財務管理硏究 第十四卷 第一號(1997. 6), 107～139

效率性推定과 生産物定義에 대한 比較硏究
- 美國 生命保險産業을 대상으로 -

김 헌 수*

<요 약>

다른 금융산업과 마찬가지로 생명보험산업의 효율성에 대한 실증연구는 두 가지 문제에 봉착하게 된다. 하나는 효율성을 실증적으로 추정하는 다양한 추정방법은 일관되게 동일한 결과를 도출하는가 하는 것이며 다른 문제는 효율성추정에 사용된 생산물정의에서 어떤 대리변수를 사용하는 것이 가장 좋으냐 하는 것이다.

Yuengert(1993)은 미국 생보산업 전체의 효율성과 추정방법간의 관계를 보고하였는데 본 연구는 추정방법 뿐만 아니라 생보산업 생산물의 정의에 따라 개별생보사의 효율성지수가 차이가 있다는 것을 248개의 미국 생명보험회사를 대상으로 검증하였다. 본 논문에서는 계량경제학적 방법중 널리 사용되는 SFA(stochastic frontier approach)중에서 비효율성이 half-normal, truncated normal, exponential 분포라고 한 방법들과 비분포방법(DFA: distribution free approach)을 사용하였다. 또 각 방법마다 거수보험료(premiums)와 claims-plus-reserve라는 새로운 생산물 대리변수로 사용하여 효율성을 측정하였다. 그리하여 총 8가지의 다른 방법으로 추정한 효율성지수를 비교, 분석하였다.

연구결과 표1과 2에서 나타난 바와 같이 SFA방법(1, 3, 5번)간에는 결과가 거의 일치하였고 같은 추정방법에서 생산물 대리변수가 다른 경우에도(1과2, 3과4, 5와6, 7과8) 결과는 큰 차이가 없었다. 이는 생보산업에서 거수보험료를 생산물 대리변수로 하는 것이 이론적 문제가 있음에도 불구하고 구조적 편견(systematic bias)은 나타나지 않았다는 Suret(1991)의 결과를 지지하고 있다. DFA방법(7과 8번)과 SFA방법(1-6번)간에는 상관계수는 낮게 나타났는데 이는 생보산업의 효율성을 각각 DFA와 SFA방법을 사용한 두 연구(Gardner and Grace, 1993; Zi, 1994) 결과의 차이와 일치하고 있다.

* 순천향대학교 경제학부 교수

** 본 연구에 대해 지속적으로 조언을 해 주신 Georgia State University의 Dr. Skipper와 Dr. Grace에게 깊은 감사의 말을 전하며 1995년 American Risk and Insurance Association 연례학술회의 참석자들에게 사의를 표합니다. 그리고 본 논문에 대한 유익한 논평과 지적을 해 주신 익명의 심사위원들에게도 감사드립니다.

I. Introduction

The life insurance industry contributes significantly to the U.S. economy and to the economic security of individuals in the country. Competition not only among life insurers but also with other financial institutions is unprecedented due to deregulation and technological change. In this regard, the cost structure of the life insurance industry is an important issue for insurance company executives, policymakers and researchers since the cost structure may determine market behavior and potentially the long-run survival of life insurers.

Most efficiency studies encounter two important conceptual issues: proper output definition and proper estimation techniques. Since life insurance companies produce intangible services, researchers have difficulty measuring the outputs of a company. Two recent studies [Grace and Timme(1992) and Gardner and Grace (1993)] used premiums while a third study[Yuengert (1993)] used additions to reserves as life insurance companies'outputs. Although premiums and reserve levels have been the most widely used output proxies in insurance cost studies, controversy remains.

Previous literature has not reached a conclusion regarding an appropriate methodology in measuring efficiency. The different estimation methodologies typically produce dissimilar results(see, e.g., Ferrier and Lovell, 1990). This is a serious challenge because unless the methodologies are sound and robust any research findings add little real information.

This paper tries to address these two problems. Specifically, this study examines the difference among eight efficiency derivation models using different distributional assumptions and two alternative output definitions.[1] For this purpose, firm-level efficiency rankings are calculated based on eight cost function models. Then the results are compared using nonparametric correlation analysis. The sensitivity result indicates that efficiency ranks

1) The authors intend to examine 24 efficiency derivation models using two alternative inputs, two alternative outputs, and six distributional assumptions.

appear generally robust with both output choices and error term distribution choices. However, efficiency ranks are slightly more sensitive to output variable choices than residual term distribution choices. The paper also improves input variable specification by recognizing agents'labor as an input factor in producing services.

1. Economic Efficiency

Economic efficiency relates to the economic theory of a firm. The theory assumes that firms try to minimize costs for given outputs(or maximize profits for given inputs). Deviation from this efficient behavior causes economic inefficiency. Economic (in)efficiency consists of scale, scope, allocative and technical (in)efficiency. Some economists classify scale and scope inefficiency as output inefficiency and allocative and technical inefficiency as input inefficiency or cost efficiency(Evanoff & Israilevich, 1991).

Output efficiency is an optimizing production behavior of efficient firms. Output efficiency includes optimizing output level(scale efficiency) and output mix(scope efficiency). Economies of scale exist if per unit cost decreases as output increases. A scale efficient firm will produce at constant returns to scale. Scope economies exist if the cost of joint production is less than the total cost of independent production. Recent life insurance efficiency studies(Grace & Timme, 1992; Yuengert, 1993) generally agree that little scope economies exist, but that significant scale economies exist in the life insurance industry, although the range of scale economies differs. The main concern of this paper is, however, not scale and scope efficiencies but cost efficiencies, i.e., the combination of allocative and technical inefficiencies.

Cost efficiency can be defined as the ratio of the minimum required costs to the actual costs utilized to produce a given output. It can be written formally as

$$Cost\ Efficiency = \frac{Minimum\ Cost\ Required}{Actual\ Cost\ Utilized} \tag{1}$$

The cost efficiency ratio varies from zero to one. The higher the ratio, the more efficient the firm. Therefore, firms on the cost frontier will have an efficiency ratio of one. By the same logic, the ratio may indicate the proportion of inputs optimally utilized in producing a given output. Economic theory suggests that cost efficiency (or input inefficiency) consists of allocative efficiency and technical efficiency.

Allocative inefficiency results from the use of a suboptimal input mix to produce a given level of output while technical inefficiency is caused by the excessive use of resources to produce a given output. For example, allocative inefficiency persists if a firm utilizes four units of labor and six units of capital to produce a widget when the optimal mix is five units of labor and five units of capital. On the other hand, technical inefficiency exists if a firm employs six units of labor and six units of capital under the same optimal input mix.

X-inefficiency is something different. According to its originator, Leibenstein(1966, 1975, 1977, 1978), X-inefficiency is neither allocative inefficiency nor technical inefficiency. X-inefficiency is related to the psychological nature of human behavior. Leibenstein observes that human organizations(i.e., firms) do not maximize their potential because of some aspects of human nature, for example, lack of motivation, bad customs, or inertia. Therefore, pure X-inefficiency can be described as the gap between actually attained minimum costs and theoretically attainable minimum production costs(referred to as Leibenstein's X-inefficiency or pure X-inefficiency to distinguish it from the currently used term X-inefficiency).

Empirically, researchers have not been successful in separating pure X-inefficiency from technical and allocative inefficiency. Previous authors have constructed a cost frontier using cost functions and have measured X-inefficiency by the distance from the cost frontier. This empirical notion of X-inefficiency includes not only Leibenstein's X-inefficiency but also allocative and technical inefficiency.[2] Recent efficiency literature seems to

2) Leibenstein also did not distinguish pure X-inefficiency from other input inefficiencies in his empirical study(Leibenstein & Maital, 1992).

adapt this liberal X-inefficiency definition to represent broad management inefficiency which includes allocative, technical and pure X-inefficiency.[3] Following this tradition, this paper employs this broad notion of X-inefficiency rather than the pure X-inefficiency definition.

While the X-inefficiency results from mismanagement or inefficient management, scale and scope inefficiencies may remain even with efficient or good management. For example, if a company operates at increasing returns to scale, scale inefficiency persists even with good management. If this is the case, the firm can take advantage of the scale efficiency by increasing outputs. For this reason, it is suspected that life insurance companies not operating at constant returns to scale can reduce costs by merging.

Ⅱ. Model And Methodology

This chapter is composed of two sections. They address the stochastic frontier approach and the distribution approach. For the stochastic frontier approach, three theoretical models using different inefficiency distribution assumptions are discussed. For the distribution free approach, hybrid translog cost functions employing the Box Cox transformation are presented.

1. Stochastic Frontier Approach

(1) Theoretical Model

To model a firm's production process, researchers frequently have developed production technology models based on input-output relationships. A cost function for a cost minimizing firm can be formally expressed as follows:

$$C(y, w) = \min_{(x)}\{\ w'x\ :\ (y, x) \text{ is in } T\ \} \tag{2}$$

3) For example, see berger, Hunter and Timme(1993) and especially the issue of the *Journal of Banking and Finance*(vol.17, 1993) on efficiency. Most authors define the term X-inefficiency as inefficiency which includes technical and allocative as well as pure X-inefficiency.

where y is an output vector(y is a scalar in the one output case), w is a vector of input prices, x is a vector of inputs, and T is the set of technologically feasible input-output combinations. At given input prices, the cost function defines the cost of producing y as the minimum cost input combination that can produce the output y.

The paper first employs the stochastic econometric frontier technology proposed by Aigner, Lovell, and Schmidt(1977). The model postulates that the observed costs of firms may deviate from the cost function of a cost minimizing producer due to inefficiencies and random errors. From equation 2, the form of the cost function for S firms in the sample is given by:[4]

$$C_i = C(w_i, y_i ; A) + u_i + v_i, \quad i=1,\dots S, \tag{3}$$

where C_i is the observed cost of firm i, A is a vector of parameters, $C(w_i, y_i ; A)$ is the predicted log cost function of a cost minimizing firm(i.e., the underlying cost frontier), v_i represents statistical white noise(i.e., N(0, σ^2)), and u_i represents inefficiency. Under the stochastic frontier model, three assumptions are employed for u_i.

(2) Error Term Specifications and Likelihood Functions

To measure a firm's efficiency, researchers use an empirical cost function like those discussed in the next section and focus on the cost function residual term as an indication of the firm's relative efficiency. Under the stochastic frontier approach, researchers have to assume a distribution for this inefficiency term. Currently, most popular assumptions are half-normal, truncated normal and exponential distributions.[5]

(3) Empirical Model

A functional form of production technology(T in equation 2) is required to model costs. Since the specific form of the cost function is not known,

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4) This model employs three inputs, five outputs and three control variables. See Chapter 5 for details.
5) Log-likelihood functional forms are available from the authors.

researchers usually approximate the function using various flexible forms. The translog cost function is known to be flexible and is used widely in cost studies. By employing a second-order translog approximation, the empirical cost equation can be written as:6)

$$
\begin{aligned}
& A_0 + \sum_{i=1}^{n} A_i \ln(Y_{is}) + \sum_{j=1}^{m} B_j \ln(W_{js}) + \sum_{K=1}^{l} P_K \ln(Z_{Ks}) \\
\ln(Cost)_s \quad = \quad & + \frac{1}{2} \sum_{i=1}^{n} \sum_{f=1}^{n} C_{if} \ln(Y_{is}) * \ln(Y_{fs}) + \frac{1}{2} \sum_{j=1}^{m} \sum_{g=1}^{m} E_{jg} \ln(W_{js}) * \ln(W_{gs}) \\
& + \sum_{i=1}^{n} \sum_{j=1}^{m} D_{ij} \ln(Y_{is}) * \ln(W_{js}) + u_s + v_s \qquad (4)
\end{aligned}
$$

In estimating equation (4), restrictions implying homogeneity of degree one in imput prices are imposed.

$$\sum_{j=1}^{3} B_j = 1, \quad \sum_{s=1}^{3} E_{jg} = 0, \quad \sum_{j=1}^{3} D_{ij} = 0.$$

Symmetry of second order coefficients is also imposed.

$$
\begin{aligned}
C_{ij} &= C_{ji} \quad \text{for } all \ i, j \\
E_{js} &= E_{sj} \quad \text{for } all \ j, s
\end{aligned}
$$

These homogeneity and symmetry restrictions are required for the empirical cost function to have the necessary properties of well-behaved traditional cost functions(Varian, 1992).

(4) Estimation of Efficiency Scores

After estimating cost functions, firm-level efficiency scores are found by the stochastic frontier approach, suggested by Aigner et al.(1977). To obtain firm-level inefficiency measurement, the approach suggested by Jondrow,

6) Control variables (Z_{ks}) are also employed for the translog cost function.

Lovell, Materov and Schmidt(1982) is employed. Since $\varepsilon_i = v_i + u_i$ and ε_i contains information of u_i, the mean or mode of the conditional distribution of u_i given ε_i can be a point estimate of u_i.

Half-Normal Distribution Case. For the half-normal stochastic frontier model, the probability density function of ε by Aigner et al.(1977), is

$$\begin{aligned} h(\varepsilon) &= \frac{2}{\sigma} f^*\left(\frac{-\varepsilon}{\sigma}\right)(1 - F^*(-\varepsilon\lambda\sigma^{-1})) \\ &= \frac{2}{\sigma}\frac{1}{\sqrt{2\pi}}\exp\left[\frac{1}{-2\sigma^2}\right](1 - F^*(-\varepsilon\lambda\sigma^{-1})) \end{aligned} \tag{5}$$

where

$$\varepsilon = v + u, \quad (v \sim N(0, \sigma^2{}_v), \quad u \sim |N(0, \sigma^2{}_v)|),$$

$$\sigma^2 = \sigma^2{}_u + \sigma^2{}_v, \quad \lambda = \frac{\sigma_u}{\sigma_v},$$

f^* = standard normal density functions, and

F^* = standard normal probability cumulative density function.

Then, the probability density functions of random variables, v and u, are

$$f(v) = (2\pi)^{-\frac{1}{2}}\frac{1}{\sigma_v}\exp\left(-\frac{1}{2}\frac{v^2}{\sigma^2{}_v}\right) \tag{6}$$

$$g(u) = 2(2\pi)^{-\frac{1}{2}}\frac{1}{\sigma_u}\exp\left(-\frac{1}{2}\frac{u^2}{\sigma^2{}_u}\right) \quad \text{for } u \geq 0 \tag{7}$$

As v and u are independent, the joint density function of v and u is the product of each density function(equations 6 and 7). The joint density function is written by

$$h(u, \varepsilon) = \frac{1}{\pi\sigma_u\sigma_v}\exp\left(-\frac{1}{2\sigma_u^2}u^2 - \frac{1}{2\sigma_v^2}(\varepsilon - u^2)\right) \tag{8}$$

By making the transformation $\varepsilon = v + u$, the conditional distribution of $h(u|\varepsilon)$ is

$$h(u \mid \varepsilon) = \frac{h(u, \varepsilon)}{h(\varepsilon)} \tag{9}$$

Then, the conditional mean can be found as[7]

$$E(u \mid \varepsilon) = \frac{\sigma_u \sigma_v}{\sigma} \left[\frac{f^*(\frac{\lambda\varepsilon}{\sigma})}{F^*(\frac{\lambda\varepsilon}{\sigma})} + \frac{\lambda\varepsilon}{\sigma} \right] \tag{10}$$

This value in equation (10) is used as a point estimate of inefficiency of each firm under the half-normal distribution assumption.[8]

Truncated Normal Distribution Case.[9] Following a similar procedure to the half-normal case, the conditional mean for the truncated normal distribution model can be derived. Formally it is

$$E(u \mid \varepsilon) = \frac{\sigma_u \sigma_v}{\sigma} \left[\frac{f^*(\frac{\lambda\varepsilon}{\sigma} + \frac{\mu}{\sigma}\lambda)}{F^*(\frac{\lambda\varepsilon}{\sigma} + \frac{\mu}{\sigma}\lambda)} + \frac{\lambda\varepsilon}{\sigma} + \frac{\mu}{\sigma}\lambda \right] \tag{11}$$

Exponential Distribution Case.[10] To obtain the counterpart for the exponential stochastic frontier model, the following equation is used:

$$E(u \mid \varepsilon) = R + \frac{\sigma_v f(\frac{R}{\sigma_v})}{F(\frac{R}{\sigma_v})} \tag{12}$$

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7) A complete derivation is available from the authors.

8) The conditional mean in equation 19 looks different from the one found in Jondrow et al.(1982), but equation 19 and their mean are identical except for the fact that the first comes from a cost function while the latter is derived from a production function.

9) For detailed derivation, see Stevenson(1980).

10) See Greene(1990) for a mathematical exposition of the exponential distribution model.

where $R = \varepsilon - \Theta \sigma_v^2$.

Next, the efficiency scores are derived using these conditional means (equations 10, 11, and 12) and each firm is ranked based on the scores.

2. Distribution Free Approach

(1) Theoretical Model

The distribution free approach(DFA) suggested by Berger(1992) begins with the same theoretical model as found in equation 8 but with different assumptions concerning the residual. That is,

$$C_{it} = C(w_i, y_i ; A) + u_{it} + v_{it}, \quad i = 1, \ldots, S, \tag{13}$$

where C_i is the observed cost of firm i, A is a vector of parameters, $C(w_i, y_i ; A)$ is the predicted log cost function of a cost minimizing firm(i.e., the underlying cost frontier), v_i represents statistical white noise, and u_i represents inefficiency. DFA assumes that the error term has two components: white noise and inefficiency. V_{it} is the company's persistent inefficiency, and u_i is white noise with mean zero over the period. DFA does not make assumptions concerning the distribution of v_{it}. Instead, DFA assumes that while white noise averages out over a period of years, the firm's inefficiency is persistent. The likelihood function is the same as that found in equation 11 with $\lambda = 0$.

(2) Empirical Model

The translog approximation of equation 13 has been employed widely in approximating cost functions with the stochastic frontier approach. This approximation has, however, a drawback: it does not allow zero output level for any output Y_i. Previous researchers have attempted to circumvent this problem either by assigning some arbitrary, close-to-zero outputs(Suret, 1991) or by not allowing observations with any zero outputs(Cummins & Weiss, 1993). In addition, a translog model cannot provide strict tests for scope economies due to its lack of a definition at a zero output level. Caves, Christensen, and Tretheway(1980) note that the use of a log metric in outputs is unnecessary for homogeneity of degree one restriction and suggest the Box-Cox metric for output quantities to allow zero output. The Box-Cox metric is written as

$$f_i(Y_i) = \frac{(Y_i^{\lambda} - 1)}{\lambda} \quad \text{for } \lambda \neq 0$$
$$f_i(Y_i) = \ln Y_i \quad \text{for } \lambda = 0 \tag{14}$$

The Box-Cox metric is well-defined at zero output if λ is positive.

$$f_i(0) = \frac{-1}{\lambda} \tag{15}$$

Following the lead set by Caves et al.(1980), Grace and Timme(1992) and Gardner and Grace(1993), this study incorporates a hybrid translog approximation using the natural log as the metric for input prices and total costs and the Box-Cox transformation for output quantities.

(3) Hybrid Translog Cost Function

The cost function to be estimated is(subscripts for time are suppressed),

$$\begin{aligned}\ln(Cost)_s = \; & A_0 + \sum_{i=1}^{n} A_i\left(\frac{Y_{is}^{\lambda}-1}{\lambda}\right) + \sum_{j=1}^{m} B_j \ln(W_{js}) \\ & + \sum_{K=1}^{L} P_K \ln(Z_{Ks}) + \frac{1}{2}\sum_{i=1}^{n}\sum_{f=1}^{n} C_{if}\left(\frac{Y_{is}^{\lambda}-1}{\lambda}\right)\left(\frac{Y_{fs}^{\lambda}-1}{\lambda}\right) \\ & + \frac{1}{2}\sum_{j=1}^{m}\sum_{g=1}^{m} E_{jg}\ln(W_{js}) * \ln(W_{gs}) + \sum_{i=1}^{n}\sum_{j=1}^{m} D_{ij}\left(\frac{Y_{is}^{\lambda}-1}{\lambda}\right) * \ln(W_{js}) \\ & + u_s + v_s \end{aligned} \tag{16}$$

Three additional share equations, using Shephard's lemma, are introduced to increase the efficiency of estimates(Diewert, 1971). By taking the first order partial derivative of equation 16 with respect to input j, the share equation is given as:

$$S_j = \frac{\partial \ln(Cost)}{\partial \ln(W_j)} \tag{17}$$
$$= B_j + \frac{1}{2}\sum_{g=1}^{m} E_{jg} \ln(W_{jg}) + \sum_{i=1}^{n} D_{ij} \ln\left(\frac{Y_{is}^{\lambda}-1}{\lambda}\right) + \varepsilon_{js} \ .$$

Since the sum of the three shared equations one, the variance-covariance matrix becomes singular. Therefore, a share equation must be omitted. Equations 25 and 26 represent a system of equations. Maximum likelihood estimates are obtained by jointly estimating the cost function and share equations using a seemingly unrelated regression technique. To avoid excessive parameter estimation, the price of labor is divided by the price of capital and employed in the labor share equation. Restrictions implying homogeneity of degree one in input prices are imposed, as are symmetry of second order coefficients.

(4) Efficiency Score Derivation

Four steps are involved in deriving the efficiency score. First, an average efficiency ratio for firms is derived by estimating five cost functions-one for each year(1988-1992). Second, an average residual U_s is computed by summing the firm's estimated residuals for each year and dividing by the number of t years:

$$\overline{U_s} = \frac{\sum_{t=1}^{n} U_{st}}{n} \ . \tag{18}$$

Third, the smallest residuals among all sample firms are found by ranking all efficiency scores in ascending order. Finally the distance between firms and the most efficient firm for the n periods is estimated. The insurance company with the lowest average residual is assumed to define the efficient frontier for that time interval. Each insurance company is then ranked according to its closeness to this frontier. By taking the antilog, the resulting efficiency measure of firm s is:

$$EFF_s = \exp(\ln \overline{U_s}^{\min} - \ln \overline{U_s}) . \tag{19}$$

The most efficient firm is defined here as the firm with the lowest residual. In addition, by ranking the firms from highest to lowest efficiency, no ad hoc distribution is imposed on the efficiency measures.

Ⅲ. Data and measurement of outputs and inputs

1. Data

The NAIC data tapes for 1988 through 1992 are used in estimating cost functions. Although the financial data on the NAIC tape are known to be more conservative than data based on the Generally Accepted Accounting Principles(GAAP), it is the only data that provide most of the necessary financial information for insurance companies.

Two approaches are employed to test sensitivity of different efficiency models. For the distribution free approach, all five-year panel data are used; one-year(1992) data are utilized for the stochastic frontier approach because of the cross-sectional nature of the methodology. To calculate labor input prices, the Bureau of Labor Statistics data are utilized.

According to the *1994 life Insurance Fact Book*, total life insurance company population varies from 2,373 to 1,944 during this study period between 1988 and 1992. Actual life insurers listed in the NAIC tape number approximately 1,800 to 1,950 companies for the sample period. All firms in the population cannot be used due to data irregularity and restrictions required by the methodology used in this paper. Sample firms are selected based on following criteria.

Companies are eliminated if the companies are inactive or the integrity of the data is questionable. For example, firms with negative total assets, negative total costs, or negative total premiums written are excluded.[11] Standard hybrid translog cost estimation requires positive input prices and non-negative output quantities for all sample firms. By eliminating companies with non-positive labor input prices, e.g., agents labor price, about 900 firms are left. This number is further reduced to 553 after excluding companies with negative outputs (premiums and claims-plus-reserves).

These 553 companies include true multiproduct firms that produce various outputs as well as pseudo multiproduct or specialty firms that have a limited product line. Therefore, all specialty firms and pseudo multiproduct firms which produce only group products, reinsurance, or individual products are eliminated.

Finally 248 life insurance companies are selected for this study. This sample size is smaller than most previous studies because more restrictions are imposed on the data selection. For example, all six outputs should be nonnegative measured in terms of claims-plus-reserves as well as premiums and the samples also must be true-multiproduct firms which produce at least four products out of the total six outputs defined in this study.

2. Variable Definitions

A new output proxy, called claim-plus-reserve, is proposed and compared to the traditional premium output variable that has been used in previous life insurance company efficiency studies(Grace & Timme, 1992; Gardner & Grace, 1993; Cho, 1986). For input variables, this paper improves on the traditional labor input price by including both employees and agents and brokers in its input price formula.

11) Total costs consist of labor costs, capital costs and material costs.

(1) Outputs Measurement

Life insurance companies produce several outputs or services. These outputs can be broadly classified as risk-bearing services and intermediation services. Risk-bearing services are defined as risk transferring from policyholders to insurance companies. Therefore, risk-bearing services include underwriting and related administrative services. Intermediation services are referred to as fund management services for policyholders.

Because of the intangible nature of the services, measuring the output of a life insurance company challenges researchers.[12] A realistic method of measurement may be counting the number of insurance policies sold, which is comparable to a manufacturing company counting the number of products it produces. Current financial statements based on SAP and GAAP, however, do not provide this sales information. Therefore, substantial new information is required to implement this method.

At least four major proxies have been employed for insurance cost studies. Those proxies are a weighted sum of activities, reserve levels, premium income and claim payments.

Many authors have used a modified form of the weighted sum of activities (e.g., Pritchett, 1973; Geehan, 1977; Hirshhorn & Geehan, 1977). For example, Hirshhorn and Geehan proxied outputs by aggregating 29 activities of life insurance companies. Each activity was weighted by an index value and summed for the output proxy. These activities included not only most product lines of life insurers but also different asset amounts. They also distinguished first-year business from renewal business.

While this approach yields a simple and precise output proxy, it has several weaknesses. First, an arbitrary weight(i.e., the unit cost of each activity) has to be given for each activity. Second, since it assumes that the dollar value of expenses equals the dollar value of life insurance outputs(e.g., ordinary life or group annuities), the method is biased for inefficient companies over efficient companies. That is, some insurers may incur more

12) See Hornstein and Prescott(1991), O'Brien(1991) and Denny(1980) for a useful discussion about the outputs of life insurance companies.

expenses not because they produce more outputs but because they are less efficient.

Reserve levels are also used to measure the outputs of insurance companies. Reserves represent the future financial obligations of insurance companies toward policyholders. They are calculated as the present value of future liabilities(benefit payments) minus the present value of future premium-in-flow(premium income and annuity considerations). Since reserves are not the flow of services provided to insureds, they may not be appropriate as output proxies. To overcome this shortcoming, Yuengert(1993) suggested that additions-to-reserves be used as proxies for outputs. Additions-to-reserves represent reserves set up for new business, new deposit funds, and existing businesses. The shortcoming of this proxy is that it underestimates outputs by not accounting for benefits provided by an insurer to its policyholders, which arguably is the major service provided by insurance companies.

Probably the most popular proxy used to measure risk-bearing services is the dollar amount of net written premiums or net earned premiums. Premiums can be viewed as including the flow of services to policyholders for a certain period. Unlike the weighted-sum-of-activities approach, the premium income method employs a vector of output proxies. This multiproduct approach enables researchers to examine the existence of scope economies.[13)]

This convenient premium proxy invites some criticism(e.g., Doherty, 1981). Critics argue that using premiums as independent variables in cost functions violates the exogenity assumption of independent variables because pricing policies of insurance companies are not independent of output measures. Particularly, when firms set premiums following a cost-plus-margin pricing policy, the dependent variable(costs) includes a significant portion of the independent variable(premium). The other potential problem is measurement error. As premiums are not output quantity but output quantity multiplied by output prices, using premiums as outputs indicates that the measured output

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13) For example, see Grace and Timme(1992) and Gardner(1993) for discussions on the U.S. life insurance industry and Suret(1991) for a discussion on the Canadian property and liability.

includes not only true output quantity but also some unknown residual term. The counter argument to this criticism is as follows. To a reasonable extent, a measurement error in empirical work may be inevitable. The selection of a proxy should be based on whether the measurement error is systematically related to independent variables or randomly distributed. If the error term is systematically related to output and cause bias, then some corrective action should be taken. The problem with insurance cost studies is that the seriousness of the measurement error has not been known. In fact, the measurement error has not been empirically measured using any available approach.[14]

Some researchers propose the dollar value of claim payments as output proxies(Doherty, 1981; Cummins & Weiss, 1993). Since the primary service provided to policyholders by insurers is benefits paid, benefit payments(or claim payments) should represent the risk-bearing services of insurers. Using claim payment as an output proxy at least overcomes the theoretical simultaneous bias, although the seriousness of the bias remains unknown. Empirical evidence shows that little difference is observed between claim payment variables and premium variables(Suret, 1991), perhaps partly due to the high correlation between these proxies and partly due to the use of more flexible cost functions and better estimation techniques.[15]

Previous discussion on output proxies demonstrates that all currently used proxies have advantages and disadvantages. Particularly, for the most popular premium proxy, two conclusions have been found. First, theoretically, the use of premiums as a output proxy may cause a simultaneous bias and measurement error while the use of claim may also result in a measurement error. Second, the seriousness of these bias and measurement errors are not known, and few empirical differences have been observed between the two proxies.

14) Doherty(1981) did discuss this issue but admitted that no proper econometric method existed to measure the variance of the measurement error and the bias.

15) Recent cost studies advance traditional cost studies in a significant way. adaption of a system of equations rather than a single equation with full information maximum likelihood estimation(FIML) technique which gives more efficient estimates than a single equation with the regression method.

This paper modifies claim payments and additions-to-reserves and proposes a new output variable, called claim-plus-reserve, which consists of earned claim payments plus changes in reserve. This variable improves the claim payments variable significantly. The problem with using the claim payment as a proxy of the risk-bearing service output is that the claim payment represents only past risk-bearing services, not current and expected future risk-bearing services. That is, researchers implicitly assume that current and future risk-bearing activities are the mirror image of past risk·bearing activities.

This assumption is not realistic. Claim payments tend to be biased against new lines of business and new companies. The present value of net future liability does deviate from the previous reserve levels set aside in the past. Therefore, insurance companies continually increase or adjust their current reserve levels to match changing future liabilities, at least on an annual basis.

Arguably, earned claim payments account for only risk-bearing service activities(benefits paid to insureds) in the past, while changes in reserve show an insurer's expected risk-bearing services in present and future time. A zero increase in reserve may indicate no change in past risk-bearing activities. If a company bears more risks(i.e., writes new business), it will increase its reserve levels which will result in change in future risk-bearing services. This claim-plus-reserve approach not only overcomes the econometric problems associated with premium variables but also improves claim payments and reserve proxies.

The claim-plus-reserve is employed for the simulation analysis for the following outputs; individual life(Y1), individual annuity(Y2), group life(Y3), group annuity(Y4), and group health(Y5). For the sensitivity analysis, both the claim-plus-reserve and the premium are used to examine the sensitivity of efficiency ranks with respect to output variable choices.

The intermediation service output is also not observable but is assumed to be proportional to the company's investment activities. The intermediation output can be estimated by measuring the dollar value of the total investment expenses(Y6). These are six outputs defined in this paper.

(2) Inputs Measurement

Measuring input is less controversial than measuring output. Input consists of labor, capital, and material. Labor input consists of the company's employees, agents and brokers. Agents and brokers are primarily responsible for marketing the insurer's products while employees labor include all management and clerical works as well as sales of the products. The volume of labor is not observable but can be estimated by using salaries, wages, employer contributions for benefit plans for employees and agents, employee and agent welfare expenses, and commissions to agents. The unit price of labor is calculated using two data sources; the NAIC data tape and annual average statewide wages by The Bureau of Labor Statistics.

This paper defines two sub-labor prices; that for employees and that for agents(including brokers). Each sub-labor price is computed by two steps. First, the average statewide wages of sub-labor(SIC 6311 for life insurance company employees and SIC 6411 for insurance agents and brokers) is multiplied by the portion of business written in the state, and summed across the states. This amount is then multiplied by the portion of each sub-labor's benefits out of total benefits paid. Finally, labor price(W1) is found by adding up the two sub-labor prices. Formally, labor price for firm i is written as:

$$Labor\ Price_i\ (W1) = Employee * \frac{EMCOM_i}{TOCOM_i} + Agent * \frac{AGCOM_i}{TOCOM_i} \qquad (20)$$

where

$$Employee_i = \sum_{j=1}^{51} \frac{Premiums\ of\ State_j * Employee\ Wage\ Average_j}{Total\ Premiums},$$

$$Agent_i = \sum_{j=1}^{51} \frac{Premiums\ of\ State_j * Agent\ Wage\ Average_j}{Total\ Premiums},$$

$EMCOM_i =$ all compensation for employees in firm I,

$AGCOM_i =$ all compensation for agents in firm I,

$TOCOM_I = EMCOM_i + AGCOM_i$

This input price advances that used in Gardner and Grace(1993) by incorporating agents'contributions into its input price formula. This labor price also provides a better approximation than that of Cummins and Weiss (1993) in which the industry average wages for both agents and employees are used.

Insurance efficiency literature has employed two variable definitions to represent the price of capital(W2): the financial capital approach and physical capital approach. Weiss(1991) and Cummins and Weiss(1993) used the first approach. These authors argue that the capital structure of the insurance industry is quite different from that of manufacturing industries and that an insurance company's capital mostly consists of financial capital. Therefore, financial capital more closely represents the real capital used in producing outputs.

The volume of capital is easily calculated by estimating capital and surplus plus the asset valuation reserve(AVR) and the interest maintenance reserve (IMR). However, measuring the price of financial capital appears to be problematic. As the price of capital is usually obtained by dividing the net income(or the net operating gains) by capital and surplus, many of insurers end up having negative input prices. Other popular financial pricing models (e.g., capital assets pricing model) cannot be adopted due to the lack of market price data for most insurance companies. Cummins and Weiss tried to circumvent these problems by using the industry average in case of negative capital prices. This method obviously invites biases in input price measurement by not allowing differences in input prices and by imposing an arbitrary price on many sample firms.

The other approach is the physical capital approach. Physical capital represents expenditure on equipment and occupancy costs. The amount of physical capital used by insurance companies in producing outputs is measured by the value of the physical capital assets. Ideally, market prices for rental cost(e.g., cost per square feet of all offices) should be used for the physical capital prices but the data are not available. For this reason, the price of capital can be proxied by dividing the dollar value of physical capital expenses by the dollar amount of physical assets. Physical capital expenses include furniture depreciation, equipment rental costs and depreciation, and building rental costs. This paper adopts the physical capital approach in order to allow real differences in the sample and to avoid arbitrariness. This physical approach is consistent with previous research; e.g., Grace and Timme(1992), Yuengert(1993), and Garnder and Grace(1993).

Material input usually includes general administrative items; e.g., postage, paper, printing, stationary, telephones and other miscellaneous items important to company operations. The volume of material input is estimated by measuring the expenses of these items. The price of material input(W3) is difficult to measure using the NAIC data. For empirical purposes, the price of material input is assumed to be constant across all firms.

(3) Costs

The concept of operating costs is used. The operating costs of a life insurance company include all costs incurred in the operation of the company. Operating costs are proxied by operating expenses, which consist of labor, capital and general expenses.

3. Control Variables

(1) Organizational Form

Mutual insurers are theoretically controlled by policyholders and managed by managers while stock insurers are owned by stockholders and managed by managers. Because of the divergent interests of owners and managers, managers are expected to maximize their own utilities rather than the owners'utilities. For stock companies, this agency problem can be eliminated by management monitoring mechanisms; e.g., the stock market or the threat of firing(Manne, 1965; Shleifer & Vishny, 1986). For mutual companies, these remedies are not available. Therefore, stock insurers should operate more efficiently, all else being equal(Mayers & Smith, 1988; Hansman, 1985). An indicative variable is used for this purpose.

(2) Asset Size

Researchers argue that a company's asset size may have a positive relation to its efficiency. Yuengert(1993) showed that average costs-total costs divided by total assets-relate to asset size. In their property and liability efficiency study, Cummins and Weiss(1993) also argued that large insurers were more efficient than small or medium size insurers. The dollar value of total assets is introduced as a proxy for this variable.

Ⅳ. Research findings

Efficiency scores are found using eight models(six models in the stochastic frontier approach and two models in the distribution free approach). Yuengert (1993) argued that heteroskedasticity biased inefficiency estimations of the life insurance companies. To examine the seriousness of the heteroskedasticity bias in this study, size effects on efficiency scores are investigated. The company size(by total assets) is marginally correlated with its efficiency rank. Eight correlation coefficients are found between the size variable and the eight ranks from the eight models. Some correlation exists between size and efficiency, but the degree is generally either low to medium. Spearman correlation coefficients vary from 0.06 to 0.57, which indicates that size and efficiency are not highly correlated.

Models 1 through 6 employ the stochastic frontier approaches, and models 7 and 8 use the distribution free approach. Models 1 and 2 assume the half-normal distribution of the inefficiency term, models 3 and 4 follow the truncated normal assumption and models 5 and 6 impose the exponentially distributed inefficiency assumption. Since the truncated-normal distribution is a general form of the half-normal distribution, no difference may exist between the models using these assumptions. This study reports efficiency ranks of both models to provide more information. Then the claim-plus-reserve and premium output definitions are used alternatively for each error term. Two models are used for a distribution free approach. Models 7 utilizes premium as its output and model 8 employs claim-plus-reserve as its output. Table 1 shows the inefficiency distribution assumption and the employed output variables of each model.

Table 1
The Description of Models

	Output Variable	Distribution Assumptions of Inefficiency	Methodology
Model 1	Premiums	Half-normal	Stochastic Frontier Approach
Model 2	Claims-plus-reserve		
Model 3	Premiums	Truncated normal	
Model 4	Claims-plus-reserve		
Model 5	Premiums	Exponential	
Model 6	Claims-plus-reserve		
Model 7	Premiums	No Assumption Imposed	Distribution Free Approach
Model 8	Claims-plus-reserve		

All sample firms are ranked by eight efficiency derivation models and compared. The rankings are examined to determine how they are correlated between different distribution assumptions in the same methodology and between different output definitions in the same distribution assumption.

One caveat is needed to aid in the interpreting the correlation results. The paper does not, *per se*, intend to compare the stochastic frontier method to the distribution free technique. The intention is rather to compare the output variable choices and the distributional assumptions within the same approach. One should be very careful in drawing any inference from comparing two efficiency derivation methodologies due to their basic differences in cost function estimation. The stochastic frontier approach employs a single equation while the distribution free approach adapts a system of equations. The other significant difference between the two approaches is that the first one uses one-year cross-sectional data(1992) while the latter utilizes five-year panel data(1988-1992).

The null hypothesis is that two ranks measured by two models are independent while the alternative hypothesis is that the two ranks are correlated. To test these hypotheses, researchers often employ the Pearson product-moment correlation matrix.

A problem arises when the distribution of the sampled population is not bivariate normal. Clearly, efficiency ranks are uniformly distributed and not bivariate normally distributed. Therefore, two nonparametric methods are considered: Spearman Rank Correlation Coefficient and Kendall's Tau.[16)]

Both methods generate values between one(perfect positive correlation) and negative one(perfect negative correlation). As shown in Tables 2 and 3, Spearman and Kendall yield similar patterns of correlation coefficients. One general statement that can be drawn from the correlation matrixes is that all ranks are correlated; all statistical tests strongly reject the null hypothesis that the two ranks are independent, thereby allowing the author to conclude that all eight models yield similar patterns of efficiency ranks.

Table 2
Spearman Correlation Coefficient for Various Models
with Different Output Choices and Distributional Assumptions

Model	1	2	3	4	5	6	7	8
1-Prem/half	1.00							
2-Claim/half	.919	1.00						
3-Prem/truncated	.999	.918	1.00					
4-Claim/truncated	.924	.997	.925	1.00				
5-Prem/exponen	.994	.915	.995	.920	1.00			
6-Claim/exponen	.918	.993	.920	.995	.917	1.00		
7-Prem/DFA	.377	.412	.381	.417	.384	.421	1.00	
8-Claim/DFA	.400	.433	.400	.437	.401	.441	.986	1.00

16) For formulas and other statistical properties of Spearman Correlation Coefficient and Kendall's Tau, see Daniel(1978).

Table 3
Kendall's Tau for Various Models
with Different Output Choices and Distributional Assumptions

Model	1	2	3	4	5	6	7	8
1-Prem/half	1.00							
2-Claim/half	.810	1.00						
3-Prem/truncated	.979	.816	1.00					
4-Claim/truncated	.816	.969	.816	1.00				
5-Prem/exponen	.948	.805	.957	.812	1.00			
6-Claim/exponen	.802	.949	.804	.806	.806	1.00		
7-Prem/DFA	.264	.288	.267	.270	.270	.288	1.00	
8-Claim/DFA	.275	.300	.278	.280	.280	.300	.908	1.00

1. Correlation within the Same Methodologies

Correlation between these six models varies from 0.99 to 0.38 under Spearman's method and from .97 to .27 under Kendall's approach. The first notable trend in this correlation analysis is a high correlation within the same methodologies. For the Spearman method, the correlation varies from .919 to .999 with the SFA while the correlation between the two in the DFA is .986. For the SFA models, the highest correlation is found between models 1 and 3(correlation coefficient =.999), and the lowest correlation is observed between models 2 and 5(.915). Although Kendall's Tau yields a slightly lower coefficient than Spearman's coefficient, the first coefficient pattern exactly resembles the latter one.

2. Correlations with the Same Distribution but Different Output Variables in the SFA

For half-normal assumption models(models 1 and 2), Spearman's correlation is .919 and for truncated normal assumption models(models 3 and 4) the correlation is .925. Finally, for exponential assumption models(models 5 and 6) the correlation is .917. Kendall's correlation between models 1 and 2, between 3 and 4, and between 5 and 6 are .810, .816 and .805 respectively. As indicated previously, Kendall's Tau generates slightly lower coefficients.

3. Correlations with the Same Output but Different Distribution Assumption in the SFA

The Correlations between models using the premium output are as follows. Spearman's correlation between models 1 and 3 is .999, between models 1 and 5 is .994, and between models 3 and 5 is .995. The counterparts of Kendall's Tau are .979, .948 and .957. Spearman's correlation between models using the claim-plus-reserve output are .997 between models 2 and 4, .993 between models 2 and 6, and .995 between models 4 and 6. Again, Kendall's Tau generates similar values that are slightly lower than Spearman's coefficient.

Correlations between models using the same output variables but different inefficiency distribution assumptions are higher than that of models using the same distribution but different output variables. This evidence may suggest that inefficiency rankings are more sensitive with the output variable choices than with the inefficiency distribution assumptions.[17]

4. Correlations Between the SFA and DFA

A relatively low correlation is noted across different methodologies. Spearman's correlation coefficients range from .377 to .437, and Kendall's Tau varies from .264 to .305. This may be due to differences in cost function estimation. That is, the stochastic frontier models use one-year cross-sectional data while the distribution free models use five-year panel

17) Using a deterministic frontier approach, a similar conclusion is drawn by Sexton et al.(1986). Using the data envelopment approach, they warned that the analysis results were more sensitive with a choice of variables rather than with a selection of models.

data. One should notice that the first method uses single translog cost equations, while the latter employs a system of hybrid-translog cost equations. By employing the same translog cost function(a single equation) for five years, Zi(1994) found that the average of correlation between exponential SFA and DFA is 0.97 and between normal-half normal SFA and DFA is 0.98.[18)]

V. Conclusion And Research Implication

A few interesting implications from this paper have been found. First one relates to the uses of premium outputs. Models using premium outputs do not perform differently from models using claim-plus-reserve outputs when efficiency ranks are compared. Correlations between models using premiums and models using claim-plus-reserve output range from .917 to .986 with the same distribution assumptions.

This fact suggests that premium outputs may not be systematically biased and that the measurement error may be randomly distributed, assuming claim-plus-reserve output correctly represents risk bearing outputs. This also supports Suret(1991), who also reported that empirical difference between premiums and claim output proxies appears minimal. High correlations(over .910) are found between efficiency ranks from the different models. Little difference is observed between models employing either premium outputs or claim-plus-reserve outputs.

This implys that the simultaneous bias and the measurement error may not be systematically distributed. Based on the correlation patterns, it is concluded that efficiency ranks are more sensitive to output variable choices than to inefficiency distributional assumptions.

Second implication is the difference between SFA and DFA. This paper shows that empirical results of these two methods could be significantly

18) The author reports that the correlation between the data envelopment approach(DEA) and other models is low, ranging from .21 to .6.

different if different functional forms are used. This makes a good contrast with previous researches which indicated that these two methods could produce very similar results. Therefore, in order to examine precious difference between SFA and DFA, further empirical research seems necessary. Final observation is that most companies in this study appears very close to the efficiency frontier. This may be due to the fact that substantial numbers of inefficient companies are deleted in the sample screening process.

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