DUPES OR INCOMPETENTS? AN EXAMINATION OF MANAGEMENT'S IMPACT ON PROPERTY-LIABILITY INSURER DISTRESS

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Abstract

Managers usually receive the blame for their firm's failure, but the extent a firm's failure is related to management's ability as opposed to factors outside its control is an open question. Using DEA frontier efficiency methods to develop proxies for the managerial quality of property-liability insurers, we discover that the ability of managers to use inputs efficiently in the production process influences both the amount of time a firm spends in distress and the likelihood of a firm's insolvency. Utilizing an original definition of financial distress, we find superior managers are able to remove their firm from financial distress sooner than relatively less adept managers. Managerial quality, measured in the year of the firm's final entrance into distress, also decreases subsequent guarantee fund assessments. While good management as we measure it is related to performance, bad luck is still an apparent reason for a significant number of property-liability insurer insolvencies.

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I. Introduction

During the mid-1980s, the property-liability insurance market witnessed an increase in the number and magnitude of insurer insolvencies. The escalation of insolvencies led to concern about the precision and accuracy of the solvency modeling tools utilized by state regulators. The federal government's investigation of the mid-1980's insolvencies, known as the *Dingle Committee Report*, criticized state regulators for inadequately monitoring solvency and exercising extreme regulatory forbearance (*Failed Promises*, U.S. House of Representatives, 1990; U.S. General Accounting Office, 1991). The report also concluded that gross mismanagement and fraud were also causes for the insolvencies.

In response to the criticism, the National Association of Insurance Commissioners (NAIC) adopted a "solvency policing agenda" in 1989. The agenda resulted in the implementation of the Financial Analysis and Surveillance Tracking (FAST) solvency monitoring system in 1993 and risk-based capital (RBC) requirements in 1994.[1] To prevent unjustified regulatory forbearance against weak insurers, the RBC system provides authority for, and in some cases requires, regulatory action when capital falls below a certain standard.[2]

The welfare maximizing objective of a well-designed solvency monitoring system is not to eliminate insolvencies altogether, but rather to maximize the identification of troubled companies at an early enough stage to allow regulators to take prompt corrective action while at the same time minimizing

[1] Klein (1995) provides additional information on the FAST system. The Insurance Regulatory Information System (IRIS), an older system that tests insurer solvency based on twelve financial ratios, is also utilized by the NAIC. The predictive accuracy of RBC is analyzed in a number of studies (Cummins, Harrington, and Klein, 1995; and Grace, Harrington, and Klein, 1998).

[2] The extent of regulatory forbearance in the insurance industry has been debated. Limits on regulatory discretion can ameliorate forbearance, but in some instances such limits may also increase the likelihood of inefficient regulatory intervention (see Harrington, 1991; Grace, Harrington, and Klein, 1998; Hall, 2000; Willenborg, 2000; and Grace, Klein, and Phillips, 2004).

the number of financially sound insurers that are identified as troubled.[3] Utilization of the NAIC's standard insolvency tracking tools—Insurance Regulatory Information System (IRIS) ratios, FAST ratios, and variables that control for firm size and organizational form—identify 18% to 85% of insolvencies (see Table 1).[4] The classification ability of these tools varies greatly depending on the year under examination. In 1990, 84.8% of insolvent firms are correctly classified, whereas in 1998 the classification rate is only 18.2%. The average classification rate of insolvent firms over the 1989-2000 period was 62.6%.

Table 1: Classification Rates using Standard Insolvency Tools (IRIS ratios, FAST ratios, Organizational Form, and Firm Size)

Year	% of Insolvent Firms Classified Correctly	% of Healthy Firms Classified Correctly	Overall % of Firms Classified Correctly
1989	84.3	79.2	79.4
1990	84.8	66.1	66.6
1991	73.2	88.4	88.1
1992	54.5	94.6	94.1
1993	58.8	95.2	94.8
1994	65.0	91.3	91.0
1995	59.1	92.3	91.9
1996	50.0	90.5	90.1
1997	53.8	87.4	87.1
1998	18.2	98.1	97.5
1999	65.0	88.2	87.9
2000	54.5	91.0	90.5
Average	62.6	88.2	87.9

Note: Models estimated are similar to those in Grace, Harrington and Klein (1998). Classification is made using the optimal cutoff point for a 40:1 relative cost ratio between the probability that a firm which subsequently fails is predicted to remain solvent (Type I error) and the probability that a firm which remains solvent is predicted to fail (Type II error).

The additional information available in financial statements for solvency monitoring is likely to be minimal. Predictive improvements, however, may come from non-balance sheet information. Although mismanagement was cited by the *Dingle Report* to be an important element in insurer insolvencies, no direct, verifiable action has been taken to combat the impact of mismanagement on property-liability

[3] Recent research suggests that earlier intervention generates better information regarding regulatory closure, which reduces the ultimate guaranty assessment (Grace, Klein, and Phillips, 2004).

[4] See Grace, Harrington, and Klein (1998) or Cummins, Grace, Phillips (1999) for a description of the insolvency prediction methodology.

insurer insolvencies. Furthermore, there is a paucity of research connecting insurer management (or rather mismanagement) to insurance company insolvencies.[5] The objective of the present paper is to determine the connection between mismanagement and insurance company distress and failure.

We proxy managerial quality by Data Envelopment Analysis (DEA) measures of frontier efficiency. The efficiency of a firm is defined using the observed and optimal values of its vector of inputs and outputs. Conditioning on a specific output vector, a firm is judged as fully efficient if its actual input usage equals optimal input usage. A firm is inefficient if actual input usage exceeds optimal input usage. As such, efficiency can be linked to managerial ability in that a higher-quality manager will utilize actual input amounts closer to the optimal amount of inputs for its firm-specific output level.

Efficiency has been used in past research to measure managerial quality. To detect bank failures Barr and Siems (1997) measure the "elusive, yet crucial, element of institutional success" via data envelopment analysis (DEA).[6] Hermalin and Wallace (1994) use Varian's weak axiom of profit maximization test (WAPM) to proxy for managerial quality in savings and loans.[7] In the property-liability insurance literature, Lee and Weiss (2003) find that econometric frontier efficiency measures add explanatory power and accuracy to failure prediction.

We examine manager's influence on property-liability insurer distress using three tests. First, we investigate whether more efficient managers are able to significantly reduce the likelihood that their firm becomes insolvent. Second, we analyze whether high quality managers are able to remove their firm from regulatory scrutiny sooner than lower quality managers. Finally, we verify if managerial ability influences the ultimate guarantee fund assessment from an insurer's insolvency.

Our findings indicate that more efficient managers reduce the likelihood their firm becomes insolvent. In addition utilizing an original definition of financial distress, we also discover that superior

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[5] The only research we are aware of that examines the cause of an insurer's failure is A.M. Best's "Best's Insolvency Study – Property-Casualty U.S. Insurers 1969-2000," (Oldwick, New Jersey, A.M. Best Company, Inc.).
[6] Barr and Siems (1997) discover that the inclusion of managerial quality in their probit models of bank failures adds explanatory power and predictive accuracy.
[7] Hermalin and Wallace (1994) discover that inefficient thrifts were 4 ½ times more likely than efficient thrifts to fail in the future.

managers are able to remove their firm from regulatory scrutiny sooner than relatively inferior managers. Finally, we find evidence that managerial quality, measured in the year of the firm's final entrance into distress, decreases the ultimate cost of insolvency. Bad luck in the form of unforeseen shocks (e.g. four hurricanes that reach land in Florida in a single year) is, however, a principal factor in property-liability insurance company insolvencies.

The remainder of the paper is organized as follows. Section II discusses the methodology we use to proxy managerial quality. Section III describes the measurement of the outputs, inputs, and prices used in estimating efficiency and our database. Section IV presents the development of our hypotheses and the estimation techniques to test those hypotheses. The results of the analyses are presented in Section V. We conclude and discuss the policy implications of our work in section VI.

II. Efficiency Model and Methodology

Frontier efficiency measures have become the state-of-the-art in measuring the performance of business firms due to the contributions of Aigner, Lovell, and Schmidt (1977) and Charnes, Cooper, and Rhodes (1978). This approach is based on the recognition that some firms will not be as successful as others in meeting firm objectives. The technique measures the performance of each firm relative to "best practice" frontiers consisting of the dominant firms in the industry. A firm is fully efficient if it lies on the frontier, and inefficient if it is not on the frontier.

We estimate efficient production, cost, and revenue frontiers giving measures of cost, allocative, technical, and revenue efficiency for each firm in our sample. The *cost efficiency* of a firm is the ratio of the minimum required costs to the actual costs utilized to produce a given level of output. A firm is considered fully efficient if its actual input usage equals optimal input usage for given output quantities and input prices. A firm is inefficient if actual input usage exceeds optimal input usage. Cost efficiency is composed of *allocative efficiency* and *technical efficiency*. Allocative inefficiency results from a firm's use of a suboptimal combination of inputs in producing a given level of output. Technical inefficiency results from not operating with the best-practice technology, i.e. a firm is utilizing excessive resources to produce a given output.

Technical efficiency can be further decomposed into *pure technical efficiency* and *scale efficiency*. Pure technical efficiency is measured relative to the variable returns to scale frontier. It is the proportion by which the firm could reduce its input usage by adopting the best technology represented by the variable returns to scale frontier. However, a firm operating on the variable returns to scale frontier is also scale inefficient because it is not operating on the constant returns to scale frontier. It is socially and economically optimal for firms to operate at constant returns to scale. Scale efficiency is measure by the ratio from the constant returns to scale frontier to the variable returns to scale frontier.

Revenue efficiency is the ratio of the revenues of a given firm to the revenues of a fully efficient firm with the same input vector and output prices. Estimating both cost and revenue efficiency is important since the objective of the firm is profit maximization. Thus to be completely efficient (i.e. to maximize profits), the firm must be both cost efficient and revenue efficient.

To estimate frontier efficiency the data envelopment analysis (DEA) methodology is employed. DEA is a linear programming technique that compares each firm in the industry to a "best-practice" efficient frontier. The program forms a convex combination of efficient firms for each firm in the sample. DEA is appropriately named since it truly envelops the entire data set, making no accommodation for random noise outside the control of each firm. Any departure from the frontier is measured as inefficiency. A firm is fully efficient (efficiency of 1.0) if it lies on the frontier and inefficient (efficiency < 1) if it is not on the frontier, which means that its outputs could be produced more efficiently by another firm or firms.

DEA has been widely used to measure efficiency for financial institutions (see Berger and Humphrey, 1997). In-depth descriptions of the DEA methodology are provided in Lovell (1993), Charnes, Cooper, Lewin, and Seiford (1994) and Zhu (2003). The methodology has also been extensively outlined in insurance studies (e.g. Cummins and Zi, 1998; Cummins, Weiss, and Zi, 1999; Cummins, Tennyson, and Weiss, 1999; Cummins and Weiss, 2001; Cummins and Nini, 2002).[8]

[8] For additional detail on the DEA Methodology see Appendix A.

Although DEA traditionally was viewed as a strictly non-parametric methodology, recent research has shown it can be interpreted as a maximum likelihood procedure (e.g., Banker 1993; Grosskopf, 1996). As such, DEA is consistent and it converges faster than other estimation methods. Furthermore, DEA efficiency measures have been shown to be more highly correlated with traditional insurance performance measures, such as expense-to-premium ratio and return on assets, than the econometric production and cost functions estimates (Cummins and Zi, 1998).

III. The Sample, Outputs, and Inputs

Output Quantities and Prices

Like other financial firms, property-liability insurer's outputs consist primarily of intangible financial services. Consistent with most of the recent literature on financial institutions, we adopt a modified version of the production (or value-added) approach to output measurement. The production approach employs as important outputs all categories that have substantial value-added, as judged by operating cost allocations (Berger and Humphrey, 1992). Operating cost allocations identify three principal services that property-liability insurers provide (Cummins and Weiss, 2001):

- *Risk-pooling and risk-bearing*: The main function of insurance is to resolve risk and uncertainty. Insurance provides a mechanism through which consumers and businesses exposed to losses can engage in risk reduction through the diversification effect of pooling. Insurers collect premiums in advance from customers and redistribute most of these funds to the policyholders that sustain losses. The actuarial, underwriting, and related expenses incurred in operating the risk pool represent the value added in the insurance industry. The equity capital that insurers hold also creates value-added by increasing economic security against unexpected losses and investment shocks.

- *"Real" financial services relating to insured losses*: Insurers provide a variety of real services for policyholders, such as the design of risk management programs (e.g. risk surveys and recommendations regarding coverage, deductibles, and policy limits), loss prevention, and the provision of legal defense in liability disputes. By contracting with insurers' to provide these services, policyholders take advantage of insurers' expertise to reduce the costs of managing risk.

- *Financial intermediation*: Insurers issue insurance policies, a type of debt contract, and invest the funds in financial assets until they are needed to pay claims. In return, policyholders receive a discount in the premiums they pay to compensate them for the opportunity costs of the funds held by the insurer. For property-liability insurers, financial intermediation is a somewhat incidental function resulting from the collection of premiums in advance of claims payment to minimize contract enforcement costs. Insurers' value-added from intermediation is represented by the net interest margin between the rate of return earned on invested assets and the rate credited to policyholders.

In defining measures for insurance output, we are searching for proxies for the quantity of insurance services provided. Accordingly, the output variables should be highly correlated with the quantity of financial services provided.

The most common proxy for the quantity of risk-pooling and real insurance services for the property-liability insurers is the present value of real losses incurred (Berger, Cummins, and Weiss 1997; Cummins, Weiss, and Zi, 1999; and Cummins and Weiss, 2001). Losses incurred are defined as the losses that are expected to be paid as a result of providing insurance coverage. Because the objective of risk-pooling is to collect funds from the policyholder pool and redistribute them to those who incur losses, proxying output by the amount of losses incurred is appropriate. In addition, the use of losses incurred is consistent with the economic theory of insurance. Risk-averse agents subject to random shocks to wealth are willing to pay more than the expected value of loss in exchange for transferring risk to the insurer. Losses are also an excellent proxy for the quantity of real services provided, since the amount of claims settlement and risk management services are also highly correlated with loss aggregates.

To capture the various risks and types of services provided by different types of insurance, the lines of insurance with similar characteristics are grouped together. We separate output measures into personal lines short-tail losses, personal lines long-tail losses, commercial lines short-tail losses, and commercial lines long-tail losses.[9] Since the payout characteristics also vary amongst the principal types of insurance, the use of present values recognizes the differences in payout tails by line of insurance (Berger, Cummins, and Weiss, 1997; Cummins, Weiss, and Zi, 1999; and Cummins and Weiss, 2001). Estimates of the payout proportions for each line of insurance are obtained by applying the Taylor separation method (Taylor, 2000; also see Cummins, 1990) to data from the Schedule P of the regulatory annual statements that provides information on reserve runoffs. Discounting is performed using U.S. Treasury yields obtained from the Federal Reserve Economic Database (FRED) maintained by the

[9] The tail length refers to the length of the loss cash flow stream. The lines of business definitions are described in Phillips, Cummins, and Allen (1998) and in the line classification in Schedule P of the U.S. National Association of Insurance Commissioners (NAIC) regulatory annual statement for property-liability companies.

Federal Reserve Bank of St. Louis. In sum, there are four output categories: present value of real losses incurred in short-tail personal lines, short-tail commercial lines, long-tail personal lines, and long-tail commercial lines.

Output prices are obtained using the following formula on each of the four output categories: $p_i = [P_i - PV(L_i)]/PV(L_i)$, where p_i is the price of insurance output *i* and P_i is the premiums earned for line *i*, *i*=1,…,4 for personal short-tail, personal long-tail, commercial short-tail, and commercial long-tail. Premiums implicitly represent the discounting of the loss cash flow stream. The use of the present value of losses to compute price preserves consistency by identifying the time value of money in both the premium and loss components of the price. The product of the price p_i and the quantity of output, $PV(L_i)$, provides the value-added from the i^{th} insurance output.

In addition to the risk-bearing and real insurance services, the intermediation services that P/L insurers provide need to be captured. Consistent with recent insurance efficiency studies average real invested assets for each year is our proxy measure for the intermediation output (e.g. Berger, Cummins, and Weiss 1997; Cummins, Weiss, and Zi, 1999; and Cummins and Weiss, 2001).

For the price of the intermediation output, a measure of the expected rate of return on the insurer's assets is used. Although P/L insurers predominately invest in fixed income securities, equities represent a significant proportion of invested assets. Correspondingly, the expected return on assets needs to include the expected returns on both the equity and debt components of an insurer's investment portfolio. Since the expected return on bonds and notes are typically close to the actual return, a ratio of actual investment income (minus dividends on stocks) to the insurer debt holdings is used to represent the rate of return on the debt component of the portfolio. The expected return on stocks is calculated as the return on the 90-day Treasury bill rate at the end of the preceding year plus the long-term (1926 to the end of the preceding year) average market risk premium on large company stocks from Ibbotson Associates. Utilizing this method assumes that insurers have equity portfolios with a market beta coefficient of 1.0. The final step is to create a weighted average of the debt and equity returns with the weights equal to the proportion of the firm's total portfolio invested in debt instruments and equity. Thus, the price of the intermediation output varies across insurers due to the variation in the return on debt securities and in the debt to equity portfolio proportions.

Input Quantities and Prices

Inputs are usually easier to identify and measure relative to outputs since the units of measurement are more tangible and directly observable. Insurer inputs in the production approach are classified into five categories: administrative labor (home-office labor), agent labor, business services and materials (including physical capital), debt capital, and financial equity capital. Since detailed information for the quantities of labor and materials used in each company is not publicly available for insurers, they are imputed from the dollar value of related expenses. That is to say, the quantity of an input is defined as the current dollar expenditures associated with the particular input divided by its current price. The price of the input is measured by its current price deflated by the CPI.

The price of administrative labor is calculated from the U.S. Department of Labor data on average weekly wage rate for the Standard Industrial Classification for property-liability insurers (SIC 6331). The price is constructed using the wage rate in the state in which the insurer's home office is located. The quantity of administrative labor is the total expenditures on home office labor—the sum of salaries, payroll taxes, and employee relations and welfare—from the regulatory annual statement divided by its price.

The price of agent labor comes from the U.S. Department of Labor average weekly wage rate for insurance agents (SIC 6411). A weighted average wage variable is utilized to obtain the price of agent labor, with weights equal to the proportion of an insurer's premiums written in each state. Current dollar expenditures for agent labor are the sum of net commissions, brokerage fees and allowances to agents. Again, the quantity of agent labor is divided by its price.

Current dollar expenditures for business services and materials are calculated as the difference of the total expenses incurred and the total labor expenses of the insurer from the regulatory annual statement. The expenditures on business service and materials are deflated using the U.S. Department of Labor average weekly wage rate for business services (SIC 7300). The national price index is used.

Financial equity capital is considered an important input in the theory of the firm and financial institutions studies (McAllister and McManus, 1993; Berger, Cummins and Weiss, 1997; Hughes and Mester, 1998; and Hughes, Mester and Moon, 2001). Besides satisfying regulatory requirements, the inclusion of financial equity capital is warranted under the modern theory of the firm where a firm's technology is looked at as including all the contractual relationships that encompass the firm. In addition, the financial theory of insurance pricing, views insurance as risky debt in which the financial equity of the insurance company plays a critical role in reducing firm's insolvency risks. The theory states that the price of insurance is inversely related to insurers' default risk and that insurers have optimal capital structures (Cummins and Danzon, 1997). Accordingly, better-capitalized insurers should obtain higher prices for their products than riskier firms, *ceteris paribus*, since more capital implies a higher probability that losses will be paid if losses are higher than expected. In sum, capital levels ultimately affect the revenue and profit of an insurer.

Financial equity capital of a P/L insurer is defined as the statutory policyholders surplus deflated to constant dollars using the CPI. The quantity of this input is measured by the real value of the average of the beginning and end-of-year capital level. The ideal price of financial equity capital is the market return of equity capital. However, a majority of P/L insurers are not publicly traded, making the market equity returns for most firms unobservable. Consequently, a book-value approach is used to measure an insurer's cost of financial equity capital. A constant cost of equity is assumed for all firms in the industry. The price of financial equity capital in the year t is set equal to the average 90-day Treasury bill rate in year t, plus the long-term (1926 to the end of year t) average market risk premium on large company stocks from Ibbotson Associates.

Finally, debt capital for insurers is mainly comprised of funds borrowed from policyholders. For P/L insurers, these funds consist of the sum of loss reserves and unearned premiums reserves deflated to constant dollars using the CPI. The cost of policyholder supplied debt capital is calculated as total expected investment income minus expected investment income attributed to equity capital divided by average policyholder-supplied debt capital. Where expected investment income attributable to equity capital is the expected rate of investment return multiplied by average equity capital for the year (Cummins and Weiss, 2001).

Inputs and Outputs: Summary

We utilize five outputs—the present value of real losses incurred for personal and commercial short-tail and long-tail lines and real invested assets. The inputs are administrative labor, agent labor, business services and materials, financial equity capital, and debt capital. All monetary-values variables are deflated to real 1984 values using the consumer price index (CPI).

The Sample and Summary Statistics

The primary source of data for the efficiency analysis is the NAIC regulatory annual statements from 1989 to 2000. The efficiency analysis is conducted on the individual units in the insurance industry, i.e., both unaffiliated and affiliated singles are analyzed. The sample is comprised of all the individual property-liability insurers for which meaningful data were available. In addition to the regulatory annual statements, input price data was obtained from the U.S. Bureau of Labor Statistics.

The inputs, input prices, and expenses of the P/L insurance industry for the period 1989-2000 are show in Table 2 Panel A. Input usage remains fairly constant over time with the exception of financial equity capital and debt capital, which increase slightly over the sample period. In percentage terms, the use of labor, materials, financial equity capital, and debt capital remains constant over the period.

The outputs are shown in Table 2 Panel B. The quantity of insurance output is roughly evenly divided between personal and commercial lines. Overall the outputs are reasonably stable over the period. The intermediation output accounts for a significant proportion of the total outputs.

Table 2: Inputs & Expenses and Outputs & Revenues

Panel A: Inputs and Expenses

This panel provides summary statistics for the input quantities and prices used in the data envelopment analysis. Quantities and prices are unweighted sample means. The average column reports averages across years. Expenses are the product of input quantities and prices. The Percent of Total Expenses reports the ratio of expense by input to total expenses.

Year	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**Average**
# of DMU'S	1589	1594	1594	1582	1626	1578	1571	1555	1448	1461	1467	1470	1545
Input Quantities (000s)													
Administrative (Home Office) Labor	1,393	1,412	1,408	1,420	1,556	1,568	1,513	1,455	1,517	1,572	1,692	1,574	1,507
Agent Labor	2,261	2,151	2,097	2,042	2,098	2,153	2,117	2,028	2,143	2,178	2,227	2,095	2,133
Materials and Business Services	4,572	4,357	4,124	4,292	4,237	4,280	4,136	3,867	3,615	3,655	3,764	3,319	4,018
Financial Equity Capital	54,786	54,366	52,427	60,602	62,508	67,676	65,700	72,799	80,438	89,005	97,391	92,640	70,861
Debt Capital	99,015	98,522	93,808	101,399	99,870	106,071	102,604	105,424	103,089	106,086	107,635	107,121	102,554
Input Prices													
Administrative (Home Office) Labor	4.712	4.795	4.849	5.064	5.078	5.204	5.326	5.503	5.630	5.771	5.776	5.731	5.286
Agent Labor	4.359	4.351	4.273	4.409	4.370	4.417	4.463	4.576	4.706	4.749	4.819	4.979	4.539
Materials and Business Services	2.781	2.832	2.832	2.909	2.856	2.850	2.951	3.047	3.194	3.374	3.648	4.037	3.109
Financial Equity Capital	17.10%	16.23%	14.27%	12.12%	11.48%	12.32%	14.36%	14.09%	14.41%	14.21%	14.08%	14.99%	14.14%
Debt Capital	8.38%	7.82%	5.76%	4.22%	3.55%	3.97%	5.64%	5.31%	5.29%	4.95%	4.74%	5.91%	5.46%
Expenses (000s)													
Administrative (Home Office) Labor	6,728	6,918	6,993	7,385	8,093	8,293	8,181	8,179	8,611	9,221	9,989	9,021	8,134
Agent Labor	9,859	9,458	9,054	9,057	9,218	9,546	9,489	9,338	10,058	10,331	10,700	10,386	9,708
Materials and Business Services	13,161	12,690	12,151	12,961	12,341	12,445	12,392	11,959	11,708	12,525	13,778	13,398	12,626
Financial Equity Capital	9,368	8,824	7,481	7,345	7,176	8,338	9,434	10,257	11,591	12,648	13,713	13,887	10,005
Debt Capital	8,321	7,732	5,540	5,034	4,085	4,268	5,830	5,548	5,477	5,446	5,165	6,325	5,731
Percent of Total Expenses													
Administrative (Home Office) Labor	12.44%	13.09%	14.16%	15.36%	16.97%	16.84%	16.25%	15.91%	16.85%	16.93%	17.37%	16.47%	15.72%
Agent Labor	22.90%	22.21%	23.24%	24.43%	24.64%	23.65%	21.93%	20.10%	20.77%	20.58%	20.25%	19.81%	22.04%
Materials and Business Services	25.17%	25.51%	27.16%	29.20%	29.03%	27.72%	25.86%	27.18%	25.03%	25.10%	25.46%	24.79%	26.43%
Financial Equity Capital	24.77%	25.42%	24.40%	22.19%	21.85%	23.49%	25.29%	25.91%	27.24%	28.04%	27.95%	28.44%	25.42%
Debt Capital	14.73%	13.78%	11.03%	8.82%	7.51%	8.31%	10.68%	10.90%	10.10%	9.35%	8.96%	10.48%	10.39%

Table 2 (*cont*)

Panel B: Outputs and Revenues

This panel provides summary statistics for the output quantities and prices used in the data envelopment analysis. Quantities and prices are unweighted sample means. The average column reports averages across years. Revenues are the product of output quantities and prices. The Revenues: Percent of Insurance Output section reports the ratio of revenue by output to total revenues.

Year	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	Average
# of DMU'S	1589	1594	1594	1582	1626	1578	1571	1555	1448	1461	1467	1470	1,545
Output Quantities (000s)													
Personal Short-Tail	5,065	4,676	4,332	4,292	4,380	4,806	5,237	1,057	5,950	6,609	7,098	7,658	5,097
Personal Long-Tail	13,344	13,556	13,695	14,573	13,736	14,232	14,007	10,560	14,926	15,524	16,401	17,943	14,375
Commercial Short-Tail	11,181	10,804	11,227	8,342	7,986	9,511	8,679	14,476	8,564	9,373	10,416	10,179	10,062
Commercial Long-Tail	10,995	10,572	9,464	10,309	4,457	7,822	4,162	3,635	5,620	5,211	4,336	7,974	7,046
Intermediation	161,630	165,126	155,320	178,482	176,483	191,482	183,761	192,912	205,006	222,504	227,204	213,384	189,441
Output Prices													
Personal Short-Tail	0.726	0.529	0.891	0.863	0.717	0.927	0.863	0.758	0.867	0.873	0.857	0.816	0.807
Personal Long-Tail	0.966	0.979	0.963	0.966	0.986	0.989	1.079	0.849	1.097	1.113	1.080	1.046	1.010
Commercial Short-Tail	1.950	1.909	1.869	1.805	1.908	1.778	1.900	1.330	1.886	1.768	1.756	1.681	1.795
Commercial Long-Tail	0.329	0.324	0.285	0.270	0.021	0.033	0.038	0.080	0.058	0.043	0.029	0.063	0.131
Intermediation	9.91%	9.46%	8.98%	8.01%	7.28%	7.13%	7.76%	7.53%	7.82%	7.68%	7.91%	7.75%	8.10%
Revenues (000s)													
Personal Short-Tail	6,021	4,029	6,600	6,126	5,107	7,200	7,020	1,454	8,389	9,427	10,179	10,352	6,825
Personal Long-Tail	16,379	16,633	17,125	17,847	17,874	18,948	19,480	10,392	21,702	22,096	22,625	23,194	18,691
Commercial Short-Tail	18,215	17,290	16,982	11,846	12,831	13,481	13,944	12,564	14,021	14,148	14,852	15,155	14,611
Commercial Long-Tail	12,564	12,139	8,958	9,200	1,021	2,780	1,940	2,377	3,299	2,333	1,676	2,888	5,098
Intermediation	17,989	17,435	15,340	15,866	14,499	15,836	16,217	16,873	18,793	19,749	22,991	19,101	17,557
Revenues: Percentages of Insurance Output													
Personal Short-Tail	8.50%	6.26%	9.27%	8.80%	8.49%	10.37%	10.20%	3.58%	10.75%	10.85%	10.87%	10.97%	9.08%
Personal Long-Tail	23.69%	24.60%	23.99%	26.36%	29.45%	27.84%	28.59%	24.58%	28.87%	28.58%	28.77%	27.69%	26.92%
Commercial Short-Tail	31.92%	32.49%	32.07%	29.37%	32.53%	31.81%	30.83%	27.24%	28.37%	28.55%	28.17%	28.59%	30.16%
Commercial Long-Tail	7.47%	7.38%	6.78%	7.96%	1.01%	1.55%	1.45%	1.82%	2.03%	1.80%	1.33%	2.16%	3.56%
Intermediation	28.41%	29.27%	27.90%	27.50%	28.52%	28.43%	28.92%	42.78%	29.99%	30.23%	30.87%	30.59%	30.29%

IV. Hypotheses and Regression Methodology

To determine whether managerial quality influences property-liability insurer financial distress and insolvency we test three broad hypotheses. First, we investigate whether more efficient managers are able to reduce the likelihood their firm becomes insolvent. Second, we analyze whether high quality managers are able to remove their firm from regulatory scrutiny sooner than lower quality managers. Finally, we examine whether managerial efficiency influences the resulting costs of insolvency.

Hypothesis 1

To date property-liability insurer insolvency prediction research has focused on financial statement data—financial ratios, rating agency assessments, risk-based capital, and cash flow simulation techniques. Pinches and Trieschmann (1974) predict insurer distress via discriminant analysis using financial ratios that capture different aspects of an insurer's operations. Ambrose and Seward (1988) add A.M. Best's ratings to insurer insolvency prediction and discover the ratings predict insolvency with comparable accuracy to a discriminant model that incorporates surplus, leverage, the loss ratio, and loss adjustment expenses.

With the advent of risk-based capital in 1994, a number of studies assessed its predictive accuracy. Cummins, Harrington and Klein (1995) discovered the predictive ability of NAIC risk-based capital to actual capital is extremely low. However, accuracy improves significantly when the components of the RBC formula are used along with variables that control for firm size and organizational form. Similarly, Grace, Harrington and Klein (1998) determine that RBC ratios are less powerful than FAST scores in identifying financially weak property-liability insurers.

Cummins, Grace and Phillips (1999) use a dynamic financial analysis cash flow simulation model to predict property-liability insurer insolvencies. The cash flow simulation variables lead to more accurate solvency prediction than the NAIC's ratios alone. The information available in financial statements for ratio based solvency monitoring has been exhausted. Predictive improvements, however, may come from non-balance sheet information.

Even though Schumpeter's (1942) theory of "creative destruction" suggests that the liquidation of some existing firms is essential to a strong economy, mangers of failed firms are often held responsible. Mangers of failed firms are often perceived as less skilled, and the failure of the firm is blamed on their poor judgment. Also when the financial condition of a firm worsens, managers become more likely to take actions that harm either the whole firm or some specific stakeholders.

Previous research has attempted to understand the extent that firm failure is due to managerial actions as opposed to factors outside managerial control. Lang and Stulz (1992) find that the announcement of bankruptcy by one firm in an industry produces a negative wealth effect on the remaining firms in the industry, suggesting that industry-specific, as opposed to firm-specific, factors are important determinants of firm bankruptcy. In addition, managers are more likely to attribute their financial difficulties on exogenous factors than on their own actions (John, Lang, and Netter, 1992).

Similarly, Khanna and Poulsen (1995) discover that the market reaction to managerial actions—such as, changes in top management; plant closings, layoffs, asset sales, or downsizing; acquisitions and expansions; loan and credit agreement extensions, and new debt; debt swaps; issuance of common or preferred stock; and stock buybacks—is not significantly different for firms that file for Chapter 11 than for a control sample of firms that performed better. They conclude that managers of financially distressed firms are unfairly blamed for their firm's poor performance. In contrast, Asquith, Gertner, and Scharfstein (1994) discover evidence of the importance of firm-specific factors in bankruptcy, firms end up in distress because they underperform their industry.

Lang and Stulz (1992), John, Lang, and Netter (1992), and Khanna and Poulsen (1995) all find that managers of failed firms are not less skilled than their contemporaries. Rather they observe that managers serve as scapegoats for their firm's performance. Whereas, Asquith, Gertner, and Scharfstein (1994) discover that distressed firms underperform in their industries. These contradictory findings suggest the following null hypothesis:

Hypothesis 1 (H1): *Management quality does not impact insurer solvency.*

To test hypothesis 1, we use a logistic regression model similar to previous property-liability insurer solvency prediction research (Grace, Harrington, and Klein, 1998; Cummins, Harrington, and Klein, 1995; and Cummins, Grace, and Phillips, 1999):

$$I_{jt} = a_0 + f(\mathrm{Eff}_{\mathrm{jt}}, \mathrm{Size}_{jt}, \mathrm{Mutual}_{jt}, \mathrm{Ratio}_{jt}) + e_{jt} \tag{5}$$

For insurer *j* and data year *t*: I_{jt} is the unobserved propensity to fail subsequent to year *t*,[10] $\mathrm{Eff}_{\mathrm{jt}}$ is the efficiency score (pure technical efficiency, scale efficiency, allocative efficiency, and/or revenue efficiency), Size_{jt} is the log of total assets, $Mutual_{jt}$ equals 1 if insurer *j* is a mutual and zero otherwise, and Ratio_{jt} is a vector IRIS and FAST ratios. There are ratios that are common to both the IRIS and FAST systems, thus shared ratios are used only once. Year dummy variables are also incorporated. State of domicile indicator variables are included in some specifications of the model.

Testing hypothesis 1 also determines if there is room for improving upon the NAIC's standard insolvency tracking tools. Logistic regression maximum likelihood techniques do not create standard "goodness of fit" measures. To compare the predictive accuracy of the logistic models that contain alternative sets of variables three approaches will be used: the pseudo R^2, the Type I/Type II error trade off, and Receiver Operating Characteristic (ROC) curves. The pseudo R^2 (likelihood ratio index) is equal to one minus the ratio of the estimated log likelihood function value relative to the value of the likelihood function when the coefficients of the model are constrained to be zero (see Greene, 2000, p. 831). The Type I error rate is defined as the probability that a firm that subsequently fails is predicted to remain solvent. The Type II error rate is the probability that a firm that remains solvent is predicted to fail. To evaluate the Type I/Type II error trade-off, Type I error rates are computed for various levels of the Type II error rate. Models with relatively low Type I error rates conditional on the Type II error rate are considered superior.

[10] A three-year prediction period for insurer insolvency is utilized. Insurers are classified as insolvent if it was subject to formal regulatory proceedings for conservation of assets, rehabilitation, receivership, or liquidation.

The goal of the ROC analysis is to provide a statistical test of whether a given model outperforms an alternative model in categorizing observations into two mutually exclusive groups for various Type II error rates (see Metz, Wang, and Kronman, 1984; and Cummins, Grace and Phillips, 1999). ROC analysis can be summarized graphically by plotting a ROC curve in a two dimensional plane where the Type II error rate is plotted along the X-axis and the complement of the Type I error rate is plotted along the Y-axis. In the analysis, two alternative models are assumed to yield unique ROC curves and the parameters of the curves are calculated using a maximum likelihood technique. The area below the ROC curve, known as the area index, is an informative statistic that summarizes the accuracy of a particular model. A model that perfectly categorizes the insolvent and solvent companies will have an area index equal to 1.0, while a model with no discriminatory power will result in an area index of 0.50.

Hypothesis 2

Prior to formal regulatory proceedings an insurance company is put under regulatory scrutiny, where the company is subject to closer inspection and perhaps a formal examination. Clearly, many companies that are subject to regulatory scrutiny do not become insolvent. In fact, many insurers remove themselves from financial distress and thereby from the regulatory radar screen. Does managerial quality influence a firm's ability to extricate itself from regulatory scrutiny, and if so, to what extent? To answer this question, we propose the following null hypothesis:

Hypothesis 2 (H2): *Management quality does not influence a firm's duration in distress.*

Before the hypothesis can be tested, we first need a definition of financial distress. Prior definitions of financial distress in the property-liability insurance literature rely on IRIS ratios.[11] Petroni (1992) and Beaver, McNichols, and Nelson (2003) define financial distress as a firm with one or more IRIS ratios (excluding those ratios that involve reserves) outside the NAIC "usual range." Neale,

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[11] The NAIC's Insurance Regulatory Information System (IRIS) is a collection of analytical tools that provide state insurance regulators a system for screening the financial condition of insurance companies operating in their state. The objective of IRIS is to select those companies that merit the highest priority in the allocation of the regulators' resources. A "usual range" for each of the twelve IRIS ratios has been established based on the experience of insolvent firms. Approximately 11% of companies fall outside the usual range on four or more ratios for any given year (see NAIC Insurance Regulatory System, 2002).

Habegger, and Peterson (2003) define general financial distress as four or more IRIS ratios outside the NAIC defined range.

Reliance on IRIS ratios in defining financial distress is potentially problematic. The IRIS system does not force a regulator to act; it merely suggests various degrees of intervention (Klein, 1995). Thus, the failure of a subset of IRIS ratios does not indicate that the firm is truly under regulatory scrutiny. It is also possible that firms with no out-of-bounds IRIS ratios are actually under surveillance. A further complication is that the IRIS ratios and their defined ranges are specified in advance and are rarely changed, making the IRIS system subject to manipulation (Gaver and Paterson, 2004).

Our definition of financial distress does not rely solely on IRIS. In contrast, we attempt to simulate the NAIC solvency screening system to obtain the firms that are truly subject to regulatory scrutiny. Accordingly, we use logistic insolvency prediction model for each year in the sample (1989-2000). The explanatory variables in our regression model are a mutual firm indicator variable, a size variable (log of assets), and factor scores of IRIS and FAST ratios.[12] The use of a size variable and a mutual indicator variable is consistent with the extant literature on property-casualty insolvency prediction. The FAST system is used in addition to the IRIS ratios because the FAST system provides more accurate solvency predictions than the IRIS system (Grace, Harrington, and Klein, 1998; and Cummins, Grace, and Phillips, 1999).

A firm is defined as distressed if it has a predicted probability of insolvency greater than an "optimal probability cutoff point." The optimal cutoff point is set using a 40:1 relative cost ratio between misclassifying a failing firm (Type I error) and misclassifying a solvent firm (Type II error). The cost of misclassifying a failing firm is the total guarantee fund assessment due to a firm's failure. The cost of misclassifying a solvent firm is the opportunity cost of the regulator's formal examination of the firm. The utilization of a 40:1 relative cost ratio is based on the ratio of the aggregate ex-ante payments from insurers to the state of New York's guaranty fund (the cost of Type I error) to the aggregate funds

[12] Factor analysis on the IRIS and FAST ratios is used to eliminate the multicollinearity among the ratios in each year.

reimbursed to the New York Department of Insurance for regulatory examinations of insurers (the cost of Type II error).[13] New York is generally considered the regulatory jurisdiction with the most rigorous solvency monitoring system and the only state that requires ex-ante guarantee fund assessments. Overall, the 40:1 relative cost ratio is a conservative estimate in that it classifies a large number of firms as "distressed" (see Table 3).

Table 3: The Number of Distressed Firms Identified for Each Year

Year	Optimal Probability Cut-Off for Solvency Prediction Model	Number of Firms	Number Identified as Distressed	% Identified as Distressed
1989	0.030	1589	368	23.16
1990	0.020	1594	573	35.95
1991	0.035	1594	213	13.36
1992	0.040	1582	97	6.13
1993	0.015	1626	169	10.39
1994	0.025	1578	150	9.51
1995	0.030	1571	133	8.47
1996	0.020	1555	157	10.10
1997	0.015	1448	190	13.12
1998	0.035	1461	29	1.98
1999	0.020	1467	185	12.61
2000	0.025	1470	143	9.73
Average	0.026	1545	201	12.88

Note: The *Optimal Probability Cutoff* is the discrete probability level for which the 40:1 relative cost ratio between Type I error and Type 2 error is minimized. Type I error is defined as the probability that a firm which subsequently fails is predicted to remain solvent. Type II error is defined as the probability that a firm which remains solvent is predicted to fail.

To estimate how managerial ability influences a firm's duration in financial distress we utilize an accelerated failure time model, which is a useful representation of the relationship between a set of explanatory variables and duration. The probability distribution of duration is specified by the distribution function $F(t) = \Pr(T < t)$, which indicates the probability that the random variable *T*, the duration, is less than *t*, a particular value in *T*. The corresponding density function is $f(t) = dF(t)/dt$. Alternatively, one can define a survivor function $S(t) = 1 - F(t) = \Pr(T \geq t)$ the probability that the random variable *T* will equal or exceed the value *t*.

[13] Source: Annual Report of the Superintendent of the Insurance to the New York Legislature, Calendar Year 2000, 2001, 2002, and 2003 (www.ins.state.ny.us).

In the accelerated failure time model, the natural logarithm of the time under regulatory scrutiny, ln t, is formulated as:

$$\ln \ t = x_i b + w_i \tag{6}$$

where $\boldsymbol{x}_i$ is a vector of explanatory variables, b is a vector of regression coefficients (i.e. the semi-elasticities of the covariates on the expected duration or elasticities if the covariates are in logarithmic form), and w_i is an error term with a density function $f()$. The distributional form of the error term determines the regression model.

Some observed durations are censored in the sample, e.g. the firm is under regulatory scrutiny for a certain time and is still under regulatory scrutiny when last observed (in 2003). To obtain estimates with desirable properties, the model is estimated using the maximum-likelihood method. Letting d_i be a censoring indicator (d_i =1 if uncensored, d_i=0 if censored) and given data on (t_i, d_i, $\boldsymbol{x}_i$) for a random sample of size N, the maximum likelihood estimator of q is obtained by maximizing:

$$\ln L = \sum_{i=1}^{N} \left\{ d_i \ln[f(t_i, q \mid x_i)] + (1 - d_i) \ln[1 - F(t_i, q \mid x_i)] \right\} \tag{7}$$

The vector parameter q is estimated using maximum-likelihood upon choice of functional form. If we let $f(\,)$ equal the logistic density, then log-logistic regression is obtained. Similarly by letting $f(\,)$ be the normal density, the lognormal regression model is obtained. Finally, by setting $f(\,)$ equal to the extreme-value density yields the exponential and the Weibull regression models. To determine the appropriate distributional form we use the model that has the optimum fit for the data as judged by the Akaike information criterion (AIC).[14]

In our model the dependent variable is time in financial distress. The time origin of our analysis is initial financial distress, the first time the firm is subject to regulatory scrutiny in the 1989-2000 period. The time scale is one year. The firm's exit from regulatory scrutiny, when the firm is no longer under regulatory scrutiny in the 1990-2003 period, is the event that ends the duration, The efficiency scores for

[14] The AIC is estimated as –2(log likelihood) + 2(r+p+1), where r is the number of covariates and p is the number of ancillary parameters in the distribution. The preferred model is the one with the smallest AIC value.

pure technical, scale, allocative, and revenue efficiency are the variables of interest. If managerial quality at the time of initial distress reduces the time an insurer spends under regulatory scrutiny, the coefficient on these variables will be negative implying, that an increase in efficiency decreases a firm's expected time under regulatory scrutiny.

To isolate the impact of managerial efficiency from other potentially conflicting factors, two sets of control variables are incorporated along with year and state of domicile fixed effects. The first set of control variables are insurer-specific—"quality", "complexity", and other general characteristics. The second group controls for "zombie" insurers. Zombie insurers are economically insolvent but continue to operate because regulators take no formal action.[15] Zombies are firms that are routinely on the regulator's watch list but for which no formal regulatory action is taken against them because for all practical purposes the insurer has ceased operations. If not appropriately controlled for, these firms may bias our results because the abnormal amount of time they spend under regulatory scrutiny.

Insurer-Specific Control Variables

We account for insurer "quality" using leverage, liquidity, and exposure to catastrophic losses. Firms with less capital are not as well equipped to absorb unexpected losses and are thereby prone to increased regulatory scrutiny.[16] Leverage is measured as the ratio of net premiums written to policyholders' surplus. To account for a firm's liquidity, we include the percent of assets each firm has in stocks, investment grade bonds, and cash. An insurer's exposure to catastrophic losses is calculated as the percentage of premiums written by an insurer in Gulf Coast and Atlantic Coast states in all property lines plus the percentage of premium volume in earthquake insurance.

To incorporate the firm's "complexity" of business at the time of their initial distress, we utilize two diversification measures and three measures of product mix. The diversification variables are a line of

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[15] "These deeply insolvent firms may be likened to "zombies" in that they are kept alive by the black magic of government…" (Kane, 2004).

[16] Downs and Sommer (1999), Hall (2000), and Grace, Klein, and Phillips (2004) all provide evidence of increased risk taking by thinly capitalized insurers.

business Herfindahl and a geographical Herfindahl.[17] Overall greater diversification is predicted to have an attenuating effect on the duration under scrutiny. The three product composition variables are the percent of total premiums written in commercial long-tail lines, the percent of total premiums written in commercial short-tail lines, and the percent of total premiums written in personal long-tail lines.

Other firm characteristic control variables are size (log of total assets), organizational form, distribution system, and group membership. The mutual dummy variable accounts for a firm's incentive for risk-taking. The ownership and customer claim is bundled in a mutual, indicating that risk-taking attempts to increase the value of ownership will be offset by a corresponding reduction in the value of the policy. Thus mutual insurers have fewer incentives to take on higher risk than stock insurers (Mayers and Smith, 1988; Lamm-Tennant and Starks, 1994; and Lee, Mayers, and Smith, 1997). To control for insurer distribution type, an indicator variable is set equal to one if the firm is a direct writer. It is hypothesized that direct selling is less expensive than the agency system (Berger, Cummins, and Weiss, 1997; and Carr, Cummins, and Reagan, 1999); thereby, direct writing provides the insurer additional operational flexibility to remove itself from regulatory scrutiny when it becomes distressed. There are two competing hypotheses for the group indicator variable. Since the parent company is capable of providing a capital infusion to a subsidiary in financial distress, group membership allows a firm to remove itself from regulatory scrutiny quicker than a non-group affiliated firm. On the other hand, groups hold a valuable option that is not available to the freestanding insurer, namely the option to permit a subsidiary that is experiencing financial difficulties to fail (Phillips, Cummins and Allen, 1998; Merton, 1974).[18] To separate these potentially countervailing effects, an interaction variable between group membership and firms that fail is included.

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[17] The line of business Herfindahl is computed as the sum of the squares of premium written in line *i* divided by its total premiums written. The geographical Herfindahl is calculated as the sum of the squares of premium written in state *i* divided by its total premium written. A larger value of the line of business (geographical) Herfindahl indicates a greater concentrated of the firm's production across the various lines of insurance (states).

[18] The option's value results from corporate law. Creditors of a group member are not permitted to access the assets of a parent or other group members except when they succeed in "piercing the corporate veil," which typically entails the presence of fraud or some other type of misconduct (Easterbrook and Fischel, 1985).

Zombie Control Variables

We use eight variables to account for the firms that regulators know are troubled but yet no regulatory action is taken. The first is an indicator variable for whether the firm ultimately fails. The second, third and fourth zombie variables--premium growth, liability growth, and the ratio of liability growth to premium growth—account for the fact that zombies do not write much new business relative to the growth of their liabilities. The change in a firm's one-year loss reserve, controls for "weak" insurers that underestimate loss reserves (Petroni, 1992; Beaver, McNichols, and Nelson, 2000; and Neale, Habegger, and Peterson, 2003). Zombies are hypothesized to have a diminished ability to generate cash flow from operations; thus, the ratio of cash flow from operations to net premiums written is included. Finally, zombies are also hypothesized to not have an extensive staff; hence, the ratio of total expenses-to-total liabilities is predicted to be negatively related to a firm's duration in distress.

Hypothesis 3

The incurred costs of resolving property-liability insurer insolvencies have been historically larger than the costs incurred for other failed financial institutions, highlighting the importance of discovering the principle sources for the high cost of resolution. Previous studies have examined the differences in the cost of resolving insolvencies across insurers (Hall, 2000; Grace, Klein, and Phillips, 2004). Hall's main hypothesis is that the incentive structure among the various stakeholders of the guaranty fund system is misaligned, which leads to a regulatory free cash flow problem. Grace, Klein, and Phillips (2004), on the other hand, examine the incentives of the management of the insurance company in addition to the incentives of regulators. Specifically, they hypothesize that management has an incentive to exploit the asymmetric gains of risk-taking due to limited liability protection (Merton, 1974) and that this incentive is stronger for stock insurers, relative to mutual insurers, when the firm is financially impaired (Lee, Mayers, and Smith, 1997).

Our study differs from the previous research, in that while controlling for the influence of the incentive structure on regulators and managers, we directly examine whether the quality of management affects the differences in the resolution costs. Accordingly we propose the following null hypothesis:

Hypothesis 3 (H3): *Management quality does not influence the relative cost of insolvency.* The relative cost of insolvency is measured as the ratio of cumulative net guaranty association assessments from the insolvency as of 2003 to the assets of the firm prior to the regulator taking formal regulatory action. A limitation of this measure for the cost of insolvency is that we only have estimates for firms with claims that are covered by guaranty associations. In addition, the cost of the insolvency has to exceed the funds that can be collected from selling the firm's assets. Therefore, we do not directly observe the net costs when the assets of the insurer are sufficient to pay the covered insurance claims. For that reason the underlying linear regression of the latent variable is of the form:

$$y_i^* = a + b_{mq}' X_i^{mq} + b_{ic}' X_i^{ic} + b_{for}' X_i^{for} + e_i \qquad (8)$$

where y_i^* = latent resolution cost variable for insurer *i* equal to the ratio of net cumulative guaranty assessments by 2003 – to – insurer *i*'s total assets in year FEY-1,

X_i^{mq} = vector of managerial quality variables for firm *i* in the year of the firm's final entrance into financial distress,

X_i^{ic} = vector of insurer characteristic variables for firm *i* in the year of the firm's final entrance into financial distress,

X_i^{for} = vector of regulatory forbearance variables in the year of the firm's final entrance into financial distress,

a = estimated intercept term,

b_{mq}, b_{ic}, b_{for} = estimated parameter vectors,

e_i = random error term.

The observed variable y_i is $y_i = y_i^*$ whenever $y_i^* > 0$ and is $y_i = 0$ otherwise. The observed variable is censored at 0, so we estimate (8) using a Tobit regression model.

Similar to hypothesis two, we want to isolate the impact of managerial efficiency from other factors. Accordingly, we include two sets of control variables along with state of domicile and year fixed effects. The first set controls for firm "quality", "complexity", and general characteristics. The second set controls for regulatory forbearance.

Insurer-Specific Control Variables

The "quality" of the insurance company is proxied by five variables. Leverage, measured by ratio of the liabilities to assets, accounts a firm's capitalization and ability to absorb unexpected losses. To account for the ease in which receivers will likely be able to sell financial assets for an amount close to their stated value, the percent of assets each firm has in stocks, investment grade bonds, and cash is included. On the other extreme, the percent of a firm's assets in occupied real estate is incorporated since receivers may have difficulty selling these properties at their annual statement value. An indictor variable equal to one if the company has a provision for uncollectible reinsurance is used to control for insurers that may encounter difficulties collecting on their reinsurance payments due. Finally, an insurer's exposure to catastrophic losses is incorporated.

To account for the "complexity" of a firm's business at the time of its final entrance into distress, two variables are used to measure the firm's degree of diversification – a geographical Herfindahl index and a line of business Herfindahl index. Other firm characteristic variables are size (log of total assets), a mutual dummy variable, and a group indicator variable. The managerial discretion literature (Mayers and Smith, 1988) predicts that the costs associated with risk-taking are larger for mutuals than for stocks (for additional evidence see Lamm-Tennant and Starks, 1994; and Lee, Mayers, and Smith, 1997). The group indicator variable is included to recognize a group's valuable option to allow a subsidiary to fail (Phillips, Cummins and Allen, 1998; Merton, 1974).

Regulatory Forbearance Variables

To account for the possibility that the regulators exhibit regulatory forbearance against certain insurers, we include three explanatory variables. The first forbearance variable is an indicator equal to one if the year that the regulatory takes formal regulatory action against the troubled insurer, referred to as the first event year (FEY), is after 1994. The distinction between pre- and post-1994 is important because the NAIC began enacting the RBC model law in 1994. The model law instituted mandatory actions that domestic regulators must take against insurers with RBC ratios that fall below certain thresholds (Klein, 1995).

The second forbearance variable is an indicator variable equaling one if the firm operates only in a single state. Single state insurers are subject to only one regulator's supervision, and thus may have a greater ability to lobby for leniency regarding possible solvency related regulatory intervention. In contrast, insurers writing in multiple jurisdictions are subject to oversight by multiple regulators limiting the amount of discretion a domiciliary regulator can apply regarding the seizure and closure of a troubled insurer (Klein, 1995; Laffont and Martimort, 1999). In fact, Willenborg (2000) finds empirical evidence that solvency-related regulatory action against property-liability insurers is significantly and positively related to the number of states in which the insurer writes business. Furthermore, he discovers a significant and inverse relationship between the likelihood of regulatory intervention and firm size for single-state insurers.

The final forbearance control variable is equal to the year an insurer is placed into liquidation minus its FEY. There are two competing hypotheses for this variable. A longer time period between the liquidation date and the FEY could suggest either the regulator's willingness to reveal the poor financial condition of the insurer or greater regulatory forbearance.

V. Estimation Results

The Data

The list of insolvent insurers for the 1990-2003 period comes from the NAIC's Report on Receiverships and the A.M. Best Company (A.M. Best, 2003). The cost of liquidating an insurer comes from the *Assessment and Financial Information Report* published by the National Conference of Insurance Guaranty Funds (NCIGF, 2003). The NCIGF report records the cumulative payments, recoveries, and net cost through 2003 for each insolvency that triggered a guaranty fund assessment since 1969. All other data for the 1989-2003 period comes from the NAIC regulatory annual statements and the A.M. Best data tapes.

Efficiency Results

The DEA efficiency results are displayed in Table 4. There is no clear pattern in the efficiency scores from year to year. The average cost efficiency over the period is 33.3 percent, suggesting that the industry, on average, could have reduced costs by 66.7 percent if all managers operated on the production frontier and chose the cost minimizing input bundles. Decomposing cost efficiency into its components, we find that average pure technical efficiency (PTE) is 65.1 percent, the average scale efficiency (SE) is

89.5 percent, and the average allocative efficiency (AE) is 58.1 percent. There is a high amount of revenue inefficiency in the industry (average revenue efficiency is 18.9), indicating that the industry, on average, could have increased revenues by 81.1 percent if managers operated on the production frontier and picked the revenue maximizing output bundles.

Table 4: Data Envelopment Analysis Efficiency Scores
This table provides summary statistics for the DEA analysis efficiency scores. Sample means and standard deviations are reported by year. The DMU count is the number of decision-making units utilized in the analysis.

Year	DMU Count		PTE	SE	TE	AE	CE	RE
1989	1589	Mean:	0.562	0.856	0.469	0.546	0.235	0.123
		Std dev:	0.283	0.180	0.254	0.224	0.144	0.252
1990	1594	Mean:	0.607	0.908	0.543	0.585	0.306	0.089
		Std dev:	0.267	0.129	0.244	0.230	0.176	0.237
1991	1594	Mean:	0.621	0.895	0.547	0.453	0.242	0.076
		Std dev:	0.225	0.133	0.203	0.178	0.130	0.218
1992	1582	Mean:	0.640	0.913	0.574	0.558	0.312	0.311
		Std dev:	0.227	0.131	0.203	0.160	0.132	0.232
1993	1626	Mean:	0.664	0.879	0.573	0.491	0.284	0.202
		Std dev:	0.217	0.148	0.198	0.144	0.154	0.217
1994	1578	Mean:	0.588	0.866	0.498	0.518	0.257	0.276
		Std dev:	0.260	0.163	0.237	0.192	0.164	0.231
1995	1571	Mean:	0.741	0.935	0.690	0.608	0.422	0.284
		Std dev:	0.186	0.094	0.181	0.149	0.162	0.246
1996	1555	Mean:	0.651	0.882	0.565	0.618	0.342	0.286
		Std dev:	0.227	0.148	0.206	0.187	0.154	0.233
1997	1448	Mean:	0.644	0.861	0.545	0.607	0.33	0.066
		Std dev:	0.208	0.145	0.184	0.184	0.151	0.199
1998	1461	Mean:	0.700	0.922	0.640	0.646	0.420	0.222
		Std dev:	0.210	0.114	0.199	0.176	0.194	0.241
1999	1467	Mean:	0.719	0.929	0.662	0.687	0.459	0.208
		Std dev:	0.196	0.105	0.182	0.158	0.175	0.255
2000	1470	Mean:	0.673	0.892	0.593	0.661	0.387	0.120
		Std dev:	0.210	0.125	0.193	0.156	0.141	0.207
Total	18535	Mean:	0.651	0.895	0.575	0.581	0.333	0.189
		Std dev:	0.226	0.135	0.207	0.178	0.156	0.231

Note: PTE is Pure Technical Efficiency; SE is Scale Efficiency; TE is Total Technical Efficiency; AE is Allocative Efficiency; CE is Cost Efficiency; and RE is Revenue Efficiency.

Hypothesis 1 - Results

In our sample there are a total of 301 insolvent firms. The small number of failures is an unavoidable limitation of the analysis. The unbalanced nature of the sample, it contains many more solvent firms (0's) than insolvent firms (1's), prejudices prediction away from the insolvent firms (Greene, 2000). However, this equally impacts each model specification and highlights the need for comparing predictive accuracy by the Type I/Type II error trade off and the Receiver Operating Characteristic (ROC) curves.

Table 5: Logistic Regression Results--Financial Ratios vs. Efficiency Scores
Years: 1989-2000

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State of Domicile Fixed Effects	Yes	Yes	Yes	No	No	No
Number of Observations	15586	15586	15586	18267	18267	18267
Number of Insolvencies	301	301	301	301	301	301
Variable						
Intercept	-12.797 ***	-13.044 ***	-12.612 ***	2.354 ***	3.220 ***	2.581
Ln(Assets)	-0.355 ***	-0.312 ***	-0.366 ***	-0.347 ***	-0.307 ***	-0.358
Mutual Dummy	-1.185 ***	-1.104 ***	-1.224 ***	-1.439 ***	-1.365 ***	-1.479
…						
Pure Technical Efficiency		-0.840 ***			-1.001 ***	
Scale Efficiency		-0.180			-0.315	
Allocative Efficiency		-1.581 ***			-1.691 ***	
Revenue Efficiency			-0.280			-0.285
Log L	-1200.277	-1186.908	-1199.602	-1302.878	-1286.087	-1302.146
Pseudo R^2	19.230	20.130	19.280	15.090	16.180	15.130
Area Index of ROC	0.8379	0.8509	0.8383	0.8194	0.8319	0.8200
			Type I Error Rate (%)			
5 Percent Type II Error Rate	57.1	56.8	57.5	62.5	62.1	62.5
10 Percent Type II Error Rate	45.2	44.5	45.5	51.8	50.2	53.2
15 Percent Type II Error Rate	38.2	33.9	37.9	42.5	37.5	41.5
20 Percent Type II Error Rate	30.6	25.6	30.9	31.9	30.9	31.2
25 Percent Type II Error Rate	26.6	19.9	25.9	26.9	23.9	26.6
30 Percent Type II Error Rate	19.6	16.9	19.9	21.3	16.3	21.3

*** significant at .01 level; ** significant at .05 level; * significant at .10 level.

The estimation results of the logistic regressions are located in Table 5.[19] The IRIS and FAST ratios have been suppressed for ease of viewing. Models 1 & 4 are the standard insolvency models used by Grace, Harrington, and Klein (1998) and Cummins, Grace, and Phillips (1999). They contain the IRIS and FAST ratios, a mutual dummy variable, and firm size. These two models serve as a baseline to verify whether incorporating managerial quality improves insolvency prediction. In addition to the

[19] The insolvency regression models were also performed separately for each year in the sample. The results are contained in an appendix that is available from the authors upon request.

standard insolvency model variables, Models 2 & 5 include the components of cost efficiency—pure technical, scale, and allocative efficiency. Models 3 & 6 include revenue efficiency as well the standard insolvency model variables. Models 1, 2, and 3 differ from models 4, 5, and 6 by the inclusion of state of domicile dummy variables.

Models 2 & 5 reveal that pure technical efficiency is negative and significant, indicating that managers capable of implementing the best practice technology are *less* likely to fail. Allocative efficiency, a measure of the mangers ability to utilize the right combination of inputs, is also negative and significant in these specifications. Thus managers who better utilize the correct input combination are *less* likely to become insolvent. Scale efficiency is not as robust as allocative efficiency or pure technical efficiency in predicting insurer insolvency and is insignificant in every specification. Revenue efficiency (models 3 & 6) is also not a strong predictor of insolvency; it has the expected sign, but it is insignificant.

The inclusion of the cost efficiency components (models 2 & 5) and revenue efficiency (models 3 & 6) increases the pseudo R^2. The improvement in the pseudo R^2 could be due to the inclusion of additional explanatory variables. The cost efficiency components, though, increase the area index of the ROC curve, demonstrating that these models *outperform* the standard model. The improvement upon the baseline model is not as great for the models that include revenue efficiency. However, models 3 & 6 marginally outperform the standard models (1 & 4).

The models with the cost efficiency components also have better Type I/Type II error trade off performance than the standard models. The models with revenue efficiency do not appear to have superior Type I/Type II error performance. Figure 1 displays the Type I/Type II error rate trade-off for models 1 thru 3. The inclusion of managerial quality variables improves insolvency prediction. For each level of Type II error, the model that includes the cost efficiency managerial ability variables has a lower Type I error. The cost efficiency components yield a considerable improvement on the standard insolvency model.

Figure 1: Type I/Type II Error Trade-Off for 1989-2000
(With State of Domicile Fixed Effects - Models 1 - 3)

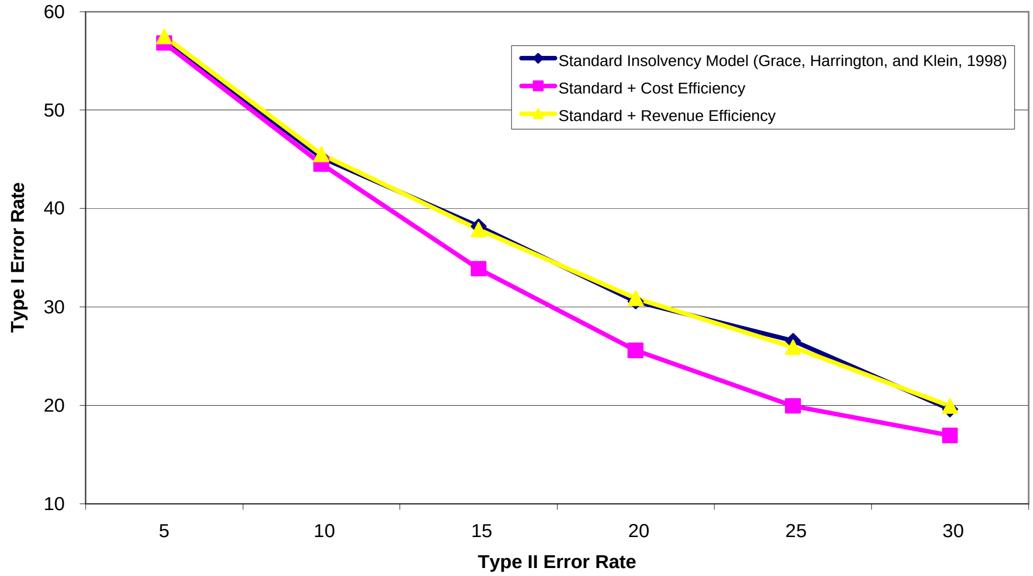

Table 6 reveals the classification rates for insolvent firms, healthy firms, and all firms in a year-by-year analysis of the standard insolvency tracking tools plus the cost efficiency measures.[20] Classification is made utilizing the yearly optimal cutoff point for a 40:1 relative cost ratio between Type I error and Type II error. The average classification rate of insolvent firms is 74.6% over the period, an 11.5 percent improvement upon the standard insolvency tools (Table 7). The inclusion of the cost efficiency variables pushes the optimal cutoff point to a higher probability level, resulting in a decrease in the total number of firms under regulatory scrutiny and a 2.0% decline in the classification of healthy firms. Even though managerial quality variables result in a reduction in the classification of healthy firms, it reduces the number of firms on the regulatory "radar-screen". Overall, the inclusion of managerial quality variables improves insolvency prediction.

[20] Again the year-by-year analysis results are contained in an appendix that is available from the authors.

Table 6: Classification Rates using Standard Insolvency Tools (IRIS ratios, FAST ratios, Organizational Form, and Firm Size) and Cost Efficiency Scores

Year	% of Insolvent Firms Classified Correctly	% of Healthy Firms Classified Correctly	Overall % of Firms Classified Correctly
1989	84.3	83.5	83.6
1990	91.3	72.0	72.6
1991	82.9	79.2	79.2
1992	95.5	78.3	78.5
1993	76.5	91.2	91.1
1994	60.0	90.1	89.7
1995	68.2	91.0	90.7
1996	66.7	79.8	79.2
1997	61.5	90.5	90.2
1998	63.6	91.1	90.9
1999	70.0	94.4	94.1
2000	68.2	92.7	92.4
Average	74.1	86.2	86.0

Note: Classification is made using the yearly optimal cutoff point for 40:1 relative cost ratio between Type I error and Type II error. Type II error is defined as the probability that a firm which remains solvent is predicted to fail. Type I error is defined as the probability that a firm which subsequently fails is predicted to remain solvent.

Table 7: Percent Improvement in Classification Rates using Cost Efficiency Scores with Standard Insolvency Tools (IRIS ratios, FAST ratios, Organizational Form, and Firm Size) compared to using only the Standard Insolvency Tools

Year	% of Insolvent Firms Classified Correctly	% of Healthy Firms Classified Correctly	Overall % of Firms Classified Correctly
1989	0.01	4.35	4.17
1990	6.52	5.90	5.92
1991	9.76	-9.29	-8.81
1992	40.91	-16.38	-15.60
1993	17.70	-4.00	-3.70
1994	-5.00	-1.22	-1.29
1995	9.09	-1.34	-1.18
1996	16.70	-10.75	-10.89
1997	7.69	3.02	3.06
1998	45.45	-7.01	-6.61
1999	5.00	6.20	6.19
2000	13.64	1.71	1.89
Average	11.50	-2.00	-1.87

Hypothesis 2 – Results

Table 8 reveals the summary statistics for distressed insurers in comparison to non-distressed insurers. Firms that are categorized as distressed are significantly more likely to be stock insurers than non-distressed insurers. In addition, distressed insurers are significantly smaller and less diversified (both geographically and in the products they write) than non-distressed firms. On a univariate basis distressed firms are significantly less allocatively and cost efficient, while non-distressed firms are significantly less technically, scale, and revenue efficient.

Table 9 displays the descriptive statistics of the variables utilized in the duration under regulatory scrutiny regression. The regression was estimated using three distributional assumptions: lognormal, log-logistic, and Weibull. The model with the optimum fit, judged by the Akaike information criterion (AIC), is the log-logistic.[21] Accordingly only the results of the log-logistic regression model are reported in Table 10. A positive coefficient implies that an increase in the variable increases the expected time under regulatory scrutiny. Similarly, a negative coefficient indicates a decrease in the expected time under watch.

Table 8: Summary Statistics of Distressed and Non-Distressed Property-Liability Insurers--1989-2000

	Means		T-Test[1]
Variable Definition	Distressed	Non-Distressed	
Number of observations	2407	16131	
Pure Technical Efficiency	0.647	0.650	-0.56
Scale Efficiency	0.902	0.894	2.71 ***
Total Technical Efficiency	0.583	0.573	1.85 *
Allocative Efficiency	0.498	0.592	-20.45 ***
Cost Efficiency	0.286	0.338	-13.06 ***
Revenue Efficiency	0.225	0.184	6.18 ***
Mutual	9.59%	25.10%	-22.44 ***
Stock	83.72%	71.93%	14.14 ***
Size (Log of Assets)	16.266	17.953	-46.75 ***
Line of Business Herfindahl	0.525	0.399	20.49 ***
Geographical Herfindahl	0.735	0.562	21.12 ***
Measured Probability of Insolvency	0.076	0.007	29.27 ***

[1]T-Test for statistical significance of differences between distressed and non-distressed firm means

*** Significant at .01 level; ** Significant at .05 level; * Significant at .10 level.

[21] The AIC for model 3 in the cost efficiency setting was 1045.9 using the log-logistic model, 1190.3 for the lognormal model and for the 1738.9 Weibull model. When revenue efficiency was used in Model 3, the AIC was 1048.8, 1192.6, and 1753.9 for the log-logistic, lognormal, and Weibull models, respectively.

When only the three components of cost efficiency are used in the regression model (model 1), pure technical efficiency is significant and negative. Managers that implement “better-practice” production technology are able to remove their firm from regulatory scrutiny sooner than less pure technically efficient managers. After including variables that control for insurer quality, firm complexity, other general firm characteristics, and for the firms that eventually fail, the coefficient on pure technical efficiency remains negative and significant. Scale efficiency also becomes negative and significant. Managerial quality significantly influences the firm’s ability to remove itself from distress.

Table 9: Summary Statistics of Duration in Financial Distress Regression

Variable	Mean	Median	Std. Dev	Min	Max
Dependent Variable					
Duration in Financial Distress	1.373	1.000	0.713	1.000	7.000
Efficiency Variables - "Quality" of Management					
Pure Technical Efficiency	0.644	0.620	0.260	0.104	1.000
Scale Efficiency	0.901	0.961	0.143	0.074	1.000
Total Technical Efficiency	0.580	0.538	0.257	0.056	1.000
Allocative Efficiency	0.501	0.492	0.214	0.038	1.000
Cost Efficiency	0.284	0.242	0.183	0.010	1.000
Revenue Efficiency	0.230	0.077	0.310	0.000	1.000
"Quality" of Firm at Initial Distress					
Net Premiums Written to Policyholders' Surplus Ratio	1.561	1.346	1.235	0.017	4.550
% of Assets in Stocks, Investment Grade Bonds, and Cash	79.57%	83.77%	17.53%	17.75%	100.00%
% Premiums in Catastrophe Prone Lines/Areas	6.70%	0.00%	16.13%	0.00%	100.00%
"Complexity" of Firm at Initial Distress					
Geographical Herfindahl	0.757	1.000	0.344	0.036	1.000
Line of Business Herfindahl	0.514	0.483	0.276	0.000	1.000
% of Total Premiums Written in Commercial Long-Tail Lines	29.43%	8.69%	35.78%	0.00%	100.00%
% of Total Premiums Written in Commercial Short-Tail Lines	29.66%	16.88%	34.18%	0.00%	100.00%
% of Total Premiums Written in Personal Long-Tail Lines	29.30%	15.16%	31.47%	0.00%	100.00%
Characteristics of Firm					
Size (Log of Total Assets)	16.349	16.213	1.644	11.505	22.997
Indicator =1 for Mutual Insurer	0.110	0.000	0.313	0.000	1.000
Indicator =1 for Direct Insurer	0.108	0.000	0.311	0.000	1.000
Indicator = 1 if Firm is Member of a Group	0.520	1.000	0.500	0.000	1.000
Zombie Control Variables					
% of Firms in Sample that Ultimately Fail	11.62%	0.00%	32.06%	0.00%	100.00%
Premium Growth Rate	0.202	0.048	0.701	-0.781	2.629
Liability Growth Rate	0.317	0.090	0.773	-0.385	3.200
Liability Growth Rate to Premium Growth Rate Ratio	13.457	0.615	446.483	-675.538	18517.560
Change in One-Year Loss Reserve	-0.516	-0.590	2.940	-8.661	9.270
Ceded premiums over Gross Premiums Written	0.434	0.369	0.345	0.000	1.250
Cash Flow from Operations over Net Premiums Written	0.136	0.109	0.558	-1.165	1.598
Total Expenses over Total Liabilities	0.498	0.410	0.352	0.031	1.531

Number of observations = 1755.

Table 10: Duration in Distress for Property-Liability Insurers-- 1989-2000

Maximum-Likelihood Log-logistic Regression Model with State of Domicile and Year Fixed Effects

	Cost Efficiency			Revenue Efficiency		
Variable	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Intercept	0.348522 ***	1.304717 ***	1.286766 ***	0.190695 ***	1.250547 ***	1.248355 ***
	(0.079834)	(0.264734)	(0.250849)	(0.014013)	(0.264404)	(0.263674)
Efficiency Variables - "Quality" of Management						
Pure Technical Efficiency	-0.128812 ***	-0.096948 ***	-0.090342 ***			
	(0.037796)	(0.032307)	(0.032307)			
Scale Efficiency	-0.093558	-0.107936 *	-0.112246 *			
	(0.07397)	(0.064043)	(0.063899)			
Allocative Efficiency	0.000106	0.030618	0.027932			
	(0.040992)	(0.040673)	(0.040826)			
Revenue Efficiency				-0.046940 *	-0.075012 ***	-0.079269 ***
				(0.025923)	(0.027432)	(0.02813)
"Quality" of Firm at Initial Distress						
Net Premiums Written to Policyholders' Surplus Ratio (*LEVERAGE*)		0.002259	0.002083		0.012003	0.01278
		(0.00267)	(0.002617)		(0.007657)	(0.008053)
% of Assets in Stocks, Investment Grade Bonds, and Cash		-0.086139 *	-0.076184		-0.111965 **	-0.106884 *
		(0.050442)	(0.049571)		(0.054894)	(0.057952)
% Premiums in Catastrophe Prone Lines/Areas (*CAT*)		-0.042155	-0.04477		-0.04854	-0.054073
		(0.053021)	(0.052834)		(0.054385)	(0.055502)
"Complexity" of Firm at Initial Distress						
Geographical Herfindahl		-0.011136	-0.010786		-0.008701	-0.007004
		(0.022395)	(0.022418)		(0.023015)	(0.023204)
Line of Business Herfindahl		-0.026959	-0.032446		-0.022578	-0.025256
		(0.025819)	(0.025668)		(0.027526)	(0.028996)
% of Total Premiums Written in Commercial Long-Tail Lines		0.052926 ***	0.052742 ***		0.114614 ***	0.11525 **
		(0.013136)	(0.013289)		(0.044589)	(0.045191)
% of Total Premiums Written in Commercial Short-Tail Lines		-0.000093	-0.000095		0.00291	0.004807
		(0.000061)	(0.000061)		(0.039768)	(0.040521)
% of Total Premiums Written in Personal Long-Tail Lines		0.113403 ***	0.114105 ***		0.15375 ***	0.157914 ***
		(0.037077)	(0.037324)		(0.059273)	(0.06029)
Characteristics of Firm						
Size (Log of Total Assets)		-0.024675 ***	-0.024010 ***		-0.029777 ***	-0.030020 ***
		(0.006195)	(0.006237)		(0.00685)	(0.007152)
Indicator =1 for Mutual Insurer		-0.079844 ***	-0.081547 ***		-0.084473 ***	-0.088095 ***
		(0.025643)	(0.025948)		(0.026792)	(0.027035)
Indicator =1 for Direct Insurer		-0.034026 *	-0.035334 *		-0.031886	-0.034751 *
		(0.019345)	(0.019134)		(0.019637)	(0.019631)
Indicator = 1 if Firm is Member of a Group (*GROUP*)		-0.017553	-0.020374		-0.015575	-0.016629
		(0.016378)	(0.01654)		(0.016751)	(0.017327)
Zombie Control Variables						
Indicator = 1 if Firm Ultimately Fails (FAIL)		0.000717	0.001386		0.063868	0.066762
		(0.041094)	(0.041222)		(0.058535)	(0.058261)
Premium Growth Rate			0.000044 ***			0.00396
			(0.000011)			(0.012921)
Liability Growth Rate			0.000053			0.003581
			(0.000481)			(0.011628)
Liability Growth Rate to Premium Growth Rate Ratio			0.000025			0.000042 ***
			(0.000016)			(0.000004)
Change in One-Year Loss Reserve			0.000029			0.001377
			(0.000231)			(0.002248)
Ceded Premiums over Gross Premiums Written			0.000000			0.000814
			(0.000000)			(0.02137)
Cash Flow from Operations over Net Premiums Written			-0.000009 *			0.008556
			(0.000006)			(0.013165)
Total Expenses over Total Liabilities			-0.000026 ***			-0.008054
			(0.000007)			(0.024988)
Interaction Variables						
Interaction Term A: *FAIL* x *CAT*		0.229909	0.233336		0.28644	0.291159
		(0.254981)	(0.254039)		(0.247641)	(0.249091)
Interaction Term B: *FAIL* x *LEVERAGE*		-0.01737 **	-0.016896 **		-0.055669 **	-0.056857 **
		(0.007811)	(0.007985)		(0.02585)	(0.025746)
Interaction Term C: *FAIL* x *GROUP*		0.078363	0.078478		0.075342	0.077111
		(0.065828)	(0.065442)		(0.066109)	(0.066668)
Log Likelihood Function Value	-878.950	-499.8218	-494.971	-884.962	-501.1154	-498.3889

Note: *** significant at .01 level; ** significant at .05 level; * significant at .10 level.
Robust Standard Errors are Reported in Parentheses.

Other factors that impact duration under regulatory scrutiny include product mix, firm size, organizational form, distribution system, and the proportion of liquid assets held. Insurers that write a greater percentage of their business in long-tail lines have a longer expected time in distress. While larger firms, mutuals, direct writers, and firms that maintain a relatively liquid asset portfolio remain under regulatory scrutiny for a significantly shorter length of time. The total effect of leverage is insignificant. However, the interaction between *FAIL* and *LEVERAGE* is significantly negative indicating that regulators take swift action against distressed firms with a high degree of leverage.

In the third specification of the model, we control for zombie insurers and the results regarding managerial influence do not change considerably. Managers that produce at the right scale and adopt the best produce technology still spend less time under regulatory scrutiny. Product mix, firm size, organizational form, and distribution system are still important determinants in a firm's ability to remove itself from distress. Cash flow from operations is also significant. Managers of firms with a higher level of cash flow from operations are more capable of extricating themselves from the regulator's watchful eye. As expected, firms with a high premium growth rate have a longer expected duration under scrutiny. Distressed firms with a higher ratio of total expenses to total liabilities spend significantly less time under scrutiny. Initially this result seems awkward. However, we believe that it provides proof of the existence of zombies, i.e. troubled insurers that the regulators know about yet take no action against because they have for all practical purposes ceased operations. The interaction term between *FAIL* and *LEVERAGE* is still significantly negative, implying regulators take relatively swift action against highly levered distressed firms.

The results of the revenue efficiency regression models are comparable to the cost efficiency models. More revenue efficient firms remain under regulatory scrutiny for a shorter length of time. Large firms, mutuals, direct writers, and firms with a higher proportion of liquid assets spend less time in distress, while insurers specializing in long-tail lines remain for a longer time period. The ratio of total expenses to total liabilities is not significant in the revenue efficiency model. Firms with a higher ratio of liability growth to premium growth spend significantly longer time under regulatory scrutiny. On the whole, higher quality managers reduce a firm's time in regulatory scrutiny.

Hypothesis 3 – Results

The summary statistics for the analysis of hypothesis 3 are located in Table 11. On average, there are 2.76 years between a firm's final entrance into financial distress prior to regulatory action. The median interval between the distress year and the first event year is 3 years. For firms that access the guaranty fund system, the average cost to resolve insolvency is roughly $1.02 for every dollar of pre-insolvency assets. The maximum cost of insolvency is an astounding $27.92 per pre-insolvency dollar of assets, and the average cost of the five most expensive insolvencies is $9.68 for every dollar of pre-insolvency assets.[22]

Table 11: Summary Statistics: U.S. Property & Liability Insolvencies 1989-2003

Variable	Num	Mean	Median	Std. Dev	Min	Max
Net GF Assessment by 2003/Pre-Insolvency Assets						
All Observations	148	0.765	0.223	2.463	0.000	27.916
Only Insurers that access the Guaranty Funds	111	1.020	0.440	2.801	0.000	27.916
First Event Year	148	1995.220	1994.000	3.955	1990.000	2003.000
Distress Year	148	1992.450	1991.000	3.628	1989.000	2000.000
First Event Year - Distress Year	148	2.764	3.000	1.808	1.000	12.000
Efficiency Variables - "Quality" of Management at Time of Distress						
Pure Technical Efficiency	148	0.5974472	0.5677283	0.268679	0.1087886	1
Scale Efficiency	148	0.9032722	0.9702257	0.146971	0.0741262	1
Total Technical Efficiency	148	0.5469291	0.5107518	0.274802	0.0741262	1
Allocative Efficiency	148	0.4590909	0.4494299	0.188779	0.0804556	1
Cost Efficiency	148	0.2508554	0.2049782	0.18787	0.0339271	1
Revenue Efficiency	148	0.2302313	0.0785155	0.30444	0.0011185	1
"Quality" of the Company at Time of Distress						
Liabilities - to - Assets ratio	148	0.6875896	0.7323945	0.189707	0.1144169	0.9740491
% of Assets in Stocks, Investment Grade Bonds, and Ca	148	0.6775338	0.6936594	0.188816	0.1854518	1
% Assets in Occupied Real Estate	148	0.0326758	0	0.083763	0	0.7169688
Indicator = 1 if Co. has a Provision for Reinsurance	148	0.2972973	0	0.458621	0	1
% Premiums in Catastrophe Prone Lines/Areas	148	0.0963841	0.0246166	0.141662	0	0.8105411
"Complexity" of the Company at Time of Distress						
Geographical Herfindahl Index	148	0.6933331	0.9290128	0.360061	0.0469508	1
Line of Business Herfindahl Index	148	0.5015757	0.4783472	0.236977	0.0151612	1
Characteristics of Firm at Time of Distress						
Size (Log of Total Assets)	148	16.5082819	16.4430927	1.502727	11.505367	22.629308
Indicator =1 for Mutual Insurer	148	0.0675676	0	0.251855	0	1
Indicator = 1 if Firm is Member of a Group	148	0.4121622	0	0.493895	0	1
Forbearance Variables at Time of Distress						
Indicator = 1 if First Event Year > 1	148	0.4662162	0	0.500551	0	1
Indicator = 1 if Single State Co.	148	0.4662162	0	0.500551	0	1
Liquidation Year - FEY	148	0.3783784	0	1.500138	0	12

[22] Not too surprising. Four of the top five most expensive insolvencies were firms that were domiciled in the state of Florida and liquidated in 1992 – the year of Hurricane Andrew.

The skewness in our dependent variable creates some econometric challenges.[23] In the standard linear regression model, skewness is not a considerable impediment since least squares estimates are consistent and unbiased even when the normality assumption is violated (the estimates, though, are generally not efficient). The situation is substantively different in the Tobit model since maximum likelihood estimates yield inconsistent estimates when the disturbances are non-normal (Arabmazar and Schmidt, 1982). To control for the extreme skewness of the dependent variable, we drop the seven observations above the 95th percentile of the dependent variable (i.e. the liquidations with a cost of insolvency greater than 2.75 times the pre-insolvency assets of the insurer). Eliminating these extreme values reduces the skewness of the remaining 105 non-zero observations to 1.78.

The estimation results of the models using the components of cost efficiency are in Table 12 and the estimation results using revenue efficiency are in Table 13. Both tables include six different model specifications. Models 1 thru 3 include all 148 of our sample observations, while models 4 thru 6 contain the results of the estimation on our reduced sample of 141 observations. Models 2 and 5 include state of domicile dummy variables and models 3 and 6 include both first event year dummy variables and state of domicile dummies.

The cost efficiency models that include all the sample observations (models 1 thru 3) reveal that managers that are relatively more skilled at producing at the appropriate scale (scale efficient) and using the best technology (purely technical efficient) are significantly associated with a lower cost of resolving insurer insolvencies. It is possible that the presence of extremely inefficient companies is driving the results of the full sample; however, we cannot be certain since the inclusion of the outliers produces an inconsistent estimator.

When the outliers are eliminated, scale efficiency is no longer significant. However, pure technical efficiency remains negative and significant, indicating that managers that implement better practice technology reduce the relative cost of insolvency resolution. In fact, pure technical efficiency is

[23] The skewness of our dependent variable for the 111 firms that access the guaranty fund system is 8.34, while the skewness is 9.4 for all firms in our sample.

the most consistent and robust factor in reducing net guarantee fund assessments. In the revenue efficiency models with the outliers eliminated (Table 13, models 4 thru 6), revenue efficiency is negative and significant when first event year and state of domicile fixed effects are utilized. Revenue efficiency is a significant factor in reducing the cost of resolving insolvencies.

The other factors that influence the cost of insolvency are fairly similar between the cost efficiency regression models and the revenue efficiency regression models. We will therefore focus our discussion on the results in the cost efficiency regression models. The degree of exposure to catastrophe losses is significantly positive in models 1-4, indicating that a large factor in the cost of insolvency is unforeseen catastrophes. The liabilities to asset ratio coefficient is positive and significant in models 3, 5 and 6 suggesting that firms with less capital and are not as well equipped to absorb unexpected losses.

Contrary to expectations, firms with a larger percent of assets in stocks, investment grade bonds, and cash have a higher cost of insolvency. Therefore, it appears that the ease in which receivers will likely be able to sell financial assets for an amount close to their stated value (when measured at the time of a firm's last entrance in distress) does not lessen guarantee assessments.

The line of business Herfindahl index is negative and significant in the models that do not include the outliers. This is consistent with the hypothesis that greater complexity increases insolvency costs and is in opposition to the hypothesis that greater diversification, by reducing the volatility of the firm's earning stream, yields lower costs of insolvency. Thus it appears that insurers operating in many lines require greater transactions costs to coordinate the activities of the guaranty associations. In model 5, the mutual dummy variable is negative and significant suggesting that the costs associated with risk-taking are larger for mutuals than for stocks. An additional significant factor in model 6 is group membership. Firms that are members of a group access the guarantee funds less than unaffiliated firms.

Table 12: Cost of Liquidating Property & Liability Insurers: 1989-2003

	Cost Efficiency					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
First Event Year Fixed Effects	No	No	Yes	No	No	Yes
State of Domicile Fixed Effects	No	Yes	Yes	No	Yes	Yes
Outliers Present	Yes	Yes	Yes	No	No	No
Number of Observations	148	148	148	141	141	141
Variable						
Intercept	-2.029	0.987	-1.622	-0.291	0.080	-0.903
	(3.801)	(4.988)	(5.236)	(1.057)	(1.243)	(1.231)
Efficiency Variables - "Quality" of Management						
Pure Technical Efficiency	-1.996 **	-2.666 ***	-2.910 ***	-0.700 ***	-1.052 ***	-1.051 ***
	(0.825)	(0.928)	(0.986)	(0.232)	(0.239)	(0.236)
Scale Efficiency	-4.597 ***	-4.709 ***	-5.181 ***	-0.150	-0.100	-0.279
	(1.557)	(1.639)	(1.703)	(0.517)	(0.495)	(0.474)
Allocative Efficiency	-0.014	-0.584	-1.661	0.092	0.160	-0.106
	(1.171)	(1.35)	(1.477)	(0.316)	(0.326)	(0.332)
"Quality" of the Company at Initial Distress						
Liabilities - to - Assets ratio	1.594	2.166	2.991 *	0.654	0.965 **	0.925 **
	(1.537)	(1.64)	(1.727)	(0.413)	(0.392)	(0.378)
% of Assets in Stocks, Investment Grade Bonds, and Cash	2.616 **	2.959 **	3.644 **	0.357	0.965 **	1.018 **
	(1.286)	(1.441)	(1.61)	(0.368)	(0.385)	(0.396)
% of Assets in Occupied Real Estate	-1.571	-1.017	0.955	-0.469	-0.315	0.431
	(3.449)	(3.613)	(3.869)	(0.844)	(0.748)	(0.769)
Indicator = 1 if Co. has a Provision for Reinsurance	-0.288	-0.313	-0.264	-0.056	0.005	-0.012
	(0.509)	(0.559)	(0.558)	(0.138)	(0.136)	(0.128)
% Premiums in Catastrophe Prone Lines/Areas	10.175 ***	12.973 ***	13.888 ***	0.938 *	0.101	0.153
	(1.628)	(2.061)	(2.078)	(0.505)	(0.574)	(0.556)
"Complexity" of the Company at Initial Distress						
Geographical Herfindahl Index	0.798	0.226	1.102	0.135	0.147	0.314
	(1.011)	(1.2)	(1.298)	(0.269)	(0.285)	(0.29)
Line of Business Herfindahl Index	0.382	0.305	1.026	-0.442 *	-0.595 **	-0.537 **
	(0.93)	(1.011)	(1.092)	(0.249)	(0.243)	(0.244)
Characteristics of Firm						
Size (Log of Total Assets)	0.203	0.131	0.189	0.037	-0.015	0.053
	(0.24)	(0.276)	(0.299)	(0.064)	(0.064)	(0.065)
Indicator =1 for Mutual Insurer	0.918	1.034	2.380	-0.261	-1.005 **	-0.361
	(0.878)	(1.339)	(1.5)	(0.262)	(0.408)	(0.44)
Indicator = 1 if Firm is Member of a Group	-0.391	-0.737	-0.651	-0.169	-0.158	-0.244 **
	(0.462)	(0.509)	(0.525)	(0.125)	(0.124)	(0.12)
Forbearance Variables						
Indicator = 1 if First Event Year > 1994	-0.071	0.007	0.343	-0.194	-0.109	-0.020
	(0.48)	(0.557)	(1.698)	(0.129)	(0.135)	(0.391)
Indicator = 1 if Single State Co.	-0.182	0.184	-0.256	0.162	0.198	0.123
	(0.724)	(0.76)	(0.828)	(0.196)	(0.184)	(0.187)
Liquidation Year - FEY	0.054	0.093	0.061	-0.034	-0.033	-0.042
	(0.134)	(0.141)	(0.139)	(0.036)	(0.033)	(0.031)
Log Likelihood Function Value	-274.424	-264.152	-254.755	-128.298	-103.69	-87.6077

Note: *** significant at .01 level; ** significant at .05 level; * significant at .10 level. Standard Errors are Reported in Parentheses.

Table 13: Cost of Liquidating Property & Liability Insurers: 1989-2003

	Revenue Efficiency					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
First Event Year Fixed Effects	No	No	Yes	No	No	Yes
State of Domicile Fixed Effects	No	Yes	Yes	No	Yes	Yes
Outliers Present	Yes	Yes	Yes	No	No	No
Number of Observations	148	148	148	141	141	141
Variable						
Intercept	-4.580	0.060	-3.030	-0.430	0.370	-0.727
	(3.931)	(5.118)	(5.258)	(1.034)	(1.219)	(1.18)
Efficiency Variables - "Quality" of Management						
Revenue Efficiency	-1.285 *	-0.925	-1.317	-0.319	-0.388 *	-0.456 **
	(0.752)	(0.803)	(0.873)	(0.204)	(0.196)	(0.196)
"Quality" of the Company at Initial Distress						
Liabilities - to - Assets ratio	1.365	1.242	2.473	0.540	0.678	0.703 *
	(1.622)	(1.744)	(1.838)	(0.422)	(0.412)	(0.396)
% of Assets in Stocks, Investment Grade Bonds, and Cash	1.858	1.684	1.888	0.261	0.559	0.557
	(1.33)	(1.483)	(1.619)	(0.375)	(0.391)	(0.39)
% of Assets in Occupied Real Estate	-3.860	-3.446	-0.894	-0.746	-0.802	-0.002
	(3.513)	(3.606)	(3.708)	(0.836)	(0.774)	(0.763)
Indicator = 1 if Co. has a Provision for Reinsurance	-0.091	-0.246	-0.205	-0.034	-0.052	-0.067
	(0.535)	(0.593)	(0.59)	(0.142)	(0.145)	(0.135)
% Premiums in Catastrophe Prone Lines/Areas	9.420 ***	11.411 ***	11.967 ***	0.766	-0.246	-0.196
	(1.687)	(2.097)	(2.109)	(0.499)	(0.572)	(0.545)
"Complexity" of the Company at Initial Distress						
Geographical Herfindahl Index	0.480	-0.779	-0.154	0.141	0.041	0.174
	(1.054)	(1.22)	(1.276)	(0.273)	(0.29)	(0.285)
Line of Business Herfindahl Index	0.503	0.315	1.222	-0.422	-0.572 **	-0.465 *
	(0.984)	(1.084)	(1.189)	(0.257)	(0.259)	(0.262)
Characteristics of Firm						
Size (Log of Total Assets)	0.105	-0.009	-0.038	0.029	-0.013	0.031
	(0.246)	(0.272)	(0.287)	(0.064)	(0.064)	(0.063)
Indicator =1 for Mutual Insurer	0.796	0.535	1.370	-0.321	-0.974 **	-0.440
	(0.883)	(1.369)	(1.451)	(0.265)	(0.437)	(0.454)
Indicator = 1 if Firm is Member of a Group	-0.404	-0.816	-0.610	-0.157	-0.161	-0.216 *
	(0.491)	(0.55)	(0.562)	(0.13)	(0.133)	(0.128)
Forbearance Variables						
Indicator = 1 if First Event Year > 1994	-0.421	-0.586	0.472	-0.248 *	-0.229 *	0.190
	(0.502)	(0.574)	(1.798)	(0.131)	(0.138)	(0.397)
Indicator = 1 if Single State Co.	0.235	0.667	0.341	0.149	0.207	0.122
	(0.746)	(0.787)	(0.834)	(0.196)	(0.188)	(0.186)
Liquidation Year - FEY	0.036	0.114	0.085	-0.029	-0.028	-0.034
	(0.141)	(0.149)	(0.145)	(0.037)	(0.035)	(0.032)
Log Likelihood Function Value	-281.27	-271.786	-262.07	-132.172	-111.976	-94.9332

Note: *** significant at .01 level; ** significant at .05 level; * significant at .10 level. Standard Errors are Reported in Parentheses.

VI. Conclusions and Policy Implications

Although mismanagement and fraud were cited to be important elements in insurer insolvencies, no direct, verifiable action has been taken to combat the impact of mismanagement on property-liability insurer insolvencies. Furthermore, to date there is a paucity research connecting insurer mismanagement to insurance company insolvencies. We attempt to find the connection between mismanagement and insurance company distress and failure.

Lang and Stulz (1992), John, Lang, and Netter (1992), and Khanna and Poulsen (1995) all find that even though managers are not less skilled than their contemporaries they do serve as scapegoats for their firm's failure. In contrast, we find a correlation between inefficient management and the likelihood of property-liability insurer insolvency. In fact, we find that when we include measures of managerial quality to the standard insolvency monitoring tools, the average classification rate of distressed firms increases by 11.5% over the 1989-2000 period. Furthermore, utilizing a definition of financial distress that does not solely rely on IRIS ratios, we find that superior managers are able to remove their firms from regulatory scrutiny sooner than inferior managers. We also find evidence that managerial quality, measured when a firm last enters distress, decreases the ultimate costs of insolvency.

Our definition of management quality is basic. Does the manager do well at minimizing cost, maximizing revenue, operating at the correct scale, and using its inputs according to their marginal productivities? Managerial quality, however, is probability much more than just this efficiency component. In fact, one can argue that firms that are over-exposed to unforeseen shocks are badly managed too. What this paper does show is that a certain type of mismanagement influences solvency prospects—managerial quality as measured by our efficiency scores improves the overall insolvency prediction rate. Nevertheless, there are still a significant number of distressed firms which are not being classified correctly (roughly 5-40% depending on the year). These misclassifications may be due to bad luck or unforeseen shocks. However, we have not gleaned all we can from management quality to say that some of the remaining unexplained failures are entirely due to factors beyond management's control.

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Appendix A – The DEA Methodology

DEA uses a standard linear programming technique to pinpoint peer groups of efficient firms for *each* firm or decision-making unit (DMU) being evaluated. A firm is fully efficient (efficiency of 1.0) if it lies on the frontier and inefficient (efficiency < 1) if it is not on the frontier, which means that its outputs could be produced more efficiently by another firm or firms.

DEA total technical efficiency is measured by estimating "best-practice" production frontiers, utilizing the input-oriented distance function (Shephard, 1970). Suppose producers use input vector $x = (x_1, x_2, ..., x_k)^T \in \Re_+^k$ to produce output vector $y = (y_1, y_2, ..., y_n)^T \in \Re_+^n$, where T denotes the vector transpose operator. A production technology that converts inputs into outputs can be modeled by an input correspondence $y \rightarrow V(y) \subseteq \Re_+^k$. For any $y \in \Re_+^n$, V(y) denotes the subset of *all* input vectors $x \in \Re_+^k$ which yield at least y. The input-oriented distance function for a specific decision making unit (DMU) is then:

$$D(x, y) = \sup\left\{q : (y, \frac{x}{q}) \in V(y)\right\} = \left(\inf\left\{q : (y, q\, x) \in V(y)\right\}\right)^{-1} \qquad (1)$$

The input distance function is the reciprocal of the minimum equi-proportional contraction of the input vector x, given outputs y. Farrell's (1957) measure of input technical efficiency TE(x,y) is equal to 1/D(x,y).

For each year, technical efficiency is estimated separately for each firm in the sample by solving linear programming problems. There are several different ways to present DEA technical efficiency linear programming problems. The simplest representation for firm *s* is the following:

$$\begin{aligned} &\left(\mathrm{D}(x_s, y_s)\right)^{-1} = \mathrm{TE}(x_s, y_s) = \min q_s \\ &\text{subject to: } Y l_s \geq y_s,\ \mathrm{X} l_s \leq q_s x_s,\ l_s \geq 0 \end{aligned} \qquad (2)$$

where *s*=1,2,…,S for each year. Y is an N x S output matrix and X is a M x S input matrix for all DMU's in the sample; y_s is an N x 1 output vector and x_s is an M x 1 input vector for firm s; and finally l_s is an S x 1 intensity vector for firm s. The constraint $l_s \geq 0$ imposes constant returns to scale (CRS). DMU's with elements of l_s that are non-zero are the set of "best-practice" reference DMU's for the firm under analysis.

Again technical efficiency can be decomposed into pure technical efficiency (PTE) and scale efficiency (SE), where TE=PTE*SE, by solving additional linear programming problems. Pure technical efficiency is measured relative to a variable returns to scale frontier, which may have segments where best practice firms operate with increasing returns to scale, constant returns to scale, or decreasing returns to scale. To obtain a variable returns to scale frontier we estimate equation (2) with the additional convexity constraint $\mathrm{i}_{\mathrm{N}} l_s = 1$, where i_{N} is an N-element vector of 1's. Pure technical efficiency is the reciprocal of the distance of firm *s* from the variable returns to scale frontier. Therefore, a firm can increase its pure technical efficiency by moving toward the variable returns to scale frontier.

If the firm is operating in the increasing returns to scale or decreasing returns to scale region of the variable returns to scale frontier, it could further improve its technical efficiency by operating with constant returns to scale. Firms with PTE=TE are operating with constant returns to scale and thereby are scale efficient, SE=1. To distinguish between firms operating in the decreasing returns to scale (DRS) region and the increasing returns to scale (IRS) region an additional linear programming problem is solved. The convexity constraint in the variable returns to scale problem ($\mathrm{i}_{\mathrm{N}} l_i = 1$) is replaced by an alternative constraint, $\mathrm{i}_{\mathrm{N}} l_i \leq 1$, that modifies the problem to account for non-increasing returns to scale (NIRS). If TE does not equal PTE and PTE equals the NIRS efficiency measure then the firm is operating with DRS. However, if TE does not equal PTE and PTE does not equal the NIRS efficiency measure then the firm is operating with IRS (Aly et al., 1990).

The DEA model can be extended to provide measures of economic efficiency—i.e. cost efficiency and revenue efficiency. In the cost efficiency framework the firms' objective is assumed to be the minimization of cost subject to the constraints imposed by input prices, output quantities, and the structure of the cost function. To obtain the firm's relative cost efficiency requires a two-step procedure. The first step solves the following problem for each firm *s*:

$$
\begin{aligned}
&\underset{x_s}{Min}\ w_s^T x_s \\
&\text{Subject to } Y?_s \geq y_i,\ i = 1,2,...,N \\
&\qquad X?_s \leq x_j,\ j = 1,2,...,M \\
&\quad \text{and } ?_s \geq 0
\end{aligned}
\tag{3}
$$

where T indicates vector transpose. The solution vector x_s^* is the cost-minimizing input vector for the input price vector, w_s, and the output vector, y_s. The second step computes firm *s*'s cost efficiency as the ratio of frontier costs to actual costs-- $Eff_{\cos t} = \frac{w_s^T x_s^*}{w_s^T x_s}$. Accordingly, cost efficiency is between zero and one. If the score is equal to 1, then the firm is fully cost efficient. A score of 0.75, on the other hand, indicates that the firm is 75 percent efficient. Implying that the firm could produce the same level of output with 75 percent of the inputs actually utilized.

As indicated earlier, cost efficiency is comprised of a technical component and an allocative component. A firm is cost efficient if, and only if, it is technically and allocatively efficient. Even if a firm produces on the production frontier, it might not be cost efficient if it is not allocatively efficient. Allocative efficiency is calculated as the ratio of cost efficiency to technical efficiency ($AE = \frac{CE}{TE}$).

Revenue efficiency is estimated in a similar way to cost efficiency. A producers' objective is assumed to be the maximization of revenue, subject to the constraints imposed by output prices, input supplies, and the structure of the production technology. Accordingly, we utilize an output-oriented model instead of the input-oriented approaches characterized above. The linear programming problem is solved for each firm for each year in the sample:

$$
\begin{aligned}
&\underset{y_s}{Max} \sum_{i=1}^{N} p_{si} y_{si} \\
&\text{Subject to } Y?_s \geq y_i,\ i = 1,2,...,N \\
&\qquad X?_s \leq x_j,\ j = 1,2,...,M \\
&\quad \text{and } ?_s \geq 0
\end{aligned}
\tag{4}
$$

The solution vector y_s^* is the revenue maximizing output vector for the output price vector p_s and the input vector x_s. Similar to the calculation of cost efficiency, the second step in the procedure is to compute firm s's revenue efficiency as the ratio of observed revenue to maximum possible revenue--

$Eff_{revenue} = \frac{p_s^T y_s}{p_s^T y_s^*}$. Revenue efficiency is less than or equal to 1. A score equal to 1 indicates that the firm is fully revenue efficient. Any score that diverges from 1 implies that the firm could produce more outputs, with the same about of inputs, than are actually produced.

Appendix B

Table B1: Summary Statistics--Logistic Regression Variables used in the Insolvency Analysis

This table provides summary statistics for the variables utilized in the logistic regression analysis. All reported values are unweighted sample means, except for the number of observations and the number of insolvent firms, which are sums.

	Year												Average
	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	
Number of Observations	1589	1594	1594	1582	1626	1578	1571	1555	1448	1461	1467	1470	1545
Insolvencies	51	46	41	22	17	20	22	18	13	11	20	22	25
Ln (Assets)	17.3958	17.4114	17.4896	17.6018	17.6480	17.7465	17.7741	17.8483	17.9377	18.0220	18.0167	18.0042	17.7413
Mutual dummy variable	0.2335	0.2409	0.2396	0.2383	0.2345	0.2307	0.2234	0.2379	0.2300	0.2170	0.2277	0.2327	0.2322
Financial Ratio Factor 1	-0.0159	-0.0199	-0.0116	-0.0214	0.0202	-0.0186	-0.0146	0.0082	-0.0251	-0.0145	-0.0193	0.0085	-0.0103
Financial Ratio Factor 2	0.0024	-0.0020	0.0128	-0.0352	0.0113	0.0009	0.0079	0.0066	0.0142	0.0186	-0.0258	0.0186	0.0025
Financial Ratio Factor 3	-0.0344	-0.0220	-0.0183	0.0019	-0.0318	0.0061	0.0559	0.0158	0.0571	-0.0152	-0.0565	0.1150	0.0061
Financial Ratio Factor 4	-0.0133	0.0265	-0.0123	0.0116	0.0045	-0.0025	0.0230	-0.0146	0.0171	-0.0337	-0.0020	0.0093	0.0011
Financial Ratio Factor 5	0.0297	0.0051	0.0130	0.0312	0.0125	0.0089	0.0051	0.0012	-0.0221	0.0055	0.0727	-0.0261	0.0114
Financial Ratio Factor 6	0.0130	0.0044	0.0128	-0.0047	-0.0166	0.0212	-0.0219	0.0379	0.0166	-0.0022	0.0011	0.0216	0.0069
Financial Ratio Factor 7	0.0341	-0.0131	0.0008	0.0112	0.0312	0.0249	0.0549	0.0574	-0.0443	0.0010	-0.0436	0.0170	0.0110
Financial Ratio Factor 8	-0.0292	0.0073	-0.0119	-0.0227	0.0241	0.0024	0.0254	0.0411	-0.0200	0.1128	0.0246	0.0161	0.0142
Financial Ratio Factor 9	-0.0136	0.0047	0.0114	0.0632	-0.0023	-0.0461	0.0066	-0.0120	-0.0519	0.0034	0.0619	-0.0574	-0.0027
Financial Ratio Factor 10	-0.0060	0.0154	0.0172	-0.0186	0.0222	0.0186	-0.0093	-0.0120	0.0239	0.0949	0.0222	-0.0011	0.0140
Financial Ratio Factor 11	0.0176	0.0191	0.0376	-0.0096	0.0287	-0.0025	0.0413	-0.0002	0.0871	-0.0115	0.0347	-0.0202	0.0185
Financial Ratio Factor 12	0.0081	-0.0247	0.0149	0.0338	-0.0086	0.0351	-0.0124		-0.0019	0.0144		0.0102	0.0069
Financial Ratio Factor 13		0.0162		0.0248	0.0269		0.0107		-0.0376	0.0038			0.0075

Note: Three-year prediction periods are used for all sample years (Cummins, Harrington, and Klein (1995); Grace, Harrington, and Klein (1998)). For instance, the 1989 data were used to predict insolvencies over the period 1990-1992. Insurers are classified as insolvent if it was subject to formal regulatory proceedings for conservation of assets, rehabilitation, receivership, or liquidation.

There are a large number of IRIS (Insurance Regulatory Information System) and FAST (Financial Analysis and Surveillance Tracking system) ratios and many are highly correlated with one another; therefore, to avoid an unmanageable degree of multicollinearity, factor analysis on the IRIS and FAST ratios was conducted. A varimax rotation to orthogonalize the factors was utilized, eliminating the problem of multicollinearity among the factors. The resulting factors are those with eigenvalues greater than one. Factor loadings vary by year making comparison between years impossible.

Table B2: Logistic Regression Results--Financial Ratios vs. Efficiency Scores
Panel A: Years 1989-1992

	Year											
	1989			1990			1991			1992		
Variable	1	2	3	1	2	3	1	2	3	1	2	3
Intercept	7.807 ***	9.453 ***	8.076 ***	3.987 **	8.833 ***	4.797 ***	3.402 *	2.436	4.149 *	3.606	7.070 **	4.734 **
Ln(Assets)	-0.685 ***	-0.690 ***	-0.699 ***	-0.451 ***	-0.566 ***	-0.493 ***	-0.436 ***	-0.484 ***	-0.473 ***	-0.493 ***	-0.377 ***	-0.542 ***
Mutual Dummy	-2.769 **	-2.749 ***	-0.699 ***	-1.297 **	-1.215 *	-1.447 **	-0.897	-0.596	-1.056 *	-0.731	-0.606	-0.820
Financial Ratio Factor 1	1.415	1.376	1.425	0.149	0.382	0.194	-0.065	0.036	-0.105	0.775 **	0.988 ***	0.725 **
Financial Ratio Factor 2	-0.238	-0.275	-0.242	0.757 ***	0.888 ***	0.747 ***	-0.174	-0.130	-0.152	0.079	0.074	0.021
Financial Ratio Factor 3	0.550 ***	0.533 ***	0.541 ***	0.008	-0.058	-0.022	2.885 ***	2.512 ***	3.060 ***	0.387 **	0.412 *	0.449 **
Financial Ratio Factor 4	-0.077	-0.071	-0.079	0.159	0.373	0.147	0.856	0.692	0.817	-1.883 *	-2.064 *	-2.251
Financial Ratio Factor 5	0.188 *	0.236 ***	0.194 **	-0.029	-0.039	-0.034	-0.370 **	-0.325 **	-0.363 **	0.151 **	0.259 ***	0.164 **
Financial Ratio Factor 6	0.278 **	0.249 **	0.274 **	-0.552	-0.498	-0.526	0.349	0.315	0.329	-0.025	-0.078	-0.043
Financial Ratio Factor 7	1.146 ***	1.133 ***	1.149 ***	0.353 ***	0.322 **	0.345 ***	0.196	0.143	0.183	0.025	0.079	0.032
Financial Ratio Factor 8	-0.153	-0.215 *	-0.169	0.480 ***	0.535 ***	0.465 ***	0.901 **	0.896 ***	0.906 **	0.092	0.032	0.146
Financial Ratio Factor 9	-0.901 ***	-0.879 ***	-0.889 ***	-0.515	-0.925	-0.521	-1.086 ***	-1.090 ***	-1.039 ***	0.142 *	0.171 *	0.172 *
Financial Ratio Factor 10	-0.344 ***	-0.315 ***	-0.339 ***	0.477 *	0.610 *	0.530 *	-0.047	-0.053	-0.043	-0.067	-0.139	-0.096
Financial Ratio Factor 11	0.192 *	0.157 *	0.183 *	-0.629 *	-0.833 **	-0.681 *	-0.226	-0.343	-0.258	-0.081	-0.113	-0.046
Financial Ratio Factor 12	-2.726 ***	-2.865 ***	-2.739 ***	-0.072	-0.114	-0.089	-1.292	-0.609	-1.270	-3.262 ***	-3.509 ***	-3.395 ***
Financial Ratio Factor 13				-0.653	-0.982 *	-0.746				-0.699 **	-0.756 *	-0.632 *
Pure Technical Efficiency		-1.675 **			-3.423 ***			-1.446 *			-2.152 *	
Scale Efficiency		0.013			-1.367			3.897			-2.173	
Allocative Efficiency		-1.448			-0.004			-2.596 **			-4.543 **	
Revenue Efficiency			-0.242			-0.928			-1.244			-1.167
Log L	-162.792	-158.874	-162.701	-167.428	-153.990	-166.524	-143.740	-138.512	-142.668	-88.444	-82.650	-87.701
Pseudo R^2	27.830	29.570	27.870	19.670	26.110	20.100	24.560	27.310	25.130	23.690	28.690	24.330
Area Index of ROC	0.889	0.900	0.890	0.832	0.894	0.838	0.874	0.894	0.878	0.886	0.915	0.879
Number of Observations	1589	1589	1589	1594	1594	1594	1594	1594	1594	1582	1582	1582
Number of Insolvencies	51	51	51	46	46	46	41	41	41	22	22	22

	Type I Error Rate (%)											
5 % Type II Error Rate	53	53	53	61	52	61	41	46	44	45	45	50
10 % Type II Error Rate	33	27	31	48	33	48	34	37	32	45	32	36
15 % Type II Error Rate	22	18	24	39	26	37	27	22	24	32	23	27
20 % Type II Error Rate	16	16	16	33	22	30	20	20	20	23	14	23
25 % Type II Error Rate	16	14	16	26	13	28	20	12	17	14	9	9
30 % Type II Error Rate	14	12	12	26	4	22	17	10	15	9	5	9

*** significant at .01 level; ** significant at .05 level; * significant at .10 level.

Table B2: Logistic Regression Results--Financial Ratios vs. Efficiency Scores

Panel B: Years 1993-1996

	1993			1994			1995			1996		
Variable	1	2	3	1	2	3	1	2	3	1	2	3
Intercept	2.328	2.992	2.822	-0.245	-4.753	-0.794	2.263	-0.749	0.613	2.493	0.818	2.371
Ln(Assets)	-0.685 ***	-0.690 ***	-0.699 ***	-0.264 *	-0.224	-0.241 *	-0.420 ***	-0.451 ***	-0.351 ***	-0.685 ***	-0.307 ***	-0.403 ***
Mutual Dummy	-2.769 **	-2.749 ***	-0.699 ***	-2.165 *	-2.187 **	-2.091 *	-0.423	-0.402	-0.252	-2.769 **	-0.512	-0.608
Financial Ratio Factor 1	1.415	1.376	1.425	0.635 *	0.614	0.614	0.118	-0.102	0.179	1.415	0.166 ***	0.179 ***
Financial Ratio Factor 2	-0.238	-0.275	-0.242	1.727 ***	1.698 ***	1.670 ***	0.219 **	0.240 ***	0.222 ***	-0.238	-0.044	-0.042
Financial Ratio Factor 3	0.550 ***	0.533 ***	0.541 ***	-0.302	-0.130	-0.379	1.344 ***	1.327 ***	1.201 ***	0.550 ***	0.003	0.016
Financial Ratio Factor 4	-0.077	-0.071	-0.079	0.420 ***	0.496 ***	0.414 ***	0.061	0.082 *	0.074 *	-0.077	0.189 ***	0.220 ***
Financial Ratio Factor 5	0.188 *	0.236 ***	0.194 **	-4.576 ***	-4.865 ***	-4.480 ***	-0.686	-0.588	-0.825	0.188 *	-0.021	-0.039
Financial Ratio Factor 6	0.278 **	0.249 **	0.274 **	0.085 **	0.104 **	0.086 **	0.141	0.168	0.108	0.278 **	0.094	0.099
Financial Ratio Factor 7	1.146 ***	1.133 ***	1.149 ***	0.033	0.044	0.043	0.332 **	0.354 *	0.312 *	1.146 ***	0.109	0.108
Financial Ratio Factor 8	-0.153	-0.215 *	-0.169	-0.260 ***	-0.298 *	-0.262 ***	-0.245	-0.405	-0.323	-0.153	0.007	-0.049
Financial Ratio Factor 9	-0.901 ***	-0.879 ***	-0.889 ***	0.008	0.104	0.026	-2.848 ***	-2.766 ***	-2.817 ***	-0.901 ***	0.048	0.034
Financial Ratio Factor 10	-0.344 ***	-0.315 ***	-0.339 ***	0.211	0.189	0.212	2.867 **	2.547 *	2.920 **	-0.344 ***	0.109	0.158
Financial Ratio Factor 11	0.192 *	0.157 *	0.183 *	0.101	0.022	0.113	-1.197 ***	-1.318 **	-1.336 ***	0.192 *	-0.050	-0.044
Financial Ratio Factor 12	-2.726 ***	-2.865 ***	-2.739 ***	0.178	0.100	0.170	1.132 **	1.085 **	1.037 **			
Financial Ratio Factor 13							0.135	0.151	0.155			
Pure Technical Efficiency		-1.675 **			0.308			0.500			1.207	
Scale Efficiency		0.013			3.160			2.134			0.096	
Allocative Efficiency		-1.448			1.415			1.859			-1.703	
Revenue Efficiency			-0.242			0.556			1.323 *			0.193
Log L	-58.201	-55.140	-58.045	-86.169	-84.160	-85.965	-92.005	-90.748	-90.646	-83.034	-81.622	-83.014
Pseudo R^2	31.220	34.830	31.400	19.650	21.520	19.840	20.510	21.600	21.690	15.410	16.840	15.430
Area Index of ROC	0.945	0.960	0.947	0.831	0.848	0.830	0.877	0.866	0.878	0.809	0.847	0.811
Number of Observations	1627	1627	1627	1578	1578	1578	1571	1571	1571	1555	1555	1555
Number of Insolvencies	17	17	17	20	20	20	22	22	22	18	18	18

Type I Error Rate (%)

5 % Type II Error Rate	33	27	33	60	50	55	59	55	55	78	78	78
10 % Type II Error Rate	20	13	20	35	40	35	36	41	36	50	56	56
15 % Type II Error Rate	13	7	13	35	35	35	27	23	27	39	39	39
20 % Type II Error Rate	13	7	7	30	30	35	18	23	18	33	33	33
25 % Type II Error Rate	0	0	0	25	30	25	14	23	14	33	28	33
30 % Type II Error Rate	0	0	0	20	30	20	9	18	9	22	17	22

*** significant at .01 level; ** significant at .05 level; * significant at .10 level.

Table B2: Logistic Regression Results--Financial Ratios vs. Efficiency Scores

Panel C: Years 1997-2000

	Year											
	1997			1998			1999			2000		
Variable	1	2	3	1	2	3	1	2	3	1	2	3
Intercept	3.184	11.523 ***	8.513 **	-5.555 *	-10.488	-5.672 **	-3.684	-3.896	-2.549	1.740	-0.648	1.520
Ln(Assets)	-0.474 ***	-0.451 *	-0.747 ***	0.023	0.167	0.026	-0.077	0.088	-0.125	-0.368 ***	-0.213	-0.358 ***
Mutual Dummy	-0.474 ***	-0.451 *	-0.747 ***	-1.072	-0.978	-1.062	-1.364	-1.252	-1.559	-1.255 *	-0.768	-1.226 *
Financial Ratio Factor 1	-0.095	0.379	0.280	-0.523	-0.403	-0.526	0.600	0.606	0.728	0.045	-0.042	0.047
Financial Ratio Factor 2	-0.142	0.098	0.156 **	-0.330	-0.355	-0.329	-1.786	-1.909	-1.630	-0.007	-0.172	-0.008
Financial Ratio Factor 3	0.060	0.027	0.113 **	3.824 ***	3.888 ***	3.794 ***	0.789 **	0.766 **	0.802 ***	0.465 **	0.519 **	0.466 **
Financial Ratio Factor 4	-0.067	-0.062	0.210	-2.657	-2.801	-2.703	-7.015 **	-8.388 ***	-6.816 **	-2.637 **	-1.795	-2.611 **
Financial Ratio Factor 5	-0.010	-0.018	0.021	-0.001	0.026	-0.003	1.006 ***	1.025 ***	1.112 ***	0.322 ***	0.189	0.322 ***
Financial Ratio Factor 6	-0.081	-0.271	-0.166	-0.265	-0.288	-0.268	0.268 *	0.196	0.233	-0.696 *	-0.910 **	-0.694 **
Financial Ratio Factor 7	0.560 **	0.216	0.437 *	0.386	0.332	0.386	0.427 *	0.446 **	0.441 *	-0.117 **	-0.091	-0.119 **
Financial Ratio Factor 8	1.850	1.979	3.669	0.059	0.086	0.058	-1.092 ***	-1.185 ***	-1.122 ***	-0.069	0.222	-0.073
Financial Ratio Factor 9	-0.261	-0.573	-0.082	-1.331 ***	-1.380 ***	-1.326 ***	0.073	0.032	0.039	0.116	0.032	0.122
Financial Ratio Factor 10	0.698	0.577	1.114 *	-1.043 ***	-1.264 ***	-1.036 ***	-0.597 **	-0.613 **	-0.629 ***	0.901 ***	0.925 ***	0.905 ***
Financial Ratio Factor 11	0.640 ***	0.730 ***	0.649 **	0.084	0.156	0.082	-0.567 ***	-0.652 ***	-0.580 ***	-0.035	0.127	-0.031
Financial Ratio Factor 12	0.093	0.189 **	0.093	-2.775 ***	-2.751 ***	-2.776 ***				-0.028	-0.001	-0.027
Financial Ratio Factor 13	-0.517 *	-0.573	-0.333	-0.628 ***	-0.717 ***	-0.627 ***						
Pure Technical Efficiency		-4.711 ***			-1.781			-1.823			-0.747	
Scale Efficiency		-4.581 *			4.200			0.568			4.542 **	
Allocative Efficiency		-3.241			-0.786			-3.377 **			-7.310 ***	
Revenue Efficiency			-16.734			0.183			-1.288			0.429
Log L	-63.940	-54.444	-56.981	-58.477	-57.043	-58.466	-85.747	-81.662	-84.896	-87.791	-73.576	-87.711
Pseudo R^2	13.840	23.100	19.510	9.670	11.890	9.690	18.930	22.790	19.730	23.180	35.620	23.250
Area Index of ROC	0.811	0.908	0.869	0.808	0.799	0.806	0.854	0.866	0.859	0.865	0.921	0.865
Number of Observations	1448	1448	1448	1461	1461	1461	1467	1467	1467	1470	1470	1470
Number of Insolvencies	13	13	13	11	11	11	20	20	20	22	22	22

	Type I Error Rate (%)											
5 % Type II Error Rate	69	62	54	73	55	73	50	45	50	55	36	55
10 % Type II Error Rate	46	23	54	64	36	64	35	30	35	45	27	45
15 % Type II Error Rate	31	23	23	45	27	64	35	25	35	41	27	41
20 % Type II Error Rate	31	8	23	45	27	45	30	25	25	27	18	23
25 % Type II Error Rate	31	8	15	18	27	18	25	25	25	18	9	23
30 % Type II Error Rate	31	8	8	9	18	9	15	20	15	18	0	18

*** significant at .01 level; ** significant at .05 level; * significant at .10 level.

Figure B1: Average Type I/Type II Error Trade-Offs for 1989-2000