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# *Measuring Cost Efficiency in the U.S. Life Insurance Industry: Econometric and Mathematical Programming Approaches*

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# Measuring Cost Efficiency in the U.S. Life Insurance Industry: Econometric and Mathematical Programming Approaches [1]

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Preliminary: Comments Welcome

Abstract: This paper presents a comparative analysis of frontier cost efficiency methodologies by applying a wide range of econometric and mathematical programming techniques to a data set consisting of 445 life insurers over the period 1988-1992. The primary objective is to provide new information on the effects of choice of methodology on efficiency estimates. We also investigate some classic industrial organization issues in the life insurance industry. The alternative methodologies give significantly different estimates of efficiency for the insurers in our sample. The efficiency rankings are quite well-preserved among the econometric methodologies; but the rank correlations are lower between the econometric and mathematical programming categories and between alternative mathematical programming methodologies. Thus, the choice of methodology can have a significant effect on the results. Most of the insurers in the sample display either increasing or decreasing returns to scale, and stock and mutual insurers are found to be equally efficient after controlling for firm size.

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**Measuring Cost Efficiency in the U.S. Life Insurance Industry: Econometric and Mathematical Programming Approaches**

## I. Introduction

Interest in "frontier" analysis of economic efficiency has grown rapidly over the past two decades; and numerous books and hundreds of papers have been written on efficiency methodologies and applications. Two primary methodologies have been developed for measuring efficiency -- the econometric approach and the mathematical programming approach.[1] Both methodologies involve the estimation of "best practice" frontiers, with the efficiency of specific decision making units (DMUs) measured relative to the frontiers. The econometric approach specifies a functional form for the cost, profit, or production frontier. The methodology is stochastic; firms can be off the frontier because they are inefficient or because of random shocks or measurement errors that have nothing to do with inefficiency. Thus, the cost function error term is hypothesized to consist of an inefficiency component and a purely random component. Efficiency is measured by separating the efficiency component from the overall error term. Some variants of the econometric approach require that specific distributional assumptions be imposed on the components of the error terms, while others do not require distributional assumptions. By contrast, the mathematical programming approach places less structure on the frontier and is non-stochastic, i.e., any departure from the frontier is measured as inefficiency.

The choice of estimation methodology has been controversial, with some researchers preferring the econometric approach (e.g., Bauer, 1990, Berger, 1993) and others the mathematical programming approach (e.g., Seiford and Thrall, 1990).[2] The econometric approach has been criticized for potentially confounding estimates of efficiency with specification errors. Mathematical programming, on the other hand, is non-parametric and thus less susceptible to specification errors but does not allow DMUs to

[1]Reviews of the two approaches appear in Lovell (1993), Greene (1993), and Ali and Seiford (1993).

[2]Lovell (1993) presents an excellent review of the advantages and disadvantages of the two methodologies.

deviate from the frontier due to purely random shocks. Advocates of the econometric approach disagree about whether distributional assumptions should be imposed on the error term and, if so, which distributions are most appropriate.[3] Some recent mathematical programming papers have criticized the prevailing data envelopment analysis (DEA) technique and proposed instead the free disposal hull (FDH) methodology, arguing that the FDH approach involves less arbitrary assumptions and provides a better fit to the data (e.g., Tulkens, 1993, Vanden Eeckaut, Tulkens, and Jamar, 1993).

The primary purpose of this paper is to provide new information on the effects of methodological choice in efficiency estimation by applying a variety of estimation techniques to the same data set. The data set consists of 445 U.S. life insurers representing nearly 90 percent of industry assets over the period 1988-1992. We compare the efficiency scores and rank correlations among the methods and also correlate the efficiency scores with traditional performance measures such as expense ratios and returns on equity. The methods include DEA, with three returns-to-scale assumptions, FDH, and eight econometric methods.

In spite of the potential benefits of a comparative analysis of methodologies, there have been few efficiency studies that have utilized more than one or two estimation techniques. A recent review of the literature on the efficiency of financial institutions (Berger and Humphrey, 1996) found only two banking studies and one prior insurance study (out of 130 studies surveyed) that compared the econometric and DEA approaches, and in each case only one variant of each methodology was used (e.g., Ferrier and Lovell, 1990). A few financial studies have compared two or three econometric methods (e.g., Bauer, Berger, and Humphrey, 1993) or two or three mathematical programming methods (e.g., DeBorger, Ferrier, and Kerstens, 1995). Although we have found no comparable surveys of applications to non-financial DMUs, the norm in the papers we reviewed is similar, i.e., most studies use only one or two

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[3] Alternative distributional assumptions are discussed in Aigner, Lovell, and Schmidt (1977), Stevenson (1980), and Greene (1990). A "distribution free" approach is developed in Schmidt and Sickles (1984) and Berger (1993).

estimation techniques.[4] Thus, the present paper is the first financial institutions study and one of the first studies in any industry to compare a wide variety of estimation techniques.

A second objective of this paper is to provide new information on efficiency in the U.S. life insurance industry by investigating two classic topics in industrial organization — economies of scale and the efficiency of alternative organizational forms. Studying efficiency in the life insurance industry is relevant because life insurers are among the most important financial institutions in the U. S. economy, managing about $2 trillion in assets and employing more than 2 million people. The industry has recently encountered solvency problems, a wave of mergers and acquisitions, conversions of major insurers from the mutual to stock ownership form, and increasing competition from non-traditional sources such as banks, mutual fund companies, and securities brokers.[5] Thus, additional information on life insurer efficiency should be valuable to regulators, managers, and shareholders.

Relatively few studies have been conducted on cost efficiency of life insurers. Yuengert (1993) and Gardner and Grace (1993) applied econometric methods to cost efficiency estimation for U. S. life insurers, while Weiss (1986) estimated total factor productivity for one stock and one mutual firm. Each of these studies employed only one of the set of the available econometric methods. Fecher et al. (1993) measure efficiency in the French life insurance industry using one mathematical programming and one econometric model. Fukuyama (1995) estimated productive efficiency and productivity change in the Japanese life insurance industry using DEA, and the efficiency of stock and mutual life insurers has been previously studied by Fields (1988) using non-frontier techniques.

The rest of this paper is organized as follows. Section II provides an overview of the econometric

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[4]Studies that compare more than two methods include DeBorger and Kerstens (1996) and Hjalmarsson, Kumbhakar, and Heshmati (1996).

[5]For discussions of these issues see Kopcke and Randall (1991), Cummins and Lamm-Tennant (1993), and Klein (1995).

and mathematical programming methodologies. Section III discusses the measurement of inputs and outputs in life insurance. Section IV presents our efficiency measures and analyses of economies of scale and efficiency differences between stock and mutual insurers, and section V concludes.

## II. Methodology

This section provides an overview of the econometric and mathematical programming methodologies. The reader is referred to Fried, Lovell, and Schmidt (1993) and the other cited references for more details.

### Econometric Approach

The primary advantage of the econometric approach is its ability to accommodate random noise in efficiency estimation. To separate random error from inefficiency, the cost function is typically specified with two error components.[6]

$$\ln C_i = \ln C(p_i, y_i, B) + u_i + v_i \tag{1}$$

for i = 1, . . ., N, where $C_i$ = observed total costs for firm i, ln $C(p_i,y_i,B)$ = the log cost function, pi= a vector of input prices, $y_i$ = a vector of output quantities, B = a vector of parameters, $u_i$ = an error term ($u_i \geq 0$) that captures cost inefficiency, and $v_i$ = a random error (statistical noise) term distributed independently of $u_i$. An extensive econometric literature exists on the estimation of equation (l), and the most important of the econometric methods are applied in this study. For the econometric methods in this study, we use the standard translog cost function specification (Christensen, Jorgenson, and Lau, 1973).

The general procedure for estimating efficiency using equation (1) is to estimate B and $w_i = u_i+v_i$ and then to calculate efficiency for each observation in the sample as the conditional expectation

[6]Our data represent a panel data set on 445 life insurers over the five-year period 1988-1992. We employ both panel estimation methodologies and year-by-year estimation. This discussion uses notation applicable to the year-by-year approach (time subscripts are suppressed).

$E(\exp(-u_i)|w_i)$ (see Greene, 1993), providing an estimate of the ratio of frontier costs to actual costs. If distributional assumptions are imposed on the error terms, the approach involves finding the density function $h(w_i)$ of $w_i$ and the joint density $f(u_i, w_i)$ and then obtaining an expression for the conditional mean of $\exp(-u_i)$ based on the distribution $f_u(u_i|w_i)$.

The most common distributional assumptions are a normal distribution for $v_i$ and an exponential, truncated normal (usually the half-normal), or gamma distribution for $u_i$. The truncated normal is:

$$f_u(u_i) = \sqrt{\frac{2}{\pi}}\frac{1}{\sigma_u} e^{-\frac{1}{2}(\frac{u_i - \xi}{\sigma_u})^2} \quad , u_i > \xi \tag{2}$$

where $\sigma_u$ is the dispersion parameter and $\xi$ is a location parameter which is also the mode of the distribution. Most applications of the truncated normal use the half normal, which has a mode at O rather than at $\xi$. In this case, the expression for the conditional mean is (see Battese and Coelli, 1988):[7]

$$E[\exp(-u_i|v_i+u_i)] = \frac{\Phi(\frac{\mu_i^*}{\sigma_*}-\sigma_*)}{\Phi(\frac{\mu_i^*}{\sigma_*})}\exp[\frac{1}{2}\sigma_*^2-\mu_i^*], \tag{3}$$

where $\mu_i^* = a\xi + (1-a)w_i$, $\sigma_*^2 = a\sigma_u^2$, $a = \sigma_v^2/(\sigma_v^2+\sigma_u^2)$, and $\sigma_v$ = the standard deviation of the n distribution of $v_i$. The estimated $w_i$ and estimated distributional parameters are substituted into equation (3) to obtain an estimate of inefficiency for each observation in the data set.

The use of mode 0 distributions to model inefficiency has been criticized for imposing "the restriction that most firms are clustered near full efficiency, with higher degrees of inefficiency being

[7]The conditional expected value of the inefficiency term with a normal distribution for the random error and an exponential distribution for the inefficiency error is given in see Aigner, Lovell, and Schmidt (1977).

increasingly unlikely" (Berger, 1993, p. 284). However, it is not necessarily true that the half normal or exponential distributions place the majority of firms "near" the mode. In the half normal, the amount of probability mass in a fixed interval to the right of 0 is decreasing in $\sigma_u$ and can be quite small for reasonable values of the interval size defined as "near full efficiency" and $\sigma_u$. Likewise, in the exponential, the amount of probability mass near the origin is increasing in the parameter value and thus can be large or small depending upon the parameter value.[8] Thus, although the monotonicity of the half normal and exponential may be a limitation for some data sets, using one of these distributions does not arbitrarily confine a high proportion of the firms to near full efficiency.

In this study, we estimate equation (1) using maximum likelihood estimation (MLE) under both the normal/half-normal and normal/exponential distributional assumptions.[9] Two versions are estimated for each set of distributional assumptions -- equation (1) is estimated separately for each year of the sample period; and a panel version of equation (1) is estimated where B is constrained to be constant over the sample period. Both formulations have merits. Allowing B to vary by year captures any changes of cost technology over time, while the panel version provides more degrees of freedom.

To test the sensitivity of the results to the monotonicity of the half normal and exponential assumptions, we also estimate equation (1) using the more general gamma distribution for $u_i$, retaining the assumption of normality for $v_i$. The disadvantage of the normal/gamma model is that a closed form for the likelihood function of the composed error term, $u_i + v_i$, is not available unless the shape parameter of the gamma has an integer value (an Erlang form). To avoid arbitrarily restricting the shape parameter, we estimate this model using the modified ordinary least squares method (MOLS) suggested by Greene (1990).

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[8] Our parameterization of the exponential is: $f(u_i) = \lambda \exp(-\lambda u_i)$, $u_i > 0$.

[9] Linear homogeneity in input prices and the standard symmetry conditions are imposed in estimating the cost function. The likelihood function for (1) is found in Greene (1993). For an application of this model to the insurance industry, see Cummins and Weiss (1993).

With panel data, it is possible to avoid imposing distributional assumptions on the error components.[10] In the 'distribution free' method of Schmidt and Sickles (1984) and Berger (1993), the inefficiency error term is assumed to be constant over time, i.e., the following specification is used:

$$\ln C_{it} = \ln C(p_{it}, y_{it}, \mathrm{B}) + u_i + v_{it} \tag{4}$$

No distributional assumptions are imposed on $u_i$ or $v_{it}$. Rather, an estimate of the efficiency is extracted by averaging the estimated overall error, $w_{it} = u_i + v_{it}$, over the sample period on the assumption that the random error $v_{it}$ will average out over time. This study estimates equation (4) using generalized least squares (GLS), as in Schmidt and Sickles (1984). We also estimate a version of equation (4) where the parameter vector is allowed to vary over the sample period, as in Berger (1993). Finally, for purposes of comparison, we estimate equation (4) by MLE using the normal/half-normal assumptions for the random and inefficiency error terms. The latter method differs from the normal/half-normal estimation of equation (1) by imposing time-invariant inefficiency on the likelihood function.

For the Schmidt and Sickles (1984) and Berger (1993) methods, cost efficiency is estimated for each firm as:

$$E[u_i \mid w_{11} \ldots w_{TN}] = \exp(\min_i(\bar{w}_i) - \bar{w}_i) \tag{5}$$

where $\bar{w}_i$ denotes the average over the sample period of the residuals $w_{it}$ for firm *i*, and $\min_i(\bar{w}_i)$ is the minimum average error term for the firms in the sample. For the normal/half-normal method, cost efficiency is estimated using equation (3) with $\bar{w}_i$ replacing $w_i$.

[10] A method which avoids distributional assumptions for cross-sectional data is the 'thick frontier' approach (TFA) (see, for example, Bauer, Berger, and Humphrey, 1993). However, because this method does not provide point estimates of efficiency for individual DMUs, it is not considered in the present paper.

**Mathematical Programming Approach**

The relative efficiency measure of Farrell (1957) also has been formulated in a mathematical programming framework (usually called data envelopment analysis (DEA)), first by Charnes, Cooper, and Rhodes (1978), and subsequently modified by Banker, Charnes, and Cooper (1984), Byrnes, Färe, and Grosskopf (1984), and Thiry and Tulkens (1988), among others. Because DEA focuses primarily on the technological aspects of production correspondences, it can be used to estimate technical and scale efficiency without requiring estimates of input and output prices. Thus, this approach has been used extensively in the regulated sector (e.g., Banker, Conrad, and Strauss, 1986) and the non-profit sector (e.g., Lewin, Morey, and Cook, 1982). If estimates of input prices are available, cost efficiency also can be measured using DEA (e.g., Aly, et al., 1990, and Ferrier and Lovell, 1990).

This study applies the three conventional DEA models, i.e., the constant (CRS), variable (VRS), and non-increasing returns to scale (NIRS) models to estimate cost efficiency. We also use the recently developed free-disposal hull (FDH) model (Tulkens, 1993), which relaxes the convexity assumption of the VRS frontier model.

The mathematical programming (MP) approach estimates the cost efficiency of firm i using a two-step procedure. For DMU i, denote $w_i = (w_{1i}, w_{2i}, \ldots, w_{Si})^T$ as the input price vector corresponding to the input vector $X_i = (X_{1i}, X_{2i}, \ldots, X_{Si})^T$, where T denotes the vector transpose and S is the number of inputs. Then, we first solve the following problem:

$$\underset{X_i}{Min} \sum_{s=1}^{S} w_{si} X_{si} \tag{6}$$

Subject to

$$X_{si} \geq \sum_j \lambda_j X_{sj} \qquad s = 1,2,\ldots,S,$$

$$Y_{mi} \leq \sum_j \lambda_j Y_{mj}, \qquad m = 1,2,..,M,$$

$$\lambda_j \geq 0 , \qquad j = 1,2,..N$$

where N is the number of firms, M is the number of outputs, $Y_{mi}$ = the m-th output volume for firm i, and $\lambda_i$ = the intensity coefficient of firm j with respect to firm *i*. The solution vector $X_i$* is the cost minimizing input vector for the input price vector $w_i$ and the output vector $Y_i$. Second, calculate the ratio $\eta_i^* = w_i^T X_i^* / w_i^T X_i$ to get the cost efficiency measure of DMU i. Returns to scale assumptions can be imposed or the convexity assumption relaxed by using one of the following additional constraints:

| | | | |
|---|---|---|---|
| | no further restrictions on $\lambda_i$ | (CRS) | **(7)** |
| | $\sum_i \lambda_i = 1$ | (VRS) | **(8)** |
| | $\sum_i \lambda_i \leq 1$ | (NIRS) | **(9)** |
| or | $\sum_i \lambda_i = 1$ and $\lambda_i \in [\,0, 1\,]$ | (FDH) | **(10)** |

The problems are solved under each set of alternative constraints for each firm in the sample, i = 1, ..., N, and for each time period if panel data are available.

One of the benefits of the mathematical programming approach is to easily decompose the measure for cost efficiency into its technical and allocative components. In order to calculate the measure of technical efficiency for firm i, four additional programming models are solved for each firm.

$$\text{Min}_{\theta, \lambda} \quad \theta_i \tag{11}$$

subject to

$$\theta_i X_{ni} \geq \sum_i \lambda_i X_{ni} , \qquad n = 1,2,..S,$$

$$Y_{mi} \leq \sum_i \lambda_i Y_{mi} , \qquad m = 1,2,..,M,$$

$$\lambda_i \geq 0 , \qquad j = 1,2,..N,$$

where S is the number of inputs, with any of the additional constraints (7) to (10).

With the cost efficiency measure, $\eta_i$*, from (6) and the technical efficiency measure, $\theta_i$*, from (11), the allocative efficiency measure of each company can be obtained by $\eta_k^*/\theta_k^*$. Moreover, as discussed below, the comparison of the three measures for technical efficiency (solutions to VRS, NIRS and CRS in (6)) reveals the potential scale economies for each firm (Aly, et al., 1990).

## III. Outputs, Inputs, and Input Prices

Defining outputs of an insurance firm has been a challenging task. Most of extant life insurance cost studies, which are mainly focused on economies of scale and scope, used premiums as proxies for outputs (e.g., Grace and Timme, 1992, and Gardner and Grace, 1993). However, premiums are not the quantity of outputs but the revenue (price times quantity) (Doherty, 1981, Yuengert, 1993).

The outputs of life insurers may be measured by the services they provide to customers. In general, life insurers provide two principal services: risk bearing/risk pooling services and intermediation services. Life insurers collect premiums and annuity considerations from customers and redistribute most of the funds to those policyholders who sustain losses (the risk bearing/risk pooling service). Funds are collected in advance of paying benefits and held in reserves until claims are paid (the intermediation service).

Incurred benefit payments are used here to proxy for the risk bearing/pooling services of a life insurance firm because benefit payments represent the delivery of contingent dollars to policyholders. This measure was first proposed by Doherty (1981) and used by a number of researchers including Weiss (1990) and Cummins and Weiss (1993). Incurred benefits are further categorized into ordinary life insurance ($Y_1$), group life insurance ($Y_2$), individual annuities ($Y_3$), group annuities ($Y_4$), and accident and health insurance ($Y_5$) to allow for the different characteristics of the major product categories in the life insurance industry. The intermediation service of an insurance firm is proxied by additions-to-reserves ($Y_6$), which denote reserves set up for new business, new deposit funds, and new reserves set up as old policies age.[11] All outputs are deflated by the CPI to the base year 1988.

Three inputs are used in this study: labor ($X_1$), financial capital ($X_2$), and materials ($X_3$). The price

[11] Yuengert (1993) was the first to use additions-to-reserves as an output measure for life insurers.

for labor input ($P_1$) is obtained by the Divisia index based on U.S. Department of Labor data on average weekly wages for employees and agents working in the life insurance sector (SIC 6311). A premium weighted index is used, with average weekly wages by state for SIC 6311 weighted by the proportion of premiums written by the insurer in each state. Financial capital is included as an input for the risk-pooling/risk-bearing function because insurers hold capital to back their promise to pay benefits if losses are larger than expected or investment returns fall below expectations.[12] The price of financial capital ($P_2$) is measured as a three-year moving average of the ratio of net income to equity capital. The price of the materials input ($P_3$) is calculated by the Divisia index of the deflators for its components, which represent the major non-labor inputs purchased by insurers.[13] Thus, all three input prices vary by insurer as well as over time.

The insurance financial data were obtained from the regulatory annual statements filed by insurers as reported on the National Association of Insurance Commissioners (NAIC) life insurance data tapes for 1988-1992. Groups of affiliated insurers under common ownership were treated as decision making units, along with unaffiliated single insurers. Recognizing the group as the decision making unit minimizes distortions arising from intra-group transactions. In order to use methodologies such as the distribution free approach or generalized least squares that require a balanced pooled sample, decision making units were included in the sample if they appear on the tapes in every year during the period 1988-1992. Very small firms (assets < $

[12]The value of physical capital held by insurers is small relative to the other input categories. Consequently, physical capital is included in the materials category.

[13]Eleven component indices were used to calculate the business services price: GNP implicit price deflator for communications (for advertising), the CPI for reading material (for books, printing, and stationery), the GNP deflator for wholesale trade (bureau and association fees), the CPI for legal services (legal fees), the implicit price deflator for capital stock (capital equipment such as computers), the GNP deflator for business services (accounting fees, claims settlement fees, etc.), the CPI index for medical care (medical exam fees), the fixed weight price index for insurance (insurance purchased), the CPI for food consumed away from home (travel expenses), the GNP deflator for tenant rental of nonfarm dwellings (rental expenses), and the overall CPI (for miscellaneous expenses).

10 million) and firms specializing in reinsurance are excluded from the sample. The final sample consists of 445 firms each year, accounting for nearly 90 percent of industry assets. Descriptive statistics for the sample are presented in Table 1.

## IV. Empirical Results

This section first reports the overall efficiency results based on the econometric and mathematical programming methodologies and then presents our tests of economies of scale and the relative efficiency of stock and mutual insurers. The section concludes with an analysis of the appropriateness of assuming a monotonic distributional error term for the firms in our sample.

### Efficiency Estimates

The average cost efficiency estimates are presented in Table 2.[14] There is no noticeable difference in the cost efficiency estimates from the year-by-year and panel versions of the normal/half-normal MLE models (labeled Half and Half_P, respectively, in the table). Likewise, there are no noticeable differences between the year-by-year and panel estimates from the normal/exponential models (Exp and Exp_P in the table). The average efficiencies are lower with the normal/half-normal models (averaging 0.61) than with the normal/exponential models (which average 0.71). Still higher efficiencies are obtained with the gamma model, averaging 0.85 for the sample period. The distribution free models, which constrain efficiency to be equal over the sample period, provide considerably lower efficiency estimates, averaging 0.44 and 0.46, respectively, for the methods of Schmidt and Sickles (1984) (labeled GLS) and Berger (1993) (labeled DFA). The MLE normal/half-normal version of the efficiency-constrained model (labeled REM) yields estimates comparable to the distribution free models. This suggests that constraining inefficiency to be equal

[14] We initially estimated the models that incorporate the half normal assumption using the more general truncated normal model, which allows a mode greater than zero. However, using likelihood ratio tests, we were unable to reject the hypothesis that the value of the mode parameter was equal to zero. Thus, the analysis presented here uses the half normal rather than the truncated normal model. Hjalmarsson, Kumbhakar, and Heshmati (1996) also failed to reject the half-normal hypothesis.

across years tends to be responsible for the lower efficiency estimates of the distribution free models in comparison with the MLE and gamma models, rather than the absence of distributional assumptions. An overall conclusion is that the choice of distributional assumptions and estimation technique has a significant effect on the values of the efficiency estimates using the econometric approach.

Our results with the normal/half-normal and normal/exponential models are consistent with those of Yuengert's (1993) normal/half-normal model, which also ranged from 0.6 to about 0.7, depending on firm size class (he did not estimate the normal/exponential model). However, our efficiency estimates from the normal/gamma model are higher than Yuengert's normal/gamma estimates which ranged from approximately 0.50 to 0.65. However, he arbitrarily set the gamma shape parameter to 2, whereas we use Greene's MOLS method to avoid constraining this parameter.[15] The results are also consistent with those of Gardner and Grace (1993), who find average efficiency of 0.47 using DFA over the period 1985-1990.

Table 3 presents the measures for cost, technical, and allocative efficiency obtained by the mathematical programming approach. Of the results using the four different models in this approach (CRS, NIRS, VRS, and FDH), we report the efficiency measures for VRS and FDH, because the underlying assumptions for these models are less stringent.[16] The VRS and FDH models yield very different results. The average levels of cost efficiency for FDH are the highest (0.90-0.92) of all methods used in this study, including the econometric models. On the other hand, the VRS efficiency scores are much lower than most of the other models (0.46 on average) and about the same as the econometric estimates that constrain efficiency to be equal across the sample period. The low level of cost efficiency for VRS is mainly due to technical inefficiency rather than allocative inefficiency. FDH leads to the opposite finding but the technical and allocative

[15]The estimated gamma shape parameters varied by year and are equal to 1.400, 0.790, 2.675, 1.224, 0.457 for 1988-1992, respectively. Yuengert's (1993) sample was for 1989, and he assumed a shape parameter of 2.0 for that year.

[16]The efficiency measures for the CRS and NIRS models are slightly less than those for the VRS model and are available from the authors upon request.

efficiency measures are fairly close to each other. The large difference between the FDH and VRS models may be explained by the fact that in the FDH model, each firm is compared only to actual observations, leading to many "self-efficient" firms, while in the VRS model, each firm is compared to a convex combination of efficient firms and thus has a much greater chance of being dominated by sets of efficient firms.

Our finding that FDH yields substantially higher efficiency estimates than DEA is consistent with prior research on other industries (e.g., Vanden Eeckaut, Tulkens, and Jamar, 1993, DeBorger and Kerstens, 1995). Thus, it is increasingly clear that researchers face an important choice not only between the econometric and mathematical programming approaches but also as to whether convexity should be imposed when using mathematical programming.

It is not surprising that the VRS estimates are lower than the normal/half-normal, normal/exponential, and normal/gamma estimates because the latter models allow insurers to depart from the frontier due to random error as well as inefficiency, whereas VRS measures any departure from the frontier is measured as inefficiency. On the other hand, it is somewhat surprising that the cost efficiency measures for VRS are very close to those for the distribution-free econometric models.

The results in Tables 2 and 3 show that the choice of methodology has an important impact on the estimated efficiency scores. However, for many purposes, such as public policy or managerial decision making, it is not so much the absolute values of the scores that matter but rather the ranking of insurers in terms of efficiency. For example, to evaluate the potential effect of mergers and acquisitions or to rate the effectiveness of alternative underwriting systems, human resource policies, etc., it is useful to know the efficiency of insurers relative to their peers.

We explore the consistency of the models in ranking insurers by presenting pairwise Spearman rank correlation coefficients of the 5 year average cost efficiencies for the insurers in the sample. The correlation coefficients, presented in Table 4, show that the econometric models are highly consistent in ranking insurers according to their efficiency, with pairwise correlation coefficients no lower than 96 percent. The only exception is the normal/half-normal model that constrains efficiency to equality over the sample period (the REM model), which has correlations with the other econometric models ranging from 61 to 72 percent. Thus, even though the distribution-free methods (GLS and DFA) produce lower efficiency scores than the normal/half-normal, normal/exponential, and normal/gamma models, they produce comparable efficiency rankings. The rank correlations between the econometric models and the mathematical programming models are much lower, mostly in the range of 50 to 60 percent. Thus, the choice between the econometric and mathematical programming approaches is important if one is interested in ranking insurers. The rank correlation coefficient *between* the two different programming models is also relatively low (67 percent), mainly due to the fact that many firms in the FDH model are self-efficient, again emphasizing the importance of the convexity assumption.

Our ranking results are consistent with those of DeBorger and Kerstens' (1996) study of Belgian municipalities. They found rank correlations of better than 99 percent among the three parametric methods they tested. However, these comparisons are not directly analogous with our econometric results because one of their three parametric methods is a deterministic frontier, which we did not estimate, and the other two compare the mean and mode estimates of efficiency from a normal/half-normal model. More directly comparable are their comparisons of the normal/half-normal model to DEA and FDH and the comparison between DEA and FDH. The rank correlation between the normal/half-normal and DEA is about 0.83 in their study and the rank correlation between the normal/half normal and FDH is about 0.60. The rank correlation between DEA and FDH in their study is 0.66, about the same as our value of 0.67.[17] The comparisons among parametric methods in Hjalmarsson, Kumbhakar, and Heshmati's (1996) study of Colombian cement plants also are not directly comparable with ours. They use the normal/half-normal panel model in all three of their stochastic frontier methods, which differ in whether and how firm-specific

[17] They estimated the DEA frontier under the assumption of variable returns to scale (VRS).

control variables are used. Their rank correlations between their normal/half-normal panel model most directly comparable with ours and (CRS and VRS) DEA are similar to ours, ranging from 0.65 to 0.73.

To investigate the relationship between efficiency and firm size, we present the average cost efficiency measures classified by asset size in Table 5 as well as the correlation coefficients between the efficiency scores and assets.[18] There is a positive relationship between size and efficiency for all of the methodologies except REM, which has a statistically significant negative correlation coefficient with assets. This provides further suggestive evidence that the assumptions imposed by REM may not be appropriate for this data set. The highest correlations between efficiency and asset size are for the two mathematical programming methods, especially VRS, which has a correlation coefficient with size more than three times larger than any of the other methods. The scores from several of the econometric methods also are significantly correlated with asset size, most notably the half normal, GLS, and DFA. However, at the 5 percent significance level, the hypothesis that efficiency is positively correlated with size would be rejected using Half_P, DFA (barely), Exp, and Gamma but not rejected using Half_P, GLS, and Half. Thus, conclusions about the size-efficiency relationship could be significantly affected by methodological choice.

The conclusion that efficiency is positively related to size in the industry is consistent with the findings of Gardner and Grace (1993). However, Yuengert (1993) found that efficiency and size were statistically unrelated.

To provide additional information on the reasonableness of the methods, we also correlate the five-year average efficiency scores with two conventional performance measures used in the insurance industry -- the ratio of expenses to premiums and the ratio of net income plus benefits to equity. The latter ratio is used because benefits incurred, an important output for insurers, is subtracted from revenues to obtain net income. The results, shown in Table 6, indicate that most of the methods produce efficiency scores that are

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[18]The value for assets are based on the year 1990.

significantly correlated with the conventional performance measures. The principal exceptions are the two distribution-free methods, which are not significantly correlated with the expense to premium ratio, and the maintained efficiency model estimated by MLE (the REM model in the table), which is positively rather than negatively correlated with the expense to premium ratio. The highest correlation with the expense to premium ratio is provided by the FDH estimates. VRS has the highest and FDH the second-highest correlations with the returns plus benefits to equity ratio. The exponential model performs relatively well among the econometric methods.

**Economies of Scale**

As mentioned above, the life insurance industry is currently experiencing a wave of mergers and acquisitions, including acquisitions of medium size regional companies by foreign and domestic financial services conglomerates as well as some "megamergers" among industry giants such as the Metropolitan Life and the New England. Because mergers and acquisitions require the approval of state insurance commissioners and are often rationalized on efficiency grounds, the issue of economies of scale is of significant relevance to policy makers. The policy implications, as well as general interest in the topic among academic researchers, motivate our analysis of scale economies in the life insurance industry.

The DEA methodology lends itself readily to the analysis of scale economies. The analysis uses the relationship that TE = PT*S, where PT = pure technical efficiency and S = scale efficiency. Technical efficiency (TE) is defined in terms of the equi-proportional reduction in inputs the firm could achieve while producing the same quantities of its outputs if it were to operate on the constant returns to scale (CRS) production frontier, i.e., $TE = TE_{CRS}$, where $TE_{CRS}$ = technical efficiency under the CRS assumption.[19] Pure technical efficiency measures the reduction in inputs that the firm could achieve if it were to use the variable returns to scale (VRS) technology, i.e., $PT = TE_{VRS}$, where $TE_{VRS}$ = technical efficiency under the

[19]The analysis here refers to *input-oriented* technical efficiency, obtained by holding output fixed and estimating the feasible reduction in inputs the DMU could achieve by operating on the frontier.

VRS assumption. Intuitively, the VRS technology envelops the data at least as closely as the non-increasing returns to scale (NIRS) technology, because the former allows for increasing returns to scale whereas the latter does not. Likewise, the NIRS technology envelops the data at least as closely as the CRS technology. Thus, $TE_{CRS} \leq TE_{NIRS} \leq TE_{VRS}$. Scale efficiency is estimated as $S = TE_{CRS}/TE_{VRS}$. If $S = 1$, the DMU is operating at CRS. However, if $S \neq 1$ and $TE_{NIRS} = TE_{VRS}$, then DRS is indicated, whereas if $S \neq 1$ and $TE_{NIRS} \neq TE_{VRS}$, then the DMU is characterized by increasing returns to scale (IRS).

The scale economy results are presented in Table 7.[20] The results reveal that the vast majority of firms in the industry are operating at either increasing or decreasing returns to scale. Only about 6 percent of the 445 firms in our sample are attaining the economic ideal of operating at constant returns to scale. About 63 percent of firms are operating in the range of increasing returns to scale. Thus, in general, mergers of firms with less than $300 million of assets have the potential to reduce production costs in the industry. On the other hand, mergers of firms with more than $1 billion in assets appear to be much more difficult to justify in terms of reductions in average operating costs. Most firms in this range are operating at decreasing returns to scale. Stock insurers are more likely to be operating at increasing returns to scale than mutuals, but this primarily reflects the size skewness within the two organizational forms — stocks are predominantly small firms and mutuals are predominantly large. This is due to the fact that it is much easier to capitalize a new stock firm than a new mutual, so that most new entrants during the past several decades have adopted the stock ownership form. Stocks and mutuals are discussed in more detail in the following section.

**Stocks and Mutuals**

Since Williamson (1963) suggested that utility-maximizing managers who are not owners of the firm may pursue their own interests, many studies have investigated the existence of "expense preference behavior," especially for regulated industries where different organizational forms, such as stocks and

[20]The results presented in Table 7 are for 1990. The results for other years are very similar and, therefore, are not shown.

mutuals, coexist (see, for example, Akella and Greenbaum, 1988, Blair and Placone, 1988, Mester, 1989, 1991, Gropper and Randolph, 1995). The expense preference hypothesis predicts that mutuals will have higher costs than stocks because the mutual form of ownership affords owners less effective mechanisms for controlling and disciplining managers than the stock ownership form (e.g., Mester, 1989).[21] Thus, managers of mutuals may engage in excessive consumption of perquisites (expense preference behavior) and may in general be less likely than stock managers to pursue the owners' objective of maximizing firm value.

A somewhat more sophisticated agency theoretic hypothesis is that firms with alternative organizational forms are sorted into market segments where they have comparative advantages in dealing with various types of principal-agent problems (see Mayers and Smith, 1981, Fama and Jensen, 1983a, 1983b). For example, the stock form of ownership is expected to be more effective than the mutual form in controlling owner-manager conflicts because of the more effective mechanisms for controlling management afforded by this ownership form. On the other hand, the mutual form of ownership is expected to be more effective in controlling owner-customer conflicts because the ownership and customer functions are merged in the mutual ownership form. This analysis suggests that mutuals may not have higher costs than stocks but rather that the alternative organizational forms may be equally efficient in the market segments where they have respective advantages. We refer to this hypothesis as the "efficient sorting" hypothesis.

The insurance industry provides a particularly interesting environment in which to study organizational form because stock and mutual insurers have coexisted in the industry for many decades. Although the overwhelming majority of firms in the industry are stock insurers, the proportion of insurance in force provided by mutuals has held steady at about 40 percent over the past quarter century and many of

[21]The stock form of ownership provides several mechanisms for controlling managers that are not available to mutuals, including the alienability of residual claims, proxy fights, and the market for takeovers (Fama and Jensen, 1983a, 1983b).

the largest life insurers are mutuals.

We now conduct empirical tests to provide evidence on the relevance of the expense preference and efficient sorting hypotheses in the life insurance industry. Recall that the expense preference hypothesis predicts that mutuals will be less efficient than stocks, whereas the efficient sorting hypothesis implies that mutuals and stocks are likely to be equally efficient.

The average cost efficiencies of stock and mutual insurers are presented in Table 8. The top panel of the table, based on the full sample, shows that mutuals have efficiency scores that are higher than those of stocks under every estimation methodology. Although this seems to contradict the expense preference hypothesis, the result may be due to scale effects because mutuals are larger on average than stock insurers. For example, the mean assets for stocks in our sample is $1.78 billion and the median is $119.5 million, whereas the mean and median assets for mutuals are $6.91 billion and $472 million, respectively.

To control for the effects of scale, we choose a size-stratified random sample of stock insurers that matches the size distribution of mutuals, where size is based on average total assets.[22] This procedure yields matched samples of 95 stock insurers and 95 mutuals. The mean and median efficiencies for the insurers in the matched samples are shown in the middle and lower panels of Table 8. Although mutual firms still show slightly higher efficiencies, the differences in cost efficiencies seem negligible between the matched samples.

To further test for efficiency differences between stocks and mutuals, we conduct analysis of variance (ANOVA) and three non-parametric tests -- the Wilcoxon, Van der Waerden, and Savage tests. ANOVA assumes that the underlying distribution is normal and tests for differences in means across groups. The non-parametric tests do not require a distributional assumption and compare the entire

[22]All stock insurers with assets greater than $13 billion are included in the sample (there are 11 stock insurers and 10 mutuals in this size category). The remaining firms are then placed in $100 million size strata and random samples of stocks are selected from each stratum to exactly match the number of mutuals in that stratum.

structure of the distribution of efficiency scores not just the central tendency. The results of these four additional tests are presented in Table 9. The overall result from Table 9 is that we generally cannot reject the hypothesis that the cost efficiency of stock and mutual insurers have the same mean (for ANOVA) or the same distribution (for the other three tests) at the 5 percent significance level. The only exceptions are provided by the normal/half-normal and normal/exponential panel methodologies under the Wilcoxan Test. Moreover, all of the Z-statistics from the non-parametric tests (except the Wilcoxon test on VRS) exhibit negative signs, suggesting that stock insurer efficiency is no greater than that of mutuals. These results are therefore not consistent with the expense preference hypothesis but rather are consistent with the efficient sorting hypothesis of the coexistence of different organizational forms in life insurance. Gardner and Grace (1993) reached a similar conclusion.

In spite of the general failure to reject the hypothesis that stocks and mutuals have different efficiencies, the hypothesis test results are stronger for the mathematical programming methods than for the econometric methods. For example, whereas the results as a whole imply a clear failure to reject the hypothesis that mutuals and stocks are equally efficient after controlling for size, the results would appear ambiguous if one were to rely solely on the normal/half normal panel model, for example. Thus, our results suggest that more than one methodology should be used in analyzing efficiency, unless there is a strong theoretical rationale for preferring a particular method or class of methods for a given data set.

**Distributional Assumptions for the Inefficiency Error**

As suggested above, the normal/half normal and normal/exponential models have been criticized because of the possibility that they may inappropriately impose monotonicity on the inefficiency component of the error term in equation (l). Following the approach in Berger (1993), we investigate the appropriateness of the monotonicity assumption by examining the five-year average residuals from the DFA and GLS models. Since the results are very similar, we discuss only the DFA residuals. The empirical probability density and distribution functions of the five-year average residuals are shown in Figure 1 along with fitted gamma density and distribution functions obtained by maximum likelihood estimation.[23] The empirical distribution has a non-zero mode and is skewed to the right. The Bowman-Shelton statistic easily rejects the normal distribution as a model for the empirical distribution, with a test statistic of 70.4.[24] The gamma distribution fits the empirical distribution well. The Kolmogorov-Smirnov statistic is 0.04, implying that we cannot reject the gamma distribution hypothesis.

The non-zero mode of the distribution of average residuals shown in Figure 1 does not imply that monotonicity is inappropriate for our data set. The reason is that the plotted DFA residuals are obtained as the five-year averages of the cost function residuals for each firm and thus (up to division by a constant) represent the convolution of the five individual-year inefficiency error terms (plus whatever component of the white noise term is not eliminated by averaging). Under the assumptions that the probability distribution of the inefficiency error is stable over time and that the random error averages out over the sample period, the inefficiency term for each year would be gamma distributed with shape parameter equal to 4.1/5 or 0.81 and scale parameter of 4.8/5 = 0.97.[25] A gamma distribution with a shape parameter of 0.81 has a mode at zero and a shape similar to that of the exponential distribution, which of course is gamma distributed with shape parameter equal to 1. Thus, neither the monotonicity assumption nor the exponential distributional

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[23]Our parameterization of the gamma is:

$$f(x) = \frac{\lambda}{\Gamma(r)} (\lambda x)^{r-1} e^{-\lambda x}$$

The estimated scale parameter ($\lambda$) = 4.8608 and the estimated shape parameter (r) = 4.0518.

[24]The Bowman-Shelton statistic is defined as: B = (sample size)*[skewness$^2$/6 + (kurtosis-3)$^2$/24], which is distributed as $\chi^2$ with 2 degrees of freedom.

[25]The shape parameter result is due to the stationarity assumption plus the fact that the convolution of independent gamma distributions with the same scale parameter is also gamma distributed with a shape parameter equal to the sum of the shape parameters of the distributions included in the convolution. The scale parameter result is due to dividing by 5 to obtain the five-year average residuals.

assumption seems to be patently inappropriate for our data set.

Checking whether the five year average residuals would have a shape similar to the empirical density function in Figure 1 if the inefficiency residual were distributed as a half-normal is more difficult because the convolution of half-normals does not have a closed form expression. To test the reasonableness of the half normal, we simulate the convolution of an error term consisting of normal and half-normal components with parameter estimates based on the half-normal panel (Half_P) model. We simulate one million sequences of five draws from the normal and half normal, summing and averaging the results in each case to simulate the results of applying DFA.[26] The resulting distribution, which is plotted in Figure 2, has a shape similar to that of the empirical probability density function of the averaged residuals from the DFA methodology. Even though the half-normal is monotonic with a mode at zero, sums of half normals have a non-zero mode and approach symmetry as the number of half normals in the sum increases. Thus, we conclude that the half normal also is consistent with the observed DFA residuals from our data set. Therefore, at least for life insurers, the monotonicity assumption does not appear to be inappropriate. Nor does the monotonicity assumption confine a high proportion of firms to near full efficiency. For example, only 2.2 percent of firms are more than 90 percent efficient based on our half normal-normal panel (HaIf_P) model.

## V. Summary and Conclusions

This paper compares cost efficiency estimates of U.S. life insurers using a variety of econometric and mathematical programming methodologies. The principal objective is to provide new information on the effects of the choice of methodology on cost efficiency estimates, and a secondary objective is to analyze some classic industrial organization issues with respect to the life insurance industry.

The findings indicate that the choice of efficiency estimation methodology makes a significant

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[26] That is we simulate $r_i = \sum_j (u_{ij} + v_{ij})/5$, where $u_{ij}$ = simulated random draw from a half-normal distribution, $v_{ij}$ = simulated random draw from a standard normal distribution, i = 1, ..., 1,000,000, and j = l, 2, . . . , 5. The parameters of the half-normal and normal distributions are obtained from the half-normal panel model (Half_P).

difference in terms of the estimated cost efficiency values. The efficiency rankings are well-preserved within the set of econometric methodologies. For all but one of the econometric methods tested, the pairwise rank correlations are no less than 96 percent. The rankings are less well-preserved between the econometric and mathematical programming methodologies (rank correlations in the 50 to 60 percent range) and likewise between the mathematical programming methodologies (the rank correlation is about 67 percent between the variable returns to scale DEA model and the free disposal hull model). Thus, the choice of methodology matters if one is interested in ranking DMUs in terms of efficiency. Even though the debate in the literature has often focused on whether to use econometric vs. mathematical programming methods, these results suggest that an equally important choice is whether to impose convexity when using mathematical programming. Both the econometric and mathematical programming efficiency scores are significantly correlated with conventional performance measures, but the correlations tend to be somewhat higher for the mathematical programming methods than for the econometric methods.

Two principal industrial organization issues are investigated — scale efficiency and the relative efficiency of alternative organizational forms. More than 63 percent of the firms in our sample demonstrate increasing returns to scale and 31 percent demonstrate decreasing returns to scale. Most firms with assets less than $300 million are characterized by increasing returns to scale, while most of those with assets greater than $1 billion display decreasing returns to scale. Thus, mergers of relatively large insurers seem difficult to justify on cost efficiency grounds. We find no evidence that mutual insurers are less efficient than stock insurers. Thus, expense preference behavior does not seem to be present in the industry. Rather, the results are consistent with the efficient sorting of alternative organizational forms into market segments where they have comparative advantages.

Finally, we analyze the cost function residuals based on the distribution free methodology and find that the pattern of residuals is consistent with a monotonic probability distribution such as the exponential or half-normal. Simulations of the normal-half normal composed error term also support this conclusion.

An overall implication is that researchers should devote more attention to exploring the appropriateness of the assumptions underlying the various methodologies. The results suggest that the controversy regarding distributional error term assumptions in the econometric approach may be a bit of a red herring, but this finding needs to be tested for robustness using other data sets and/or simulation analysis. Our analysis confirms prior findings that the data envelopment analysis (DEA) and the free disposal hull (FDH) mathematical programming methodologies tend to give significantly different results. Thus, the appropriateness of the convexity assumption in mathematical programming needs further investigation. Although our tests of economic hypotheses are generally robust to the choice of estimation methodology, it is probably advisable in most cases to use more than one methodology when analyzing efficiency to ensure that the findings are not being driven by specification errors.

Table 1
Descriptive Statistics: 445 U.S. Life Insurers
Averages 1988-1992

| Variable | Mean | Standard Deviation | Maximum | Minimum |
|---|---|---|---|---|
| Output (mil. \$) | | | | |
| $Y_1$ | 34.5 | 116.0 | 1494.6 | 0 |
| $Y_2$ | 20.8 | 120.9 | 3073.0 | 0 |
| $Y_3$ | 18.8 | 60.4 | 818.4 | 0 |
| $Y_4$ | 34.7 | 202.6 | 2671.2 | 0 |
| $Y_5$ | 79.2 | 295.4 | 4539.2 | 0 |
| $Y_6$ | 492.9 | 1667.4 | 25228.0 | 0 |
| Input | | | | |
| $X_1$ (thous.) | 159.4 | 383.6 | 4974.3 | 2.02 |
| $X_2$ (mil.) | 2419.3 | 8299.6 | 155216.2 | 2.83 |
| $X_3$ (mil.) | 20.0 | 56.4 | 914.6 | 0.51 |
| Input Price | | | | |
| $P_1$ | 499.1 | 33.29 | 628.5 | 363.1 |
| $P_2$ | 0.12 | 0.10 | 1.02 | 0.01 |
| $P_3$ | 1.09 | 0.07 | 1.26 | 0.85 |
| Cost (mil.) | 313.4 | 867.3 | 13015.6 | 1.79 |

Note: $Y_1$ = individual life insurance benefit payments
$Y_2$ = group life insurance benefit payments
$Y_3$ = individual annuities benefit payment
$Y_4$ = group annuities benefit payments
$Y_5$ = accident and health insurance benefit payments
$Y_6$ = additions to reserves
$X_1$ = quantity of labor input
$X_2$ = quantity of financial capital input
$X_3$ = quantity of materials input
$p_1$ = price of labor input
$p_2$ = price of financial capital input
$p_3$ = price of materials input

All dollar valued quantities are expressed in constant 1988 dollars.

Table 2. - Cost Efficiency Measures: Econometric Approach

| | Half | Exponential | Half_P | Exp_P | DFA | GLS | REM | Gamma |
|---|---|---|---|---|---|---|---|---|
| (1988) | | | | | | | | |
| Mean | 0.58 | 0.70 | 0.61 | 0.71 | 0.47 | 0.44 | 0.46 | 0.86 |
| Std. Dev. | 0.22 | 0.17 | 0.18 | 0.16 | 0.04 | 0.04 | 0.09 | 0.08 |
| Max | 0.94 | 0.92 | 0.92 | 0.92 | 1.00 | 1.00 | 0.97 | 0.90 |
| Min | 0.05 | 0.07 | 0.07 | 0.07 | 0.04 | 0.04 | 0.09 | 0.23 |
| (1989) | | | | | | | | |
| Mean | 0.63 | 0.73 | 0.61 | 0.70 | 0.47 | 0.44 | 0.46 | 0.86 |
| Std. Dev. | 0.17 | 0.15 | 0.18 | 0.16 | 0.04 | 0.04 | 0.09 | 0.07 |
| Max | 0.92 | 0.92 | 0.93 | 0.93 | 1.00 | 1.00 | 0.97 | 0.93 |
| Min | 0.09 | 0.08 | 0.08 | 0.08 | 0.04 | 0.04 | 0.09 | 0.21 |
| (1990) | | | | | | | | |
| Mean | 0.61 | 0.71 | 0.61 | 0.71 | 0.47 | 0.44 | 0.46 | 0.79 |
| Std. Dev. | 0.18 | 0.16 | 0.18 | 0.16 | 0.04 | 0.04 | 0.09 | 0.10 |
| Max | 0.93 | 0.93 | 0.94 | 0.93 | 1.00 | 1.00 | 0.97 | 0.90 |
| Min | 0.09 | 0.10 | 0.09 | 0.10 | 0.04 | 0.04 | 0.09 | 0.32 |
| (1991) | | | | | | | | |
| Mean | 0.61 | 0.69 | 0.61 | 0.71 | 0.47 | 0.44 | 0.46 | 0.86 |
| Std. Dev. | 0.20 | 0.19 | 0.18 | 0.16 | 0.04 | 0.04 | 0.09 | 0.08 |
| Max | 0.94 | 0.94 | 0.91 | 0.92 | 1.00 | 1.00 | 0.97 | 0.94 |
| Min | 0.05 | 0.06 | 0.07 | 0.07 | 0.04 | 0.04 | 0.09 | 0.20 |
| (1992) | | | | | | | | |
| Mean | 0.63 | 0.73 | 0.61 | 0.71 | 0.47 | 0.44 | 0.46 | 0.86 |
| Std. Dev. | 0.18 | 0.16 | 0.17 | 0.15 | 0.04 | 0.04 | 0.09 | 0.07 |
| Max | 0.93 | 0.93 | 0.91 | 0.91 | 1.00 | 1.00 | 0.97 | 0.90 |
| Min | 0.06 | 0.06 | 0.06 | 0.06 | 0.04 | 0.04 | 0.09 | 0.12 |
| (5-Year Average) | | | | | | | | |
| Mean | 0.61 | 0.71 | 0.61 | 0.71 | 0.47 | 0.44 | 0.46 | 0.85 |
| Std. Dev. | 0.17 | 0.15 | 0.16 | 0.14 | 0.18 | 0.18 | 0.21 | 0.07 |
| Max | 0.90 | 0.90 | 0.87 | 0.89 | 1.00 | 1.00 | 0.97 | 0.91 |
| Min | 0.07 | 0.07 | 0.07 | 0.07 | 0.04 | 0.04 | 0.09 | 0.22 |
| Median | 0.63 | 0.75 | 0.63 | 0.75 | 0.45 | 0.42 | 0.42 | 0.87 |

NOTE: Half = half-normal distribution for inefficiency error term, estimated year-by-year;
Exponential = exponential distribution for inefficiency error term, estimated year-by-year;
Half_P = half-normal inefficiency assumption, estimated using entire panel;
Exp_P = exponential inefficiency assumption, estimated using entire panel;
DFA = distribution free method (Berger, 1993);
GLS = random effects model estimated using GLS (Schmidt and Sickles, 1984);
REM = random effects model estimated using maximum likelihood;
Gamma = gamma distribution for inefficiency error term, estimated year-by-year (Greene, 1990).

Table 3. - Efficiency Measures: Mathematical Programming Approach

| | Free Disposal Hull | | | Variable Returns to Scale | | |
|---|---|---|---|---|---|---|
| | CE | TE | AE | CE | TE | AE |
| (1988) | | | | | | |
| Mean | 0.92 | 0.98 | 0.93 | 0.42 | 0.56 | 0.77 |
| Std. Dev. | 0.18 | 0.07 | 0.17 | 0.24 | 0.27 | 0.23 |
| Max | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Min | 0.06 | 0.30 | 0.06 | 0.02 | 0.13 | 0.10 |
| (1989) | | | | | | |
| Mean | 0.91 | 0.98 | 0.92 | 0.46 | 0.58 | 0.82 |
| Std. Dev. | 0.19 | 0.10 | 0.17 | 0.25 | 0.28 | 0.22 |
| Max | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Min | 0.07 | 0.27 | 0.07 | 0.04 | 0.09 | 0.11 |
| (1990) | | | | | | |
| Mean | 0.90 | 0.98 | 0.92 | 0.45 | 0.56 | 0.83 |
| Std. Dev. | 0.19 | 0.09 | 0.17 | 0.24 | 0.27 | 0.21 |
| Max | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Min | 0.09 | 0.16 | 0.09 | 0.04 | 0.14 | 0.10 |
| (1991) | | | | | | |
| Mean | 0.92 | 0.98 | 0.93 | 0.48 | 0.61 | 0.81 |
| Std. Dev. | 0.18 | 0.09 | 0.16 | 0.24 | 0.27 | 0.22 |
| Max | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Min | 0.08 | 0.29 | 0.08 | 0.04 | 0.14 | 0.13 |
| (1992) | | | | | | |
| Mean | 0.92 | 0.98 | 0.93 | 0.50 | 0.60 | 0.85 |
| Std. Dev. | 0.18 | 0.09 | 0.16 | 0.25 | 0.27 | 0.21 |
| Max | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Min | 0.04 | 0.20 | 0.07 | 0.03 | 0.10 | 0.11 |
| (5-Year Average) | | | | | | |
| Mean | 0.91 | 0.98 | 0.93 | 0.46 | 0.58 | 0.82 |
| Std. Dev. | 0.16 | 0.06 | 0.15 | 0.22 | 0.25 | 0.18 |
| Max | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Min | 0.07 | 0.46 | 0.07 | 0.04 | 0.17 | 0.12 |

NOTE: CE = Cost efficiency.
TE = Technical efficiency.
AE = Allocative efficiency.

Table 4. - Spearman Correlation Coefficients Among Alternative Efficiency Measures
Five-Year Average (1988-1992)

| | DFA | Half_P | Exp_P | Half | Exp | GLS | Gamma | REM | FDH | VRS |
|---|---|---|---|---|---|---|---|---|---|---|
| DFA | 1.00 | | | | | | | | | |
| Half_P | 0.98 | 1.00 | | | | | | | | |
| Exp_P | 0.97 | 0.99 | 1.00 | | | | | | | |
| Half | 0.98 | 0.98 | 0.97 | 1.00 | | | | | | |
| Exp | 0.98 | 0.98 | 0.98 | 0.96 | 1.00 | | | | | |
| GLS | 0.98 | 0.98 | 0.98 | 0.96 | 0.96 | 1.00 | | | | |
| Gamma | 0.99 | 0.97 | 0.97 | 0.97 | 0.98 | 0.97 | 1.00 | | | |
| REM | 0.68 | 0.65 | 0.65 | 0.61 | 0.61 | 0.72 | 0.68 | 1.00 | | |
| FDH | 0.51 | 0.55 | 0.56 | 0.55 | 0.56 | 0.52 | 0.52 | 0.20 | 1.00 | |
| VRS | 0.59 | 0.58 | 0.57 | 0.60 | 0.59 | 0.57 | 0.56 | 0.21 | 0.67 | 1.00 |

NOTE: Half = half-normal distribution for inefficiency error term, estimated year-by-year;
Exp = exponential distribution for inefficiency error term, estimated year-by-year;
Half_P = half-normal inefficiency assumption, estimated using entire panel;
Exp_P = exponential inefficiency assumption, estimated using entire panel;
DFA = distribution free method (Berger, 1993);
GLS = random effects model estimated using GLS (Schmidt and Sickles, 1984);
REM = random effects model estimate using maximum likelihood;
Gamma = gamma distribution for inefficiency error term, estimated year-by-year;
FDH = free disposal hull;
VRS = DEA estimate with variable returns to scale constraint;

Table 5. - Efficiency Measures by Asset Size Class:
Five Year Averages (1988-1992)

| Asset Size Class | VRS | FDH | Half_P | Exp_P | DFA | GLS | REM | Half | Exp | Gamma |
|---|---|---|---|---|---|---|---|---|---|---|
| 10M-30M | 0.47 | 0.84 | 0.63 | 0.72 | 0.53 | 0.51 | 0.66 | 0.63 | 0.71 | 0.86 |
| 30M-50M | 0.41 | 0.88 | 0.64 | 0.73 | 0.51 | 0.49 | 0.63 | 0.64 | 0.73 | 0.86 |
| 50M-100M | 0.43 | 0.90 | 0.64 | 0.73 | 0.51 | 0.49 | 0.56 | 0.63 | 0.73 | 0.86 |
| 100M-300M | 0.34 | 0.90 | 0.59 | 0.69 | 0.43 | 0.40 | 0.43 | 0.59 | 0.69 | 0.83 |
| 300M-1B | 0.41 | 0.95 | 0.59 | 0.70 | 0.43 | 0.40 | 0.36 | 0.59 | 0.70 | 0.84 |
| 1.0B-2.5B | 0.49 | 0.97 | 0.59 | 0.70 | 0.43 | 0.39 | 0.32 | 0.59 | 0.70 | 0.84 |
| 2.5B-5.0B | 0.49 | 0.92 | 0.56 | 0.66 | 0.40 | 0.36 | 0.56 | 0.56 | 0.66 | 0.81 |
| 5.0B-10.0B | 0.69 | 1.00 | 0.62 | 0.72 | 0.46 | 0.41 | 0.41 | 0.62 | 0.72 | 0.85 |
| ≥ 10.0B | 0.84 | 1.00 | 0.65 | 0.75 | 0.47 | 0.44 | 0.24 | 0.66 | 0.76 | 0.86 |
| Correlation* | 0.389 | 0.108 | 0.094 | 0.078 | 0.092 | 0.099 | -0.155 | 0.106 | 0.083 | 0.039 |
| P-Value** | 0.000 | 0.022 | 0.047 | 0.096 | 0.051 | 0.035 | 0.001 | 0.025 | 0.080 | 0.405 |

*Pearson correlation coefficient between efficiency score and assets.
**Probability value for test of the null hypothesis that correlation coefficient is equal to zero.
NOTE: M = millions of dollars; B = billions of dollars.
Half = half-normal distribution for inefficiency error term, estimated year-by-year;
Exp = exponential distribution for inefficiency error term, estimated year-by-year;
Half_P = half-normal inefficiency assumption, estimated using entire panel;
Exp_P = exponential inefficiency assumption, estimated using entire panel;
DFA = distribution free method (Berger, 1993);
GLS = random effects model estimated using GLS (Schmidt and Sickles, 1984);
REM = random effects model estimate using maximum likelihood;
Gamma = gamma distribution for inefficiency error term, estimated year-by-year;
FDH = free disposal hull;
VRS = DEA estimate with variable returns to scale constraint;

Table 6
Pearson Correlation Coefficients Between Efficiencies And Other Performance Measures

| Ratio | VRS | FDH | Half_P | Exp_P | DFA | GLS | REM | Half | Exp | Gamma |
|---|---|---|---|---|---|---|---|---|---|---|
| Expense Ratio | -0.17 | -0.36 | -0.14 | -0.19 | -0.07 | -0.04 | 0.16 | -0.17 | -0.22 | -0.18 |
| | 2.84E-04 | 1.55E-15 | 2.89E-03 | 4.78E-05 | 1.38E-01 | 3.97E-01 | 6.45E-04 | 2.84E-04 | 2.26E-06 | 1.19E-04 |
| RBOE | 0.35 | 0.24 | 0.12 | 0.12 | 0.13 | 0.14 | 0.12 | 0.14 | 0.15 | 0.13 |
| | 1.11E-14 | 2.28E-07 | 1.08E-02 | 1.08E-02 | 5.71E-03 | 2.89E-03 | 1.08E-02 | 2.89E-03 | 1.40E-03 | 5.71E-03 |

NOTE: Numbers in parentheses are probabilities of obtaining the indicated correlation coefficient by chance under the null hypothesis that the correlation = 0.

Expense Ratio = the ratio of expenses to premiums
RBOE = the ratio of returns plus benefits to equity
Half = half-normal distribution for inefficiency error term, estimated year-by-year;
Exp = exponential distribution for inefficiency error term, estimated year-by-year;
Half_P = half-normal inefficiency assumption, estimated using entire panel;
Exp_P = exponential inefficiency assumption, estimated using entire panel;
DFA = distribution free method (Berger, 1993);
GLS = random effects model estimated using GLS (Schmidt and Sickles, 1984);
REM = random effects model estimate using maximum likelihood;
Gamma = gamma distribution for inefficiency error term, estimated year-by-year;
FDH = free disposal hull;
VRS = DEA estimate with variable returns to scale constraint;

Table 7

Economies of Scale in the U.S. Life Insurance Industry: 1990

| Asset | Returns to Scale | | | | | |
|---|---|---|---|---|---|---|
| | Increasing | | Constant | | Decreasing | |
| Size Class | Stocks | Mutuals | Stocks | Mutuals | Stocks | Mutuals |
| 10M - 30M | 65 | 6 | 3 | 1 | 0 | 0 |
| 30M - 50M | 44 | 4 | 0 | 2 | 1 | 0 |
| 50M - 100M | 40 | 6 | 2 | 1 | 5 | 0 |
| 100M - 300M | 55 | 14 | 2 | 0 | 6 | 5 |
| 300M - 1B | 21 | 14 | 6 | 0 | 15 | 8 |
| 1B - 2.5B | 5 | 2 | 3 | 0 | 26 | 6 |
| 2.5B - 5B | 2 | 1 | 2 | 0 | 17 | 5 |
| 5B - 10 B | 1 | 0 | 1 | 1 | 14 | 7 |
| > 10B | 0 | 0 | 3 | 1 | 11 | 11 |
| Total: Number | 233 | 47 | 22 | 6 | 95 | 42 |
| Percent: Stocks | 78.5% | | 7.4% | | 32.0% | |
| Percent: Mutuals | | 49.5% | | 6.3% | | 44.2% |
| Percent: Overall | | 62.9% | | 6.3% | | 30.8% |

Note: M = millions of dollars, B = billions of dollars.

Table 8. - Efficiency Comparison: Stocks vs. Mutuals

Means From Entire Sample

| | N | VRS | FDH | Half_P | Exp_P | DFA | GLS | REM | Half | Exp | Gamma |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Stock | 350 | 0.44 | 0.90 | 0.60 | 0.70 | 0.46 | 0.43 | 0.46 | 0.60 | 0.70 | 0.84 |
| Mutual | 95 | 0.54 | 0.97 | 0.66 | 0.75 | 0.51 | 0.48 | 0.45 | 0.67 | 0.76 | 0.87 |

Means From Matched Samples

| | N | VRS | FDH | Half_P | Exp_P | DFA | GLS | REM | Half | Exp | Gamma |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Stock | 95 | 0.53 | 0.96 | 0.63 | 0.73 | 0.48 | 0.47 | 0.40 | 0.63 | 0.74 | 0.86 |
| Mutual | 95 | 0.54 | 0.97 | 0.66 | 0.75 | 0.51 | 0.48 | 0.45 | 0.67 | 0.76 | 0.87 |

Medians From Matched Samples

| | N | VRS | FDH | Half_P | Exp_P | DFA | GLS | REM | Half | Exp | Gamma |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Stock | 95 | 0.48 | 1.00 | 0.68 | 0.75 | 0.46 | 0.43 | 0.36 | 0.64 | 0.76 | 0.87 |
| Mutual | 95 | 0.48 | 1.00 | 0.69 | 0.80 | 0.51 | 0.49 | 0.41 | 0.71 | 0.80 | 0.89 |

NOTE: Half = half-normal distribution for inefficiency error term, estimated year-by-year;
Exp = exponential distribution for inefficiency error term, estimated year-by-year;
Half_P = half-normal inefficiency assumption, estimated using entire panel;
Exp_P = exponential inefficiency assumption, estimated using entire panel;
DFA = distribution free method (Berger, 1993);
GLS = random effects model estimated using GLS (Schmidt and Sickles, 1984);
REM = random effects model estimate using maximum likelihood;
Gamma = gamma distribution for inefficiency error term, estimated year-by-year;
FDH = free disposal hull;
VRS = DEA estimate with variable returns to scale constraint;

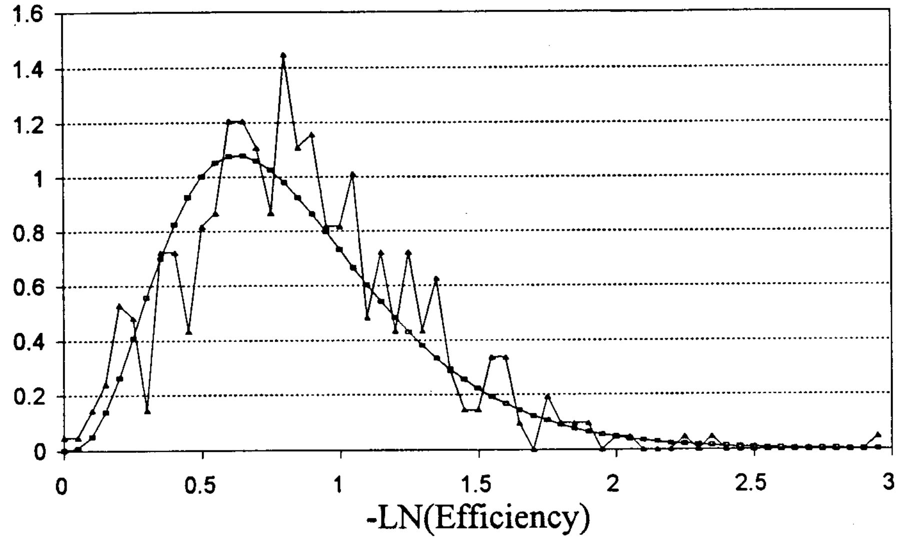
Table 9. Nonparametric Analysis of Efficiency Measures: Stocks vs. Mutuals (matched samples)

| | Analysis of Variance F (Prob > F) | Wilcoxon Test Z (Prob > Z) | Van der Waerden Test Z (Prob > Z) | Savage Test Z (Prob > Z) |
|---|---|---|---|---|
| VRS | 0.032 | 0.037 | -0.161 | -0.345 |
| | (0.86) | (0.97) | (0.87) | (0.73) |
| FDH | 0.128 | -0.349 | -0.409 | -0.333 |
| | (0.72) | (0.73) | (0.68) | (0.74) |
| Half_P | 3.483 | -2.156 | -1.827 | -1.506 |
| | (0.06) | (0.03) | (0.07) | (0.13) |
| Exp_P | 2.584 | -2.113 | -1.795 | -1.436 |
| | (0.11) | (0.04) | (0.07) | (0.15) |
| DFA | 1.643 | -1.574 | -1.305 | -1.046 |
| | (0.20) | (0.12) | (0.12) | (0.30) |
| GLS | 1.985 | -1.765 | -1.455 | -1.099 |
| | (0.16) | (0.08) | (0.15) | (0.27) |
| Half | 2.307 | -1.810 | -1.525 | -1.146 |
| | (0.13) | (0.07) | (0.13) | (0.15) |
| Exp | 1.129 | -1.744 | -1.422 | -1.256 |
| | (0.257) | (0.08) | (0.16) | (0.21) |
| Gamma | 1.596 | -1.823 | -1.539 | -1.223 |
| | (0.21) | (0.07) | (0.12) | (0.22) |

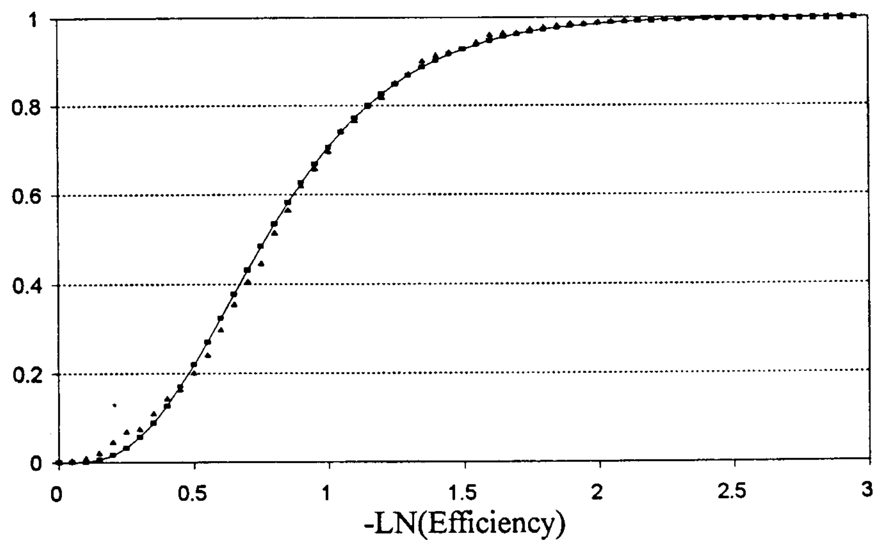
NOTE: Half = half-normal distribution for inefficiency error term, estimated year-by-year;
Exponential = exponential distribution for inefficiency error term, estimated year-by-year;
Half_P = half-normal inefficiency assumption, estimated using entire panel;
Exp_P = exponential inefficiency assumption, estimated using entire panel;
DFA = distribution free method (Berger, 1993);
GLS = random effects model estimated using GLS (Schmidt and Sickles, 1984);
REM = random effects model estimate using maximum likelihood;
Gamma = gamma distribution for inefficiency error term, estimated year-by-year.

Figure 1
Empirical and Fitted Distributions of DFA Average Residuals

Density Functions

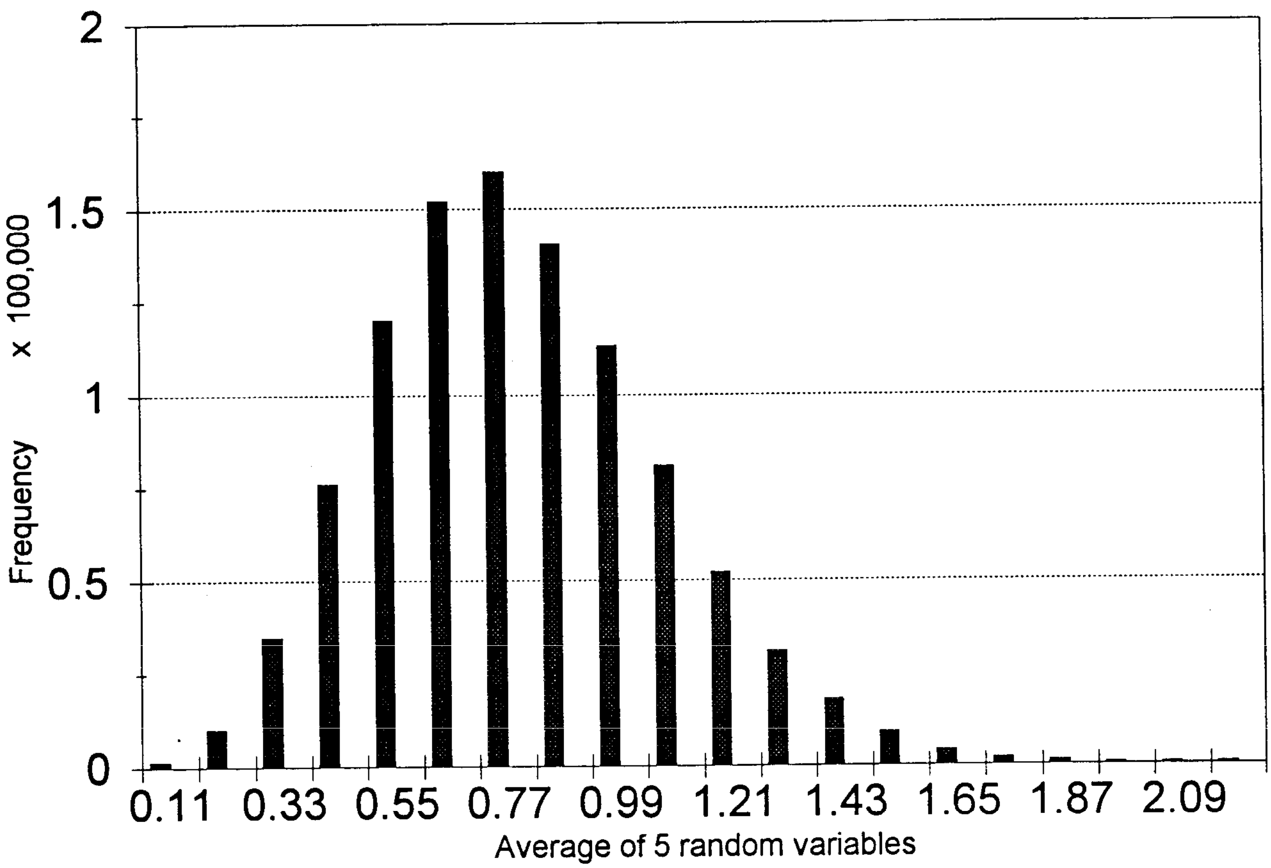



Distribution Functions




Note: The graphs are based on individual firm average residuals obtained by averaging the cost function residuals for each firm across the sample period 1988-1992. The empirical density function is defined as n(i)/N, where n(i) = number of firms with average residuals r in the range p(i-1) < r <= p(i), where p(0) = 0, p(1) = 0.05, . . . , normalized so that the sum under the empirical density sums approximately to 1.0. Recall that the estimate of efficiency under the DFA method is cost efficiency = exp(-r), so the horizontal axes in the charts plots the DFA estimates of the inefficiency component of the cost function residual. The fitted gamma distribution has scale parameter = 4.8608 and shape parameter = 4.0518.

**Figure 2**
Simulated Normal-Half Normal Residuals



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