W_i/b)} \frac{\partial (W_i/b)}{\partial W_i} = \tilde{\alpha}_i X_i, \qquad i = 1,2,3. \tag{4}$$

The subscript i corresponds to the three inputs utilized in stage two. Recall that the actual i^{th} input quantity in the second stage is equal to $\tilde{\alpha}_i X_i$, rather than X_i. The emergence of technical inefficiency b in (3) lowers the firm's effective input quantities by a factor of $(1-b)$, which in turn pushes the firm's costs up as shown in (2). The cost share equation of the i^{th} input factor is defined as:

$$S_i(y, W) \equiv \frac{\partial \ln C^*}{\partial \ln W_i} = \frac{\partial C^*}{\partial W_i}\frac{W_i}{C^*} = \frac{\tilde{\alpha}_i W_i X_i}{C^*}, \quad \forall i, \tag{5}$$

where the numerator signifies the expenditure of the i^{th} input attributable to the second stage.

Using (5) we can relate the actual expenditure function to the optimal cost as:

$$E = \sum_{i=1}^{3} W_i X_i = \sum W_i \frac{C^* S_i}{\tilde{\alpha}_i W_i} = C^* \sum S_i \tilde{\alpha}_i^{-1} = C^* G(y, W), \tag{6}$$

where $G(y, W) = \sum_{i=1}^{3} S_i \tilde{\alpha}_i^{-1}$. Taking natural logarithms on both sides of (6) and appending a stochastic disturbance term $v_2 \sim N(0, \sigma_{v2}^2)$, we obtain the following regression equation:

$$\ln E = \ln C(y, W) - \ln b + \ln G(y, W) + v_2 \\ = \ln C(y, W) + \ln G + v_2 + u_2 \tag{7}$$

Here, $u_2 \equiv -\ln b$ represents the increase in the firm's actual expenditure incurred by managerial inability. We assume that $u_2 \sim N^+\left(0, \sigma_{u2}^2\right)$ and is mutually independent of the two-sided error $v_2 \sim N\left(0, \sigma_{v2}^2\right)$.

The expenditure share equation of input i can be similarly associated with the optimal cost share equation of (5). Adding an error term of η_i to each share equation leads to the following share regression equations:

$$\frac{W_i X_i}{E} = \frac{W_i}{E}\frac{S_i C^*}{\tilde{\alpha}_i W_i} = \frac{S_i \tilde{\alpha}_i^{-1}}{G} + \eta_i \ , \quad i = 1,2,3. \tag{8}$$

Equations (1), (7), and (8) should be simultaneously estimated in such a way as to identify all parameters of interest shown in (1) and (7), including fractional parameter α. Those share equations contain the same unknown parameters as in the cost function of $C(\cdot)$, which can be identified by (7). Therefore, the inclusion of share equations (8) is mainly for the identification of α.[4]

The cost function in (7) is set to be the standard translog function form as:

$$\begin{aligned}\ln C(y,W) = \beta_0 + \beta_y \ln y + \sum_i \beta_i \ln W_i + \frac{1}{2}\beta_{yy}\left(\ln Y\right)^2 + \\ \frac{1}{2}\sum_i\sum_k \beta_{ik} \ln W_i \ln W_k + \sum_i \gamma_i \ln W_i \ln y + \beta_t t + , \\ \frac{1}{2}\beta_{tt} t^2 + \sum_i \beta_{ti} t \ln W_i + \beta_{ty} t \ln y, \quad i,k = 1,2,3\end{aligned}$$

where β and γ are technology parameters to be estimated, and t is the time trend that captures technical changes. The corresponding cost share equations are:

$$S_i(y,W) \equiv \frac{\partial \ln C}{\partial \ln W_i} = \beta_i + \sum_k \beta_{ik} \ln W_k + \gamma_i \ln y + \sum_i \beta_{ti} t, \quad i,k = 1,2,3.$$

Recall that premiums are treated as an output in the first stage and are employed to produce final products in the second stage. This interrelationship between stages can be described by a simultaneous equations model, consisting of (1), (7), and (8). This non-linear model has to be jointly estimated by the maximum likelihood (ML) in order to account for this interdependence and to identify all unknown parameters. Both (1) and (7) contain composed errors with skewed normal distributions. It is difficult to derive their joint probability density function (pdf). The copula method appears to be a feasible and natural choice, because it allows the composed errors in (1) and (7) and the single errors in (8) to be mutually correlated.

Our simultaneous equations model incorporates four regression equations with four random errors, denoted by $\varepsilon_1, \varepsilon_2, \eta_1$, and η_2. Recall that $\varepsilon_1 = v_1 - u_1$ and $\varepsilon_2 = v_2 + u_2$ are composed errors coming from equations (1) and (7), while η_1 and

[4] One of the three share equations has to be removed to avoid the singularity problem, arising from the fact that the sum of the three shares is restricted to be equal to unity. As a by-product, another benefit of including share equations in the simultaneous equations model is the ability to improve the efficiency of parameter estimates.

η_2 are the conventional random disturbances. It is difficult to derive the joint distribution of ε_1 and ε_2 without the use of copula methods. This paper appears to be the first one introducing copula methods into a study of insurers' production performance under the framework of a network production process, which enables us to find the joint probability density function (pdf) for equations (1), (7), and (8) and to then conduct the estimation job. We show how to obtain their joint pdf in Appendix A. The corresponding log-likelihood function is (A6) in the appendix, under the assumption of *N* observations, which our empirical study will apply later.

It is noteworthy that we select the Gaussian copula to construct the joint pdf. There are, in fact, many multivariate copulas that can be used, e.g., the multivariate Student's t copula, Archimedean copula, Gumble n-coplua, Clayton n-copula, etc. Cherubini et al. (2004) provide an excellent review of the copula functions. 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. Similar to Lai and Huang (2013) and Huang, Liu, and Kumbhakar (2016), the current paper uses the Gaussian copula, because it covers the entire range of dependence and offers tractability. Lai and Huang (2013) briefly mention some existing tools in choosing a valid copula, e.g., the goodness of fit tests reviewed in Genest et al. (2009), the moment test suggested by Amsler et al. (2014), the Akaike information criterion, and the Bayesian information criterion. See Trivedi and Zimmer (2005) for more discussion on the model selection criteria. The robustness of empirical results to alternative copulas is worth further investigation in future studies.

4. Data and Variable Definitions

The data are compiled from several sources, including the databank of Taiwan Economic Journal (TEJ), Insurance Yearbook of the Republic of China (R.O.C.), Annual Report of Life Insurance, R.O.C., Taiwan Insurance Institute, and the financial reports of individual insurance companies. Some insurers are excluded, because of a merger, incomplete data, short sample period, or changing their operational type into telemarketing. The unbalanced panel data contain 26 life insurance companies with 266 observations, spanning from 2000 to 2012.[5]

[5] According to the insurance yearbook of 2012, Republic of China, there are 30 insurance companies in Taiwan, including domestic and foreign insurers. Our sample contains 21 out of the 30 firms. The

Choosing appropriate inputs and outputs in the efficiency analysis on the financial service industry is important. Three methodologies are widely used: the asset (or intermediation), the production (or value-added), and the user-cost approaches. Cummins and Weiss (2013) argue that the value-added approach is the most acceptable method to evaluate the performance of the insurance sector. They suggest that the primary and appropriate outputs of life insurers are the sum of incurred benefits and additions to reserves, instead of the premium. Following this vein, the salient feature of this article is the selection of output, where we treat the premium as the single intermediate output in the first production stage. This intermediate output constitutes one of the three inputs in the second stage utilized to produce the final output: investment revenues. Our output factors are consistent with Gardner and Grace (1993), Meador et al. (2000), Greene and Segal (2004), and Yao et al. (2007). Similar to those works, we define labor and physical capital as our input variables. Although Eling and Luhnen (2010) claim that it is difficult to obtain public data on the number of employees in most insurance literature, the current paper is able to further divide input labor into two types (number of internal staffs and number of field staffs) like that used by Fukuyama (1997).

We assume life insurers employ three inputs (internal staff members ($\alpha_1 X_1$), physical assets ($\alpha_2 X_2$), and field staff members (X_3)) to produce a single intermediate output (premiums (Z)) in the first stage. In the second stage, $\left(1-\alpha_1\right) X_1$, $\left(1-\alpha_2\right) X_2$, and Z are used to produce a final output (investment revenues (y)). Input prices are calculated as the ratios of the individual expenses to the corresponding input quantities. Table 1 summarizes detailed variable definitions. All dollar valued variables are deflated by Taiwan's consumer price index (CPI) with base year 2011.

[Insert Table 1 Here]

The price of intermediate output Z is not directly observed, but it has to be used with the cost function as one of the three inputs in the second stage. Following Kumbhakar and Lovell (2000), we choose to estimate a cost function to derive the shadow price of Z as a proxy to its actual price.[6] This cost function regards Z as a quasi-fixed input, together with two variable inputs (internal staff members (X_1) and

ratio of total assets from the excluded 9 insurers, arising from either incomplete data or short sample period, to that of the 30 insurers is around 7.2%, implying that the consequence of precluding those insurers should be insignificant.

[6] Kumbhakar and Lovell (2000), pages 145-146.

fixed assets (X_2)) and a single output (investment revenues (*y*)). The translog normalized cost regression equation is specified as:

$$
\begin{aligned}
\ln E &= c_0 + c_1 \ln Z + c_2 \ln Y + c_3 \ln W_2^* + c_4 t + 0.5c_5 (\ln Z)^2 + 0.5c_6 (\ln Y)^2 \\
&\quad + 0.5c_7 (\ln W_2^*)^2 + 0.5c_8 t^2 + c_9 \ln Z \ln Y + c_{10} \ln Z \ln W_2^* + c_{11} t \ln Z \\
&\quad + c_{12} \ln Y \ln W_2^* + c_{13} t \ln Y + c_{14} t \ln W_2^* + \xi
\end{aligned} \tag{9}
$$

Here, $W_2^* = W_2 / W_1$, $E = \left(W_1 X_1 + W_2 X_2\right) / W_1 = C / W_1$, and ξ denotes the error term. Please see Appendix B that presents the estimation results. Once coefficient estimates are found through the least squares, one can calculate the shadow price of premiums, W_3, as follows:[7]

$$W_3 = -\frac{\partial C}{\partial Z}. \tag{10}$$

Table 2 summarizes the descriptive statistics of all variables, including W_3. The table reveals that the size of sample firms varies substantially. For example, the smallest life insurer merely has 75 and 11 internal and field staff members, respectively, while the largest one employs 6703 and 83676, respectively.

[Insert Table 2 Here]

5. Empirical Results

The system equations of (1), (7), and (8) are supposed to be jointly estimated by ML. Since the corresponding log-likelihood function is highly non-linear in unknown parameters, it is quite difficult for practitioners to get coefficient estimates that satisfy the convergence condition for the log-likelihood function. We alternatively adopt a two-step procedure to deal with the problem. In the first step we simultaneously estimate equations (1), (7), and (8) by non-linear least squares (NLS). This step results in consistent slope parameter estimates (including fractional parameters of inputs), because the one-sided errors present in (1) and (7) are assumed to have a half-normal distribution such that their mean values are unknown constants absorbed by intercept terms in (1) and (7). Therefore, only those intercepts, instead of slope parameters, tend to be biased. In the second step all slope parameter estimates obtained in the previous step are regarded as given. Equations (1) and (7) are simultaneously re-estimated by maximizing the log-likelihood function (14), involving only ε_1 and ε_2, to yield the remaining parameters such as intercepts σ_1, λ_1, σ_2, and λ_2. This

[7] We initially attempt to specify ξ as a composed error, consisting of a two-sided error and a technical inefficiency term, and estimate (9) by ML. However, according to (10) the calculated shadow prices for some observations turn out negative, which lacks any economic justification.

simplified log-likelihood function is easier for achieving convergence. Note that the two-step procedure leads to consistent coefficient estimates at the expense that the resultant estimates lack efficiency. Tables 3 and 4 summarize parameter estimates from the above two-step procedure.

[Insert Tables 3 and 4 Here]

Tables 3 and 4 show that the vast majority of the parameter estimates are statistically significant at least at the 10% level. Particularly, the dependence parameter between $\Phi^{-1}(F_1(\varepsilon_1))$ and $\Phi^{-1}(F_2(\varepsilon_2))$, Ω_{12}, is equal to -0.2524 and is significant at the 1% level. This justifies the use of copula methods allowing for the correlation between equations. Fractional parameters of internal staff and fixed assets are found to be equal to 0.412 and 0.9389, respectively, indicating that the representative insurer employs 41.2% of internal staff members and 93.89% of total fixed assets in the first stage of premiums' generation. These figures appear to be consistent with the actual operations of insurance companies in Taiwan. Premiums' generation heavily relies on field staff members, as well as a portion of internal staff members who design new insurance products and deal with administration affairs. In addition, our sample companies utilize most of their total assets, including computing equipment and branch offices, to support field staff members selling insurance products. In the second production process, an insurer devotes resources to create revenues from various investment opportunities that require a large number of internal staff members as well as some amounts of computer resources and offices.

For the purpose of comparison and accentuating the importance of two-stage production processes, we re-estimate the translog cost frontier in the context of the traditional, single production process. This time, an insurer is assumed to hire three inputs (internal staff members (X_1), total fixed assets (X_2), and field staff members (X_3)) to provide two outputs (premiums (Z) and investment revenues (Y)). Table 5 presents the empirical results, where slightly less than one half of estimates are significant at the 5% level. The two variance measures of $\sigma^2 (= \sigma_v^2 + \sigma_u^2)$ and γ $(= \sigma_u^2 / \sigma^2)$ are significantly estimated and equal 0.5007 and 0.8337, respectively. This means that 83.37% of the total variance comes from the variation in managerial inability, confirming the presence of the inefficiency term in the composed error term.

[Insert Table 5 Here]

It is important to characterize the two-stage production process by means of scale elasticities and technical change, calculated using the parameter estimates in Tables 3 and 4 together with the data. Table 6 gives their respective definitions and displays sample statistics. The average values of scale elasticities in the two stages are equal to 1.3462 and 0.7205, respectively, verifying the presence of scale economies that are not exhausted in both production stages. The sample life insurers are suggested to expand their production scale in order to reduce their long-run average cost. Moreover, the average values of technical change in the two stages are equal to 0.0772 and -0.0372, respectively, indicating that both stages are experiencing technical advancements during the sample period. The production (cost) frontier shifts up (down) over time at a rate of 7.72% (3.72%) per annum. The measures of average scale elasticity and technical change, derived from the conventional single production process, equal 0.8865 and -0.0637, respectively. Both economies of scale and technical progress prevail in the sample companies as a whole. This finding is consistent with Fenn et al. (2008) for European insurance companies. We note that only our network SFA is able to describe the characteristics of different subunits in a firm.

[Insert Table 6 Here]

Figure 2 depicts the trend of average scale elasticities across the sample period 2000-2012 for the production frontier. The production scale in the first stage gradually increases over time toward constant returns to scale as the average measures of scale elasticities decrease with a small magnitude. Figure 3 shows that the average scale elasticities in the second stage fluctuate roughly between 0.6 and 0.8, exhibiting no clear trend. These two figures may imply that the sample firms try to generate more premiums by raising resources in the first production stage, while maintaining the scale of investment activities in the second stage. Figure 4 depicts the monotonically upward trend of technical change in the production frontier. Figure 5 shows the downward, slightly varying trend on production costs. Both support the existence of technical progress during the sample period, and their speeds accelerate over time.

Several reasons may justify technical progress on premiums' generation in the first stage. An aging society with fewer children in Taiwan has aroused potential demand for long-term care insurance, retirement insurance, mirco-insurance, etc. More importantly, the platform of bancassurance under the structure of a financial holding company (FHC) (that was allowed to be set up starting in 2001) allows insurers to absorb large amounts of low-interest-earning deposits from the FHC's bank channel to investment-oriented linkages or other quasi-deposit insurance products of the FHC's insurer through reliable wealth management representatives in the bank. With regard to the technology improvement of the second investment stage, most insurers suffer a severe negative spread on traditional insurance products, and hence Taiwan's government authority since 2001 has encouraged insurance companies to create innovative products such as an investment-oriented link policy. Starting from 2007, the ratio of overseas investment was further deregulated, increasing to its highest level of 45% and providing insurers with a diversified investment and risk management channel to gain higher profits. Insurance companies were also permitted in 2012 to invest in overseas real estate. The above reasons may contribute to the finding that technology in our data improves in the second investment stage.

[Insert Figures 2 to 5 Here]

Table 7 lists average technical efficiency measures in the two production stages and the traditional, single production stage for the purpose of comparison. The mean output-oriented technical efficiency measure in the first stage equals 0.6714, indicating that the representative life insurer can produce 33.86% more output of premiums, given its current input mix, should it become fully technically efficient. The average second stage input-oriented technical efficiency measure equals 0.7290, implying that the representative life insurer can reduce 27.1% of its current cost, given the current output levels, provided it is producing on the efficient cost frontier. Managers should endeavor to improve their first-stage managerial abilities, because the degree of technical inefficiency is higher in this stage than in the second stage.[8]

Given that the main source of technical inefficiency is found in the marketing stage, the sample firms are suggested to either decrease (increase) input usages (qualities) and/or increase output quantities. With regard to input savings, life insurers are recommended to invest in, e.g., new information technology (such as big data), human capital, and professional on-the-job-training for employees. This should help diminish the demand for labor. To promote output, insurers are encouraged to make good use of financial technology applicable to, e.g., the Internet insurance market and personalized policy. These financial innovations can assist in procuring more sales of new insurance products, create more premiums, and prompt technical efficiency in the first production stage as a result. All the foregoing measures must be taken into account in the formulation of management strategies.

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[8] Our finding is inconsistent with Hwang and Kao (2006) and Kao and Hwang (2008) who confirm that the efficiency of the first stage is significantly higher than that of the second stage.

As for the single, traditional production process, the average technical efficiency score equals 0.6135, meaning that the best-practice life insurer in the sample consumes only 61.35% of the actual cost spent by an average life insurer, given the current output levels. Although this measure is lower than those from the two-stage model, they are not directly comparable, because some of the inputs and outputs defined by the two models differ from each other. Note that the single-stage model regards the DMU simply as a black-box with inputs entering and outputs leaving, thus ignoring the DMU's internal operations. The DMU's performance is presumed to be a function of a set of selected inputs and outputs. Therefore, this overall measure for life insurers fails to identify individual efficiencies for the separate stages or divisions of the firm. Regulators, business consultants, and managers cannot recognize whether managerial inability comes from the marketing and/or investment stages, based on the overall measure, not to mention how to take steps to improve production efficiency and to achieve cost savings.

[Insert Tables 7 and 8 Here]

Table 8 presents the trends of average technical efficiency scores for both stages and the traditional single stage. Figures 6 to 8 plot their trends. The average efficiency measure in the first stage equals 0.6131 in 2000, increases to 0.7309 in 2004, and decreases to 0.6215 in 2012. We observe that cost efficiency in the second stage has a similar trend to the first stage. In 2000 the average cost efficiency score equals 0.6694, rises to 0.7899 in 2007 with slight variations, and finally goes down to 0.6665 in 2012. Entry into the World Trade Organization in 2002 and the financial restructuring policy launched by Taiwan's government in 2003-2004 appear to positively affect the first-stage performance of insurers versus the second-stage performance.[9] The decrease in the number of insurers helps enhance marketing efficiency. However, the occurrence of the U.S. subprime crisis in 2008 seems to adversely impact the second-stage performance more than the first-stage performance. To weather such a financial tsunami and reduce potential investment losses, financial institutions must carefully evaluate new investment projects and scrutinize loan applicants. These contractionary measures are likely to restrict life insurers from producing a given level of investment revenues on the efficient cost frontier. The trend of the traditional single-stage model differs from that of the second-stage model, although it captures the negative impact from the subprime crisis.

[9] This policy encourages merger and acquisition between financial institutions and aims to cut the number of banks, especially those belonging to financial holding companies, by one half.

[Insert Figures 6 to 8 Here]

We next divide the sample insurers into different groups and compare their performance. Table 9 presents the average efficiency for the groups of domestic and foreign insurance companies. The average efficiency scores of domestic life insurers in the two production stages equal 0.6836 and 0.7384, respectively, which are significantly higher than those foreign life insurers (0.5588 and 0.6423). Those two groups of firms have similar rates of technical change in the two stages. However, the outcomes from the traditional one-stage SFA method conclude that there is no difference in technical efficiency scores and technical gains between domestic and foreign insurers in Taiwan. The structure of Taiwan's life insurance market has been altered dramatically in recent years due to financial deregulation and innovations. Faced with new competitors and a changing demand for insurance products, arising from population aging, low birth rate, and wealth distribution, insurers must offer new products to satisfy consumers' needs. This more challenging and competitive atmosphere appears to stimulate domestic insurance firms' managerial abilities more so than it does for foreign firms' managerial abilities. Conversely, the traditional model fails to reflect such conditions.

[Insert Table 9 Here]

Taiwan's financial holding company law was enacted in 2001. The set-up of FHCs emerged in Taiwan starting from the end of 2001 through the integration of banks, securities companies, insurance companies, etc. under one umbrella. An FHC is expected to enjoy synergy effects in marketing, information sharing, product diversification, and production scale. Our sample contains five life insurance companies that are a member of a FHC.[10] We thus split the sample into two groups, i.e., FHC and non-FHC. Table 10 shows that the FHC group in both stages outperforms the non-FHC group, while only the first stage attains statistical significance. Those two groups have similar speeds of technical progress in the two stages. This finding may be justified by the fact that insurers in a FHC have access to various channels created by other subsidiaries of the FHC, especially the information channel from a commercial bank. Although the traditional one-stage SFA method supports that on average FHC firms have higher efficiency measures and grow at a faster speed than non-FHC firms, one fails to recognize which subunit in an insurer contributes to those efficiency and productivity gains. Therefore, no feasible recommendations can be raised to managers.

[10] The five companies are Bank Taiwan Life, Cathay Life, Shin Kong Life, Fubon Life, and CTC Life.

[Insert Table 10 Here]

Before 1992 there were only seven domestic life insurers in Taiwan. These old insurance firms have more or less market power and enjoy the advantage of scale economies. The government deregulated the insurance market in 1992 and permitted foreign life and new life insurance companies to enter the market. New competitors are devoted to adopting new innovations and to providing new insurance products that meet clients' needs at a low cost and/or to expand their investment revenue in order to be more profitable and viable. It is an interesting question for whether new entrants have outperformed existing firms. We divide the entire sample into two groups: old life insurers existing before 1992 and new life insurers established after 1993. The old insurers are PCA Life, Cathay Life, China Life, Nan Shan Life, Kuo Hua Life, and Shin Kong Life. Table 11 reveals that the average technical efficiency scores and technical progress of new life insurers in both stages are significantly higher than those of old life insurers, except for the technical efficiency in the second stage. Conversely, the traditional single-stage model suggests that the technical progress of old firms is faster than that of new firms, and that the two groups of life insurers have similar efficiency scores on average.

[Insert Table 11 Here]

Conclusion

Taiwan's life insurance market structure has experienced drastic adjustments over the past two decades due to the passage of the financial holding company law in 2001 and the country entering WTO in 2002. It is interesting to investigate issues such as production characteristics in different subsectors, changes in efficiency scores, technical progress, and performance comparisons between different forms of life insurers. Important policy and economic implications may naturally result from studying these issues. One potential innovation is that we develop the network SFA model that allows for examining the performance of various sectors of an insurer without relying on disaggregate data. Conversely, the network DEA model requires either the availability of sectoral disaggregate data or some ad hoc assumption on the distribution of inputs among subunits of a firm. The traditional single production stage model can mislead the characterization of an insurer's production technology and the assessment of its performance.

To exemplify the network SFA model, we compile data from Taiwan's insurance industry that contain twenty-six life insurance companies spanning the period 2000-2012. The main empirical results can be summarized as follows. First, life insurance companies in Taiwan employ 41.2% of internal staff members and 93.89% of physical capital in the first stage of premiums' generation (marketing stage). Second, the average efficiency score in the second investment stage is greater than that of the first stage. Third, the sample life insurers enjoy economies of scale in both stages, which are not exhausted. Moreover, technical progress prevails in the two stages. Fourth, the managerial abilities of domestic life insurers are found to be superior to those of foreign insurers in both stages, although their rates of technical advancement are similar. Fifth, an average FHC insurer has a higher efficiency score than that of an average non-FHC insurer in the first stage, and those two types of insurers have similar technology gains in both stages. The advantage that a representative FHC insurer has in the marketing stage may be ascribable to the synergy effects within the FHC. Sixth and finally, newly established life insurance companies are found to outperform old insurers in the first stage, and the former have significantly greater technology gains than the latter in both stages. Note that the traditional single-stage model leads to quite a different picture.

Appendix A. Deriving the joint pdf of $\varepsilon_1, \varepsilon_2, \eta_1,$ and η_2

According to Sklar's theorem (1959), the joint cumulative distribution function (CDF) of the four random variables, $F(\cdot)$, for the i^{th} observation can be represented by the copula function, $CC(\cdot)$, as follows:

$$F(\varepsilon_{1i},\cdots,\eta_{2i}) = CC(F_1(\varepsilon_{1i}),\cdots,F_4(\eta_{2i});\rho), \tag{A1}$$

where $F_j(\cdot)$, $j=1,\cdots,4$, is a one-dimensional marginal CDF of the j^{th} random variable, and ρ is a vector of parameters representing dependence among those marginal CDFs. Taking partial derivatives of (A1) with respect to ε_1, ε_2, η_1, and η_2, the corresponding joint pdf is formulated as:

$$f(\varepsilon_{1i},\cdots,\eta_{2i}) = c(F_1(\varepsilon_{1i}),\cdots,F_4(\eta_{2i});\rho)\times\prod_{j=1}^{2} f_j(\varepsilon_{ji})\times f_3(\eta_{1i})\times f_4(\eta_{2i}). \tag{A2}$$

There are in fact many copula functions to date. Following Lai and Huang (2013), we select the Gaussian copula to construct the joint CDF, which takes the form:

$$F(\varepsilon_{1i},\cdots,\eta_{2i}) = \Phi_4(\Phi^{-1}(F_1(\varepsilon_{1i})),\cdots,\Phi^{-1}(F_4(\eta_{2i}));\Omega), \tag{A3}$$

where $\Phi^{-1}(\cdot)$ is the inverse CDF function of the univariate standard normal, and

$\Phi_4(\cdot)$ is the joint CDF of the 4-variate standard normal distribution with zero means and a 4×4 symmetric correlation matrix Ω:

$$\Omega=\begin{pmatrix} 1 & \Omega_{12} & \Omega_{13} & \Omega_{14} \\ & 1 & \Omega_{23} & \Omega_{24} \\ & & 1 & \Omega_{34} \\ & & & 1 \end{pmatrix}.$$

Here, Ω_{jk} denotes the dependence between two variables, $\Phi^{-1}\left(F_j\right)$ and $\Phi^{-1}\left(F_k\right)$. The joint pdf of Gaussian copula for the i^{th} sample is written as:

$$\begin{aligned} f(\varepsilon_{1i},\cdots,\varepsilon_{4i}) &= c(F_1(\varepsilon_{1i}),\cdots,F_4(\varepsilon_{4i});\Omega)\times\prod_{j=1}^{2} f_j(\varepsilon_{ji})\times f_3(\eta_{1i})\times f_4(\eta_{2i}) \\ &= \frac{1}{|\Omega|^{1/2}}\exp\left[\frac{-1}{2}\zeta_i'(\Omega^{-1}-I_4)\zeta_i\right]\times\prod_{j=1}^{2} f_j(\varepsilon_{ji})\times f_3(\eta_{1i})\times f_4(\eta_{2i}) \end{aligned} \quad \text{(A4)}$$

We note $\zeta_i=(\Phi^{-1}(F_1(\varepsilon_{1i})),\cdots,\Phi^{-1}(F_4(\eta_{2i})))'$, and I_4 is a 4×4 identity matrix.

The log-likelihood function of simultaneous equations (1), (7), and (8), assuming *N* observations, is shown to be:

$$\ln L(\theta)=\sum_{i=1}^{N}\ln f(\varepsilon_{1i},\cdots,\varepsilon_{4i})$$

$$=\sum_{i=1}^{N}\ln c(F_1(\varepsilon_{1i}),\cdots,F_4(\eta_{2i});\Omega)+\sum_{j=1}^{2}\sum_{i=1}^{N}\ln f_j(\varepsilon_{ji})+\sum_{i=1}^{N}\ln f_3(\eta_{1i})+\sum_{i=1}^{N}\ln f_4(\eta_{2i}) \quad \text{(A5)}$$

$$=\frac{-N}{2}\ln|\Omega|-\frac{1}{2}\sum_{i=1}^{N}\zeta_i'(\Omega^{-1}-I_4)\zeta_i+\sum_{j=1}^{2}\sum_{i=1}^{N}\ln f_j\left(\varepsilon_{ji}\right)+\sum_{i=1}^{N}\ln f_3(\eta_{1i})+\sum_{i=1}^{N}\ln f_4(\eta_{2i}), \quad \text{(A6)}$$

where θ is the vector of unknown parameters, including the dependence Ω. Under the regularity conditions for the asymptotic maximum likelihood theory, the ML estimator can be shown to be consistent, asymptotically efficient, and asymptotic normal. The first term in (A5) reflects the correlations between the four equations, and the second term is the log-likelihood function that ignores correlations between ε_js, η_1, and η_2. Although the separate regression of the last three terms may still give consistent estimates and valid standard errors under correctly specified marginal densities, the standard errors are inefficient. Maximizing (A5) gives rise to consistent and more efficient ML estimators, provided the correct copula density is considered.

It is well-known that the marginal pdfs of $f_1(\varepsilon_1)$ and $f_2(\varepsilon_2)$ can be respectively expressed as follows.

$$f_1(\varepsilon_1) = \frac{2}{\sigma_1}\phi(\frac{\varepsilon_1}{\sigma_1})\Phi(-\frac{\lambda_1\varepsilon_1}{\sigma_1}),\ \ \sigma_1^2 = \sigma_{u1}^2 + \sigma_{v1}^2,\ \ \lambda_1 = \frac{\sigma_{u1}}{\sigma_{v1}} \tag{A7}$$

$$f_2(\varepsilon_2) = \frac{2}{\sigma_2}\varphi(\frac{\varepsilon_2}{\sigma_2})\Phi(\frac{\lambda_2\varepsilon_2}{\sigma_2}),\ \ \sigma_2^2 = \sigma_{u2}^2 + \sigma_{v2}^2,\ \ \lambda_2 = \frac{\sigma_{u2}}{\sigma_{v2}}. \tag{A8}$$

Note that the composite errors of ε_1 and ε_2 have skew normal distribution without closed forms. This hinders one from deriving their CDFs, i.e., $F_1(\varepsilon_{1i})$ and $F_2(\varepsilon_{2i})$, not to mention their inverse functions of $\Phi^{-1}(F_1(\varepsilon_{1i}))$ and $\Phi^{-1}(F_2(\varepsilon_{2i}))$. The corresponding CDFs are re-written as:

$$F_1(Q_1) = \int_{-\infty}^{Q_1} f(\varepsilon_1)d\varepsilon_1 = \int_{-\infty}^{Q_1}\frac{2}{\sigma}\phi(\frac{\varepsilon_1}{\sigma_1})\Phi(-\frac{\lambda_1\varepsilon_1}{\sigma_1})d\varepsilon_1$$

$$= \frac{2}{\sigma}\int_{-\infty}^{Q_1}(\int_{-\infty}^{-\frac{\lambda_1\varepsilon_1}{\sigma_1}}\phi(\xi)d\xi)\phi(\frac{\varepsilon_1}{\sigma_1})d\varepsilon_1 = \frac{2}{\sigma_1}I_1(Q_1)$$

$$I_1(Q_1) = \int_{-\infty}^{Q_1}(\int_{-\infty}^{a_1\varepsilon_1}\phi(\xi)d\xi)\phi(b_1\varepsilon_1)d\varepsilon_1,\ \ a_1 = -\frac{\lambda_1}{\sigma_1} < 0,\ \ b_1 = \frac{1}{\sigma_1}$$

$$F_2(Q_2) = \int_{-\infty}^{Q_2} f_2(\varepsilon_2)d\varepsilon_2 = \int_{-\infty}^{Q_2}\frac{2}{\sigma_2}\phi\left(\frac{\varepsilon_2}{\sigma_2}\right)\Phi\left(\frac{\lambda_2\varepsilon_2}{\sigma_2}\right)d\varepsilon_2$$

$$= \frac{2}{\sigma_2}\int_{-\infty}^{Q_2}(\int_{-\infty}^{\frac{\lambda_2\varepsilon_2}{\sigma_2}}\phi(\xi_2)d\xi_2)\phi\left(\frac{\varepsilon_2}{\sigma_2}\right)d\varepsilon_2 = \frac{2}{\sigma_2}I_2(Q_2)$$

$$I_2(Q_2) = \int_{-\infty}^{Q_2}(\int_{-\infty}^{a_2\varepsilon_2}\phi(\xi_2)d\xi_2)\phi(b_2\varepsilon_2)d\varepsilon_2,\ \ a_2 = \frac{\lambda_2}{\sigma_2} > 0,\ \ b_2 = \frac{1}{\sigma_2}.$$

Some numerical integrations or simulated ML procedures (e.g., Greene (2003, 2010)) may be used to approximate the integration in computing $I_j\left(Q_j\right),\ j = 1,2$. In this paper we instead follow Tsay et al. (2013) to acquire the approximation functions of $I_j\left(Q_j\right)$, $j=1,2$, $I_j^{app}(Q_j)$, as follows:

$$\begin{aligned} I_1^{app}(Q_1) &= \frac{1}{2b_1}\left[1+erf(\frac{b_1Q_1}{\sqrt{2}})(\frac{1-sign(Q_1)}{2})\right] \\ &\quad -\frac{1}{4\sqrt{b_1^2-a_1^2c_2}}\exp(\frac{a_1^2c_1^2}{4(b_1^2-a_1^2c_2)})\left\{1+erf\left[\frac{-a_1c_1-\sqrt{2}Q_1(b_1^2-a_1^2c_2)sign(Q_1)}{2\sqrt{b_1^2-a_1^2c_2}}\right]\right\} \end{aligned} \tag{A9}$$

$$\begin{aligned} I_2^{app}(Q_2) &= \frac{\exp\left(\dfrac{a_2^2c_1^2}{4b_2^2-4a_2^2c_2^2}\right)}{4\sqrt{b^2-a_2^2c_2}}\left[1-erf\left(\frac{-a_2c_1+\sqrt{2}Q_2(b_2^2-a_2^2c_2)+sign(Q_2)}{2\sqrt{b_2^2-a_2^2c_2}}\right)\right] \\ &\quad +\frac{erf\left(\dfrac{b_2Q_2}{\sqrt{2}}\right)}{2b_2}\frac{1+sign(Q_2)}{2}. \end{aligned} \tag{A10}$$

Here, $c_1=-1.09500814703333$, $c_2=-0.75651138383854$, and $erf(z)=\frac{2}{\sqrt{\pi}}\int_0^z e^{-t^2}dt=2\int_0^{\sqrt{2}z}\phi(t)dt$ is the error function, which can easily be computed with a standard statistical package. Constants c_1 and c_2 are so derived that we can approximate the error function very well by another function, $g(z)=1-\exp\left(c_1z+c_2z^2\right)$, for $z\ge 0$. The derivation of $I_j^{app}(Q_j)$ is quite tedious and hence ignored. Readers can refer to Tsay et al. (2013) who also demonstrate that $F_j^{app}(Q_j)=\frac{2}{\sigma_j}I_j^{app}(Q_j)$, j = 1, 2, delivers a very accurate approximation to $F_j(Q_j)$.

Appendix B. Parameter estimates of equation (9)

Six out of fifteen coefficients are significant at least at the 10% level. The null hypothesis that all slope parameters are jointly zeros is decisively rejected. The tests for homoscedastic errors cannot be rejected, because the test statistics of LM and Ramsey's RESET2 are insignificant. In addition, the adjusted R^2 are as high as 0.89. The cost function appears to fit well, and the coefficient estimates are then used to compute the shadow price of Z according to formula (10).

Variables	**Estimated Parameter**	**Standard Error**
Intercept	6.12827	4.7025

$\ln Z$	1.33128	1.1811
$\ln Y$	-2.14698**	0.9024
$\ln W_2^*$	0.3016	0.2963
t	0.3308***	0.1054
$0.5\times(\ln Z)^2$	-0.1797	0.1915
$0.5\times(\ln Y)^2$	-0.0727	0.1547
$0.5\times\left(\ln W_2^*\right)^2$	0.0670***	0.0164
$0.5\times t^2$	0.0179***	0.0038
$\ln Z\times\ln Y$	0.1878	0.1659
$\ln Z\times\ln W_2^*$	0.0305	0.0472
$\ln Z\times t$	-0.0441**	0.0169
$\ln Y\times\ln W_2^*$	-0.0115	0.0399
$\ln Y\times t$	0.0206	0.0143
$\ln W_2^*\times t$	0.0087*	0.0052
Adjusted R^2	0.89	
Number of observation	266	
LM het. test	1.1211	*p*-value = 0.290
Ramsey's RESET2	0.0474	*p*-value = 0.828

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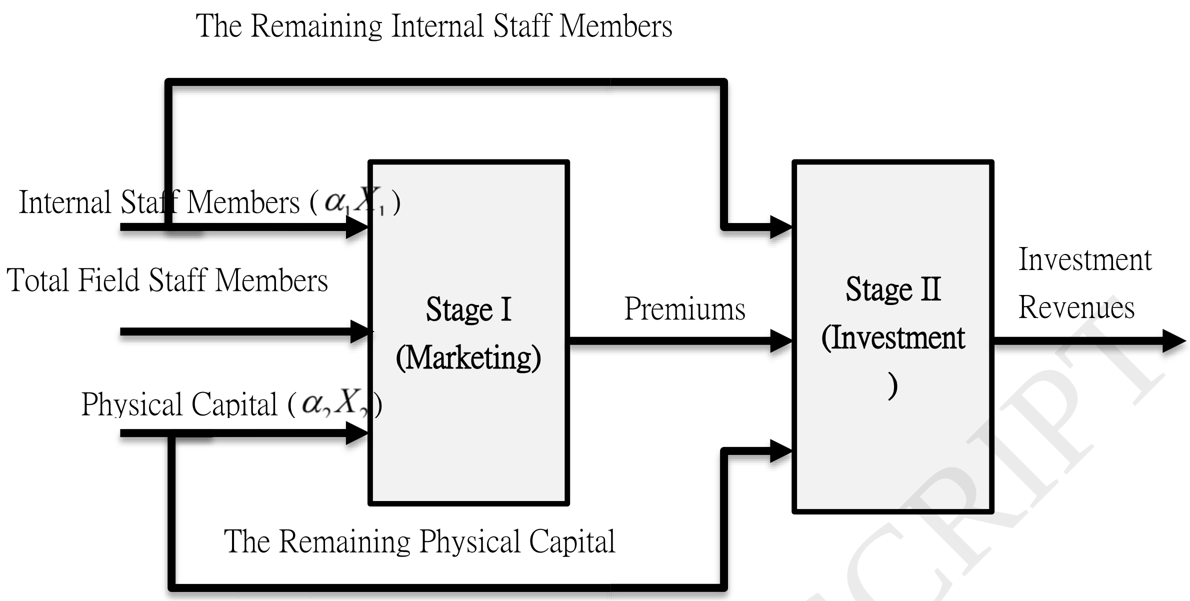

Note： α_1 and α_2 are the percentage of internal staff members and physical capital, respectively, employed in Stage I.

Figure 1. Network Production Process of the Insurance Company

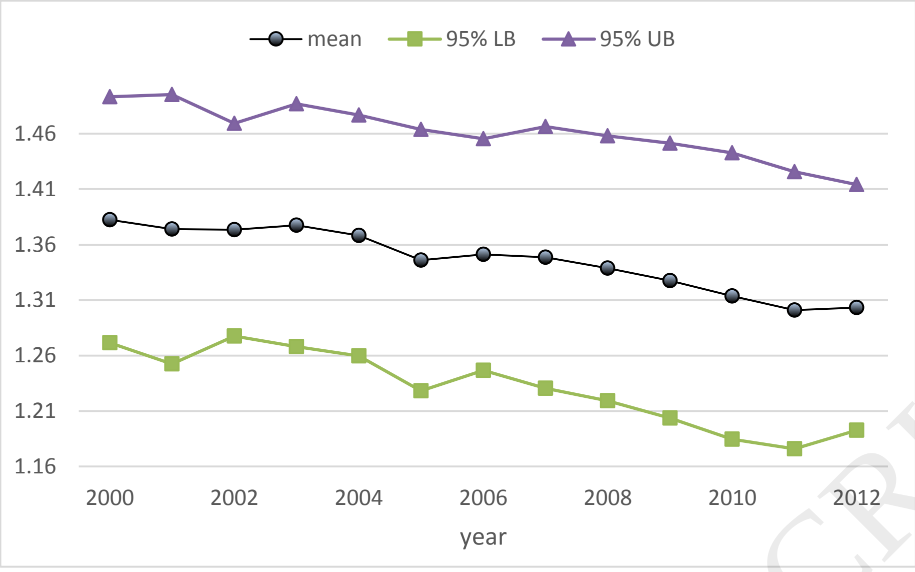

Figure 2. The trend of average scale elasticities-production

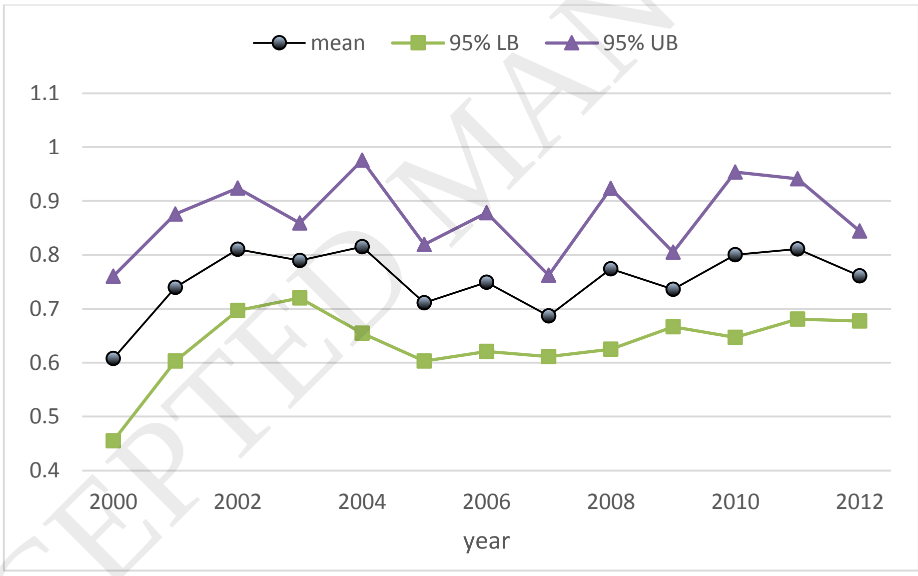

Figure 3. The trend of average scale elasticity-cost

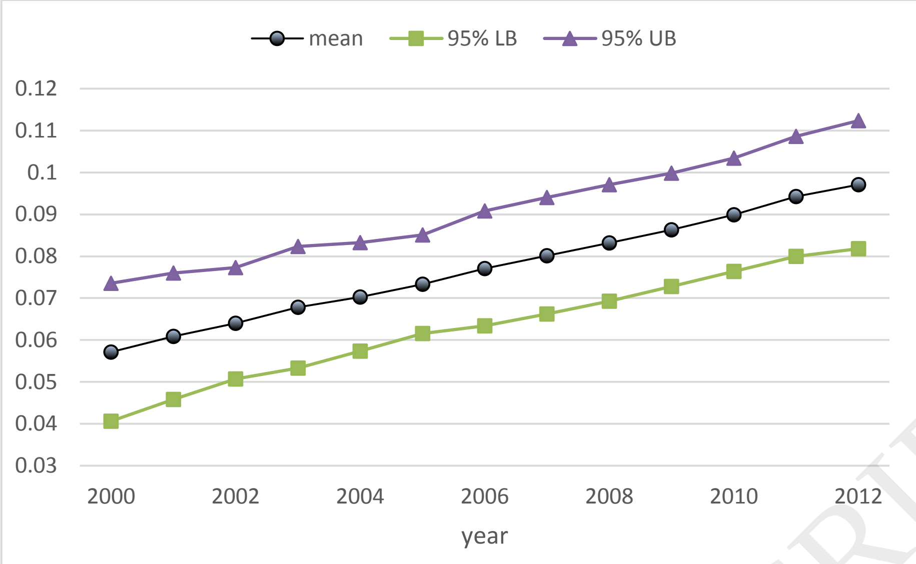

Figure 4. The trend of average technical change-production

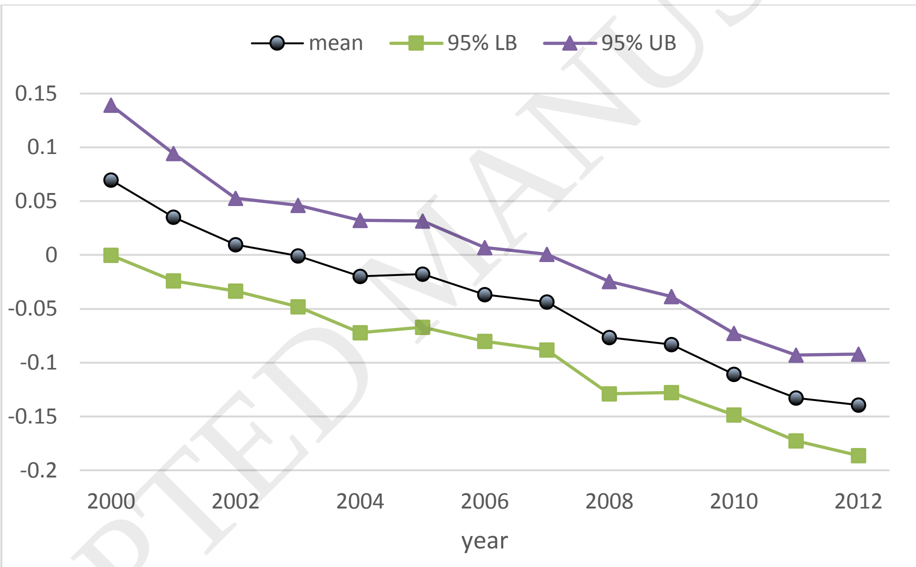

Figure 5. The trend of average technical change-cost

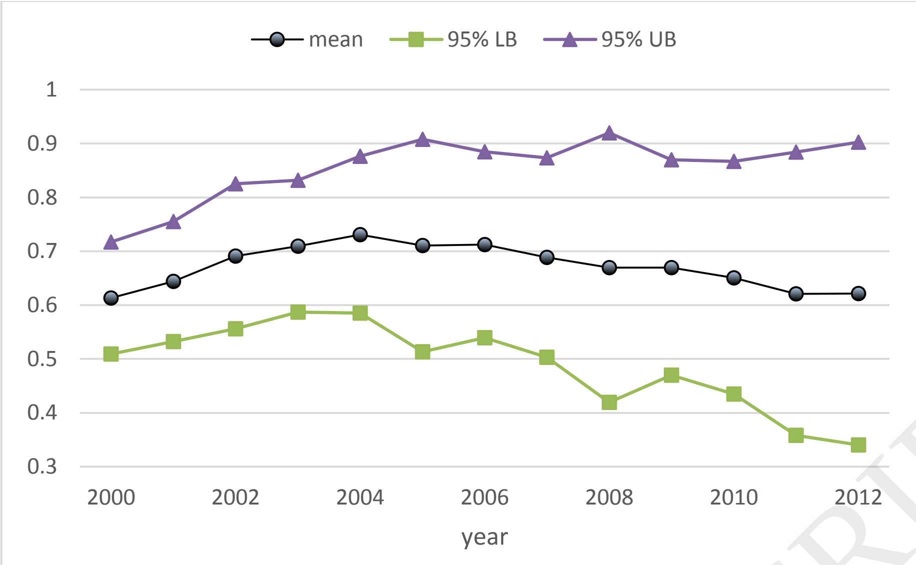

Figure 6. Trend of technical efficiency-production

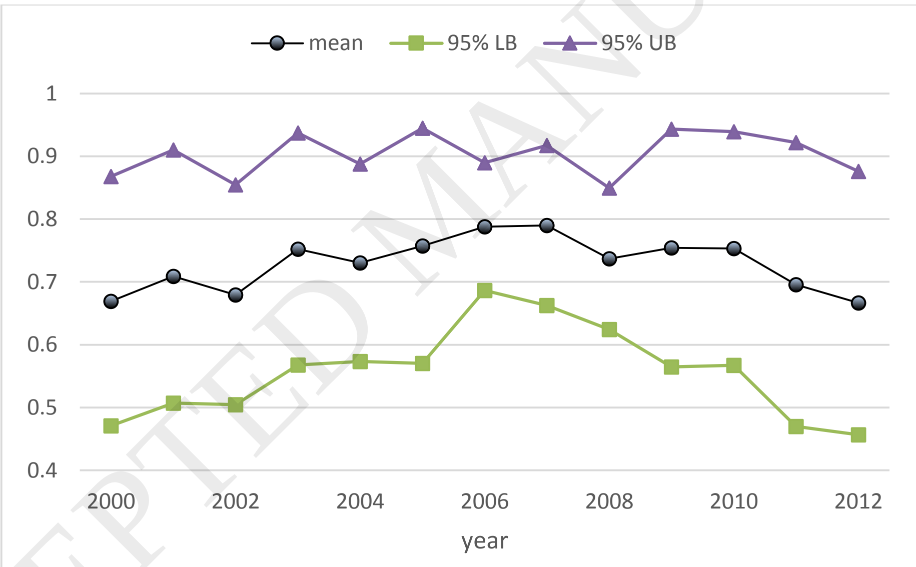

Figure 7. The trend of technical efficiency-cost

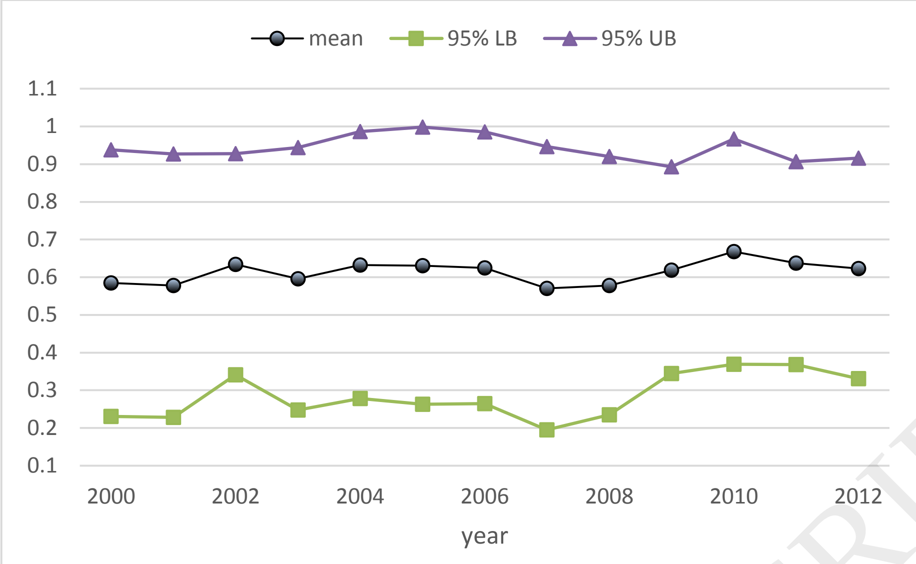

Figure 8. The trend of technical efficiency-traditional cost

Table 1. Variable definition

Variable Name	Definition
Outputs	
Premiums (*Z*)	The sum of premiums from life insurance, health insurance, and personal injured insurance.
Investment revenues (*y*)	The sum of interest revenues, security investment revenues, and real estate investment revenues.
Inputs	
Number of internal staffs (X_1)	Including department and office managers, business staffs, branch managers, business supervisors, and training staffs.
Total fixed assets (X_2)	A balance sheet item, including land, buildings, machines, equipment, and other related facilities.
Number of field staffs (X_3)	Including certified and registered sales representatives.
Input Prices	
Price of internal staffs (W_1)	The ratio of personnel expenses to the number of internal staffs
Price of fixed assets (W_2)	The ratio of the sum of expenditures on depreciation, maintenance, amortization, and bad debt to total fixed assets
Shadow price of premiums (W_3)	Calculated by taking a partial derivative of an estimated cost function with respect to *Z* that is treated as a quasi-fixed input in that cost function. See the text for detailed derivation.
Price of field staffs (W_4)	The ratio of salesman allowance to the number of field staffs

Table 2. Descriptive statistics

	Mean	Standard deviation	Minimum	Maximum
Premiums*	62220961	93414500	559323	522179000
Investment revenues*	14381609	25253900	55240	171235000
Internal staffs	1123.0677	1303.5206	75	6703
Total fixed assets*	3079886	4713337	16730	20120600
Field staffs	9678.2481	15372.0806	11	83676
Price of internal staffs*	1462	1885.1119	127.7375	20525
Price of fixed Assets	0.3776	0.8484	0.0019	11.3744
Shadow price of premiums	0.0285	0.0329	0.0010	0.1872
Number of observations	266			

Note: *: measured by thousands of New Taiwan Dollars and deflated by the consumer price index of Taiwan with base year 2011.

Table 3. Slope parameter estimates from the nonlinear LS

Panel A : Production Function		
Variables	**Estimates**	**Standard error**
α_1	0.4120***	0.0174
α_2	0.9389***	0.0026
$\ln(\alpha_1 X_1)$	1.7001***	0.1904
$\ln(\alpha_2 X_2)$	-0.0077	0.1078
$\ln(X_3)$	-0.2915**	0.1292
t	0.1018***	0.0210
$0.5[\ln(\alpha_1 X_1)]^2$	-0.2211***	0.0746
$0.5[\ln(\alpha_2 X_2)]^2$	-0.0397***	0.0131
$0.5[\ln(X_3)]^2$	-0.0222	0.0196
$0.5t^2$	0.0036**	0.0017
$\ln(\alpha_1 X_1)\ln(\alpha_2 X_2)$	0.0525**	0.0267
$\ln(\alpha_1 X_1)\ln(X_3)$	0.0402	0.0340
$\ln(\alpha_2 X_2)\ln(X_3)$	0.0184	0.01434
$t\ln(\alpha_1 X_1)$	-0.0057	0.0058
$t\ln(\alpha_2 X_2)$	-0.0031	0.0026
$t\ln(X_3)$	0.0031	0.0033
Panel B : Cost Function		
Variables	**Estimates**	**Standard error**

$\ln(Y)$	1.0895***	0.0310
$\ln(W_2/W_1)$	0.1687***	0.0067
$\ln(W_3/W_1)$	1.314***	0.0233
t	-0.1655***	0.0145
$0.5[\ln(Y)]^2$	-0.0045*	0.0024
$0.5[\ln(\mathrm{W}_2/W_1)]^2$	0.0020***	0.0002
$0.5[\ln(\mathrm{W}_3/W_1)]^2$	0.1021***	0.0016
$0.5t^2$	-0.0192***	0.0009
$\ln(Y)\ln(W_2/W_1)$	0.0028***	0.0003
$\ln(Y)\ln(W_3/W_1)$	0.0345***	0.0011
$t\ln(Y)$	0.0149***	0.0011
$\ln(W_2/W_1)\ln(W_3/W_1)$	0.0185***	0.0005
$t\ln(W_2/W_1)$	0.0029***	0.0002
$t\ln(W_3/W_1)$	-0.0058***	0.0008

Note: *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 4. Parameter estimates from the ML

Variables	Estimates	Standard error
Intercept of the production function	9.9465***	0.1256
Intercept of the cost function	4.3015***	0.0958
$\lambda_1 \left(=\sigma_{u1} / \sigma_{v1}\right)$	1.0243**	0.4028
$\lambda_2 \left(=\sigma_{u2} / \sigma_{v2}\right)$	1.1435**	0.4573
$\sigma_1 \left(=\sqrt{\sigma_{u1}^2 + \sigma_{v1}^2}\right)$	0.7321***	0.0776
$\sigma_2 \left(=\sqrt{\sigma_{u2}^2 + \sigma_{v2}^2}\right)$	0.5535***	0.0618
Ω_{12}	-0.2524***	0.0578
Log likelihood = -392.516		

Note: *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Table 5. Parameter estimates of the stochastic cost frontier under the traditional single production process

Variables	Estimates	Standard error
Intercept	7.7178	6.1139
$\ln(Z)$	1.3123	1.5839
$\ln(Y)$	-2.5974**	1.2169
$\ln(W_2/W_1)$	0.1710	0.3987
$\ln(W_4/W_1)$	-1.3850***	0.4970
t	0.4916***	0.1417
$0.5[\ln(Z)]^2$	-0.1647	0.2579
$0.5[\ln(Y)]^2$	-0.2674	0.2075
$0.5[\ln(W_2/W_1)]^2$	0.0257	0.0249
$0.5[\ln(W_4/W_1)]^2$	-0.0504	0.0364
$0.5t^2$	0.0134**	0.0057
$\ln(Z)\ln(Y)$	0.2835	0.2210
$\ln(Z)\ln(W_2/W_1)$	0.1584**	0.0664
$\ln(Z)\cdot\ln(W_4/W_1)$	0.0989	0.0638
$t\ln(Z)$	-0.0762***	0.0220
$\ln(Y)\ln(W_2/W_1)$	-0.1734***	0.0581
$\ln(Y)\ln(W_4/W_1)$	-0.0561	0.0534
$t\ln(Y)$	0.0451**	0.0195
$\ln(W_2/W_1)\ln(W_4/W_1)$	-0.0824***	0.0294

$t\ln(W_2/W_1)$	0.0036	0.0076
$t\ln(W_4/W_1)$	0.0120	0.0097
σ^2	0.5007***	0.0776
γ	0.8337***	0.0692
Log likelihood = -178.5098		

Note: 1. *** denotes significance at the 1% level; ** denotes significance at the 5% level.

2. W_4 is the price of field staffs.

Table 6. Measures of scale elasticities and technical change

Network SFA			
Measures	**Definition**	**Mean**	**Standard deviation**
Scale elasticity-production	$\sum_{i=1}^{3}\frac{\partial \ln Z}{\partial \ln X_i}$	1.3462	0.0639
Scale elasticity-cost	$\frac{\partial \ln C}{\partial \ln Y}$	0.7205	0.0436
Technical change-production	$\frac{\partial \ln Z}{\partial t}$	0.0772	0.0143
Technical change-cost	$\frac{\partial \ln C}{\partial t}$	-0.0372	0.0680
Single Production Process			
Measures	**Definition**	**Mean**	**Standard deviation**
Cost elasticity	$\frac{\partial \ln C'}{\partial \ln Z}+\frac{\partial \ln C'}{\partial \ln Y}$	0.8865	0.1907
Technical change-cost	$\frac{\partial \ln C'}{\partial t}$	-0.0637	0.0696

Note: C' denotes cost function under the traditional single production process.

Table 7. Average technical efficiency measures

	Network SFA Model		Cost efficiency under the traditional single production process
	First stage (Production Frontier)	Second stage (Cost Frontier)	
Mean	0.6714	0.7290	0.6135
Standard Deviation	0.1033	0.0976	0.1675

Table 8. Average Efficiency Scores across Time

	Stage I Marketing Activity		Stage II Investment Activity		Traditional Single Stage
Year	**Mean**	**Standard deviation**	**Mean**	**Standard deviation**	**Mean**
2000	0.6131	0.0531	0.6694	0.1013	0.5844
2001	0.6438	0.0569	0.7087	0.1027	0.5777
2002	0.6908	0.0686	0.6794	0.0893	0.6343
2003	0.7096	0.0625	0.7523	0.0942	0.5958
2004	0.7309	0.0744	0.7304	0.0802	0.6322
2005	0.7106	0.1007	0.7574	0.0955	0.6307
2006	0.7123	0.0881	0.7880	0.0518	0.6251
2007	0.6885	0.0944	0.7899	0.0649	0.5707
2008	0.6697	0.1276	0.7368	0.0575	0.5776
2009	0.6699	0.1020	0.7541	0.0966	0.6186
2010	0.6507	0.1102	0.7532	0.0948	0.6679
2011	0.6210	0.1342	0.6957	0.1153	0.6372
2012	0.6215	0.1433	0.6665	0.1070	0.6234
Average	0.6714	0.1033	0.7290	0.0976	0.6135

Table 9. Performance comparisons between domestic and foreign insurers

Category	Observations	Network SFA				Traditional Single Stage	
		Stage I (Marketing Activity)		Stage II (Investment Activity)			
		Technical Efficiency	Technical Change	Cost Efficiency	Technical Change	Cost Efficiency	Technical Change
Domestic Company	240	0.6836 (0.0954)	0.0769 (0.0136)	0.7384 (0.0915)	-0.0424 (0.0648)	0.6175 (0.1679)	-0.0648 (0.0677)
Foreign Company	26	0.5588 (0.1068)	0.0793 (0.0194)	0.6423 (0.1104)	-0.0470 (0.0828)	0.5764 (0.1616)	-0.0534 (0.0864)
t-statistics		6.2599***	-0.8174	4.9779***	0.3338	1.1917	-0.4272

Note: Numbers in parentheses are standard deviations and *** denotes significance at the 1% level.

Table 10. Performance comparisons between FHC and non-FHC insurers

Category	Observations	Network SFA				Traditional Single Stage	
		Stage I (Marketing Activity)		Stage II (Investment Activity)			
		Technical efficiency	Technical change	Cost efficiency	Technical change	Cost efficiency	Technical change
FHC Insurers	40	0.7386 (0.0512)	0.0776 (0.0130)	0.7411 (0.0702)	-0.0424 (0.0590)	0.6936 (0.1004)	-0.0966 (0.0558)
Non-FHC Insurers	226	0.6595 (0.1057)	0.0771 (0.0145)	0.7268 (0.1016)	-0.0430 (0.0679)	0.5993 (0.1730)	-0.0579 (0.0703)
t-statistics		4.6312***	0.2245	0.8551	0.0456	3.3449***	-3.3064***

Note: Numbers in parentheses are standard deviations and *** denotes significance at the 1% level.

Table 11. Performance comparisons between old and new insurers

Category	Observations	Network SFA				Traditional Single Stage	
		Stage I (Marketing Activity)		Stage II (Investment Activity)			
		Technical efficiency	Technical change	Cost efficiency	Technical change	Cost efficiency	Technical change
Old	76	0.6471 (0.0854)	0.0697 (0.0138)	0.7161 (0.0920)	-0.0195 (0.0703)	0.5945 (0.1549)	-0.0994 (0.0588)
New	190	0.6811 (0.1083)	0.0802 (0.0133)	0.7341 (0.0995)	-0.0523 (0.0628)	0.6211 (0.1720)	-0.0494 (0.0686)
t-statistics		-2.4514**	-2.4205**	-1.3651	3.7162***	-1.1738	-5.5792***

Note: Numbers in parentheses are standard deviations and ** and *** denote significance at the 5% and 1% level, respectively.