EFFICIENCY AND SCALE ECONOMIES IN THE US PROPERTY-LIABILITY INSURANCE INDUSTRY

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By

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Abstract

The paper examines efficiency and scale economies in the U.S. property-liability insurance industry. Pure technical, scale, cost, and revenue efficiency are estimated over the period 1993-2002 using data envelopment analysis (DEA). Panel data regressions are utilized to explore the relationships between firm characteristics, efficiency, and scale economies. The results indicate that the majority of firms below median size in the industry are operating with increasing returns to scale, and the majority of firms above median size are operating with decreasing returns to scale. However, a significant number of firms in each size decile have achieved constant returns to scale. The regression analysis shows that product mix, distribution system, organizational form, and capitalization are important determinants of insurers' efficiency. Multinomial logit analysis demonstrates that such characteristics can also help predict a firm's probability of operating with constant returns to scale.

1. Introduction

The U.S. property-liability (P-L) insurance industry has undergone a period of dynamic change over the past fifteen years. The industry has incorporated new computer and communications technologies and experienced significant restructuring due to rapid growth in mergers and acquisitions (M&As) and to a lesser extent entry and exit.[1] The risk-landscape in the industry has also changed significantly with the increased exposure to catastrophic risk and changes in the legal and regulatory environment. Periods of rapid structural change provide both challenges and opportunities for the firms operating in an industry. In particular, such an environment provides opportunities for firms to improve their efficiency and economies of scale by adapting to new technologies but also poses challenges for firms that are unable to keep pace with the market leaders.

Considering the rapid changes that have taken place, the U.S. P-L insurance industry provides a particularly interesting environment in which to analyze efficiency and scale

[1] For example, in 1991, there were 37 M&As, with a total value disclosed of $5.1 billion, while in 1997, 111 M&As took place with a value of $30.9 billion (Conning & Company 1998).

economies. Although the potential for enhancing efficiency and realizing economies of scale are often cited as leading motivations for M&As and other structural changes in an industry, limited evidence exists that industry restructuring consistently enhances efficiency or produces scale economies.[2] In particular, there have been no significant studies of efficiency or scale economies in the U.S. P-L industry using data subsequent to the 1980s. Hence, the objective of this paper is to analyze the performance of firms in the P-L insurance industry, given the backdrop of industry restructuring during the 1990s and early 2000s. Pursuant to this objective, we analyze efficiency and scale economies in the P-L insurance industry over the sample period 1993-2002.

We measure efficiency by estimating "best practice" production, cost, and revenue frontiers for each year of the sample period, using data envelopment analysis (DEA), a non-parametric technique (Cooper, et al. 2000). A production frontier gives the minimum inputs required to produce any given output vector, the cost frontier measures the minimum costs to produce the output vector, and the revenue frontier indicates the maximum attainable revenues conditional on input utilization. Efficiency, which is measured for each firm in the sample in each year, ranges from 0 to 1, with firms operating on the frontier measured as fully efficient (efficiency of 1), and firms not operating on the frontier measured as inefficient (efficiency less than 1). DEA provides a particularly convenient way to decompose overall cost and revenue efficiency into pure technical, scale, and allocative efficiency and thus facilitates the analysis of economies of scale. In this study, we innovate by analyzing efficiency using both an input-orientation, where firms minimize input usage and costs conditional on output levels, and an output-orientation, where firms maximize output quantities and revenues conditional on inputs. Using both orientations enables us to provide a complete picture of the success of insurers in achieving the economic goals of cost minimization and revenue maximization. Decomposing cost and revenue efficiency into pure technical, scale, and allocative

[2] Previous studies of financial institutions show that although scale economies do exist, the benefits cease to be meaningful beyond a threshold that many companies have already exceeded. Berger and Humphrey (1997) provide a review of the financial institutions efficiency literature, including the literature on scale economies. The insurance efficiency literature is reviewed in Cummins and Weiss (2000).

efficiency allows us to provide valuable information on the sources of (in)efficiencies in the industry.

Economies of scale are present if average costs per unit of output decline as the volume of output increases. The usual source of scale economies is the spreading of the firm's fixed costs over a larger volume of output. Fixed costs are present for insurers due to the need for relatively fixed factors of production such as computer systems, managerial expertise, and financial capital. Economies of scale also can arise if operating at larger scale permits managers to become more specialized and therefore more proficient in carrying out specific tasks. Operating at larger scale can reduce the firm's cost of capital if income volatility is inversely related to size. This source of scale economies may be especially important in the insurance industry due to the risk-reducing impact of the law of large numbers in insurance risk pools.

However, expansion of the firm through organic growth or M&As also has the potential to create inefficiencies. As a company expands, it may see the efficiency benefits gradually eroded with additional costs. Most of these costs come from management inefficiency and the decreasing productivity of variable inputs. Internal communication and control of large organizations require expensive systems and extra tiers in the hierarchical managerial structure, which can lead to higher costs. Larger organizations also have more potential to create managerial conflict and agency costs, because the cost of monitoring managerial performance and the cost of incentive contracting may increase. On the other hand, technological progress may have made the optimal scale of firms in an industry larger than before. Therefore, it is important for a firm to keep up with new technology, achieve optimal scale, and realize the objectives of minimizing costs and maximizing revenues. This paper will therefore investigate the degree to which U.S. P-L insurers have been able to accomplish these economic objectives.

In spite of the level of interest in insurance efficiency research over the past fifteen years, there have been surprisingly few studies of efficiency and scale economies in the U.S. P-L insurance industry. A pioneering study by Cummins and Weiss (1993) analyzed efficiency and scale economies for the U.S. P-L industry over the sample period 1980-1988. They conclude that small and medium size firms are characterized by economies of scale, while large firms exhibit mild scale diseconomies. Hanweck and Hogan (1996), using data from 1981-1985, also conclude that small P-L insurers realize economies of scale but that scale diseconomies characterize the largest firms. Berger, et al. (1997) and Cummins, et al. (1999), respectively, analyze the efficiency of property-liability distribution systems and organizational form using data from 1981-1990. Brockett, et al. (2004) study efficiency in the U.S. P-L industry using 1989 data but do not investigate scale economies. Cummins and Nini (2002) estimate P-L insurer efficiencies for the period 1993-1998, but their paper focuses on capital utilization and does not specifically consider scale economies and the determinants of efficiency.

The P-L insurance industry in Finland has been investigated by Toivanen (1997), who finds diseconomies of scale at the firm level. Hirao and Inoue (2004) study the Japanese non-life insurance industry and find significant economies of scale for insurers in Japan. Cummins and Rubio-Misas (2005) study the efficiency of the Spanish life and non-life insurance industries during the 1990s and conclude that economies of scale largely disappear at about median firm size in the Spanish market although some larger insurers have realized constant returns to scale.

Several efficiency studies have investigated the life insurance industry. U.S. studies include Yuengert (1993), Gardner and Grace (1993), Cummins and Zi (1998), Cummins, Tennyson and Weiss (1999), Cummins (1999), and Greene and Segal (2004). A finding that spans most of these studies is that scale economies exist in the life insurance industry, but only up to a relatively small size limit, and that most large firms exhibit decreasing returns to scale. Fukuyama (1997) measures the efficiency of the Japanese life insurance industry, Katrishen and Scordis (1998) study scale economies of multinational insurers, Klumpes (2004) studies the efficiency of U.K. life insurers, and Mahlberg and Url (2003) investigate the Austrian insurance market. Except for Klumpes, who does not investigate scale economies, these studies find evidence of scale economies. This brief literature review suggests that there is significant interest in the analysis of insurance efficiency and scale economies worldwide and that the U.S. P-L industry has been somewhat neglected by efficiency researchers. The objective of this paper is to remedy this limitation in the existing literature. This paper is the only extant U.S. P-L insurance scale economies study to analyze a sample period subsequent to 1990.

The remainder of the paper is organized as follows. Section 2 gives an empirical overview of the US P-L insurance industry. Section 3 describes our data, methodology, and sample selection criteria for efficiency analysis. Section 4 presents the results of the efficiency estimation and economies of scale and discusses their implications for insurers' operations. Section 5 presents an analysis to find determinants of efficiencies for insurers. Section 6 presents the multinomial logit regression results to identify the characteristics of firms that help judge their returns to scale, and section 7 concludes and summarizes.

2. The structure of the P-L insurance industry

This section provides an overview of the P-L insurance industry in the United States as a background for the efficiency analysis. The number of insurers reporting data to the National Association of Insurance Commissioners (NAIC) from 1993 to 2002 is shown in Table 1. During this period, the number of companies with a group affiliation increased dramatically from 1,630 to 1,919, while the number of unaffiliated single companies decreased from 1,025 to 762. The number of groups also decreased from 462 to 441 (groups control about 90% of the industry assets and premiums). The total number of decision-making units (DMUs), defined as groups and unaffiliated companies, declined dramatically (from 1,487 to 1,203), and the average firm size, adjusted for price level change, increased nearly 20%, from $741 to $888 million. Among the explanations for this change are: more unaffiliated companies became affiliated, companies or groups merged into larger groups, and inefficient DMUs exited the market. The remainder of the paper focuses on DMUs (groups and unaffiliated companies) because the operating decisions of affiliated companies are determined by the groups to which they belong.

The four, eight, and twenty-firm concentration ratios, as well as the industry Herfindahl indices, for assets and net premiums written by groups and unaffiliated companies are presented in Table 2. The eight-firm concentration ratios for assets and premiums increased by 5 and 6.1 percentage points, respectively, during the sample period. The four- and twenty-firm concentration ratios also confirm that concentration has been increasing over time, and the Herfindahl indices demonstrate the same trend. However, the US P-L insurance market overall is a very competitive market – the industry's Herfindahl index of approximately 300 is far below the benchmark level of 1,000 for a moderately concentrated market.[3]

3. Data and methodology

This section begins by discussing the efficiency estimation methodology utilized in this paper. We then describe the database and sample selection criteria and the measurement of inputs, input prices, outputs, and output prices used in our analysis.

3.1 Estimation methodology

The basic idea of efficiency analysis is to separate production units that perform well from those that perform poorly. This is done by estimating "best practice" efficient frontiers consisting of the dominant firms in an industry and comparing all firms in the industry to the frontier. Firms operating on the frontier are fully efficient (with efficiency scores of 1.0) and firms not on the frontier are inefficient (with efficiency scores between 0 and 1.0).

[3] The U.S. Department of Justice's horizontal merger guidelines define a market as moderately concentrated if the Herfindahl index is between 1,000 and 1,800 and concentrated if the index exceeds 1,800. U.S. Department of Justice (1997).

Two major categories of methodologies – parametric and non-parametric – have been developed to estimate efficient frontiers. The parametric approaches require the specification of a functional form for the frontier (e.g., a cost or revenue function) and also require assumptions about the probability distributions describing the error terms of the model. Non-parametric approaches do not require assumptions about either the functional form of the frontier or the error term distributions. The primary advantage of the parametric approach is that firms are allowed to deviate from the frontier due to random error as well as inefficiency, whereas the non-parametric approaches measure all departures from the frontier as inefficiency. The disadvantage of the parametric approach is that efficiency estimates can be confounded by specification error if the wrong assumptions are made about the functional form and error term distributions.

Although there was some debate in the early financial institutions efficiency literature about whether the parametric or non-parametric approach was more appropriate, research by Cummins and Zi (1998) for insurance and Casu, et al. (2004) for banking show that parametric and non-parametric approaches generally produce consistent results. Moreover, Cummins and Zi (1998) show that non-parametric approaches tend to correlate better with conventional performance measures such as return on equity. Accordingly, and also because data envelopment analysis (DEA) provides a particularly convenient way to decompose overall efficiency and estimate scale economies, we adopt a non-parametric methodology (DEA) in this paper.[4] DEA is also quite appealing intuitively because it implements micro-economic theory by constructing efficient frontiers specified as optimization problems whereby DMUs minimize costs or maximize revenues (Cooper, et al. 2000).

DEA also has excellent asymptotic statistical properties. DEA is equivalent to maximum likelihood estimation, with the specification of the production frontier in DEA as a

[4] For further discussion of alternative methodologies, see Cummins and Weiss (2000), Cummins and Zi (1998), and Casu, et al. (2004).

nonparametric monotone and concave function instead of a parametric form linear in parameters (Banker 1993). DEA estimators also are consistent and converge faster than estimators from other frontier methods (Kneip, Park and Simar 1998; Grosskopf 1996); and DEA estimators are unbiased if we assume no underlying model or reference technology (Kittelsen 1995).

Five types of frontiers are estimated by DEA in this study: production frontiers with constant returns to scale (technical efficiency), production frontiers with variable returns to scale (pure technical efficiency), production frontiers with non-increasing returns to scale (NIRS technical efficiency), cost frontiers, and revenue frontiers. The cost and revenue frontiers are estimated under the assumption of constant returns to scale, i.e., firms are allowed to deviate from the frontiers due to scale inefficiency as well as pure technical and allocative inefficiency.

All five types of efficiency are estimated for each individual firm in each year of the sample period. To standardize notation, we assume that there are N firms in the industry in a given year and that each firm uses k inputs $x = (x_1, x_2, ..., x_k) \in \Re_+^k$ to produce m outputs $y = (y_1, y_2, ..., y_m) \in \Re_+^m$. The input price vector is $w = (w_1, w_2, ..., w_k) \in \Re_+^k$, and the output price vector is $p = (p_1, p_2, ..., p_m) \in \Re_+^m$. DEA is then used to construct a frontier (production, cost, or revenue) such that all observed firms lie on or below the frontier. Firms lying on the frontier are regarded as "best practice" firms, and those below the frontier are inefficient relative to the "best practice" ones in a given year.

3.1.1 Production frontiers and technical efficiency

We employ both input-oriented the output-oriented distance functions introduced by Shephard (1970) to estimate production frontiers. The input-oriented distance function relies on the *input attainability* assumption that all output vectors can be obtained from the rescaling of any non-zero input vectors. Let the correspondence $y \to V(y) \in \Re_+^k$ denote the production technology that transforms inputs into outputs. Then for any $y \in \Re_{+}^{m}$, $V(y)$ is the subset of all input vectors $x \in \Re_{+}^{k}$ that yields at least y. The input distance function is therefore defined as

$$D(x,y) = \sup\left\{\phi : \left(\frac{x}{\phi}, y\right) \in V(y)\right\} = \frac{1}{\inf\left\{\theta : (\theta x, y) \in V(y)\right\}}$$

Farrell's (1957) input-oriented technical efficiency (TE) is then defined as

$$\mathrm{TE}(x,y) = \frac{1}{\mathrm{D}(x,y)} = \inf\left\{\theta : (\theta x, y) \in V(y)\right\}$$

Technical efficiency reflects a firm's ability to minimize the inputs utilized to produce a given bundle of outputs. I.e., $\mathrm{TE}(x,y)$ represents the radial contraction in inputs for a firm to produce a given output vector y if it operated on the production frontier. Fully efficient firms lie on the production frontier and have efficiency scores equal to 1.0. Inefficient firms have efficiency scores between 0 and 1, and 1- $\mathrm{TE}(x,y)$ is the inefficiency due to not adopting the best production technology.

Farrell technical efficiency can be measured with respect to production frontiers characterized by constant returns to scale (CRS), variable returns to scale (VRS) and non-increasing returns to scale (NIRS) (Aly, et al. 1990). DEA frontiers are estimated by solving linear programming problems. The problem setups are specified below.

Input-oriented CRS technical efficiency (TE_{CRS}^{I}) for firm j is estimated by solving:

$$\begin{aligned}
& \mathrm{TE}_{\mathrm{CRS}}^{\mathrm{I}}(x,y) = \mathrm{Min}\ \theta_{CRS}^{I} \\
\text{Subject to} \quad & \sum_{\mathrm{j}=1}^{\mathrm{N}} \lambda_{\mathrm{j}} y_{ij} \geq y_{ij} && \forall\ \mathrm{i}=1,\ldots,\mathrm{m} \\
& \sum_{\mathrm{j}=1}^{\mathrm{N}} \lambda_{\mathrm{j}} x_{rj} \leq \theta_{CRS}^{I}\ x_{rj} && \forall\ \mathrm{r}=1,\ldots,\mathrm{k} \\
& \lambda_{\mathrm{j}} \geq 0 && \forall\ \mathrm{j}=1,\ldots,\mathrm{N}
\end{aligned}$$

Input-oriented VRS technical efficiency (pure technical efficiency) for firm j is estimated using the same problem setup except that a convexity constraint is imposed by including the following condition in the optimization: $\sum_{j=1}^{N} \lambda_j = 1$. Input-oriented NIRS technical efficiency is estimated by changing the constraint to $\sum_{j=1}^{N} \lambda_j \leq 1$.

Overall input-oriented technical efficiency, TE_{CRS}^{I}, can be decomposed into pure technical efficiency and scale efficiency. A firm has achieved pure technical efficiency if it operates on the VRS frontier and has achieved full technical efficiency if it operates on the CRS frontier. Scale efficiency for a given firm is measured as the total technical efficiency not explained by pure technical efficiency, i.e., $\mathrm{SE}^{I}(x,y) = \frac{\mathrm{TE}_{\mathrm{CRS}}^{I}(x,y)}{\mathrm{TE}_{\mathrm{VRS}}^{I}(x,y)}$, where SE^{I} = input-oriented scale efficiency and TE_{VRS}^{I} = input-oriented VRS technical efficiency. If SE^{I} = 1, the firm in on the CRS frontier; and if SE^{I} < 1, the firm is not on the CRS frontier. If SE^{I} < 1 and TE_{VRS}^{I} ≠ NIRS efficiency, the firm operates with increasing returns to scale; and if SE^{I} < 1 and TE_{VRS}^{I} = NIRS efficiency, it is characterized by decreasing returns to scale (Aly, et al. 1990).

We utilize input-oriented production frontiers in conjunction with cost minimization problems. The firm is assumed to take output levels as fixed and to minimize input consumption as a component of minimizing costs. We use output-oriented production frontiers in conjunction with revenue maximization. The assumption in this case is that the firm takes input utilization as given and seeks to maximize revenues by increasing outputs. Input-oriented and output-oriented technical efficiency is then used in the decomposition of cost and revenue efficiency, respectively, as explained below.

The linear program for output-oriented CRS technical efficiency is specified as follows:

$$\mathrm{TE}^{\mathrm{O}}_{\mathrm{CRS}}\left(x,y\right)=\mathrm{Max}\ \theta^{O}_{CRS}$$

$$\text{Subject to} \quad \sum_{\mathrm{j=1}}^{\mathrm{N}} \lambda_{\mathrm{j}} y_{ij} \geq \theta^{O}_{CRS}\ y_{ij} \qquad \forall\ \mathrm{i=1,...,m}$$

$$\sum_{\mathrm{j=1}}^{\mathrm{N}} \lambda_{\mathrm{j}} x_{rj} \leq x_{rj} \qquad \forall\ \mathrm{r=1,...,k}$$

$$\lambda_{\mathrm{j}} \geq 0 \qquad \forall\ \mathrm{j=1,...,N}$$

As in the case of input-oriented technical efficiency, output-oriented VRS technical efficiency estimation imposes the constraint $\sum_{\mathrm{j=1}}^{\mathrm{N}} \lambda_{\mathrm{j}} = 1$, and output-oriented NIRS technical efficiency uses the constraint $\sum_{\mathrm{j=1}}^{\mathrm{N}} \lambda_{\mathrm{j}} \leq 1$. Overall output-oriented technical efficiency can also be decomposed into output-oriented pure technical and scale efficiency, analogously to the input-oriented case.

3.1.2 Cost frontiers and cost efficiency

The cost efficiency program utilized in this paper is input-oriented. Here, the objective is to minimize cost by choosing input quantities while holding constant the input prices w and output quantities y. The linear programming problem for firm j is:

$$\mathrm{C}^{*}\left(x,y\right)=\mathrm{Min}_{\lambda,x_{j}^{*}} \sum_{\mathrm{r=1}}^{\mathrm{k}} w_{rj}\ x_{rj}^{*}$$

$$\text{Subject to} \quad \sum_{\mathrm{j=1}}^{\mathrm{N}} \lambda_{\mathrm{j}} y_{ij} \geq y_{ij} \qquad \forall\ \mathrm{i=1,...,m}$$

$$\sum_{\mathrm{j=1}}^{\mathrm{N}} \lambda_{\mathrm{j}} x_{rj} \leq x_{rj}^{*} \qquad \forall\ \mathrm{r=1,...,k}$$

$$\lambda_{\mathrm{j}} \geq 0 \qquad \forall\ \mathrm{j=1,...,N}$$

where $x_{j}^{*} = \left\{x_{1j}^{*}, x_{2j}^{*}, ..., x_{rj}^{*}, ..., x_{kj}^{*}\right\}$ is the cost-minimizing vector of input quantities for firm j. The cost efficiency (CE) of the firm is the ratio of frontier cost over actual cost, i.e., $\mathrm{CE}(x,y)=\dfrac{\sum_{r=1}^{k} w_{rj_0} x_{rj_0}^{*}}{\sum_{r=1}^{k} w_{rj_0} x_{rj_0}}$, where $x_j=\{x_{1j},x_{2j},...,x_{rj},...,x_{kj}\}$ is the observed input quantity vector of the firm. The value of CE is bounded between 0 and 1 with CE=1 for fully cost efficient firms.

Cost efficiency captures both technical efficiency and allocative efficiency, where allocative efficiency measures the success of the firm in choosing cost minimizing combinations of inputs. Even if a firm produces on the production frontier, it is not fully cost efficient if it is not allocatively efficient. Allocative efficiency is calculated residually from cost and technical efficiency as follows: $\mathrm{AE}^{I}(x,y)=\dfrac{\mathrm{CE}(x,y)}{\mathrm{TE}_{\mathrm{CRS}}^{I}(x,y)}=\dfrac{\mathrm{CE}(x,y)}{\mathrm{TE}_{VRS}^{I}(x,y)*\mathrm{SE}^{I}(x,y)}$. The complement 1-AE measures the cost inefficiency of a firm due to its failure to adopt the optimal combinations of inputs given the input prices and output quantities.

3.1.3 Production frontiers and revenue efficiency

Another important objective of firms is to maximize revenues by choosing optimal output quantities while holding constant output prices p and input quantities x. Revenue efficiency is output-oriented and based on Shephard's (1970) output distance function. The output distance function is based on the assumption of "output attainability" that *all* input vectors are feasible in the production of any rescaled nonzero output vector. The linear programming problem to estimate the revenue efficiency for firm j is specified as:

$$\mathrm{R}^{*}(x,y)=\mathrm{Max}_{\lambda,y_j^{*}} \sum_{\mathrm{i=1}}^{\mathrm{m}} p_{ij} y_{ij}^{*}$$

Subject to

$$\sum_{\mathrm{j=1}}^{\mathrm{N}} \lambda_j y_{ij} \geq y_{ij}^{*} \qquad \forall \text{ i=1,...,m}$$

$$\sum_{\mathrm{j=1}}^{\mathrm{N}} \lambda_j x_{rj} \leq x_{rj} \qquad \forall \text{ r=1,...,k}$$

$$\lambda_j \geq 0 \qquad \forall \text{ j=1,...,N}$$

where $y_j^* = \left\{ y_{1j}^*, y_{2j}^*, ..., y_{ij}^*, ..., y_{mj}^* \right\}$ is the revenue-maximizing vector of output quantities for firm j. The revenue efficiency of the firm is then given as the ratio of observed revenue over optimal revenue:. $\mathrm{RE}(x, y) = \frac{\sum_{i=1}^{m} p_{ij} y_{ij}}{\sum_{i=1}^{m} p_{ij} y_{ij}^*}$, where $y_j = \left\{ y_{1j}, y_{2j}, ..., y_{ij}, ..., y_{mj} \right\}$ is the firm's observed output quantity vector. Efficient firms have RE = 1 and inefficient firms have RE between 0 and 1.

Analogously to cost efficiency, revenue efficiency can be decomposed into output-oriented scale efficiency and revenue allocative efficiency, where revenue allocative efficiency is a measure of the firm's success in choosing revenue maximizing combinations of outputs. The calculation is: $\mathrm{AE}^O(x, y) = \frac{\mathrm{RE}(x, y)}{\mathrm{TE}_{\mathrm{CRS}}^O(x, y)} = \frac{\mathrm{RE}(x, y)}{\mathrm{TE}_{VRS}^O(x, y) * \mathrm{SE}^O(x, y)}$. Thus, to be fully revenue efficient, the firm must maximize its outputs and produce outputs in the optimal combination.

3.2 Data and sample selection

The primary data used in our study are drawn from regulatory annual statements filed by insurers with the NAIC over the period 1993-2002. The decision-making units used in the study consist of groups of affiliated insurers under common ownership and unaffiliated single insurers. Originally, the sample consisted of all groups and unaffiliated insurers for which data are available from the NAIC. We then eliminated firms with zero or negative net worth, premiums, or inputs, firms with an unrealistic premiums-to-surplus ratios (e.g., ratio greater than 6), and firms whose organizational forms are not recognized by the NAIC files or by Best's. Risk retention groups, U.S. Lloyds, and state worker's compensation fund programs are also excluded from the sample. Since firms that are extremely small are atypical and may bias the estimation, we eliminated firms whose assets are below \$1.5 million. The final sample used to estimate efficiency consists of 8,025 firms over the entire sample period.

Summary statistics on the firms in the sample are presented in Table 3. Firms in the sample have average assets of $1.2 billion and average premium of $361 million. The premiums-to-surplus ratio averages 1.2 for the period, relatively low by historical standards. The average Herfindahl index by line of business is 0.507 and the average geographical Herfindahl index is 0.630, indicting that the average firm is highly concentrated by line of business and by state. The proportion of mutuals in the sample is 41.2%. Inputs, outputs, and prices are discussed below.

3.2 Outputs and output prices

Consistent with most of the recent financial institutions efficiency literature, we adopt a modified version of the value-added approach to define insurance outputs (Berger and Humphrey 1992, Cummins and Weiss 2000). The value-added approach considers all asset and liability categories that have significant value-added as important outputs, as judged using operating cost allocations.

We define outputs based on the three principal types of services provided by property-liability insurers: *risk pooling and risk bearing, real financial services, and financial intermediation services*. The actuarial, underwriting, claim settlement, and other expenses incurred in operating the risk pools are major components of value-added relating to risk pooling and risk bearing. Real financial services include risk surveys, coverage program design, recommendations regarding deductibles and policy limits, and loss prevention and loss reduction services. The value-added of the intermediation function of P-L insurers is represented by the net interest margin between the rate of return earned on assets and the rate credited to policyholders.

Since detailed transaction data on insurers is not publicly available, the quantity of P-L insurance output is proxied by the present value of losses incurred (Berger, Cummins and Weiss 1997, Cummins and Weiss 2000). Losses incurred are the total amount of losses expected to be pooled and redistributed by the insurers as a result of their providing insurance coverage and thus is a good proxy for the amount of risk pooling conducted. It is also a good proxy for the amount of real services provided since these services are highly correlated with aggregate losses. In P-L insurance, because lines of coverage offered by insurers have different risks and payout schedules, we group together lines with similar characteristics.

Four insurance outputs are calculated: personal lines short-tail losses, personal lines long-tail losses, commercial lines short-tail losses, and commercial lines long-tail losses. The tail refers to the length of the loss redistribution period, as defined by Schedule P of the NAIC regulatory statements. The payout proportion of a loss is calculated from data in Schedule P of *Best's Aggregates and Averages* using the chain-ladder method (Lemaire 1985, 1995). Loss discounting factors are computed from U.S. Treasury yield curves released by the Federal Reserve Board of Governors.[5] The quantity of the intermediation output is measured by the average of the beginning and end-of-year invested assets. The values of losses incurred and invested assets are deflated to real 2000 values using the consumer price index (CPI).

In insurance economics, the value-added of insurance outputs is measured by the Pratt-Arrow concept of the insurance premium (risk premium). In practice, this value-added is the loading of the insurance premium. Accordingly, the price of insurance output is then defined as premiums per $1 of present value of incurred losses and loss adjustment expenses.[6]

Although using losses as outputs can be justified by economic theories of insurance as well as actuarial or statistical theories of insurance, losses are still subject to an "errors-in-variables" problem because realized losses have a random component. For example, if losses are

[5] We utilize the constant maturity Treasury yields obtained from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis. Yields are obtained by linear interpolation for maturities where constant maturity yields are not published in FRED.

[6] Let P_i denotes the price of insurance output i, PE_i denotes the real premiums earned of insurance output i, and LLE_i denotes the real present value of losses and loss adjustment expenses incurred of insurance output i, then $P_i = \frac{PE_i - LLE_i}{LLE_i}$.

larger than expected, insurers are measured as providing more output. This is not necessarily problematic because insurers have in fact provided more services if losses are higher than expected. Nevertheless, the randomness of losses remains a potential concern, although it is arguably less serious for a non-parametric methodology than for an econometric methodology. Accordingly, we conduct the efficiency estimation using two sets of insurance outputs and output prices – (1) realized (unadjusted) incurred losses and prices, and (2) adjusted (smoothed) incurred losses and prices. The smoothing procedure is designed to adjust for errors in variables while still giving insurers credit for paying unexpected claims.[7] A smoothing procedure was also adopted for insurance output prices because we noticed that some insurers had rather extreme values of the unadjusted prices. The smoothing procedure is described in the Appendix. In order to conserve space, we only report the results based on the smoothed losses and prices. However, the efficiencies from the smoothed and unsmoothed estimations are highly correlated and the results of the two estimations support the same conclusions.[8]

The price of the intermediation output is defined as the expected return on invested assets. Invested assets are divided into two categories – stocks and interest-bearing assets (mainly bonds and short-term debt instruments). The price of the intermediation output is then the weighted average expected investment return equal to the expected return on stocks weighted by the proportion of invested assets in stocks plus the expected return on interest-bearing assets weighted by the proportion of the portfolio in this asset type. The expected return on stocks is calculated as the average 30-day Treasury bill rate in year t plus the long-term (1926 to the end of the preceding year) average market risk premium on large company stocks from Ibbotson

[7] We thank Richard Phillips for these valuable suggestions.

[8] The correlation of efficiencies based on the smoothed and unsmoothed losses and prices (10 year average) are 0.94 for technical efficiency, 0.95 for pure technical efficiency, and 0.94 for scale efficiency, 0.94 for allocative efficiency, 0.94 for cost efficiency, and 0.84 for revenue efficiency.

Associates (2005). This approach assumes that insurers hold equity portfolios with a market beta coefficient of 1.0. The expected return for interest-bearing assets is estimated as their realized income return in year t, because their expected return is generally close to the actual income return. The realized return on interest-bearing assets equals the total net investment income of the insurer, minus dividends on stocks, divided by the average amount of interest-bearing assets during the year. Thus, the price of the intermediation output differs across insurers.

Summary statistics on outputs, output prices, and revenues are shown in Table 4. Output quantities and revenues are aggregates for the firms in the sample, and revenues are defined as the products of output quantities and prices. Prices are unweighted sample means. The last two panels of the table show the percentage breakdown of total revenues by revenue source and the percentage breakdown of total insurance revenues by line of insurance, respectively. The table shows that the prices of commercial lines were much higher than those of personal lines, which is not surprising given that commercial lines tend to be more complex and risky than personal lines. Because of the higher prices, approximately 54% of insurance revenue comes from commercial lines even though commercial lines represent only about 46% of total insurance output. Among the insurance outputs, personal lines short-tail business contributes about 8.5% of the total revenues in the industry, personal lines long-tail contributes about 16.6%, commercial lines short-tail contributes 9.3%, and commercial lines long-tail contributes about 19.9%. The intermediary output was the largest source of total revenues of insurers (about 45.6%).

3.3 Inputs and input prices

Insurance inputs are classified into four categories—administrative labor, agent labor, materials and business services (including physical capital), and financial equity capital. Because detailed information on number of employees or hours worked are not available by company, we impute the quantities of administrative labor, agent labor, and materials and business services from the dollar value of related expenses. That is, the quantity of an input is defined as the current dollar expenditures related to this input divided by its *current* price. The price of this input is calculated as its *current* price deflated by the CPI, with 2000 as the base year. Thus, the product of the input quantity and the input price equals the constant dollar expenditure on the input.

Current dollar expenditures for administrative labor input are defined as the sum of salaries, payroll taxes, and employee benefits in an insurer's regulatory statements. Current dollar expenditures for agent labor input are the sum of net commissions, brokerage fees, and allowances to agents. Current dollar expenditures for materials and business services are calculated as the difference between total expenses incurred and the total administrative and agent labor expenses of the insurer.

The price of administrative labor comes from the US Department of Labor average weekly wage rate for property and liability insurance companies (SIC (Standard Industrial Classification) 6331). The category became NAICS 524126 (North American Industry Classification System) in 2001. The price of agent labor comes from the US Department of Labor average weekly wage rate for insurance agents (SIC 6411, NAICS 524210 since 2001). National average weekly wage rates are used here to reduce missing observations.[9] All of these wage variables are deflated to real 2000 values by the CPI to obtain the real prices of the inputs. The current price of the materials and business services input is calculated as a weighted average of price indices for business services from the component indices representing the various categories of expenditures from the expense page of *Best's Aggregates and Averages*. The base year of the price index is 2000. These price indices also are from the U.S. Department of Labor.

[9] Some studies (e.g. Cummins and Nini, 2002) use home state wage rate for administrative labors, and state-weighted average weekly wage rate for agent labors. However, Cummins, Tennyson, and Weiss (1999) conduct a robustness check for alternative types of wages rate for the U.S. life insurance industry and conclude that using the alternative labor price variables do not materially affect the results.

Financial equity capital is considered as an important input, consistent with modern theories of the firm and financial institutions efficiency research (e.g., McAllister and McManus 1993; Berger, Cummins and Weiss 1997; Hughes and Mester 1998; and Cummins and Nini 2002). In the financial theory of insurance pricing, insurance is viewed as a risky debt where the financial equity of insurance companies plays an important role in reducing insolvency risk. Including equity capital as an input is especially important in studies of scale economies, as shown in Hughes and Mester (1998), who argue that ignoring capitalization in financial institutions studies generally leads to scale economy puzzles.

The financial equity capital of an insurer is the sum of statutory policyholders' surplus and reserves required by statutory accounting principles (SAP) but not recognized by generally accepted accounting principles (GAAP). The quantity of this input is measured by the real value of the average of the beginning and end-of year capital, deflated by the 2000 CPI. It is ideal to use the market return of equity capital as its price. However, because the majority of insurers are not publicly traded, market equity returns are not observed for most firms in the database. Several approaches measuring cost of capital are discussed in Cummins and Weiss (2000). In this paper, we follow Cummins and Nini (2002) to adopt an approach that assumes a constant cost of equity across all firms in the industry, i.e., the price of financial equity capital in the year t equals the average 30-day Treasury bill rate in year t plus the long-term (1926 to the end of year t-1) average market risk premium on large company stocks from Ibbotson Associates.[10]

Summary statistics for inputs and input prices are shown in Table 3. Although these quantities are not shown by year due to space considerations, it is noteworthy that the percentage of total expenses going for administrative labor remained relatively constant during the sample period, while the percentages expenses attributable to agent labor and business services declined.

[10] Robustness checks carried out in prior papers show that the results of the analysis generally are not affected by this assumption. See Cummins, Tennyson, and Weiss (1999) and Cummins and Nini (2002).

The share of expenses attributable to financial equity capital increased from 20.2% in 1993 to 32.8% in 2000, but then declined in 2001 and 2002, back to 20.5% in 2002. The run-up in capital costs was attributable to the industry's accumulating more equity capital during the soft market period of the late 1990s through 2000 (Cummins and Nini 2002). The adoption of a risk-based-capital (RBC) system and the booming stock market also contributed to the rising capitalization. The bursting of the stock market bubble in 2000 and the World Trade Center terrorist attack in 2001 depleted capital in the P-L industry in the last two years of the sample period.

4. Estimation results: Efficiency and scale economies

This section presents our estimation results for the US P-L insurance industry. We first analyze the overall efficiency of the industry and then consider economies of scale.

4.1 Overall efficiency of the industry

The results of the DEA efficiency estimation are presented in Table 5. Both input and output-oriented results are shown in the table. Recall that cost efficiency is decomposed in our analysis into the product of input-oriented pure technical efficiency, input-oriented scale efficiency, and cost (input-oriented) allocative efficiency. Revenue efficiency decomposes into the product of output-oriented pure technical efficiency, output-oriented scale efficiency, and revenue (output-oriented) allocative efficiency.[11]

Despite fluctuation from year to year, Table 5 shows a slight efficiency improvement in this industry over time. For example, the cost efficiency level rose from 43% in year 1993 to 46% in the year 2002, with the best year of 54% taking place in 1999. Scale efficiency (both input-oriented and output-oriented) increased slightly from year 1993 to year 2002, as does allocative efficiency. Pure technical efficiency and revenue efficiency hardly improved during the sample period. In general, we see a higher efficiency level during the time period of 1998-

[11] These product decompositions are precise for individual firms but do not necessarily hold exactly for the averages shown in the table.

2001 as compared to the period 1993-1997.

The average cost efficiency of the industry is 49% over the sample period. This implies that P-L insurers, on average, could have reduced costs by 51% by operating on the production frontier and choosing their input bundles correctly. Decomposing cost efficiency into (input-oriented) pure technical, scale, and allocative efficiency provides further information on the sources of cost inefficiency. The average input-oriented pure technical efficiency of the industry is 75% over the sample period. A possible reason for the technical inefficiency might be that many insurers failed to adapt to the rapidly changing technology during the sample period. The average allocative efficiency of the industry is 74%, suggesting that firms could reduce their costs by 26% if they had used the optimal input combinations.

The average input-oriented scale efficiency of the industry is 89%, indicating that 11% of the inputs were wasted by the industry because the firms did not produce at the optimal scale. Scale efficiency of the industry did not improve very much over the sample period despite the structural changes in the industry. The average scale efficiency was 86% in 1993 and 89% in 2002. One possibility is that technical progress caused the optimal operating scale to rise to a new level. It is also possible that while some insurers involved in restructuring were successful in achieving optimal scale and improving cost efficiency, the performance of others worsened as a result of scale diseconomies and the inefficient allocation of resources.

The average revenue efficiency of the industry is 44% during the sample period. Decomposing revenue efficiency into the output-oriented pure technical, scale, and allocative efficiency provides information about the sources of revenue inefficiency. The average output-oriented pure technical efficiency level of the industry is 74%, the average output-oriented allocative efficiency level is 66%, and the average output-oriented scale efficiency level is 90%. Thus, the main sources of revenue inefficiency for P-L insurers are the failure to achieve pure technical efficiency and the choice of suboptimal output combinations.

The efficiencies are graphed by size decile in Figure 1, where size is based on total assets and decile 1 is the smallest size decile.[12] Cost efficiency is shown furthest to the left in the figure, followed by the decomposition into input-oriented pure technical, scale, and allocative efficiency. Revenue efficiency is then shown, followed by the corresponding output-oriented decomposition. Figure 1 shows that cost efficiency is monotonically increasing in firm size. This finding is consistent with previous insurance efficiency studies (Gardner and Grace 1993, Cummins and Weiss 1993, Cummins and Zi 1998, and Cummins 1999). Scale efficiency peaks in the median deciles and is lower for relatively small and relatively large firms. Large firms on average lose efficiency due to sub-optimal scale, but they compensate by having higher pure technical and allocative efficiency, leading to the monotonic relationship between size and cost efficiency.

There is no clear relationship between size and revenue efficiency, except that the firms in the two smallest size deciles are the least revenue efficient. Revenue efficiency peaks in deciles 4 and 5 and is more or less constant for firms above the median. Output-oriented scale efficiency has a similar size relationship as input-oriented scale efficiency, and large firms tend to achieve higher levels of output-oriented pure technical efficiency. However, unlike the input-oriented case, large firms do not offset their scale inefficiency by being more allocatively efficient than smaller firms. Hence, large firms do not seem to perform very well in choosing optimal output combinations, perhaps suggesting that the greater complexity of larger organizations makes output mix choices more difficult to control.

4.2 Economies of scale

As microeconomic theory indicates, one objective of firms is to operate with constant returns to scale (CRS) in order to minimize costs and maximize revenues. In the short run, firms

[12] The figure illustrates the relationship between efficiency and asset size for the year 1998. Using the 2002 data and the 1993-2002 data reach exactly the same conclusion.

might operate with increasing returns to scale (IRS) or decreasing returns to scale (DRS). However, in the long run, they will move toward CRS by becoming larger or smaller to survive in the competitive market. The process might involve changes of a firm's operating strategy, M&As, or divestitures. The scale economies of an industry also have implications for regulatory policy regarding industry consolidation and antitrust laws. The average input-oriented scale efficiency of the US P-L insurance industry during our sample period is 89%, and the output-oriented scale efficiency of the industry is 90%. Both of these scores indicate that the industry is relatively scale efficient but could improve its performance if more firms were to achieve CRS.

4.2.1 Scale economies of the P-L industry

The returns to scale of firms during the period 1993-2002 are presented in Table 6. Panel A gives the number and percentage of firms operating with IRS, CRS and DRS. The percentage of CRS firms averages 11.2% for the sample period as a whole based on the input-oriented estimates and 10.6% based on the output-oriented estimates. Based on the input-oriented estimates, on average 45.1% of the firms in the industry operate with IRS and 43.7% of firms operate with DRS. Based on the output-oriented estimates, on average about 37.8% of firms operate with IRS and about 51.6% of firms operate with DRS.[13]

Estimation of linear time trend regressions with the percentage of firms with IRS, CRS, and DRS as dependent variables shows a statistically significant downward trend in the percentage of firms with DRS and a statistically significant upward trend in the percentage of firms with CRS and IRS over the sample period, the only exception being the input-oriented IRS equation, where the time trend is not statistically significant. Hence, there is some evidence of an improvement in scale efficiency in the industry over the sample period. In general, the results

[13] It is expected that we will find more firms operating with DRS under the output-oriented estimation. This type of estimation holds inputs fixed and measures efficiency in part by determining how much inefficient firms could expand output if they operated on the efficient frontier. Output expansion can result in a firm moving from increasing or constant to the decreasing returns to scale segment of the frontier. Input-oriented estimates are less likely to encounter this issue because output is held fixed in the input-oriented estimations.

suggest that it is not easy to attain scale efficiency in this industry; and the fairly high percentage of firms with DRS indicates that rationalization of further consolidation on scale efficiency grounds should be viewed with considerable skepticism.

Panel B of Table 6 provides Kappa coefficients of the agreement between the input-oriented and output-oriented classification of firms as operating with IRS, CRS, or DRS. High Kappa scores indicate high levels of agreement between the two methods, with a Kappa of 1.0 indicating perfect agreement.[14] The average Kappa and weighted Kappa scores of 0.87 and 0.88 indicate a high level of agreement between the input-oriented and output-oriented classifications.

4.2.2 Scale economies and firm size

After observing that few firms in the industry operate with CRS, it becomes interesting to study what types of firms operate with IRS and what types of firms operate with DRS. As a first look at this issue, we consider Figure 2, which plots the proportion of firms in each asset size decile operating with IRS, CRS, and DRS. To simplify the presentation, only the input-oriented results are shown. The output-oriented results are very similar.[15] Figure 2 indicates clearly the relationship between returns to scale and firm size. In the five smallest asset size deciles, the majority of firms operate with IRS and the proportion of firms with IRS declines monotonically with the size deciles. In the five largest asset size deciles, the majority of firms operate with DRS, and the percentage with DRS rises monotonically with the size deciles. However, a significant number (but small percentage) of firms in each size decile operate with CRS. Thus, it is possible for even the largest and smallest firms to attain CRS, indicating that there may be important managerial lessons to be learned from case-study analyses of scale efficient insurers. The pattern shown in Figure 2 is consistent with results for the U.S. life insurance industry in

[14] For further discussion of Kappa coefficients see Agresti (1996).

[15] The figure displays the relationship between returns to scale and asset size for the year 1998. A similar result is found when using the 2002 data and the entire sample of 1993-2002.

Cummins (1999) and for the Spanish insurance industry in Cummins and Rubio-Misas (2005).

The upper bound assets for the firms in each size decile, also shown on the horizontal axis, reveal that DRS begin to dominate at constant dollar asset size of about $100 million, whereas. the asset size at which scale economies become exhausted in the life insurance industry is about 1 billion dollars (Cummins and Zi (1998)). This suggests that the minimum efficient scale of operation may be considerably larger for life insurers than for P-L insurers.

5. Determinants of efficiency

The next step in the analysis is to examine the factors that affect insurers' efficiency and explain the variations in efficiency scores. In this section, we analyze the relationship between firm characteristics and efficiency scores by conducting a panel data regression analysis on the firms in the industry. The dependent variables in the regressions are efficiency scores, and the independent variables are firm characteristics. The regressions are conducted using unbalanced panel data methods in order to maximize the number of firms included in the analysis and avoid any problems with survivor bias that might be inherent in the use of a balanced panel. We estimate one-way and two-way fixed and random effects models (see Greene 2003). Testing reveals that the models with two-way random effects provide a better fit to the data than the models with two-way fixed effects or one-way effects.[16] As a result, only the two-way random effects regression results are presented. However, all models support similar conclusions.

The random effects model for a two-way design is summarized as follows:

$$y_{it} = \alpha + \beta' x_{it} + \varepsilon_{it} + u_i + w_t ,$$

where i indexes firms (DMUs) and t indexes the time periods. The dependent variable y_{it} is firm i's efficiency in year t, and the independent variables in the vector x_{it} are described below. The random error term u_i controls the random effects for different DMUs, the random error term

[16] This is based on likelihood function values.

w_t controls for the random effects for years, and ε_{it} is the overall regression error. Allowing for random effects in estimating the regressions helps to control for the tendency for DEA to measure all departures from the frontier as random error. We performed the two-way random effects analysis with LIMDEP, which adopts an ANOVA estimator for the variance components.

5.1 Insurer characteristics and efficiency

The regression results are reported in Table 7. We conduct overall regressions for cost and revenue efficiency and analyze the decomposition of cost and revenue efficiency by also conducting regressions for input and output-oriented pure technical, scale, and allocative efficiency. The discussion emphasizes the cost and revenue efficiency regressions because they provide the best measures of the overall performance of the firms in the sample. However, the efficiency decomposition regressions provide valuable information on the sources of cost and revenue (in)efficiency.

To control for the possibility that efficiency differs by type of insurance, three output composition variables are included in the model – the percentage of premiums written in personal short-tail lines, personal long-tail lines, and commercial long-tail lines. The category omitted to avoid singularity is commercial lines short-tail. The three business composition variables are all statistically significant and positive in the cost efficiency regression, suggesting that insurers emphasizing these lines of business are more efficient than those with higher proportions of commercial short-tail business. However, the coefficient of the commercial lines long-tail variable is quite small in comparison with the personal lines variables suggesting that insurers emphasizing personal lines tend to be much more cost efficient than those emphasizing commercial lines, as expected if it is easier to make mistakes in designing technologies or allocating resources in the more complex commercial lines. From the decomposition regressions, it is clear that the primary source of the cost efficiency advantage in the personal lines is allocative efficiency, reinforcing the inference that resource allocation is more difficult in the commercial lines. However, pure technical and scale efficiencies are also higher in the personal lines, as expected if size and automated systems are more advantageous in the personal lines.

The only business composition variable that is significant in the revenue efficiency regression is personal lines long-tail, which has a negative coefficient. Thus, firms with higher proportions of personal lines long-tail tend to be somewhat less efficient but otherwise there are no significant differences in revenue efficiencies by business mix. The revenue decomposition regressions show that the reason for the overall revenue efficiency result is that personal lines insurers tend to be less allocatively efficient in terms of revenues than commercial lines insurers, implying that it may be more difficult to choose revenue maximizing output combinations in the personal lines. The allocative efficiency disadvantage in the personal lines offsets higher output-oriented pure technical and scale efficiencies for firms emphasizing personal lines, leading to the generally insignificant revenue efficiency differences by business mix. It is possible that the output-oriented allocative efficiency disadvantage of the personal lines reflects the fact that auto liability and physical damage coverages are usually sold as a package, so that personal lines insurers have somewhat less control over their business mix allocations than commercial lines insurers. The result that commercial lines are equal or more revenue efficient than personal lines, even though they are less cost efficient, also could be attributable to the higher output prices in the commercial lines (see Table 4), which reflect their higher risk and complexity.

Herfindahl indices by line of business and geographical area are included in the regressions to control for the impact of diversification on efficiency. The expected signs of these variables are ambiguous. On the one hand, there is growing literature documenting the tendency of diversified firms to perform poorly relative to firms that adopt the strategy of strategic focus (e.g., Comment and Jarrell 1995, Martin and Sayrak 2003). This "diversification discount" literature predicts that diversified insurers will be less efficient than focused insurers. On the other hand, diversification across lines and geographical areas tends to reduce risk, and diversified firms may benefit from scope economies on the revenue side if buyers prefer one-stop shopping, possibly predicting a positive relationship between diversification and efficiency.

The regressions support the hypothesis that strategic focus is superior to diversification as a corporate strategy. The line of business and geographical Herfindahl indices are significant and positively related to both cost and revenue efficiency, implying that diversified firms are less efficient than strategically focused firms.[17] This implies that the benefits from risk diversification tend to be offset by the extra costs arising from management coordination, allocation of resources, and dealing with various regulations when operating in multiple lines and states. On the cost side, the decomposition regressions show that most of the advantage of strategic focus is attributable to pure technical efficiency, perhaps suggesting that it is more difficult to design technology systems that span multiple lines and states. On the revenue side, the strategic advantage of focusing by line of business is primarily attributable to output-oriented pure technical and allocative efficiency. This reinforces the cost efficiency inference about technology and also suggests that focused firms face fewer challenges in choosing optimal combinations of outputs. The only surprising finding is that the line of business Herfindahl is negatively related to input-oriented allocative efficiency, suggesting that more diversified firms may do a better job in choosing cost minimizing combinations of inputs. However, on an overall basis, strategic focus seems to be superior to diversification in terms of both cost and revenue efficiency.

5.2 Capitalization of insurers

The ratio of net premiums written to policyholders' surplus is included in the model as a

[17] Ferrier, Grosskopf, Hayes and Yaisawarng (1993) find a similar result in the banking industry, where greater diversification in outputs tends to reduce cost efficiency.

control variable for differences in capitalization among firms in the sample. This variable is predicted to be positively related to cost efficiency because firms with higher premiums-to-surplus ratios use less of the capital input relative to revenues. The predicted relationship with revenue efficiency is ambiguous. Higher ratios of premiums-to-surplus could indicate an efficient use of resources, i.e., could be associated with more efficient risk management that permits firms to use less capital, predicting a positive relationship. On the other hand, higher premiums-to-surplus ratios can be associated with higher insolvency risk, implying that such firms would receive lower output prices and therefore have lower revenue efficiencies than better capitalized firms. The regressions support the efficiency interpretation – the premiums-to-surplus ratio is positive and significant in both the cost and revenue efficiency regressions. In the cost efficiency case, the positive effect is primarily attributable to a positive relationship between premiums-to-surplus and pure technical efficiency, which offsets a negative relationship between this variable and input-oriented allocative efficiency. The latter effect would be consistent with the argument that firms with relatively high (low) ratios are using too little (too much) capital. On the revenue side, the overall positive relationship is primarily attributable to pure technical efficiency, although the variable is also positive and significant in the output-oriented scale and allocative efficiency regressions. We conclude that the efficient use of capital is a core competency which tends to be an important driver of performance in the insurance industry.

5.3 Distribution systems

The relationship between distribution systems and efficiency in the insurance industry has been analyzed extensively in the prior literature. Insurance provides an interesting industry in which to analyze this issue because multiple distribution systems have coexisted in the industry over long periods of time. The principal distribution systems in P-L insurance include direct writing (exclusive agents or company employees), independent agents, and brokerage distribution. Independent agents and brokers tend to be similar, in that they represent more than one insurer, but tend to differ in that brokers are often larger and are more likely to focus on the commercial lines insurance for medium to large-scale buyers. The traditional finding in the P-L insurance industry has been that independent distributors tend to have higher costs than direct writers. However, Berger, Cummins, and Weiss (1997) provide evidence that, although independent distributors tend to be less cost efficient, the higher costs represent the provision of additional services that are valued by buyers such that independent and direct distributors are roughly equal in revenue and profit efficiency.[18] Our study revisits the issue investigated by Berger, Cummins, and Weiss (1997) using data from a more recent period (their study focused on 1981-1990) and a different methodology (DEA versus econometric efficiency analysis). We extend most prior analyses by breaking independent distribution into two categories – independent agency and brokerage – and also by considering firms with mixed distribution systems (i.e., those using both independent and direct distribution systems) as a separate category. Three distribution system categories are included in the regressions, for the direct writing, brokerage, and mixed distribution systems, with the omitted category being independent agents.

Firms using the direct writing (vertically integrated) distribution system are predicted to be more efficient to the extent that such firms can more easily recognize cost savings through automation and more fully realize the benefits of technology investments in customer databases and marketing than can insurers using less vertically integrated distribution systems (Carr, Cummins, and Regan 1999). We do not have a strong prediction on the brokerage distribution system. On the one hand, to the extent that brokers are able to exploit their size and relationships

[18] The efficiency of distribution systems also has been investigated in the U.S. life insurance industry (Grace and Timme 1992; Gardner and Grace 1993; Cummins 1999). Grace and Timme (1992) find that agency and non-agency companies exhibit different cost structures, where agencies exhibit higher costs and lower overall economies of scale, but Gardner and Grace (1993) find no significant efficiency differences among life insurance different distribution systems. Cummins (1999) finds that, in general, companies that primarily use independent distributors (called brokers in the life insurance industry) are more efficient than those using exclusive agents.

with commercial buyers to extract rents from insurers, firms using brokers may be less efficient. On the other hand, to the extent that brokers are more professional and technologically advanced than independent agents, brokers may be more efficient than other independent distributors.

The regression results support earlier findings that direct writing insurers are more cost efficient than independent agency insurers and also show that brokers and firms using mixed distribution systems are significantly more efficient than independent agency firms. The advantage of these three distribution systems over independent agents is primarily attributable to pure technical efficiency, providing support for the argument that vertical integration is associated with higher efficiency because of the ability to better exploit automation in reducing costs and increasing revenues. Firms using direct marketing, brokerage, and mixed distribution systems have <u>lower</u> allocative efficiencies than independent agents, perhaps suggesting that more resource allocation is conducted at the agency level in the case of independent agents.[19]

Contrary to Berger, Cummins, and Weiss (1997), we find that direct writing insurers are more revenue efficient than independent agency firms and that firms using brokers and mixed distribution systems are also more revenue efficient. The different finding may be due to our more recent sample period to the extent that technological advantages have become more important over time, giving an advantage to vertically integrated firms and reinforcing the disadvantages of the more decentralized independent agency system. Another possibility is that Berger, Cummins, and Weiss (1997) obscured the relative performance of independent agency and brokerage firms by lumping together these two types of firms in a single category. The revenue efficiency advantage of brokerage firms over independent agency firms is likely due to their competitive advantage in dealing with medium and large scale commercial buyers. In

[19] Although this also might seem to be true for brokers, who are also independent distributors, the brokerage market tends to deal with larger and more complex risks than the independent agency market, potentially posing significantly greater resource allocation problems.

addition, independent agency firms face stiff competition from direct writers for much of their business, whereas direct writers have little presence in the brokerage market. The decomposition regressions imply that the revenue efficiency advantage of direct, brokerage, and mixed distribution system insurers over independent agency firms is primarily attributable to output-oriented pure technical and allocative efficiency. Overall, our results imply that the independent agency distribution system is clearly inferior from both a cost and revenue perspective.

5.4 Other firm characteristics

Covariates such as size (measured by log assets of a firm) and organizational form are also included as control variables in the regressions.[20] The square of the size variable is also included in the model to allow for the possibility of a non-linear relationship between efficiency and firm size. To control for the fact that mutual firms tend to be smaller than stock firms, we also include an interaction term of the mutual dummy and firm size in the model.

The signs of these variables are generally consistent with prior insurance efficiency research. Firm size is positively related to both cost and revenue efficiency, confirming earlier findings (Cummins 1999, Cummins and Zi 1998, Cummins and Weiss 1993). Based on the square of size variable, the size effect is concave and attenuates for larger firms. Somewhat surprisingly, size is inversely related to both input and output-oriented pure technical efficiency. This is contrary to the conclusions that would be drawn from the univariate relationship alone (see Figure 1) and emphasizes the importance of investigating these relationships in a multivariate context. The inverse relationship between size and technical efficiency may indicate difficulties in implementing efficient technologies as firm scale increases, after controlling for other firm characteristics. However, a positive sign on size square indicates that

[20] A dummy variable telling whether an insurer is a group or an unaffiliated single company was originally included in the model, but it was dropped because this variable does not change over time and it causes problems when fitting a two-way random effects model

once a firm passes certain size test, the benefit of investing more in technologies grows, and the firm will gain more technical efficiency. Size is positively related to both input and output-oriented scale efficiency but this relationship is eroded as firm size increases, as shown by the size-squared variable. Finally, size is positively related to input-oriented allocative efficiency but is not significantly related to output-oriented allocative efficiency. In general, the results with the size variables implies that optimal firm sizes exist in the P-L insurance industry – it is clearly possible to be too small or too large.

Mutual companies are more cost efficient than stock companies. This parallels prior findings in the insurance efficiency literature (e.g., Cummins, Weiss, and Zi 1999). It is usually argued that mutuals are measured as being more cost efficient because they operate in less complex and risky lines of business requiring less managerial discretion and thus fewer inputs on average than firms with more complex operations (Cummins, Weiss, and Zi 1999). However, the mutual cost efficiency advantage dissipates as firm size increases, as shown by the mutual dummy*size variable interaction term. This is not surprising in that larger mutuals are likely to encounter scale diseconomies and more difficulties in allocating resources efficiently. Mutuals are also more revenue efficient that other types of firms, although this relationship too dissipates as size increases. Interestingly, large mutuals have lower input and output-oriented pure technical efficiency than other types of firms, indicating that their output consumption is excessive relative to inputs. This perhaps provides some evidence of “expense preference” behavior, whereby mutual managers are less aggressive in pursuing new technologies due to the relatively weak managerial monitoring and control mechanisms in the mutual ownership form.

6. Determinants of returns to scale

Though the general findings on scale economies are consistent with the common understanding of returns to scale in economics, it is still difficult to judge whether a firm realizes scale economies based on their observable characteristics. To identify the factors that help determine a firm's returns to scale, we run a multinomial logit regression. A firm can "choose" or fall into three categories of returns to scale—CRS, IRS, or DRS. Obviously, the ideal choice for a firm is CRS, but it is difficult to rank the IRS and DRS, because a slight deviation from CRS towards DRS might be better than an extreme deviation from CRS towards IRS and vice versa. Consequently, the multinomial logit model is more appropriate than the ordered logistic regression. The multinomial logit model is as following:

$$p_{ki} = prob(y_i = k) = \frac{\exp(\beta_k^{'} X_i)}{\sum_{k=1}^{K} \exp(\beta_k^{'} X_i)},$$

where k =0, 1, 2, if a firm operates with CRS, IRS, or DRS respectively. The vector of independent variables, X_i, in the logit model is the same as in the efficiency regressions discussed above. Estimation of the multinomial logit model is discussed in Greene (2003).

Because the dependent variable is not linear in the independent variables, it is difficult to interpret the coefficients (β_k) of the logit model directly. Consequently, we estimate the marginal effect at the mean level of the variables. The marginal effects are estimated as: $\frac{\partial p_{ki}}{\partial x_{ji}} = p_{ki}(\beta_{kj} - \sum_{k=0}^{K} p_{ki}\beta_{kj})$, for k=0, 1, 2, where β_k is the coefficient of x for returns to scale type k. The marginal effects for the multinomial logit function depend on the point of valuation, and their sign can differ from that of the coefficients β_k. The marginal effect of an independent variable illustrates the change in the probability that the firm is in a given returns to scale category in response to the deviation of an independent variable from its sample mean.

The estimated marginal effects by returns to scale are presented in Table 8. Not surprisingly, the most important factor that affects a firm's scale economies category is the size of the firm. The results show that there exists a non-linear relationship between size and the probability of operating with CRS, measured using either the input or output-orientation. At the sample mean, further increases in firm size tend to reduce the probability of operating with CRS but at an increasing rate. Using the input-oriented results, the relationship of size and the probability of operating with DRS is purely linear at the sample mean, i.e., an increase in size is unambiguously associated with a higher probability of DRS. However, in the output-oriented case, DRS is not significantly related to size. This is consistent with the findings of Berger, at al. (2000) that larger firms are more likely to realize significant economies of scope, which would be associated with revenue efficiency. The IRS results fall somewhere in between the CRS and DRS results, with a negative second-order effect. The conclusion we can draw from the logit regressions is that as a firm grows larger than the average firm size of the industry, it becomes less likely to operate with CRS and more likely to operate with DRS.

The marginal effects of the business mix variables show that firms with higher proportions of business in short-tail personal lines are more likely to realize CRS, and less likely to realize DRS based on both input and output-oriented results. Firms with more businesses in long-tail commercial lines are less likely to operate with CRS and more likely to operate with output-oriented IRS but are otherwise not statistically different from firms emphasizing short-tail commercial lines. We view the business mix variables primarily as control variables in these regressions, and they do not show a clear pattern among the various business lines.

The line of business and geographical Herfindahl index variables show a clear pattern – they are both significantly positively related to the probability of operating with CRS and significantly negatively related to the probability of operating with DRS. Thus, at the sample means, further diversification across states and across business lines increases the probability of moving the firm towards scale diseconomies in terms of both the cost and revenue frontiers, providing further evidence that focusing firms are more efficient than diversifying firms and perhaps helping to explain the source of the diversification discount.

The marginal effects of the capitalization ratio show that firms with higher premium-to-surplus ratios have higher probabilities of operating with CRS and lower probabilities of operating with IRS, based on both the input and output-oriented results. Such firms also have higher probabilities of operating with input-oriented DRS but the relationship of this variable with output-oriented DRS is not statistically significant. Thus, at least with respect to revenue efficiency, this variable has an unambiguous favorable relationship with economies of scale.

The distribution system variables provide further evidence of the superiority of the direct writing, brokerage, and mixed distribution system relative to the independent agency system. All three of the non-independent agent distribution systems are associated with higher probabilities of operating with CRS and lower probabilities of operating with DRS, although the input-oriented DRS coefficient for the mixed distribution system is not statistically significant. Thus, the poor performance of firms using the independent agency system may be partly attributable to disadvantages in operating at larger scale. Lastly, the regression shows that mutual firms have a higher probability of operating with CRS, but the significant negative marginal effect of the interaction of the mutual dummy and firm size shows that this effect dissipates for larger mutuals.

7. Conclusion and discussion

This paper examines economies of scale and efficiency in the US P-L insurance industry during the period 1993-2002. The investigation is motivated by dynamic structural changes in the industry over the past decade. Pure technical, scale, allocative, cost, and revenue efficiency are estimated for the largest available sample of insurers using the DEA method. We innovate by estimating both input-oriented and output-oriented production, cost, and revenue frontiers. Panel data regression analysis is performed to explore the relationships between firm characteristics and efficiency, and a multinomial logit model is estimated to examine the factors that affect the returns to scale of a firm.

On average, the industry operates with low cost and revenue efficiency, averaging 49% and 44%, respectively, and these figures have not improved dramatically over time. Moreover, the efficiency scores are widely dispersed among firms in the industry, indicating that some firms at the lower end of the industry do a poor job of minimizing costs and maximizing revenues. The main reasons for cost inefficiency are allocative inefficiency (averaging 26%), pure technical inefficiency (averaging 25%), and scale inefficiency (averaging 11%). The main reasons for revenue inefficiency are allocative inefficiency (averaging 34%), pure technical inefficiency (averaging 26%), and scale inefficiency (averaging 10%).

Medium size firms are found to be the most scale efficient, most small firms operate with scale economies, and most large firms demonstrate scale diseconomies. The majority of firms in the five smallest asset size deciles are operating with increasing returns to scale, while the majority of firms in the five largest asset size deciles are operating with decreasing returns to scale. However, a significant number of firms in all size deciles have achieved constant returns to scale, indicating the presence of "best practices" which may provide lessons for inefficient firms. Scale economies begin to diminish at the asset size level of $202.1-476.6 million, based on the 1998 industry. The interval increases to a little higher asset level in 2002.

To find factors that affect efficiency of insurers, we performed a two-way random effects panel data regression analysis of efficiency versus a set of variables proxying insurers characteristics in terms of diversification, capitalization, distribution systems, and organizational form. Most of our findings are consistent with hypotheses developed in previous literature. The results indicate that personal lines insurers tend to be more efficient than commercial lines insurers. Higher diversification across either product lines or geographical areas is associated with lower efficiency, supporting the argument that strategic focus is a better strategy than diversification. Higher premiums-to-surplus ratios correspond to higher efficiency of a firm, reflecting better capital management. Firms using the independent agency distribution system are less efficient than firms using the direct writing, brokerage, and mixed distribution systems. In terms of cost efficiency, this finding is consistent with most of the prior literature. However, this is the first study to find that independent agency firms are also less revenue efficient than firms using other distribution systems. We attribute the latter finding to our using a more recent sample period than prior researchers and separating the independent distributor category into independent agency and brokerage distributors. An inverse U-shaped relationship is found between firm size and both cost and revenue efficiency.

The multinomial logit model for returns to scale provides further information on the relationship between firm characteristics and performance. Both geographic and line of business diversification are shown to be negatively related to the probability of operating with constant returns to scale and positively related to the probability of operating with decreasing returns to scale, providing further evidence that strategic focus is a better strategy than diversification. The direct writing, brokerage, and mixed distribution systems are shown to be positively related to the probability of constant returns to scale and negatively related to the probability of decreasing returns to scale, providing further evidence that these distribution systems are superior to the independent agency system.

In terms of future research, it would be interesting to provide further exploration of the best practice firms in the industry to examine the strategies, organizational structures, and technologies that are responsible for their superior performance. Such an analysis could be conducted as a series of case studies. It would also be useful to explore the relationships between frontier efficiency scores and the market value performance of firms in the insurance industry.

Appendix: Smoothing Procedure for Losses and Prices

The smoothing procedure involved three stages, beginning with prices: (1) Companies are ranked by their market share in terms of premiums earned for each of the four insurance outputs. This is designed to identify insurers that play a "significant" role in the market for each of the insurance outputs. The rationale is that insurers that have significant market shares are more likely to have reliable loss and price information. Firms that fall into the top 95th percentile for a given insurance output are identified as significant firms and other firms are "insignificant" firms for that output.[21] We then determine the 10th, 25th, 75th, and 90th percentiles of the price ratio for each insurance output (premiums earned divided by the present value of losses incurred) for the significant companies. For the insignificant companies, if their price ratios fall between the 25th and 75th percentiles of significant company prices, we use their actual calculated price ratios. However, if their price ratios fall below the 25th percentile and above the 75th percentile of significant company prices, we use the 25th percentile and 75th percentile, respectively. For a significant company, if its price ratio is below the 10th percentile or above the 90th percentile, we truncate the price to the 10th percentile or 90th percentile, respectively. (2) We fit a linear time trend to the new price ratio series for each company and then calculate a smoothed price ratio series. (3) We divide the company's actual premiums earned by the new smoothed price ratio as an estimate of the smoothed losses of the company.

[21] That is, we ranked firms by market share and added market shares in descending order until the total equaled 95%. Firms above the 95th percentile then were identified as significant firms.

Table 1
The US Property-Liability Insurance Industry:
Number of Firms and Average Firm Size

Year	Affiliated Companies	Unaffiliated Companies	Groups	Total Companies	DMUs*	Average Firm Size: Assets/DMUs
1993	1,630	1,025	462	3,117	1,487	741
1994	1,686	995	478	3,159	1,473	734
1995	1,725	963	491	3,179	1,454	765
1996	1,782	926	501	3,209	1,427	776
1997	1,834	887	504	3,225	1,391	827
1998	1,902	855	499	3,256	1,354	870
1999	1,915	779	482	3,176	1,261	901
2000	1,947	752	468	3,167	1,220	858
2001	1,924	774	439	3,137	1,213	855
2002	1,919	762	441	3,122	1,203	888

Source: Best's Key Rating Guide (BKR) and NAIC database – Property-Liability Insurance.
*DMUs (Decision making units) = groups + unaffiliated companies. Firm size in millions of dollars adjusted to constant price level using the Consumer Price Index with 2000 = 1.0.

Table 2
Concentration Ratios for the US Property-Liability Insurance Industry:
Groups and Unaffiliated Single Companies

Year	Assets (%)				Net Premiums Written (%)			
	Top 4	Top 8	Top 20	Herfindahl	Top 4	Top 8	Top 20	Herfindahl
1993	22.7	34.3	54.3	229	25.2	35	51.6	276
1994	22.7	34	53.9	223	25.2	34.8	51	279
1995	25.2	37.7	56.9	259	26.4	37.2	54	296
1996	24.7	37.7	57	257	26.4	37.3	54.3	296
1997	25.9	39.6	59.1	275	26.1	37.1	55.5	296
1998	28.3	42.8	61.1	308	27.9	39.8	58.4	313
1999	30.1	44	63.6	334	28.5	40.4	60.4	319
2000	31	45	64.3	349	27.7	40.3	61	310
2001	29.9	43	63	325	27.8	40.6	60.8	316
2002	25.4	39.3	61.6	277	27.9	41.1	60.7	315

Source: Calculated from NAIC database—Property-Liability insurance.

Table 3
Summary Statistics: Property-Liability Insurers, Averages 1993-2002

Variable	N	Mean	Std Dev
Invested assets*	8025	958	4,755
Total assets*	8025	1,180	5,973
Total Premium written*	8025	361	1,855
Personal lines short-tail premiums/Total premiums**	8025	0.09	0.15
Personal lines long-tail premiums/Total premiums**	8025	0.28	0.29
Commercial lines long-tail premiums/Total premiums**	8025	0.38	0.38
Herfindahl index by line of business (premiums)	8025	0.51	0.29
Herfindahl index by state (premiums)	8025	0.63	0.38
Premium-to-surplus ratio	8025	1.18	0.80
Direct Selling dummy variable	8025	0.18	0.38
Brokerage dummy variable	8025	0.06	0.24
Mixed distribution system dummy variable	8025	0.18	0.38
Firm size: Log(assets)	8025	18.0	2.2
Firm size*Firm size	8025	330.3	81.4
Mutual company dummy variable@	8025	0.41	0.49
Mutual dummy variable*Firm size	8025	7.4	8.9
Home office labor input quantity*	8025	4.4	22.8
Agent labor input quantity*	8025	5.5	27.3
Business services input quantity*	8025	61.0	298.2
Equity capital input quantity*	8025	416.8	2316.1
Personal lines short-tail output quantity*	8025	40.7	335.0
Personal lines long-tail output quantity*	8025	95.4	766.3
Commercial lines short-tail output quantity*	8025	28.2	134.6
Commercial lines long-tail output quantity*	8025	87.6	389.7
Home office labor input price***	8025	9.56	0
Agent labor input price***	8025	8.19	0
Business services input price***	8025	0.96	0
Equity capital input price***	8025	0.13	0
Personal lines short-tail output price	8025	0.21	0.23
Personal lines long-tail output price	8025	0.23	0.18
Commercial lines short-tail output price	8025	0.65	0.46
Commercial lines long-tail output price	8025	0.43	0.25
Invested assets price	8025	0.07	0.02

Data Source: Calculated from NAIC database—Property-Liability insurance industry, and Best's Key Rating Guide (BKR).
The stats are calculated by first averaging within years across all firms, and then averaging across years.
* in 2000 dollar and in million units
**averaging based on firm level, not based on industry aggregates
***National wage index or price index, same for all firm
@include both mutual firms and reciprocals

Table 4
Summary Statistics for Outputs, Output Prices, and Revenues

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	Mean
Output quantities (Industry aggregates, in $ million)											
Personal Short-Tail	26,329	26,555	27,601	29,362	31,871	34,313	35,889	34,918	35,971	39,836	32,265
Personal Long-Tail	68,337	70,515	71,847	73,591	76,267	79,021	78,592	75,560	77,949	87,807	75,949
Commercial Short-Tail	19,450	20,299	19,888	20,104	20,617	20,941	21,899	21,889	27,964	29,696	22,275
Commercial Long-Tail	66,825	68,741	68,578	67,024	67,187	67,250	66,933	68,755	72,965	83,199	69,746
Intermediation	632,873	679,837	705,713	732,586	798,606	857,307	855,336	805,449	773,991	783,244	762,494
Output prices (average across firms)											
Personal Short-Tail	0.28	0.24	0.23	0.21	0.2	0.19	0.19	0.18	0.18	0.17	0.21
Personal Long-Tail	0.24	0.24	0.24	0.23	0.23	0.23	0.23	0.22	0.21	0.2	0.23
Commercial Short-Tail	0.72	0.69	0.69	0.68	0.67	0.65	0.62	0.59	0.58	0.58	0.65
Commercial Long-Tail	0.47	0.48	0.48	0.46	0.44	0.42	0.41	0.39	0.36	0.36	0.43
Intermediation	0.07	0.07	0.08	0.08	0.08	0.08	0.08	0.08	0.07	0.06	0.07
Revenues (Industry aggregates, in $ million)											
Personal Short-Tail	12,079	11,683	11,553	11,752	12,270	13,123	13,411	12,688	12,642	13,578	12,478
Personal Long-Tail	22,652	23,873	24,662	25,184	25,919	25,378	24,727	22,995	22,926	24,644	24,296
Commercial Short-Tail	11,930	12,928	13,315	13,585	13,827	13,967	13,887	13,431	14,194	15,189	13,625
Commercial Long-Tail	31,466	32,437	32,066	31,176	30,171	28,225	26,452	25,352	25,151	27,826	29,032
Intermediation	53,166	57,199	65,729	67,222	76,895	79,569	78,905	75,867	63,645	54,396	67,259
Insurance Revenues	78,127	80,921	81,596	81,698	82,187	80,693	78,476	74,466	74,913	81,236	79,431
Total Revenues	131,293	138,120	147,325	148,920	159,082	160,262	157,381	150,332	138,559	135,632	146,691
Revenue: percentage of total revenue (based on industry aggregates)											
Personal Short-Tail	9.2	8.5	7.8	7.9	7.7	8.2	8.5	8.4	9.1	10.0	8.5
Personal Long-Tail	17.3	17.3	16.7	16.9	16.3	15.8	15.7	15.3	16.5	18.2	16.6
Commercial Short-Tail	9.1	9.4	9.0	9.1	8.7	8.7	8.8	8.9	10.2	11.2	9.3
Commercial Long-Tail	24.0	23.5	21.8	20.9	19.0	17.6	16.8	16.9	18.2	20.5	19.9
Intermediation	40.5	41.4	44.6	45.1	48.3	49.6	50.1	50.5	45.9	40.1	45.6
Revenues: percentage of insurance revenues (based on industry aggregates)											
Personal Short-Tail	15.5	14.4	14.2	14.4	14.9	16.3	17.1	17.0	16.9	16.7	15.7
Personal Long-Tail	29.0	29.5	30.2	30.8	31.5	31.4	31.5	30.9	30.6	30.3	30.6
Commercial Short-Tail	15.3	16.0	16.3	16.6	16.8	17.3	17.7	18.0	18.9	18.7	17.2
Commercial Long-Tail	40.3	40.1	39.3	38.2	36.7	35.0	33.7	34.0	33.6	34.3	36.5

Note: Prices are unweighted sample means. Revenues are defined as the products of output quantities and prices.
"Revenues: percentage of insurance revenues" calculates the ratio of revenues attributable to different insurance outputs to the total insurance revenue (total revenue minus intermediary output revenue).

Table 5
Efficiency Estimates: U.S. Property-Liability Insurers, 1993-20002

Year	DMUs	Input-Oriented				Output-Oriented			
		Cost	Pure Technical	Scale	Allocative	Revenue	Pure Technical	Scale	Allocative
Mean									
1993	816	0.43	0.75	0.86	0.7	0.4	0.74	0.87	0.64
1994	869	0.46	0.75	0.87	0.72	0.46	0.74	0.88	0.7
1995	873	0.48	0.75	0.88	0.73	0.45	0.74	0.89	0.69
1996	858	0.48	0.76	0.9	0.72	0.48	0.75	0.91	0.71
1997	837	0.43	0.74	0.88	0.68	0.38	0.73	0.9	0.58
1998	816	0.53	0.75	0.91	0.78	0.45	0.74	0.92	0.65
1999	779	0.54	0.76	0.91	0.78	0.46	0.76	0.92	0.66
2000	739	0.53	0.77	0.91	0.76	0.47	0.77	0.92	0.67
2001	711	0.53	0.76	0.91	0.77	0.42	0.75	0.92	0.62
2002	727	0.46	0.72	0.89	0.73	0.42	0.71	0.9	0.66
Sample average		**0.49**	**0.75**	**0.89**	**0.74**	**0.44**	**0.74**	**0.9**	**0.66**
Correlation[a]		**Pure Technical**		**Scale**		**Allocative**			
		0.973		**0.878**		**-0.269**			
Standard Deviation									
1993	816	0.16	0.2	0.16	0.16	0.21	0.21	0.14	0.23
1994	869	0.16	0.19	0.14	0.14	0.2	0.2	0.12	0.2
1995	873	0.18	0.19	0.14	0.17	0.2	0.21	0.12	0.2
1996	858	0.17	0.19	0.12	0.17	0.21	0.2	0.1	0.19
1997	837	0.16	0.2	0.14	0.17	0.23	0.21	0.12	0.24
1998	816	0.18	0.2	0.13	0.15	0.22	0.21	0.11	0.21
1999	779	0.18	0.18	0.12	0.15	0.2	0.19	0.1	0.2
2000	739	0.17	0.18	0.11	0.15	0.22	0.19	0.1	0.22
2001	711	0.2	0.19	0.12	0.17	0.22	0.21	0.1	0.24
2002	727	0.17	0.21	0.13	0.16	0.21	0.22	0.12	0.23
Sample average		**0.17**	**0.19**	**0.13**	**0.16**	**0.21**	**0.20**	**0.11**	**0.22**

Note: This table presents the average efficiency scores of the US Property-Liability insurance industry during the period 1993-2002. Six types of efficiencies: technical, pure technical, scales, allocative, cost, and revenue efficiency, are estimated using data envelopment analysis (DEA). Both input-oriented efficiency and output-oriented efficiency are estimated. For technical efficiency, the input-oriented and output oriented values are the same. Technical efficiency is not reported in the table, but it can be imputed by production of pure technical efficiency and scale efficiency. Cost efficiency is input-oriented, and revenue efficiency is output oriented.

a: This is the Pearson Product-moment correlation. The Spearman rank order correlation and Kendall's tau-b correlation give similar results.

Table 6
Returns to Scale of Firms in the US Property-Liability Insurance Industry

Panel A: Frequency distribution of firms by returns to scale

		IRS		CRS		DRS		IRS%		CRS%		DRS%	
Year	**DMUs**	**Input-oriented**	**Output-oriented**	**Input-oriented**	**Output-oriented**	**Input-oriented**	**Output-oriented**	**Input-oriented**	**Output-oriented**	**Input-oriented**	**Output-oriented**	**Input-oriented**	**Output-oriented**
1993	816	374	297	82	79	360	440	45.8	36.4	10	9.7	44.1	53.9
1994	869	378	317	83	79	408	473	43.5	36.5	9.6	9.1	47	54.4
1995	873	375	315	82	79	416	479	43	36.1	9.4	9	47.7	54.9
1996	858	311	249	99	92	448	517	36.2	29	11.5	10.7	52.2	60.3
1997	837	348	286	89	85	400	466	41.6	34.2	10.6	10.2	47.8	55.7
1998	816	362	313	104	95	350	408	44.4	38.4	12.7	11.6	42.9	50
1999	779	404	350	96	90	279	339	51.9	44.9	12.3	11.6	35.8	43.5
2000	739	342	296	99	97	298	346	46.3	40.1	13.4	13.1	40.3	46.8
2001	711	316	255	86	83	309	373	44.4	35.9	12.1	11.7	43.5	52.5
2002	727	395	338	74	70	258	319	54.3	46.5	10.2	9.6	35.5	43.9
Mean		**360.5**	**301.6**	**89.4**	**84.9**	**352.6**	**416**	**45.1**	**37.8**	**11.2**	**10.6**	**43.7**	**51.6**

Panel B: Agreement test between input-oriented estimation and output-oriented estimation

	1993	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**1993-2002**
Simple Kappa Coefficient	0.83	0.87	0.87	0.86	0.86	0.88	0.87	0.89	0.85	0.86	0.87
Weighted Kappa Coefficient	0.85	0.89	0.89	0.87	0.88	0.89	0.89	0.91	0.87	0.88	0.88

Note: This table tabulates the returns to scale of the firms in the US P-L insurance industry. Both input-oriented and output-oriented results are presented. A firm operates with constant returns to scale (CRS) if its technical efficiency and pure technical efficiency are equal; A firm operates with decreasing returns to scale (DRS) if its technical efficiency and pure technical efficiency are not equal, but its pure technical efficiency and non-increasing returns to scale technical efficiency are equal; otherwise, a firm is said to operate with increasing returns to scale (IRS).
The Kappa coefficients between the estimation from input-oriented DEA and output oriented DEA are presented to measure their agreements. A high Kappa value implies a high level agreement of estimations

Table 7
Factors Affect Insurer's Efficiency Scores—Two-Way Random-Effects GLS Regressions

Dependent variable (Type of efficiency):	**Input-Oriented**				**Output-Oriented**			
Independent Variables	**Cost**	**Pure Technical**	**Scale**	**Allocative**	**Revenue**	**Pure Technical**	**Scale**	**Allocative**
Personal lines short-tail premiums/Total premiums	0.3452 (0.0121)***	0.1786 (0.0219)***	0.0643 (0.009)***	0.2392 (0.0117)***	0.0241 (0.024)	0.2013 (0.0228)***	0.0374 (0.0085)***	-0.1117 (0.0264)***
Personal lines long-tail premiums/Total premiums	0.2275 (0.0078)***	0.0668 (0.0148)***	0.0856 (0.0057)***	0.1867 (0.0074)***	-0.0937 (0.0163)***	0.0803 (0.0154)***	0.0682 (0.0054)***	-0.2087 (0.0177)***
Commercial lines long-tail premiums/Total premiums	0.0277 (0.0058)***	0.0039 (0.0118)	0.0082 (0.0042)*	0.0319 (0.0054)***	0.0171 (0.013)	0.012 (0.0123)	-0.0051 (0.0039)	0.056 (0.0139)***
Herfindahl index by line of business (premiums)	0.0893 (0.0066)***	0.1076 (0.0117)***	0.0491 (0.0049)***	-0.0446 (0.0064)***	0.1741 (0.0128)***	0.1172 (0.0122)***	0.0433 (0.0046)***	0.1205 (0.0141)***
Herfindahl index by state (premiums)	0.0647 (0.0056)***	0.0935 (0.0104)***	0.0107 (0.0041)***	0.0136 (0.0054)**	0.0848 (0.0114)***	0.0888 (0.0108)***	0.023 (0.0039)***	0.0099 (0.0125)
Premium-to-surplus ratio	0.0213 (0.0017)***	0.0864 (0.0026)***	0.0176 (0.0013)***	-0.0704 (0.0017)***	0.1018 (0.0028)***	0.0937 (0.0027)***	0.0072 (0.0012)***	0.0467 (0.0032)***
Direct selling dummy variable	0.0425 (0.0045)***	0.0343 (0.008)***	0.0138 (0.0033)***	-0.0153 (0.0043)***	0.0583 (0.0088)***	0.031 (0.0084)***	0.0109 (0.0031)***	0.0578 (0.0097)***
Brokerage dummy variable	0.0204 (0.0071)***	0.0351 (0.0135)***	0.0017 (0.0052)	-0.0394 (0.0067)***	0.0585 (0.0149)***	0.0329 (0.0141)**	0.0032 (0.0049)	0.0506 (0.0162)***
Mixed distribution system dummy variable	0.018 (0.004)***	0.019 (0.0065)***	0.0082 (0.003)***	-0.0067 (0.0039)*	0.0319 (0.0071)***	0.02 (0.0068)***	0.0018 (0.0028)	0.0402 (0.008)***
Firm size: Log (assets)	0.1365 (0.0109)***	-0.2836 (0.0218)***	0.552 (0.0079)***	0.0227 (0.0101)**	0.1584 (0.0241)***	-0.1406 (0.0228)***	0.3832 (0.0074)***	0.0072 (0.026)
Firm size*Firm size	-0.0026 (0.0003)***	0.0086 (0.0006)***	-0.0146 (0.0002)***	-0.0002 (0.0003)	-0.0036 (0.0006)***	0.0051 (0.0006)***	-0.0105 (0.0002)***	-0.0004 (0.0007)
Mutual company dummy variable	0.2736 (0.0301)***	0.1446 (0.0599)**	0.0662 (0.0219)***	0.192 (0.028)***	0.0714 (0.0661)	0.1971 (0.0626)***	-0.0576 (0.0205)***	-0.1316 (0.0713)*
Mutual dummy variable*Log(assets)	-0.0136 (0.0017)***	-0.0076 (0.0033)**	-0.0037 (0.0012)***	-0.0087 (0.0015)***	-0.0049 (0.0037)	-0.0104 (0.0035)***	0.003 (0.0011)***	0.0061 (0.004)
Constant	-1.3611 (0.1032)***	2.7622 (0.2055)***	-4.3552 (0.075)***	0.3929 (0.0958)***	-1.4836 (0.2271)***	1.3055 (0.2147)***	-2.6235 (0.0703)***	0.5661 (0.2448)**
Breusch and Pagan Lagrange Multiplier Test (for random effect)	28177.62	7389.91	11449.28	12600.6	9770.88	6958.43	10388.83	9256.23
Hausman test (for fixed effect vs. random effect)	139.25	90.54	50.55	76.87	94.47	93.37	52.57	106.66

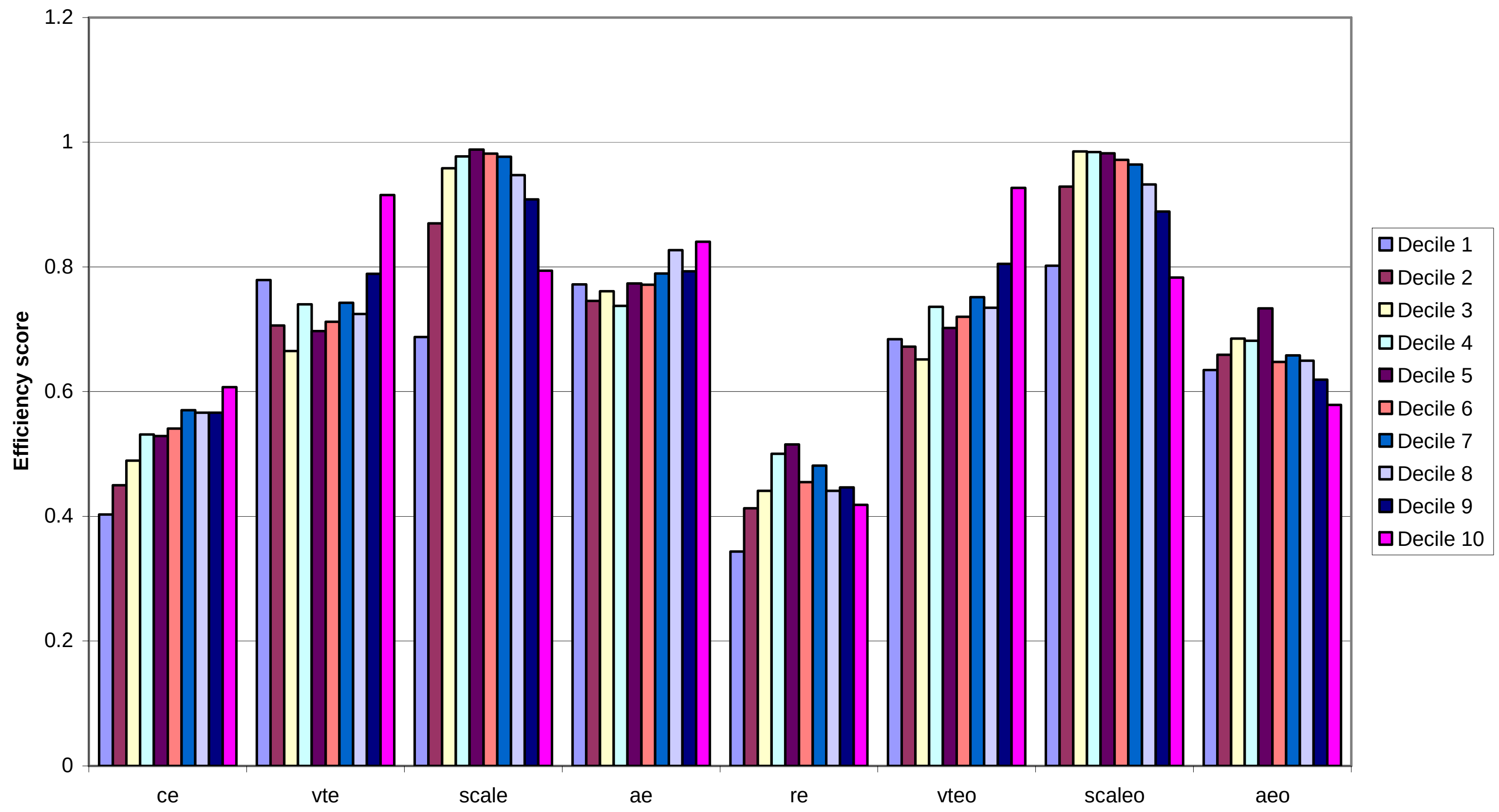
* Significant at 10%; ** significant at 5%; *** significant at 1%; Standard errors are reported in parentheses.

Table 8
Factors Affecting Insurers' Returns to Scale—Multinomial Logit Regressions

Dependent variable (returns to scale)	Input-Oriented			Output-Oriented			Sample Mean (independent variables)
Independent Variables	**CRS**	**IRS**	**DRS**	**CRS**	**IRS**	**DRS**	
Personal lines short-tail premiums/Total premiums	0.2924 (0.042)***	-0.1297 (0.0644)**	-0.1627 (0.0841)*	0.2695 (0.0383)***	0.0046 (0.0322)	-0.2741 (0.0596)***	0.09
Personal lines long-tail premiums/Total premiums	-0.0436 (0.0307)	-0.038 (0.0401)	0.0816 (0.0488)*	-0.0027 (0.0269)	0.0407 (0.0205)**	-0.038 (0.0361)	0.28
Commercial lines long-tail premiums/Total premiums	-0.0688 (0.0215)***	0.0136 (0.0282)	0.0552 (0.0339)	-0.0376 (0.0186)**	0.0391 (0.0146)***	-0.0015 (0.0251)	0.38
Herfindahl index by line of business (premiums)	0.2964 (0.0275)***	-0.0896 (0.035)**	-0.2068 (0.0388)***	0.2707 (0.0236)***	-0.0033 (0.0179)	-0.2674 (0.0298)***	0.51
Herfindahl index by state (premiums)	0.1819 (0.0221)***	0.0067 (0.0273)	-0.1886 (0.0289)***	0.1723 (0.0189)***	0.0169 (0.0146)	-0.1892 (0.0229)***	0.63
Premium-to-surplus ratio	0.0862 (0.007)***	-0.1766 (0.0122)***	0.0905 (0.0125)***	0.0717 (0.006)***	-0.0612 (0.0082)***	-0.0106 (0.0103)	1.19
Direct selling dummy variable	0.1597 (0.016)***	-0.1133 (0.0242)***	-0.0464 (0.0256)*	0.1476 (0.0138)***	-0.0252 (0.0128)**	-0.1225 (0.0194)***	0.18
Brokerage dummy variable	0.1188 (0.026)***	0.0027 (0.0354)	-0.1215 (0.038)***	0.1134 (0.0224)***	-0.0176 (0.02)	-0.0958 (0.0303)***	0.06
Mixed distribution system dummy variable	0.125 (0.0166)***	-0.09 (0.0234)***	-0.035 (0.0272)	0.1205 (0.0146)***	-0.0092 (0.0118)	-0.1113 (0.0203)***	0.17
Firm size: Log (assets)	-0.6353 (0.0674)***	0.2135 (0.1626)	0.4217 (0.1366)***	-0.4558 (0.0469)***	0.3183 (0.0715)***	0.1375 (0.0839)	18.03
Firm size*Firm size	0.0184 (0.0018)***	-0.0161 (0.0043)***	-0.0023 (0.0036)	0.0126 (0.0012)***	-0.0145 (0.0016)***	0.002 (0.002)	330.04
Mutual company dummy variable	0.306 (0.1304)**	-0.1918 (0.2767)	-0.1142 (0.2772)	0.3575 (0.1108)***	0.0868 (0.1508)	-0.4444 (0.1938)**	0.43
Mutual dummy variable*Log(assets)	-0.0176 (0.0072)**	0.0104 (0.0157)	0.0072 (0.0152)	-0.0205 (0.006)***	-0.0048 (0.0088)	0.0253 (0.0108)**	7.62
Constant	4.8552 (0.6223)***	1.7534 (1.5391)	-6.6085 (1.3007)***	3.5167 (0.4396)***	-1.0724 (0.7613)	-2.4442 (0.8586)	
Log Likelihood function		-4006.7			-3952.8		
Observations		7638			7638		

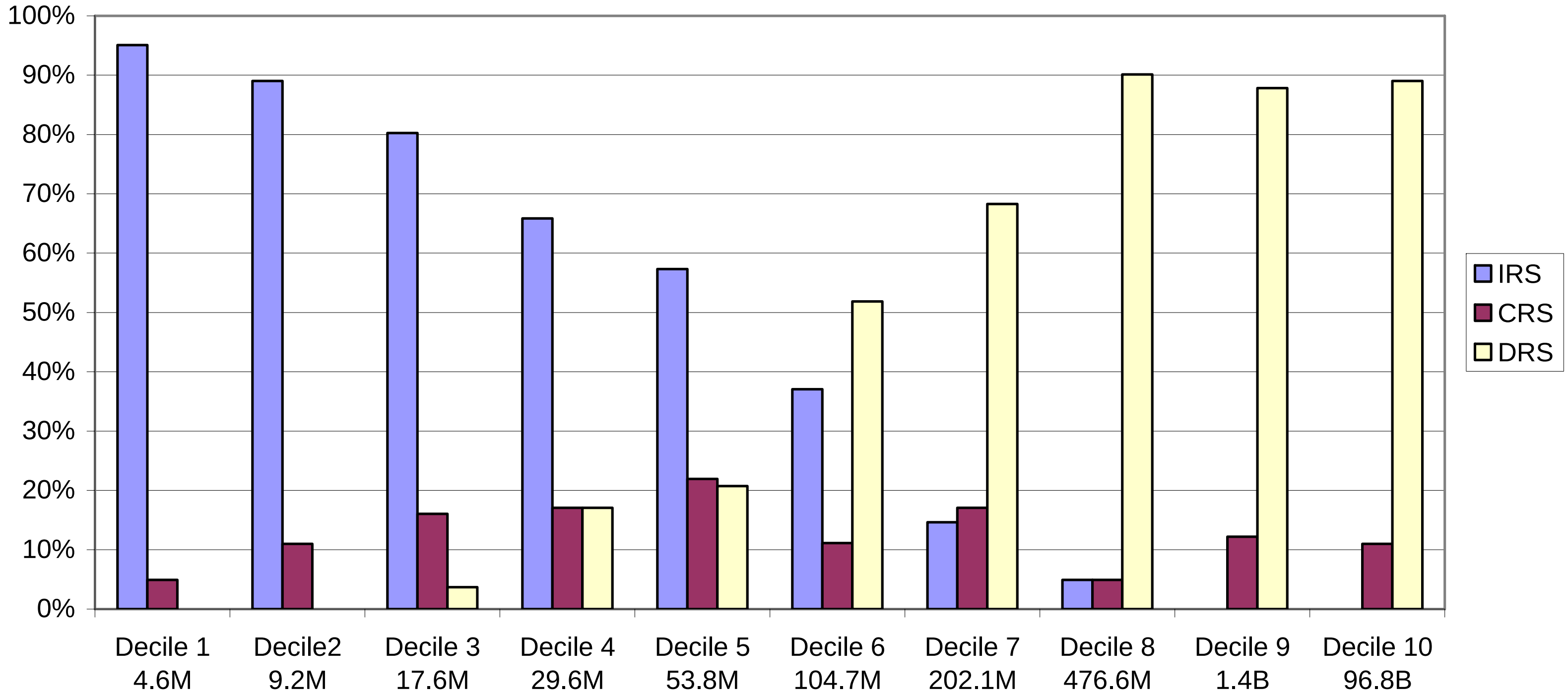
* Significant at 10%; ** significant at 5%; *** significant at 1%. The value reported is the marginal effects of independent variables, calculated at the sample mean level. Standard errors are reported in parentheses.

Figure 1 Efficiency by Asset Deciles, 1998



Note: this figure presents the efficiency of US P-L insurance firms by asset deciles, with decile 1 being the smallest in asset level.
ce: cost efficiency; vte: pure technical efficiency; scale: scale efficiency; ae: allocative efficiency. They are all input-oriented.
re: revenue efficiency; “vteo”, “scaleo”, and “aeo” refer to output-oriented pure technical efficiency, scale efficiency and allocative efficiency.

Figure 2 Returns to Scale by Asset Deciles, the US Property-Liability insurers, 1998



Note: This figure presents the distribution of returns to scale for firms in the US P-L insurance industry by asset deciles, with decile 1 the smallest in asset level. Only input-oriented estimation of returns to scale is reported.
IRS: increasing returns to scale; CRS: Constant returns to scale; DRS: Decreasing returns to scale.

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