Is Efficiency an Important Determinant of A.M. Best Property-Liability Insurer Financial Strength Ratings?

David L. Eckles¹ and Steven W. Pottier²

Abstract: Insurance regulators, policyholders, and investors are interested in the ability of insurers to fulfill their financial obligations. Economic and finance theory suggests that, all else equal, more efficient firms should be financially stronger firms. Efficiency scores represent a quantitative measure that summarizes in a single value the relative effectiveness of a firm in achieving a stated objective, such as cost minimization. However, efficiency scores do not explicitly measure firm risk. Efficiency scores compare firms with similar inputs and outputs whereas insurer financial strength ratings compare insurers within a particular segment of the industry, such as property-liability insurance, even though inputs and outputs may differ greatly. The purpose of this study is to examine the relation between insurer efficiency and insurer financial strength ratings. We find firm efficiency scores are a weak predictor of financial strength ratings in that they do not provide significant incremental predictive power over a model with even a few widely recognized rating determinants. Further, efficiency scores perform no better at predicting ratings than simply predicting ratings based on the modal rating category. These results suggest that users of efficiency scores should not use these measures to make inferences regarding insurer financial strength. [Key words: Efficiency, ratings, regulation.]

INTRODUCTION

Insurance regulators, policyholders, and investors are interested in the ability of insurers to fulfill their financial obligations. Economic and finance theory suggests that, all else equal, more efficient firms should be financially stronger firms. Efficiency scores represent a quantitative measure

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that summarizes in a single value the relative effectiveness of a firm in achieving a stated objective, such as cost minimization. However, efficiency scores do not explicitly measure firm risk. Efficiency scores compare firms with similar inputs and outputs whereas insurer financial strength ratings compare insurers within a particular segment of the industry, such as property-liability insurance, even though inputs and outputs may differ greatly. A higher insurer financial strength rating is equivalent to a higher likelihood that an insurer will fulfill its obligations to policyholders, and therefore, a lower risk of insolvency. Existing research on insurer financial strength rating determinants generally examines the predictive ability of financial statement ratios rather than efficiency scores.

The purpose of this study is to examine the relation between insurer efficiency and insurer financial strength ratings, and thereby extend the literature on determinants of insurer ratings. Efficiency scores could be an important determinant of ratings if the rating agencies explicitly use efficiency scores or if the efficiency scores are correlated with other variables used by rating agencies. Leverty and Grace (2004) find that efficiency scores marginally improved upon ratings as predictors of insolvency, likewise suggesting that efficiency scores contain information relevant to insolvency not reflected in insurer FSRs.

Efficiency scores are derived from many financial statement items, result from a comparison of each sample firm to other sample firms (specifically to firms in the “efficient set”), and are singularly important just as summary risk measures, such as ratings. For instance, efficiency scores have been used to examine mergers, ownership form, distributions systems, insolvency, and regulatory issues. Given the singular importance of efficiency scores in the insurance academic literature and expectation that efficiency scores may be an important rating determinant, we think that it is an interesting and important question whether efficiency scores are important rating determinants. Regardless of the answer, we feel that the question itself is important.

The present study provides evidence on the extent that efficiency scores are reflected in financial strength ratings. Specifically, while we find that efficiency scores are statistically significant in a ratings determinants model, they do not provide significant incremental predictive power over a model with even a few widely recognized rating determinants. Further, efficiency scores do no better at predicting ratings than simply predicting ratings based on the modal rating category.

For insurers, marginal benefits accrue to safer firms in the form of higher premiums relative to expected claims (Sommer, 1996; Cummins and Danzon, 1997). The marginal costs associated with holding more equity capital to cushion against unexpected fluctuations in financial performance,
or improving policyholder service or underwriting expertise to strengthen competitive market position, must be weighed against the expected marginal benefits. An insurer that makes better choices in terms of costs and benefits, or similarly between input and output combinations, is more efficient, and is expected to be rewarded with higher financial strength ratings. The same rationale holds true for any firm that makes the most efficient choices, and is ultimately rewarded with better financial strength ratings, and therefore incurs a lower cost of debt capital.

The remainder of this paper is organized as follows. First, we formulate hypotheses regarding the relation between financial strength ratings, efficiency measures, and several key risk characteristics. Second, we describe the data used and explain the procedure employed to estimate efficiency measures, and specify the empirical models. Third, the empirical results are presented and discussed. Finally, some concluding remarks are offered.

**Hypotheses and Variables**

In this section, we discuss firm-specific characteristics expected to influence rating agency decisions regarding insurer financial strength ratings and formulate hypotheses based on economic and financial theory. Best makes publicly available a general description about important quantitative and qualitative rating factors, and specifically identifies a small subset of the “over 100 key financial tests” it uses in the rating process (Best, 2001). In what follows, we focus on the broadest and most important factors, and do not attempt to replicate the extensive analysis performed by Best.

**Best’s Financial Strength Ratings**

Strong financial ratings give insurers better access to capital markets. Insurer ratings also have a direct impact on the cost of capital, since the primary source of debt capital to insurers is policy liabilities and lower-rated firms will likely have to sell their policies at lower prices compared to higher rated firms (Cummins and Danzon, 1997; Epermanis and Harrington, 2006). Ratings also provide a valuable tool for regulators in assessing the financial strength of insurers (NAIC, 2002).

Best’s letter ratings are summary measures of financial strength. Unlike regulatory or rating agency risk-based capital measures, financial strength ratings are overall insolvency risk measures, and reflect the rating agency’s opinion of the insurer’s overall financial strength and ability to meet its policyholder obligations. Letter ratings are based on both quantitative and qualitative analysis. The ratings process considers quantitative and qualitative factors related to capitalization/financial leverage, holding
company issues, profitability, liquidity, reinsurance, loss reserves, asset quality, and diversification, among others. Thus, ratings are the most comprehensive summary measure of overall financial strength produced by the private sector. Further, in contrast to insolvency prediction models based on actual, ex-post insolvencies, financial strength ratings are ex-ante measures of risk.

Business profile issues considered in the rating process include an insurer’s competitive market position. A low cost structure, effective use of technology, strong franchise recognition, easy and inexpensive access to capital, and underwriting expertise in non-commodity product lines are factors examined in the evaluation of competitive market position. We expect that these factors will be reflected in cost efficiency measures and associated with our control variables, particularly size and capitalization (Smith and Watts, 1992).

**Efficiency**

In neoclassical economics, the firm’s objective function is to maximize profits subject to the constraints imposed by its technological capabilities (Kreps, 1990). A profit-maximizing firm will maximize revenues given a set level of inputs and minimize costs given a set level of output, taking input and output prices as given. In essence, profit-maximizing firms are fully efficient in both a revenue sense and a cost sense. Conversely, an inefficient firm is not maximizing profit. The neoclassical theory of the firm has been refined to account for agency costs and various transactions costs, including taxes, regulation, and information (Hart, 1995). While some of these costs may be reflected in our cost measures discussed below, we include variables that may help control for them.

A key concept we use in analyzing insurer financial strength is that of cost efficiency, which measures the insurer’s attainment of cost minimization. Cost efficiency is defined as the ratio of costs that a fully efficient firm incurs to the costs a particular firm actually incurs for a given level of output. Thus, fully efficient firms have cost efficiencies of 1, and inefficient firms have cost efficiency between 0 and 1. A fully cost efficient firm might choose a different technology or mix of inputs than an inefficient one.3

**Control Variables**

Consistent with prior literature on insolvency prediction and rating determinants, we include measures of insurer size, capitalization, and

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3 While revenue efficiency is not considered in our analysis, we note that a fully revenue efficient firm might choose a different technology or mix of outputs than an inefficient one.
organizational form as control variables. Larger and better capitalized insurers have been shown to have higher FSRs and lower rates of insolvency (see Pottier and Sommer, 1999 and 2002). Insurer efficiency is likely to be positively associated with firm size due to economies of scale and economies of scope (Cummins and Zi, 1998). Firm size is measured as the natural logarithm of assets. The singular importance of capital to insurer solvency and ratings is acknowledged by regulators (NAIC, 2002) and rating agencies (Best, 2001). Cummins and Sommer (1996) find that insurers choose an optimal combination of portfolio risk and capitalization for a targeted likelihood of insolvency. Capitalization is also related to many other firm characteristics (Cummins and Nini, 2002). The ratio of equity capital to assets is used to measure the insurer’s capitalization. An indicator variable that equals one for mutual insurers and zero otherwise is used to control for the different risk characteristics of stock and mutual insurers (see Mayers and Smith, 1981 and 1988; Lee, Mayers, and Smith, 1997; Lamm-Tennant and Starks, 1993).

Data and Methodology

We rely on the financial statement data reported to the NAIC for the calculation of the efficiency estimates and the other firm-specific measures. The ratings data come from Best’s Key Rating Guide (Best, 2001) and the insurer company data are provided by the NAIC. In order to obtain a reasonable efficiency calculation, we limit our sample to firms that appear to have at least a minimal activity level. Specifically, we require that the insurers have admitted assets, capital, and net premiums written of two million dollars or more. We further require that firms have a positive expense ratio and loss ratio. These screens, while not particularly restrictive, allow us to be reasonably confident that our firms are viable participants in the insurance market and are not simply in runoff or otherwise inactive. We further require that our firms have reasonable levels of inputs and outputs, as firms with negative inputs or outputs are also eliminated. Lastly, we require that each sample firm received a letter rating from Best in each year the firm is included in our sample.4

Our analysis is conducted on the individual firm level because solvency regulation, and hence financial strength concerns, primarily focuses

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4From the NAIC data, there were 13,294 individual firms between 1996 and 2000. Requiring each firm to have positive assets, loss ratio, and total expenses reduces the sample to 10,412. Requiring each firm to have nonnegative inputs and outputs reduces the sample to 7960. Requiring each firm to have total assets, net premium written, and total capital greater than or equal to $2 million each, and a capital-to-asset ratio less than or equal to 1, reduces the sample to 6545. Of these, we have rating data for 5790 observations.
on individual firms rather than groups. Performing our analysis at the individual company level is consistent with extant research on insurer ratings and insolvency, with the exception of Gaver and Pottier (2005), who examine group-level insurer ratings on publicly-traded P/L insurers.

The present study examines the relation between cost efficiency and financial strength ratings. In the cost efficiency or input-oriented approach, the level of outputs produced by a firm and input prices are held constant, and the ability of the firm to reduce and/or reallocate inputs is examined. In general, this input-oriented approach considers the degree to which firms can reduce total costs while maintaining the same level of outputs.

Cost efficiency is the product of pure technical efficiency, scale efficiency, and allocative efficiency. Technical efficiency is a measure of the degree to which firms can reduce input quantities while maintaining the same level of outputs, measured relative to the optimal constant returns to scale frontier. This measure can be further disaggregated into pure technical efficiency and scale efficiency. Pure technical efficiency measures the degree to which firms can reduce inputs, with no constraint on the frontier with respect to returns to scale. Scale efficiency is the component of technical (in)efficiency brought upon by firms not operating with constant returns to scale. Finally, allocative efficiency measures a firm’s success in choosing the cost-minimizing combination of inputs. Pure technical, scale, and allocative efficiency combined measure the degree to which firms can reduce their total expenses while continuing to produce the same level of outputs.

Data Envelopment Analysis (DEA) is a linear optimization method (see Charnes et al., 1994) and the prevalent methodology currently employed to examine insurer efficiency. When calculating efficiency scores, we utilize DEA to estimate the “best practice” efficiency frontiers for our sample firms. DEA constructs the efficient frontier via a convex combination of the best practice firms, and assigns the remaining firms efficiency scores based on their distance from the efficient frontier. DEA has been used in numerous efficiency studies within the property-liability insurance industry.

When calculating efficiency scores, we must determine the appropriate inputs and outputs for our firms. Like any other financial institution, insurance firms primarily sell services. We measure the outputs of insur-

\[5\] Scale efficiency is the ratio of the technical efficiency with the constant returns to scale constraint to technical efficiency without any returns to scale constraint (i.e., variable returns to scale are permitted).

\[6\] Cummins and Nini (2002), and Brockett et al. (2004) are representative of recent studies and contain numerous references to other efficiency studies of property-liability insurers.
ance firms by utilizing the “modified value-added” approach given by Berger and Humphrey (1992). Berger and Humphrey suggest that an output of a financial service firm is one in which significant operating costs are allocated. Consistent with prior literature in the US property-liability insurance industry (Cummins and Weiss, 1993; Berger, Cummins, and Weiss, 1997; Cummins, Weiss, and Zi, 1999; Cummins and Nini, 2002) we define the insurer service output to include the risk pooling/risk bearing function, the “real” financial services related to insured losses, and finally, financial intermediation.

The risk pooling/risk bearing service provided by insurers is perhaps the most basic output of an insurer. Insurers allow policyholders to reduce their non-systematic risk by pooling their risk with other insureds. In providing this service, insurers incur significant underwriting expenses. Insurers augment this risk bearing service by holding additional capital in an effort to bear the residual risk. The “real” services provided by property-liability insurers are usually in the form of risk management consulting, loss control consulting, claims processing, and, in the case of liability coverage, significant legal services. Finally, like banks, insurers provide a valuable intermediation service by investing premiums. Positive returns generated by investing the premiums serve to reduce the cost of the insurance to the insured.

Consistent with the property-liability efficiency literature (Berger, Cummins, and Weiss (1997), Cummins, Weiss, and Zi (1999), Leverty and Grace (2004)), we use five outputs to proxy for these services provided by insurers. Our first four outputs proxy for the risk bearing and real services outputs by considering the present value of the incurred losses, defense and allocated loss adjustment expenses incurred for four categories of insurance: personal short-tail lines, personal long-tail lines, commercial short-tail lines, and commercial long-tail lines. The present value of incurred losses within these lines are those expected to be paid as a result of providing insurance, and is therefore considered a good proxy for the value of the risk bearing service. The defense and allocated loss adjustment expenses incurred serves to proxy for the “real” services provided by insurers. As the fifth output, we consider the firm’s invested assets as a proxy for the intermediation service provided by the insurers.

Insurance inputs are classified into four groups: agent labor, administrative labor, business services, and financial capital. These inputs are all

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7 We utilize the definitions for what constitutes short (long)-tailed personal (commercial) lines used by many P/L efficiency studies, e.g., Berger, Cummins, and Weiss (1997). Similarly, the present value of the losses incurred is calculated using payout pattern and discounting methodologies consistent with this literature.
extensively used by insurers in the production of the aforementioned outputs. While the total expenses incurred by insurance companies are mostly observable, the quantity of inputs used must be derived using the total expenditures and the unit prices. The total expenditures for agent labor, administrative labor, and business services are reported to the NAIC. To obtain the quantity of agent labor, we divide the expenses incurred for agent labor (commissions and allowances to managers and agents) by the national average weekly agent labor cost for property-casualty agents reported by the US Bureau of Labor Statistics (USBLS). The quantities of administrative labor and business services are similarly constructed by dividing the expenditures related to administrative labor (salaries, payroll taxes, and employee relations and welfare) by the national average weekly administrative labor cost for property-casualty insurers and dividing the remaining insurer expenses by the national average weekly business services wage rate for property-casualty insurers, respectively, both from the USBLS. The weekly wage rates mentioned above are further used as the prices for the respective inputs. As our fourth input, we use the total capital with regards to policyholder surplus reported to the NAIC. The use of capital as an input allows an insurer to increase the quality of the insurance product being offered. Increasing the level of capital allows the insurer to decrease the probability of default and meet regulatory requirements, and thereby increase the quality of the product being sold. However, holding capital is costly. In order to estimate the cost of capital, we use the average short-term (90-day) T-bill rate from the St. Louis Federal Reserve Bank plus the average market risk premium for property-casualty insurers (see, e.g.: Ibbotson Associates, 2006) for the appropriate year as the cost of capital for the insurers.

The dependent variable in our empirical models is based on the actual rating categories assigned by Best to property-liability insurers for the 1996 to 2000 financial statement years. Insurer financial strength ratings, like corporate bond ratings, are inherently ordered (Pottier and Sommer, 1999). Since ratings are ordinal variables, we use ordered logit to estimate the regression for the variables hypothesized to be associated with these ratings.

Rating categories are combined as shown in Table 1 to conform to the correspondence of the verbal descriptions provided by A.M. Best. Each

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8Our results do not appear sensitive to any particular categorization of the ratings. As robustness tests, we ran the models using a number of different categorizations. In each case, the results were qualitatively unchanged. We focus on the six-category specification because of the verbal descriptions of the ratings and the very low frequency of ratings of C and below (see Table 1).
rating category is assigned an ordered numerical value as shown in Table 1, where a higher value indicates a higher rating. As shown in Table 1, over 78 percent of sample firms are rated “A–” or higher by Best. Ratings of “C” or lower, which include 23 firms, are grouped together for empirical analysis.

Table 2 presents sample summary statistics on selected firm-specific variables. The firms range in size from $3 million to $80 billion in admitted assets. Approximately 23 percent of the firms are mutual insurers. The median rating is an “A/A–,” or “excellent.” The median firm is operating at a cost efficiency of 44 percent, implying that a best practices firm with the same level of output operates with costs 56 percent lower. On average, P/L insurers are well-capitalized, with a median capital-to-assets ratio of slightly over 37 percent.

Spearman rank correlations are presented in Table 3. Insurer financial strength ratings are most highly, and positively, correlated with firm size (.45). The high positive correlation (.17) between ratings and allocative efficiency suggests that financially stronger insurers are more successful in choosing the optimal combination of inputs. Likewise, the significant correlation between cost efficiency and ratings (.04) suggests that cost-efficient firms are being rewarded with higher ratings. Among the cost-efficiency components, pure technical efficiency is most highly correlated (.65) with cost efficiency.

**EMPIRICAL RESULTS**

The results of our ordered logit regressions are presented in Table 4. Model 1 includes log of assets, capital to assets, and a mutual indicator as
To correct for potential bias arising from firm effects, the results reported utilize standard errors clustered at the firm level (Peterson 2009). We also estimate our models with year effects and find no substantive change in results.

Table 2. Summary Statistics, 5790 Sample Observations, 1996–2000

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best’s rating</td>
<td>4.970</td>
<td>5.000</td>
<td>0.865</td>
<td>1.000</td>
<td>6.000</td>
</tr>
<tr>
<td>Capital-to-assets</td>
<td>0.408</td>
<td>0.374</td>
<td>0.160</td>
<td>0.014</td>
<td>1.000</td>
</tr>
<tr>
<td>Assets ($000,000)</td>
<td>639.000</td>
<td>93.00</td>
<td>2950.000</td>
<td>3.080</td>
<td>80100.000</td>
</tr>
<tr>
<td>Mutual indicator</td>
<td>0.227</td>
<td>0.000</td>
<td>0.419</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Pure Technical Efficiency (PTE)</td>
<td>0.684</td>
<td>0.670</td>
<td>0.217</td>
<td>0.042</td>
<td>1.000</td>
</tr>
<tr>
<td>Scale Efficiency (SE)</td>
<td>0.873</td>
<td>0.933</td>
<td>0.157</td>
<td>0.002</td>
<td>1.000</td>
</tr>
<tr>
<td>Allocative Efficiency (AE)</td>
<td>0.745</td>
<td>0.785</td>
<td>0.172</td>
<td>0.037</td>
<td>1.000</td>
</tr>
<tr>
<td>Cost Efficiency (CE)</td>
<td>0.443</td>
<td>0.441</td>
<td>0.181</td>
<td>0.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Table 3. Spearman Correlations, Across 5790 Observations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Rating</th>
<th>Cap._assets</th>
<th>Assets</th>
<th>Mutual</th>
<th>PTE</th>
<th>SE</th>
<th>AE</th>
<th>CE</th>
<th>FAST</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cap._assets</td>
<td>0.065</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Assets</td>
<td>0.448</td>
<td>−0.286</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mutual</td>
<td>−0.097</td>
<td>0.169</td>
<td>−0.083</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PTE</td>
<td>−0.075</td>
<td>−0.285</td>
<td>0.071</td>
<td>−0.023</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SE</td>
<td>−0.009</td>
<td>−0.102</td>
<td>0.025</td>
<td>−0.025</td>
<td>0.036</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AE</td>
<td>0.167</td>
<td>0.077</td>
<td>0.121</td>
<td>0.127</td>
<td>−0.095</td>
<td>0.002</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CE</td>
<td>0.039</td>
<td>−0.298</td>
<td>0.169</td>
<td>0.051</td>
<td>0.645</td>
<td>0.345</td>
<td>0.446</td>
<td>1.000</td>
<td></td>
</tr>
</tbody>
</table>

All pairwise correlations are significant at the 1% level with the exception of those italicized and bolded. The italicized correlations are significant at the 10% level, and the bolded correlations are not significant.
explanatory variables, and is designated the “Financial Ratios” model. Model 2 includes the three components of cost efficiency—pure technical efficiency, scale efficiency, and allocative efficiency—as explanatory variables, and is designated the “Efficiency Scores” model. Model 3 contains all regressors in both models 1 and 2, and is designated the “Financial Ratios and Efficiency Scores” model. As each model shows, the financial ratios and efficiency scores have a strong association with insurer financial strength ratings. The coefficient of each explanatory variable is statistically significant at the one percent level or better in every model, except for scale efficiency.

According to Model 3, which includes efficiency scores and firm-specific factors expected to be related to financial strength as well as important control variables, larger firms, better capitalized firms, and more allocatively efficient firms have higher ratings. Mutuals and more pure technically efficient firms have lower ratings. We do not find a significant relationship between scale efficiency and ratings. Since scale efficiency only indicates whether a firm is operating with constant returns to scale, it is not immediately clear that we would expect a significant result. If a firm is efficient along other dimensions, the degree to which a firm has achieved constant returns to scale is perhaps less important. The positive coefficient on allocative efficiency suggests that firms that are more successful choosing a cost-minimizing combination of inputs are perceived as financially stronger. The negative coefficient on pure technical efficiency implies that without any constraint on returns to scale, firms that are more technically efficient have lower ratings.

The positive coefficient on the log of assets is consistent with better diversification and investment opportunities, higher managerial quality, and lower capital costs accruing to larger firms. The positive coefficient on the capital-to-assets ratio supports the argument that a better capitalized firm has lower insolvency risk and greater ability to absorb risk. Finally, the negative coefficient on the mutual indicator variable is consistent with the claim that mutual insurers are less effective at controlling expenses.

\[\text{10While cost efficiency increases as PTE increases, an increase in PTE is not a sufficient condition for an increase in CE. Pure technical efficiency reflects the ability of a firm to minimize inputs to produce a given quantity of outputs. All else equal, we would expect firms with higher pure technical efficiency to have higher ratings. We have two possible explanations of this result. First, PTE does not reflect the cost of inputs or prices of outputs, which are clearly important to profitability. Second, lower inputs relative to outputs may be due to underpricing of outputs, which would ultimately increase firm risk even though it may increase demand for outputs. On the other hand, allocative efficiency measures a firm’s ability to minimize costs using inputs in the optimal proportions, given their relative prices, and, therefore, is more directly relative to cost minimization.}\]
related to managerial perquisite consumption and face higher capital costs because of limited access to capital.

The models were tested for multicollinearity and heteroskedasticity. The highest variance inflation factor was 1.20 for capital to assets. The results were qualitatively the same using White’s heteroskedasticity-adjusted standard errors. We also ran identical regressions truncating explanatory variables at the 1st and 99th percentile values, and the results were qualitatively the same.

Table 4. Ordered Logit Regression, Dependent Variable: Six Category Financial Strength Rating

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>β</td>
<td>β</td>
</tr>
<tr>
<td></td>
<td>(p-value)</td>
<td>(p-value)</td>
<td>(p-value)</td>
</tr>
<tr>
<td>Financial ratios:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital to assets</td>
<td>3.171 (0.001)</td>
<td>3.154 (0.001)</td>
<td></td>
</tr>
<tr>
<td>Log of assets</td>
<td>0.698 (0.001)</td>
<td>0.687 (0.001)</td>
<td></td>
</tr>
<tr>
<td>Mutual indicator</td>
<td>−0.409 (0.001)</td>
<td>−0.517 (0.001)</td>
<td></td>
</tr>
<tr>
<td>Efficiency scores:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pure technical</td>
<td>−0.600 (0.003)</td>
<td>−0.817 (0.001)</td>
<td></td>
</tr>
<tr>
<td>Scale</td>
<td>0.158 (0.536)</td>
<td>0.349 (0.153)</td>
<td></td>
</tr>
<tr>
<td>Allocative</td>
<td>1.677 (0.001)</td>
<td>1.520 (0.001)</td>
<td></td>
</tr>
<tr>
<td>Intercept 1</td>
<td>18.023 (0.001)</td>
<td>−4.603 (0.001)</td>
<td>8.551 (0.001)</td>
</tr>
<tr>
<td>Intercept 2</td>
<td>9.255 (0.001)</td>
<td>−3.382 (0.001)</td>
<td>9.790 (0.001)</td>
</tr>
<tr>
<td>Intercept 3</td>
<td>10.872 (0.001)</td>
<td>−1.824 (0.001)</td>
<td>11.435 (0.001)</td>
</tr>
<tr>
<td>Intercept 4</td>
<td>12.548 (0.001)</td>
<td>−0.0329 (0.001)</td>
<td>13.168 (0.001)</td>
</tr>
<tr>
<td>Intercept 5</td>
<td>15.438 (0.001)</td>
<td>2.050 (0.001)</td>
<td>16.120 (0.001)</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>−6038.4</td>
<td>−6789.5</td>
<td>−5958.8</td>
</tr>
<tr>
<td>% correctly classified:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same category</td>
<td>55.8</td>
<td>52.3</td>
<td>55.6</td>
</tr>
<tr>
<td>Within one category</td>
<td>94.4</td>
<td>94.1</td>
<td>95.0</td>
</tr>
<tr>
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<td>5790</td>
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The statistical strength of the associations between efficiency measures and insurer financial ratings is evaluated in several ways. First, we examine the joint statistical significance of the three efficiency measures in the model that includes efficiency with the selected financial ratios (i.e., Model 3). Second, we examine the incremental change in classification rates when efficiency measures are added to Model 1. The three efficiency measures are jointly significant at the 1% level of significance using the likelihood ratio test. The classification rates improve significantly (p-values 0.01 or better) based on a paired-sample t-test, with the model including financial ratios and efficiency measures the best overall based on the ability to correctly predict ratings within one category of the actual level. The only paired t-test that was not significant is for the comparison of Models 1 and 3 classification rates for same-category predictions. That is to say, Model 3 classification rates are significantly better than Model 1 (and 2) for within-one category predictions. However, while efficiency scores are statistically significant in Model 2, their ability to predict ratings is not any better than a “random” (or “modal”) model that predicts all insurers to have the most frequent rating (A, A–). Thus, our results indicate that efficiency scores provide incremental information relevant to insurer financial strength, but in isolation (i.e., Model 2) are weak predictors of ratings. Additionally, the economic significance of adding efficiency to a rating determinants model is very weak. The statistically significant improvement in ratings prediction within one category (94.4% to 95.0%) represents an improvement of fewer than 35 firms (out of 5790) correctly classified.

**CONCLUSION**

Economic and finance theory suggests a positive association between firm efficiency and financial strength. A.M. Best, the leading purveyor of insurer financial strength ratings, identifies competitive market position as an important business profile issue in their evaluation of insurance firms.

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11Firms are classified into the rating category to which they have the highest predicted probability of belonging.

12For example, if an insurer is predicted to be in the “B++, B+” rating category and its actual rating is either one category higher (A, A–) or one category lower (B, B–), then the insurer is considered classified correctly based on the criterion that the prediction is correct if “within one category” of the actual rating category.

13The “random” (or “modal”) approach predicts that all “insurers will be rated “A, A–” since this is the rating category with the greatest frequency. Under this approach, the percent correctly classified will be equal to the number of insurers actually rated “A, A–” divided by the total number of sample insurers: (3029/5790) or 52.3 percent (see Table 1).
They specifically recognize efficiency characteristics such as a low cost structure, effective use of technology, and easy and inexpensive access to capital as part of their business profile analysis. We find that firm efficiency scores are related to financial strength ratings, but are, by themselves, and incrementally, weak predictors of financial strength ratings.

Although we expect efficiency to be an important rating factor because of its relation to firm profitability, financial strength ratings consider the risk taken to achieve a particular level of profits, and the ability to bear risk. Consequently, we examine the role of capital, firm size, and organizational form because of the ability of these measures to gauge many dimensions of risk and risk-bearing capacity. Our findings suggest that efficiency is best considered along with other firm-specific characteristics as a determinant of insurer financial strength ratings. In summary, our study extends the literature on rating determinants by examining efficiency scores, and finds that despite the importance of these measures in insolvency prediction, they add little explanatory power to a rating determinants model based on firm size, capitalization, and organizational form. The relative importance of qualitative (rather than quantitative) factors in the insurer rating process is a likely explanation of the unexplained variation in insurer financial strength ratings.

REFERENCES


