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Risk-Based Capital and Solvency Screening in Property-Liability Insurance: Hypotheses and Empirical Tests

Martin F. Grace
Scott E. Harrington
Robert W. Klein

ABSTRACT

For a fixed probability of wrongly classifying a strong insurer as being weak (Type I error), this paper examines the classification power (the probability of correctly identifying a weak insurer as being weak) for two potential solvency detection methods. The first is to classify insurers using ratios based on risk-based capital (RBC) standards and the second is to use the Financial Analysis Tracking System (FAST) solvency screening mechanism created by the National Association of Insurance Commissioners (NAIC). We test the hypothesis that the RBC system has at least as much power for identifying financially weak insurers as the FAST scoring system does. Our empirical results are largely inconsistent with this hypothesis: RBC ratios are less powerful than FAST scores in identifying financially weak property-liability insurers during our sample periods. We also provide limited evidence that RBC ratios and FAST scores are jointly more powerful in identifying weak insurers than FAST scores alone, which suggests that RBC ratios may convey new information about insolvency risk despite their relatively low power on a univariate basis.

INTRODUCTION

The National Association of Insurance Commissioners (NAIC) concluded in 1990 that risk-based capital (RBC) standards for insurers were feasible and preferable to traditional fixed minimum capital standards. The NAIC subsequently adopted RBC formulas for life-health insurers (effective in 1994) and property-liability insurers (effective in 1995) and a RBC model law that allows or requires certain regulatory

Martin F. Grace is Professor of Risk Management and Insurance and Legal Studies and is Associate Director, Center for Risk Management and Insurance Research at Georgia State University. Scott E. Harrington is Professor of Insurance and Finance and Francis M. Hipp Distinguished Faculty Fellow in the College of Business Administration, University of South Carolina. Robert W. Klein is Associate Professor of Risk Management and Insurance and Director, Center for Risk Management and Insurance Research, Georgia State University.

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actions when insurers fail to meet minimum RBC thresholds. The stated overall purpose of the NAIC RBC requirements is to establish more meaningful minimum standards of capital adequacy related to an insurer's risk of insolvency than fixed minimum capital requirements. At the same time, the NAIC has emphasized that the ratio of an insurer's capital to its RBC should not be used as a measure of its overall financial strength, and the model law prohibits the use of RBC ratios in marketing for both property-liability insurers and life-health insurers.

Despite this caveat concerning the purpose of RBC, the RBC standards have significant implications for the financial regulation and operation of insurers. The standards raise a number of issues for insurance regulators, including their utilization in solvency screening or "early warning" systems for financially troubled insurers. Regulatory solvency screening systems, such as the NAIC's Financial Analysis Tracking System (FAST) developed in the early 1990s and the earlier Insurance Regulatory Information System (IRIS), are designed to screen and prioritize insurance companies for more in-depth financial analysis.[1] The practical objective is to identify insurers that are in, or headed toward, financial trouble to facilitate timely regulatory intervention to prevent insolvency or reduce the costs of insolvencies that do occur.

As a measure of capital adequacy, RBC can be expected to play some role in solvency screening systems, because an insurer's actual capital (surplus) compared to its RBC requirement should provide information concerning the insurer's financial strength.[2] An important question is how well the ratio of an insurer's capital to its RBC (or, alternatively, the ratio of RBC to capital) will predict the likelihood of an insurer becoming financially impaired or insolvent, including insurers whose actual capital exceeds their minimum RBC requirement.[3] Empirical comparisons of RBC ratios for property-liability insurers that later became insolvent to those for insurers that survived indicate that insolvent firms on average had significantly lower ratios of capital to RBC than solvent insurers (Grace, Harrington, and Klein (GHK), 1993; Cummins, Harrington, and Klein (CHK), 1995). However, these studies also indicate that fewer than half of the insurers that later failed had an RBC ratio below the threshold level needed to avoid increased regulatory scrutiny and that RBC ratios have fairly low power to identify weak companies. In addition, the NAIC RBC formula has been criticized on a variety of conceptual and theoretical grounds including its static nature, its alleged reliance on worst case scenarios to establish underwriting risk factors, its failure to include charges for interest rate risk, and its reliance on book values of fixed income securities.[4]

The development of the life-health and property-liability RBC formulas by NAIC working groups was a highly visible process that involved extensive input

[1]Klein (1995) provides detailed discussion of NAIC solvency screening systems and regulation.

[2]The NAIC reviews insurer RBC results as part of its overall solvency screening activities.

[3]A large empirical literature estimates models of insurance company insolvency risk. Willenborg (1992) provides a survey. Also see BarNiv and McDonald (1992) and Lamm-Tennant, Starks, and Stokes (1995). Examples of theoretical work on insurer insolvency risk include Munch and Smallwood (1982) and Finsinger and Pauly (1984).

[4] Other possible approaches to RBC include cash flow and options pricing models. Cummins, Harrington, and Niehaus (1995) outline the conceptual framework for establishing RBC and describe several alternative methods of developing RBC standards.

from both regulators and industry. Exposure drafts of the formula were widely disseminated and debated. While some of the components of the final RBC ratio for both property-liability and life-health insurers are calculated from confidential information that the insurer reports to regulators, the final formula is publicly available, and an insurer's RBC and actual capital are public information reported in its annual statement.

In contrast to RBC, the FAST system was developed in relative privacy by regulators. The FAST score (described below) is based on a set of financial ratios with individual scores assigned to various ranges for each ratio. The sum of these individual scores is the overall FAST score. While the variables used in the FAST system are now publicly disclosed (see appendix), neither the FAST score nor its components are publicly available.

This study compares the power of FAST and RBC to identify financially weak insurers. We develop and provide evidence concerning the hypothesis that RBC should have at least as much power to identify weak insurers as the private (or at least quasi-private) FAST scoring system in order to minimize possible costly distortions associated with the public RBC system and encourage market discipline for weak insurers. As we elaborate below, our evidence generally is inconsistent with this hypothesis: RBC is less powerful than FAST in identifying weak insurers. This finding might indicate that a relatively crude RBC system is somehow only efficient when combined with a more powerful private screening system, or it might indicate that political pressure prevented increased accuracy in the publicly-disclosed RBC system. Regardless of the reason, RBC might nonetheless convey new information about insolvency risk. We also investigate this new information hypothesis by examining whether RBC and FAST are jointly more powerful than FAST alone.

Our comparisons of the power of FAST scores and RBC ratios to identify financially weak insurers use data for large samples of property-liability insurers that conducted business during 1989, 1990, and 1991.[5] We first provide evidence of the power of FAST scores and RBC ratios to identify insurers that became insolvent during the three years following the data year. We then consider power to identify a broader category of "troubled insurers" that includes insurers that either became insolvent within three years or which were placed in the highest category for additional regulatory scrutiny by the NAIC based on more in depth regulatory analysis of their financial results for the data year in conjunction with IRIS.[6]

The principal findings concerning power to identify insurers that subsequently failed are: (1) the FAST score generally has greater power to identify insurers than the ratio of an insurer's RBC to its surplus, and (2) including the RBC ratio (or its

[5]An early version of this study also considered the IRIS screening system with similar implications. Cummins, Grace, and Phillips (1997) have recently extended our analysis to compare the predictive ability of selected FAST ratios, RBC ratios, and a measure of financial strength produced by a dynamic cash flow model.

[6]This categorization is not available to the public. We obtained this information and the FAST scoring methodology from the NAIC as part of contract research. (See GHK, 1995.) Cordell and King (1995) use confidential regulatory assessments of bank financial condition in their analysis of risk-based capital systems in banking.

separate components, see below and CHK, 1995) in insolvency prediction models that also include the FAST score generally leads to little or no increase in power. With respect to the expanded samples of troubled insurers that include insurers placed in the highest category for regulatory scrutiny through IRIS, univariate comparisons indicate that the FAST score again generally has more power to identify these insurers than the RBC ratio. However, combining the RBC ratio with the FAST score often increases power to identify this broader category of financially troubled insurers, suggesting that the development of RBC may have produced new information concerning insolvency risk that could be useful in regulatory monitoring.

Although we also find some improvement in the performance of the RBC ratio compared to the FAST score for identifying larger insolvent or troubled insurers, as noted above our overall results concerning the relative power of RBC and FAST suggest either that an RBC system with limited accuracy is somehow beneficial when accompanied by a more accurate private screening system or that political pressure caused the RBC formula to be relatively crude despite potential efficiency gains from greater accuracy.[7] We cannot distinguish between these possible explanations, but our findings and discussion should help motivate and frame the relevant issues for possible subsequent exploration of these alternatives. In addition, our results concerning the power of combining FAST scores and RBC ratios should be of interest to regulators that are exploring ways of using RBC information in solvency screening.

In other tests we examine whether the predictive accuracy of models that include both the FAST score and the RBC ratio is improved by including measures of firm size and whether the firm is a mutual versus a stock (see GHK, 1993; CHK, 1995). We find that firms with larger assets and mutual firms were generally significantly less likely to fail or become troubled during our sample periods after controlling for the FAST score and the RBC ratio. However, the inclusion of the size and organizational form variables only increases power to identify smaller insolvencies and troubled insurers. Inclusion of these variables decreases power, sometimes substantially, for larger insolvent and troubled insurers.[8] We also compare the power of the premium-to-surplus ratio, which has long been used as a measure of property-liability insurer financial strength, to the power of the FAST score and the RBC ratio. We find that the power of the premium-to-surplus ratio sometimes compares quite favorably to the FAST score and the RBC ratio in univariate comparisons during our sample periods.

The next section provides background on the NAIC RBC standards and the FAST screening system. We then describe our hypotheses concerning the relative

[7]It might be suggestive in this latter regard that a firm size factor recommended by the actuarial advisory group for RBC was eliminated because of regulatory concerns that it would have an adverse impact on small insurers. (But note below our results concerning the adverse effects of including a measure of firm size in our multivariate prediction models on the power to identify larger failed or troubled insurers.) The NAIC also rejected alternative weights or risk charges by line recommended by the actuarial advisory group based on a historical analysis of the relative variability in underwriting results among the different lines.

[8]There might be advantages to employing a separate FAST system for small and large insurers.

power of RBC and FAST to identify financially weak insurers. The data and methodology are described next, followed by presentation of the empirical results. The main findings are briefly summarized in the concluding section.

BACKGROUND ON RBC AND FAST

RBC Standards

Prior to the development of RBC, state solvency regulation relied on fixed minimum capital (surplus) standards, which generally averaged in the area of $2 million for a multi-line insurer. These fixed standards were more appropriate for start-up operations than for established companies with significant premium volume and risk exposure. While regulators could and sometimes did take action against a troubled insurer before its capital fell below fixed minimum standards, such actions could be subject to legal challenges by the insurer, especially if the insurer's capital was much larger than the statutory minimum. Given that the value of insurer liabilities and some assets cannot be readily verified, it can be difficult for regulators to prove that an insurer has excessive insolvency risk or is already economically insolvent until it is patently obvious that an insurer is failing or will fail.

According to the NAIC, the RBC requirements are to provide a standard of capital adequacy that: (1) is related to risk, (2) raises the safety net for insurers, (3) is uniform among states, and (4) provides authority for and in some cases requires regulatory action when capital falls below the standard.[9] This last aspect of the requirements also may help prevent unjustified regulatory forbearance against weak insurers.[10]

The NAIC's property-liability RBC formula encompasses four major risk categories: (1) asset risk (default and market value declines), (2) credit risk (uncollectible reinsurance and other receivables), (3) underwriting risk (pricing and reserve errors), and (4) off-balance sheet risk (e.g., guarantees of parent obligations, excessive growth). The formulas apply factors to various amounts reported in (or related to) the annual statement to determine RBC charges for each type of risk. A covariance adjustment is made to the accumulated RBC charges to account for diversification between major risk categories.

Under the model RBC law, certain company and regulatory actions are required if a company's Total Adjusted Capital (TAC, which either equals or approximately equals total surplus for most insurers) falls below its calculated level of RBC. Four levels of company and regulatory action are established with more severe action required at lower levels. The "authorized control level," which is equal to the RBC

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[9]See NAIC (1993) for details. See Cummins, Harrington, and Niehaus (1993) for further discussion of the objectives of RBC and potential market dislocations and other problems in implementing RBC standards.
[10]The extent of regulatory forbearance in the insurance industry has been debated. See, for example, Harrington (1991) and Hall (1997). Limits on regulatory discretion can help mitigate forbearance, but as we discuss below, such limits also might increase the likelihood of inefficient regulatory intervention in some instances.

formula result, is used as the primary point of reference. Other levels are calculated as a percentage of the authorized control level:

Company Action Level. An insurer with TAC below the company action level RBC, which is 200 percent of the authorized control level RBC, must file a plan with the insurance commissioner that explains its financial condition and how it proposes to correct its deficiency.

Regulatory Action Level. When an insurer's TAC falls below the regulatory action level, which is 150 percent of its authorized control level RBC, the commissioner is required to examine the insurer and institute corrective action, if necessary.

Authorized Control Level. If an insurer's TAC falls below 100 percent of its authorized control level, the commissioner has the legal grounds to rehabilitate or liquidate the company.

Mandatory Control Level. If TAC is less than the mandatory control level RBC, which is 70 percent of its authorized control level RBC, the commissioner is required to seize the company.

FAST

Solvency screening systems rely heavily on annual and quarterly financial statements that must be filed by every insurer. Insurers that appear to be weak based on key financial results are prioritized for more in depth scrutiny and examination by regulators. The NAIC's IRIS served as a baseline solvency screening system for the NAIC and state regulators from the mid-1970s until the development of the FAST system in the early 1990s. The computational phase of IRIS involves calculating 11 financial ratios for an insurer and comparing each ratio to its specified "usual range." In the analytical phase, insurers are then selected for a more detailed assessment of their financial results based on a number of criteria, including whether an insurer has four or more ratios outside the designated usual ranges. Following this detailed analysis, insurers are placed into one of five categories -- first, second, third, no priority, and no synopsis required. Domiciliary regulators are advised to schedule their analysis of companies accordingly.

The FAST system represents an expanded solvency screening model and analytical process that was designed to identify financially weak "nationally significant" insurers (insurers that write business in 17 or more states and have gross premiums written in excess of $50 million for life-health companies and $30 million for property-liability insurers, averaged over the previous three years) and to facilitate regulatory peer review of domiciliary regulation of these insurers. The objective of the NAIC's peer review process, as exercised through its Financial Analysis Working Group (FAWG), is to encourage domiciliary regulators to take effective action with respect to nationally significant insurers that are in financial difficulty. Under FAST, the NAIC's Financial Analysis Division calculates a FAST score for each insurer, which is used to prioritize companies for further analysis.

FAWG reviews the FAST scores, establishes thresholds, and identifies those insurers/states that will be subject to peer review.[11]

FAST consists of approximately 25 financial ratios and variables (plus lagged values of some of the variables). Unlike IRIS, FAST assigns different point values for different ranges of ratio results. As noted above, the cumulative score for each company is then used to prioritize it for further analysis. Regulators classify companies either as immediate, priority, or routine based on their score and specified cut-off points. The FAST ratios and point scheme were developed using regulatory experience and judgment, as well as a limited amount of statistical analysis, in large part with the objective of producing a high score for insurers that were currently perceived as being financially weak (we return to this subsequently). This system has evolved considerably since its inception, and separate models are used for life, health and property-liability insurers. Although the FAST scoring system and results have remained confidential, the NAIC has authorized the publication of the FAST ratios, which are listed in the appendix.[12]

HYPOTHESES

Detecting insurers that are in, or heading toward, a hazardous condition is a major function of solvency regulation. If it is not possible to detect problems early enough so that they can be corrected before insolvency, the normative objective is for regulators to take action quickly in order to minimize costs caused by an insurer's failure. In addition to helping identify weak insurers, an efficient solvency screening system will minimize the total expected costs of insolvencies and monitoring by: (1) helping to establish legal grounds for regulatory action against weak insurers, (2) encouraging regulators to take timely action even though political pressure may encourage forbearance, and (3) encouraging insurers to reduce risk for which private incentives for safety are suboptimal.

The focus of our analysis is on the power of alternative measures of financial strength to identify financially weak insurers. To facilitate discussion and presentation of our hypotheses and results, we assume that there are two types of insurers, "weak" and "strong," where the weak insurers have excessive insolvency risk.[13] In order to explain the hypotheses and results in terms of statistical power to identify weak insurers, we use the underlying null hypothesis that a given insurer is

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[11]For these insurers/states, FAWG queries the domiciliary state on various aspects of the insurers' financial condition and regulatory actions with respect to those insurers. If FAWG determines that the domiciliary regulator has taken the appropriate actions, then FAWG may close the file or continue to monitor the company. If FAWG determines that further measures are desirable, it will recommend the appropriate corrective action to the domiciliary state. If the domiciliary regulator fails to follow FAWG's recommendation, FAWG will alert other states accordingly and coordinate their actions against the troubled company.

[12]GHK (1995) conduct extensive analysis of the ability of the FAST score and the FAST variables to predict insolvencies and whether alternative variables and scoring methods could improve predictive accuracy.

[13]By excessive here we mean that weak insurers have insolvency risk in excess of the level that would arise in a well-functioning market in which consumers are well-informed about insolvency risk (and would be harmed significantly by insurer failure).

strong; the alternative hypothesis is that the insurer is financially weak. Given this convention, the Type I error probability (rate) is the probability that a strong insurer is incorrectly classified as weak. The Type II error probability (rate) is the probability that a weak insurer is incorrectly classified as strong. Power is the probability of rejecting the null hypothesis (strong insurer) when it is false (the insurer is actually weak). Thus, power is the probability that a weak insurer is correctly classified.[14]

Letting $\Pi(x)$ denote the power of the variable x (or vector of variables) for a given Type I error rate, our two hypotheses concerning the relative power of RBC and FAST to identify weak insurers are:

(1) RBC is at least as powerful as FAST to minimize costly distortions and encourage beneficial market discipline $\Pi(\text{RBC}) \geq \Pi(\text{FAST})$. The alternative hypothesis is that $\Pi(\text{RBC}) < \Pi(\text{FAST})$.

(2) If $\Pi(\text{RBC}) \leq \Pi(\text{FAST})$, RBC nonetheless conveys new information about insolvency risk so that $\Pi(\text{FAST, RBC}) > \Pi(\text{FAST})$. The alternative hypothesis is that $\Pi(\text{FAST, RBC}) \leq \Pi(\text{FAST})$.

Hypothesis 1: RBC is at Least as Powerful as FAST to Minimize Costly Distortions/Encourage Market Discipline

Solvency monitoring with FAST (or IRIS) can be broadly viewed as consisting of two stages. In the first stage, insurers are initially screened for in depth evaluation and possible remedial action in the second stage.[15] Under an efficient monitoring system, the initial screening system and the in depth review process should be jointly designed to minimize expected total costs of insolvencies and monitoring. The principal benefit from initially screening companies is to economize on the greater costs of in depth analysis.

Direct costs of initial screening include the costs of obtaining and analyzing data. Indirect costs include the cost of Type I errors; i.e., the costs of subsequent in depth analysis and the adverse effects on strong insurers that are incorrectly classified in the initial screen. These costs include the costs of responding to regulatory requests for additional information, the effects of possible regulatory pressure on insurer decisions, and the effects on sales and renewals if information

[14]Power equals one minus the Type II error probability, which depends on the Type I error probability. An alternative convention used in some studies is the null hypothesis that a given insurer is weak. The Type I error rate is then the probability of failing to classify a weak insurer correctly, the Type II error rate is the probability of failing to classify a strong insurer correctly, and power is the probability of correctly classifying a strong insurer. CHK (1995) used this convention and reported Type I error rates (defined as proportions of insolvent insurers incorrectly classified as strong) for given Type II error rates (defined as proportions of solvent insurers incorrectly classified as weak). The power figures in our study for different Type I error rates correspond to one minus the Type I error rates shown in the CHK study.

[15]Note that FAST (and IRIS) actually involve at least three stages: an initial screen, more in depth review by a team of analysts, and possible further detailed analysis and action by domiciliary or non-domiciliary regulators.

concerning the poor financial assessment of the insurer becomes available in the marketplace. Efficiency requires investing in information until the marginal benefits of greater accuracy equal the marginal cost of information. Efficient screening systems can be expected to utilize all low cost information that helps predict insolvency risk. The costs of Type I errors from initial screening can be reduced if the results of the initial screen are confidential. However, keeping the results private also reduces possible desirable incentive effects that could be created if the results of an accurate screening system became public information. The case for making the results public increases with the accuracy of the system.

The NAIC RBC system in certain respects is analogous to a two-stage solvency monitoring system. The ratio of an insurer's capital to its RBC is analogous to a score from a screening system. On average, a lower ratio should indicate a greater likelihood of insolvency. Required company and regulatory actions for insurers with RBC ratios below the specified thresholds are analogous to the in-depth regulatory analysis and possible actions that accompany adverse rankings by a screening system. There is a difference, however, in that the RBC model law compels certain regulatory actions when an insurer's capital falls below certain RBC thresholds, whereas regulators have greater flexibility in interpreting and acting on early warning system results.

In principle, a RBC system could be designed to achieve approximately the same ranking of insurers as any existing screening system. As is true for an efficient screening system, an efficient RBC system would equate the marginal benefits of increased accuracy in the formula with the marginal cost of information. If the benefits and costs of increased accuracy differ between a public RBC system and a private screening system, the efficient level of accuracy could differ between the approaches. At least two factors suggest that the optimal level of accuracy could (at least initially) be greater for a public RBC system. First, the possibility of greater market reactions to a publicly available RBC ratio provides an additional incentive for accuracy compared to a confidential screening system. Greater accuracy will increase beneficial market discipline against weak insurers; it will reduce costly distortions in the form of adverse market reactions for insurers whose financial strength is underestimated. Second, regulatory responses to RBC ratios are more constrained (less discretionary) than the responses to FAST scores, which could increase distortions from inefficient interventions against insurers whose RBC ratio overstates financial weakness. This also provides an incentive for additional accuracy.

It has been argued that the RBC minimum capital threshold(s) should be drawn fairly conservatively in order to reduce the likelihood of potentially severe market dislocations (i.e., costly Type I errors; see Cummins, Harrington, and Niehaus, 1993). Conservative thresholds reduce the Type I error rate for company/regulatory actions and the possible adverse consequences of limited discretion. It nonetheless can be argued that the possibility of undesirable distortions (or possibly beneficial market discipline) for insurers with RBC ratios above the minimum thresholds still provides an additional incentive for accurately ranking insurers' financial strength compared to a private screening system. If so, the additional incentives for accuracy due to the possibility of costly distortions from a public RBC system imply that an efficient RBC system will initially have at least as much power to identify weak insurers as an efficient solvency screening system. The implication is that RBC will have at least as much power to identify weak insurers as FAST at the time that RBC is developed.

The efficiency criterion also implies that a previously efficient screening system will be modified following the development of an efficient RBC system if incorporating information on RBC could increase accuracy of the screening system. Alternatively, the screening system might even become redundant and thus be supplanted by the RBC system (i.e., insurers with RBC ratios above the stipulated thresholds for company and regulatory action would be prioritized for in depth analysis based on their RBC ratios).

The alternative to Hypothesis 1 is that RBC is less powerful than FAST in identifying financially weak insurers. As suggested in the introduction, there are at least two possible explanations for this type of result. The first is that a relatively crude RBC system is somehow efficient when combined with a more powerful private screening system. This conceivably might be true because: (1) the marginal benefits of increased accuracy for a RBC system are reduced by the existence of a private, solvency screening system such as FAST, and (2) possible increases in the inappropriate use of information for a public RBC system with greater accuracy could produce costs that exceed the benefits. Despite its crudity, the RBC system could still promote additional market discipline against weak insurers, help regulators to take efficient action against the weakest insurers, and discourage regulatory forbearance.

Although the argument that less accuracy is better does not seem compelling, it is not inconsistent with statements by the NAIC that the RBC ratio should not be used as an overall measure of financial strength, with the RBC model bill's prohibition against using RBC ratios in marketing, and with the NAIC's stated rationale for the RBC system, which suggests that accurate assessment of insolvency risk is not the pre-eminent goal of RBC. This less-is-better argument is also related to a major argument for keeping the results of screening private: the possibility that releasing the results would have undesirable market consequences that would outweigh any benefits of increased market discipline.[16] On the other hand, the argument that a crude RBC formula will help prevent undesirable market reactions assumes that the RBC formula's crudity can be credibly conveyed to the same parties who otherwise would over-react to more accurate information, or that the system can be designed to reduce the likelihood that the less accurate information will be obtained and subsequently misused by uninformed consumers or other parties. Otherwise, the cost of distortions would presumably decline and the benefits of increased market discipline would presumably increase as accuracy increases.

Another possible reason that RBC might be less powerful than FAST is that political pressure against greater accuracy could be greater for a public RBC system than for a private screening system. Increased accuracy in solvency

[16]Note that regulators often take informal actions against troubled insurers in to attempt to resolve problems that might be compromised by adverse publicity.

screening and/or RBC systems will produce winners and losers among firms (and possibly consumers). The economic theory of regulation (e.g., Becker, 1983) posits under these conditions that regulation will be designed to maximize political support (or, equivalently, minimize opposition) from affected constituencies. The theory suggests that while efficiency will be considered when designing and implementing regulation, interest group pressure generally will lead to inefficient redistributions of wealth.

Because efficiency gains from increased accuracy in a RBC formula are likely to be diminishing and may be modest in size before the efficient level of accuracy is reached, the net political pressure against increased accuracy might become progressively greater as accuracy (or proposed accuracy) increases. Although political support for increased accuracy by the majority of firms that are financially strong may initially outweigh opposition by weak firms, the level of accuracy that maximizes political support may nonetheless fall short of the efficient level. Relatively weak firms that would experience substantial losses from increased accuracy of solvency monitoring will have a large incentive to become informed about and actively oppose additional changes. The resulting opposition could outweigh the support by more numerous firms that beyond some point would receive modest benefits per-firm from additional accuracy. Support for additional accuracy by relatively strong firms also will be undermined by free rider problems and by uncertainty concerning the possible effects of additional changes in RBC or solvency screening formulas on these firms (which could lead to some bias towards the status quo).

Because of the public nature of RBC, political opposition against increased accuracy could be expected to be stronger than against private screening systems. In addition, because RBC standards are codified and regulatory discretion is constrained, more evidence may be required to overcome opposition to changes in the RBC formula that would increase its accuracy, including possible legal challenges, than would be needed in the case of accuracy-enhancing changes in a private screening system. If so, political pressure could constrain accuracy more for a RBC system than for a private screening system.

Hypothesis 2: RBC Conveys New Information

If RBC is less powerful or no more powerful than FAST either due to efficiency considerations or political pressure, it is still possible that RBC and FAST could be jointly more powerful in identifying weak insurers than FAST alone; i.e., (FAST, RBC) > (FAST). This result would imply the predictive accuracy of FAST could be enhanced by adding information about an insurer's RBC. Why might RBC convey new information that helps identify financially weak insurers even if it is less accurate than FAST on a univariate basis? One possibility is that the research and analysis involved in developing a RBC system could still uncover new information about variables related to insolvency risk or new ways of combining information that helps predict insolvencies.

DATA AND METHODOLOGY

We analyze the relationship between insolvency risk, RBC ratios, and FAST scores using the FAST scoring system as of 1993 for property-liability insurers with available data for 1989, 1990, and 1991. The samples include all stock, mutual, reciprocal, and Lloyds property-liability insurers with admitted assets and net written premiums of at least $1 million in 1990 dollars that were included in the NAIC's RBC database, which excludes certain specialty insurers (e.g., financial guaranty and title insurers) and insurers that did not file statements with the NAIC. We also exclude professional reinsurers as classified by the NAIC.[17] We analyze data for individual companies, as opposed to groups of affiliated insurers. The RBC standards presently apply to individual insurers, and the primary focus of state solvency regulation is on individual insurers rather than groups. These criteria produce samples of 1567, 1616, and 1606 companies in 1989, 1990, and 1991, respectively.

We identified insurers that became insolvent during the three-year period following each data year using NAIC and A.M. Best lists of single and multi-state insurer insolvencies.[18] Sixty-four insurers with available data in 1989 failed during 1990 through 1992 (nine in 1990, nineteen in 1991, and thirty-six in 1992). Fifty-eight insurers with available data in 1990 failed during 1991 through 1993 (four insurers in 1990, thirty-eight in 1991, and sixteen in 1992). Forty-nine insurers with available data in 1991 failed during 1992 through 1994 (twenty-four in 1992, fifteen in 1993, and ten in 1993).

In univariate tests we compare the power of an insurer's RBC to surplus ratio (RBC/S), its FAST score, and its premium-to-surplus (P/S) ratio to identify insurers that failed within the three-year period after the data year at various Type I error rates.[19] We investigate the new information hypothesis using a multiple logistic regression model that includes both RBC/S and the FAST score. Given the evidence presented by CHK (1995) that an insolvency prediction model that includes the separate components of RBC/S often has greater power to identify failed insurers than a model that includes RBC/S, we also examine the predictive accuracy of multiple logistic regression models that include the FAST score and the separate components of RBC (relative to surplus) as opposed to RBC/S. We also

[17]The NAIC RBC formula for professional reinsurers differs from the formula for primary insurers. A company is designated a professional reinsurer if it has premiums assumed from non-affiliates in excess of 75 percent of the sum of direct premiums written plus premiums assumed from non-affiliates.

[18] We classify an insurer as insolvent if it was subject to any public or formal regulatory proceedings such as conservation of assets, rehabilitation, receivership, or liquidation.

[19] The NAIC calculated the insurer RBC levels and the ratio of TAC to RBC using a scale factor for formula RBC of 0.4. We adjusted these ratios to reflect the subsequent increase in the scale factor to 0.5. The RBC ratio provided to us was calculated for each insurer based solely on annual statement data. The NAIC formula utilizes some non-statement information that was not available for this study but the annual statement result is a good approximation for most companies. TAC equals surplus for most companies, and we use the conventional term surplus when describing the RBC ratio. We analyze the ratio of RBC to surplus, which produces the same power as the ratio of surplus to RBC in univariate comparisons and has conceptual/statistical advantages when estimating models that include separate components of RBC to surplus (see CHK, 1995). We calculated all other variables from the NAIC data tapes, including the FAST variables. We then used the FAST scoring system to calculate the FAST score.

estimate a model that includes RBC/S, the FAST score, a measure of insurer size (log of assets), and organizational form (a dummy variable equal to one for mutuals and zero for other companies).[20] The multiple logistic models are estimated using truncated values of all variables to reduce the possible effects of outliers. The values of each variable are truncated at the 1st and 99th percentile values of the variable in the sample. We use the approximate jackknife procedure described by Pregibon (1981) to calculate predicted probabilities of insolvency (or financial trouble) in the multivariate comparisons to reduce the upward bias in classification accuracy that occurs with within sample predictions.

For 1990 and 1991, we obtained confidential information on insurers that were classified as high priority for regulatory scrutiny based on the IRIS analysis (after both the statistical and analytical phase) of their data for the given year. We use this information to replicate the preceding analysis for "troubled companies" (insurers that were classified as high priority or which became insolvent within three years). A limitation of this analysis is that it may involve some circularity: regulatory measures of financial strength are used to predict companies that were previously classified as financially weak by regulators, albeit with a different system (IRIS versus FAST or RBC).[21] This analysis will nonetheless provide insight into the extent to which newer measures of financial strength (the RBC ratio and the FAST score) are related to prior regulatory assessments of financial strength that purportedly go well beyond simple statistical analysis of financial ratios.

Another potential limitation of our analysis is that predictive accuracy of both the RBC ratio and the FAST score will likely be biased upward because these systems were developed in the early 1990s in view of information about the causes of insolvencies prior to 1994. As noted earlier, the FAST system was developed primarily with the goal of producing high scores for insurers that were viewed as being financially weak. This development primarily reflected regulatory judgment in view of a wide variety of information about weak insurers. While some statistical analysis was used, the FAST scoring methodology was not developed from detailed statistical analysis of financial ratios that predicted prior insolvencies.[22] In general, any "look ahead" bias should not undermine our major comparisons because both FAST and the RBC formula were influenced to some extent by historical experience and regulators' concerns about the problems causing previous insolvencies. For example, if a finding that the FAST score has greater power to identify troubled insurers than the RBC ratio in part reflects possible

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[20]CHK (1995) provide evidence that disaggregating the RBC ratio produces some increase in predictive accuracy. Estimating the coefficients for the separate RBC components modifies the weights for these components compared to the RBC formula, which can improve the predictive accuracy of the model (see CHK, 1995). GHK (1993) and CHK (1995) provide evidence that insurer size and organizational form are significantly related to insolvency risk.

[21]It should be noted, however, that regulators' classification of insurers is not based solely on IRIS or FAST results, but on a combination of this information and other information reviewed in additional financial analysis. This process is intended to reduce the number of Type I errors; i.e., insurers with poor IRIS/FAST results that that are caused by anomalies and that are not in financial difficulty.

[22]Indeed, the authors later conducted for the NAIC an extensive statistical analysis of ability of the FAST formula used in this paper to predict prior insolvencies (see GHK 1995).

modifications in the FAST system to reflect new information on the causes of insolvencies during part of our sample period, this finding would nonetheless imply that the RBC formula failed to incorporate the same information at the time it was adopted.[23]

EMPIRICAL RESULTS

Descriptive Statistics

Table 1 shows the sample means for the variables used in the analysis and selected percentile values of RBC/S and the FAST score by data year for four samples of insurers: (1) insurers that failed within three years of the data year ("failed"), (2) insurers that were solvent after three years ("solvent"), (3) insurers that either failed within three years or that were classified as high priority for regulatory scrutiny in the year after the data year ("troubled"), and (4) insurers that neither failed nor were classified as high priority ("sound"). For each year, RBC/S, the FAST score, and the premium-to-surplus ratios are larger on average for the failed and troubled company samples than for the solvent and sound samples, respectively. The failed and troubled insurer samples also on average have a smaller log of assets and relatively fewer mutual insurers each year than the solvent and sound samples, respectively.[24]

The differences in means and medians between the troubled and sound samples for both RBC/S and the FAST score exceed the corresponding differences for the failed and solvent samples, which suggests that both variables have better power to distinguish between troubled and sound insurers than between failed and solvent insurers. The percentage difference between the means and medians generally is larger for RBC/S than for the FAST score. In 1990, for example, the difference in the mean value of RBC/S between the troubled and sound samples is 0.52 (0.76-0.24), which is three times larger than the difference of 0.16 (0.44-0.28) between the means for the failed and solvent samples. The difference in medians between the troubled and sound insurers is 0.26 (0.45-0.19) compared to a difference of 0.18 (0.37-0.19) between the failed and solvent samples. These results and the other percentile values indicate that the frequency of relatively large values of RBC/S is much greater for the troubled company sample than for the failed, solvent, and sound samples.

Consistent with earlier studies of RBC ratios for failed and solvent insurers (GHK, 1993; CHK, 1995), relatively few insurers that later failed had values of RBC/S that would have required regulatory or company action. For example, an

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[23]Look-ahead bias would be more of a problem if the predictive accuracy of FAST and/or RBC were compared to measures of insolvency risk that were developed without considering the information provided by insolvencies in the early 1990s. See Cummins, Grace, and Phillips (1997) for another approach to the look-ahead bias problem.

[24]We conducted statistical tests of the differences illustrated in Table 1. Wilcoxin signed rank tests indicated significant differences in the distributions of RBC/S, the FAST score, P/S, and log of assets for the failed-solvent and troubled-sound samples each year. The difference in the proportions of mutuals was significantly different from zero at the 0.05 level for a one-tailed test except for the troubled/sound comparison for the 1991 data.

insurer with a value of RBC/S greater than 0.5 (which corresponds to a value of S/RBC greater than 200 percent) would violate the RBC "company action level" threshold. Over two-thirds of the failed companies had RBC/S values less than 0.5 each year. The performance of RBC on this dimension improves somewhat when comparing the troubled and sound insurer samples. However, the median RBC/S values of 0.45 and 0.47 in 1990 and 1991, respectively, still indicate that over half of the troubled insurers had values of RBC/S below the company action cutoff (i.e., had values of S/RBC greater than 200 percent).

Bivariate correlation coefficients between RBC/ S, the FAST score, and the P/S ratio are shown below:

Correlation between:	1989	1990	1991
RBC/S and FAST score	0.28	0.35	0.52
RBC/S and P/S	0.40	0.48	0.59
FAST score and P/S	0.41	0.40	0.41

While significantly positive, the magnitude of these correlations suggests that the variables could differ considerably in terms of their power to identify weak insurers.

Univariate and Multivariate Power Comparisons: Failed vs. Solvent Firms

Tables 2, 3, and 4 provide evidence with respect to Hypotheses 1and 2 by showing univariate multivariate comparisons of power to distinguish insurers that failed within three years of the data year from insurers that survived using data for 1989, 1990, and 1991. Table 5 shows the logit regression model estimates used to generate the multivariate power figures shown in Tables 2, 3, and 4.

The power figures equal the percentages of companies that subsequently failed that would have been identified as high risk prior to their failure by alternative variables/models at Type I error rates for solvent companies of 5, 10, 15, 20, 25, and 30 percent (i.e., percentages of solvent companies classified as high risk). Percentages are shown for the full sample of insurers that failed within three years and for three subsamples of failed insurers: (1) failed insurers with direct premiums written less than $25 million, (2) failed insurers with direct premiums written greater than $25 million, and (3) failed insurers with direct premiums written greater than $50 million. Other things being equal, higher power is more desirable for larger insolvent or troubled insurers given the larger costs of insolvency (e.g., Lamm-Tennant, Starks, and Stokes, 1995). Note, however, that the number of failed insurers in the larger premium sub-samples is small, which suggests caution in interpreting the results.[25]

[25]Also note that the Type I error rates shown for the two subsamples of failed companies are based on the entire solvent company sample.

Table 1
Descriptive Statistics for Samples of Failed, Solvent, Troubled, and Sound Insurers: 1989-1991

Variable	Statistic	1989 Data		1990 Data				1991 Data			
		Failed	Solvent	Failed	Solvent	Troubled	Sound	Failed	Solvent	Troubled	Sound
RBC/S	Mean	0.57	0.29	0.44	0.28	0.76	0.24	0.50	0.24	0.60	0.22
	10%	0.05	0.05	0.14	0.06	0.15	0.06	0.17	0.06	0.20	0.06
	25%	0.18	0.10	0.24	0.11	0.27	0.11	0.26	0.10	0.28	0.11
	50%	0.34	0.19	0.37	0.19	0.45	0.19	0.40	0.19	0.47	0.18
	75%	0.52	0.27	0.50	0.30	0.75	0.28	0.56	0.28	0.75	0.27
	90%	0.80	0.45	0.78	0.45	1.79	0.42	0.95	0.43	1.50	0.38
FAST Score	Mean	587	317	646	339	679	320	652	310	693	291
	10%	263	100	210	105	375	100	165	100	370	90
	25%	413	170	405	180	523	175	445	165	495	160
	50%	610	280	665	300	663	290	695	265	700	255
	75%	728	425	910	435	875	440	915	415	910	390
	90%	900	570	1025	625	1020	560	1040	590	1040	540
P/S	Mean	2.87	1.67	2.76	1.62	3.10	1.53	2.62	1.54	2.90	1.46
Log Assets	Mean	16.4	17.7	16.6	17.7	16.7	17.7	16.7	17.8	16.8	17.8
Mutual	Mean	0.06	0.24	0.09	0.24	0.18	0.24	0.12	0.23	0.19	0.23
Sample Size		64	1503	58	1558	136	1480	49	1557	121	1485

Note: "Failed" insurers became insolvent within three years of the data year; "Solvent" insurers survived for at least three years. "Troubled" insurers either failed within three years or were classified as high priority for regulatory scrutiny based on regulatory analysis of their data for the data year; "Sound" includes all other insurers.

Table 2

Power to Identify Failed Companies (in percent): Univariate and Multivariate Comparisons with 1989 Data.

Category of Failed Co.	Type I Error Rate	Univariate			Multivariate		
		P/S	RBC/S	FAST	FAST, RBC/S	FAST, RBC/S components	FAST, RBC/S, Log Assets, Mutual
All (64 co.)	5%	23	22	**30**	28	*36*	**45**
	10	44	31	**61**	59	53	**63**
	15	56	47	**67**	64	64	**70**
	20	59	52	**72**	70	**73**	**75**
	25	64	53	**73**	72	73	**83**
	30	64	61	**80**	78	**84**	**86**
Direct Premiums < $25 mill. (45 co.)	5%	20	20	**27**	27	**31**	**49**
	10	36	29	**56**	53	49	**67**
	15	47	42	**62**	60	60	**76**
	20	51	47	**69**	67	**73**	**82**
	25	56	49	**71**	69	**73**	**91**
	30	56	60	**78**	78	**84**	**93**
Direct Premiums > $25 mill. (19 co.)	5%	32	26	**37**	32	**47**	37
	10	63	37	**74**	74	63	53
	15	**79**	58	**79**	74	74	58
	20	**79**	63	**79**	79	74	58
	25	**84**	63	79	79	74	63
	30	**84**	63	79	79	**84**	68
Direct premiums > $50 mill. (8 co.)	5%	13	**38**	25	25	25	13
	10	38	38	**50**	50	38	13
	15	**63**	**63**	**63**	50	63	13
	20	63	**75**	63	63	63	13
	25	**75**	**75**	63	63	63	25
	30	**75**	**75**	63	63	**75**	38

Note: Power is the percent of failed insurers in the given sample that would be classified as high risk at the specified Type I error rates (percent of solvent firms that also are classified as high risk). "Failed" insurers became insolvent within three years of the data year; "Solvent" insurers survived for at least three years. Maximum power for a given sample / Type I error rate for the univariate comparisons is highlighted in bold. Power for multivariate model is highlighted in bold if it exceeds the maximum power for the univariate comparisons.

Table 3

Power to Identify Failed Companies (in percent): Univariate and Multivariate Comparisons with 1990 Data

Category of Failed Co.	Type I Error Rate	Univariate			Multivariate		
		P/S	RBC/S	FAST	FAST, RBC/S	FAST, RBC/S components	FAST, RBC/S, Log Assets, Mutual
All (58 co.)	5%	22	17	**40**	**41**	**41**	**48**
	10	34	34	**53**	**55**	**55**	**59**
	15	47	45	**66**	64	66	64
	20	50	53	**67**	67	**69**	**74**
	25	57	60	**69**	67	69	**74**
	30	62	67	**72**	72	72	**76**
Direct premiums < $25 mill. (37 co.)	5%	11	8	**38**	**41**	**43**	**54**
	10	19	27	**51**	51	**57**	**62**
	15	30	38	**62**	62	62	**68**
	20	35	46	**65**	65	**68**	**78**
	25	43	51	**65**	65	**68**	**78**
	30	49	62	**70**	70	**73**	**81**
Direct premiums > $25 mill. (21 co.)	5%	**43**	33	**43**	43	38	38
	10	**62**	48	57	**62**	52	52
	15	**76**	57	71	67	71	57
	20	**76**	67	71	71	71	67
	25	**81**	76	76	71	71	67
	30	**86**	76	76	76	71	71
Direct premiums > $50 mill. (12 co.)	5%	**58**	42	42	42	33	33
	10	**83**	50	50	**58**	42	50
	15	**92**	58	75	67	75	58
	20	**92**	75	75	75	75	75
	25	**92**	**92**	83	75	75	75
	30	**92**	**92**	83	83	75	75

Note: Power is the percent of failed insurers in the given sample that would be classified as high risk at the specified Type I error rates (percent of solvent firms that also are classified as high risk). "Failed" insurers became insolvent within three years of the data year; "Solvent" insurers survived for at least three years. Maximum power for a given sample / Type I error rate for the univariate comparisons is highlighted in bold. Power for multivariate model is highlighted in bold if it exceeds the maximum power for the univariate comparisons.

Table 4

Power to Identify Failed Companies (in percent): Univariate and Multivariate Comparisons with 1991 Data

Category of Failed Co.	Type I Error Rate	Univariate			Multivariate		
		P/S	RBC/S	FAST	FAST, RBC/S	FAST, RBC/S components	FAST, RBC/S, Log Assets, Mutual
All	5%	29	24	**51**	49	51	51
(45 co.)	10	33	45	**55**	55	53	55
	15	39	61	**61**	61	**63**	**67**
	20	47	67	**69**	69	69	**73**
	25	53	69	**78**	78	76	73
	30	61	73	**82**	82	82	80
Direct	5%	29	20	**54**	**55**	54	**57**
premiums	10	31	43	**60**	60	57	60
< $25 mill.	15	40	63	**66**	66	63	**77**
(35 co.)	20	46	71	**71**	71	71	**80**
	25	51	74	**83**	83	80	80
	30	54	80	**86**	86	86	86
Direct	5%	29	36	**43**	36	43	36
premiums	10	36	**50**	43	43	43	43
> $25 mill.	15	36	**57**	50	50	**64**	43
(14 co.)	20	50	57	**64**	64	64	57
	25	57	57	**64**	64	64	57
	30	**79**	57	71	71	71	64
Direct	5%	**33**	**33**	**33**	22	33	22
premiums	10	**44**	**44**	33	33	33	33
> $50 mill.	15	44	**56**	33	33	**56**	33
(9 co.)	20	**56**	**56**	**56**	56	56	44
	25	**67**	56	56	56	56	44
	30	**89**	56	67	67	67	56

Note: Power is the percent of failed insurers in the given sample that would be classified as high risk at the specified Type I error rates (percent of solvent firms that also are classified as high risk). "Failed" insurers became insolvent within three years of the data year; "Solvent" insurers survived for at least three years. Maximum power for a given sample/Type I error rate for the univariate comparisons is highlighted in bold. Power for multivariate model is highlighted in bold if it exceeds the maximum power for the univariate comparisons.

To facilitate interpretation, the largest power for each Type I error rate and failed insurer subsample is highlighted in bold for the univariate comparisons. The power for each multivariate model that has greater power than the most powerful variable on a univariate basis is also shown in bold.

The univariate power comparisons shown in Table 2 for 1989 generally indicate that the RBC ratio is less powerful than the FAST score and thus are inconsistent with Hypothesis 1. The FAST score has the greatest power for the full sample of failed insurers and small failed insurer subsample for each Type I error rate. The FAST score also has higher power than RBC/S for each Type I error rate for failed insurers with direct premiums greater than $25 million. The P/S ratio has power equal to or greater than the FAST score for this subsample for Type I error rates greater than 10 percent. For the subsample of 8 insolvent insurers with direct premiums above $50 million, the RBC ratio has greater power than the FAST score for Type I error rates of 5, 20, 25, and 30 percent, but the difference only reflects the correct classification of one additional insurer compared to the FAST score. The P/S ratio is just as powerful as RBC/S for four of the six Type I error rates for this subsample.

RBC/S fares little better in the multivariate comparisons for 1989. A striking result is that adding RBC/S to the FAST score never increases power compared to the FAST score alone. This includes the subsample of failed insurers with direct premiums greater than $50 million, which undermines the already fragile evidence of superior performance of RBC/S in the univariate comparisons for this subsample. Including the separate components of the RBC/S along with the FAST score occasionally leads to some increase in power compared to the FAST score alone. Including the log of assets and the mutual dummy variable produces the highest power for each Type I error rate for the full sample of failed insurers and the subsample of small failed insurers, but it also produces a material reduction in power for the subsamples of larger failed insurers.

The results of comparisons of power to distinguish between failed and solvent insurers using data for 1990 and 1991, which are shown in Tables 3 and 4, are generally similar to those for 1989. The FAST score has uniformly higher power on a univariate basis for the full sample of failed insurers and the subsample of small failed insurers. RBC/S sometimes has equal or greater power than the FAST score for the subsamples of larger failed insurers. The P/S ratio often has power equal to or greater than both RBC/S and the FAST score for these subsamples, and this is always the case for the 1990 data. Including RBC/S with the FAST score seldom increases power compared to the FAST score alone; including the separate components of RBC/S occasionally produces a modest increase in power. Including the log of assets and the mutual dummy variable with the FAST score and RBC/S generally produces the highest power for the full sample of failed insurers and subsample of small failed insurers for 1990 but not for 1991. Including these variables again reduces power for the subsamples of larger failed insurers.

Table 5

Multivariate Logistic Regression Results for Failed vs. Solvent Companies

Variable	1989 Data			1990 Data			1991 Data		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
FAST Score	0.493	0.485	0.453	0.550	0.517	0.519	0.523	0.543	0.465
	(8.72)	(6.71)	(7.51)	(8.95)	(6.90)	(8.15)	(7.39)	(6.77)	(6.29)
RBC/S	-0.055		-0.010	-0.384		-0.196	0.007		0.280
	(0.40)		(0.08)	(1.38)		(0.74)	(0.02)		(0.58)
Investment RBC/S		-1.056			0.972			0.131	
		(0.79)			(0.69)			(0.08)	
Credit RBC/S		-0.900			-0.842			-1.527	
		(0.86)			(0.67)			(1.28)	
Loss Res. RBC/S		-0.172			-1.156			-0.050	
		(0.49)			(2.11)			(0.10)	
Written Prem. RBC/S		0.463			0.169			0.591	
		(1.12)			(0.36)			(0.89)	
Growth RBC/S		3.079			1.423			0.231	
		(3.94)			(1.97)			(0.22)	
Covariance Adj./S		-0.185			0.518			0.22	
		(0.30)			(0.50)			(0.18)	
Log Assets			-0.593			-0.385			-0.321
			(5.21)			(3.77)			(2.84)
Mutual			-1.559			-1.325			-0.587
			(2.82)			(2.67)			(1.24)
Model χ^2	85.08	107.57	129.41	93.61	105.54	116.56	90.63	97.24	100.88

Note: Absolute t-statistics in parentheses. The models also included an intercept. Coefficients for FAST score multiplied by 100. "Failed" insurers became insolvent within three years of the data year; "Solvent" insurers survived for at least three years.

The coefficient estimates and t-values shown in Table 5 for the multivariate prediction models provide further evidence of bleak results for the RBC ratio. Consistent with the failure of RBC/S to increase power when included with the FAST score, the coefficient for RBC/S is never significant and frequently is negative. In contrast, the coefficient on the FAST score is always positive and highly significant. The coefficients on the separate components of RBC/S are generally insignificant and are often negative for investment, loss reserve, and written premium RBC relative to surplus. However, consistent with the evidence of a modest increase in power for some Type I error rates, the coefficient on growth RBC/S is positive and significant in 1989 and 1990, and a likelihood ratio test rejects the null hypothesis that the coefficients on the RBC components are jointly equal to zero at the 0.05 level for 1989 and 1990 but not 1991. Compared to the equation that includes the separate components, the equation that includes RBC/S constrains the coefficients on the separate components of RBC/S to be equal. A likelihood ratio test also rejects this constraint at the 0.05 level for 1989 and 1990 but not 1991. This finding is consistent with CHK's (1995) comparisons of models that included RBC/S versus its separate components without including the FAST score. Along with the power comparisons, this finding might suggest a greater potential for improving predictive accuracy by supplementing FAST with information on the separate components of RBC as opposed to aggregate RBC.

The coefficient on the log of assets is negative and significant each year; the coefficient on the mutual dummy is negative and significant with the exception of 1991. However, as noted earlier, including these variables increases power only for the subsample of small failed insurers; it decreases power for the subsamples of larger failed insurers.

Power Comparisons: Troubled vs. Sound Firms

Power comparisons for the troubled and sound firm samples using data for 1990 and 1991 are shown in Tables 6 and 7. Coefficient estimates and t-values for the corresponding multiple logistic regression models are shown in Table 8. The implications of the results for the troubled versus sound insurer samples generally are similar to those for the failed versus solvent insurer samples. The most notable difference is that including RBC/S or its separate components with the FAST score increases power more often than was the case for the failed versus solvent insurer comparisons. Consistent with this result, the coefficient on RBC/S in the multiple logistic model that includes RBC/S and the FAST score (Table 8) is positive and highly significant for both data years, and a likelihood ratio test strongly rejects the null hypothesis that the coefficients on the separate RBC components are jointly equal to zero for both years. A likelihood ratio test rejects the hypothesis that the coefficients for the separate components of RBC/S are equal (as implied by the constrained model that includes RBC/S rather than the separate components) for 1990 but not 1991. These results are consistent with the hypothesis that the development of RBC provided new information about insolvency risk.

Table 6

Power to Identify Troubled Companies (in percent): Univariate and Multivariate Comparisons with 1990 Data

		Univariate			Multivariate		
Category of Troubled Co.	Type I Error Rate	P/S	RBC/S	FAST	FAST, RBC/S	FAST, RBC/S components	FAST, RBC/S, Log Assets, Mutual
All (136 co.)	5	38	38	**47**	**54**	**57**	**60**
	10	49	54	**71**	71	**72**	69
	15	55	63	**77**	**78**	**80**	76
	20	60	69	**79**	**82**	**82**	**83**
	25	65	72	**85**	85	85	**87**
	30	67	77	**86**	85	85	**89**
Direct premiums < $25 mill. (90 co.)	5	33	33	**49**	**57**	**58**	**64**
	10	44	48	**72**	70	69	**74**
	15	50	58	**77**	77	**79**	**78**
	20	58	62	**79**	**80**	**81**	**87**
	25	61	66	**84**	84	**86**	**90**
	30	66	72	**87**	86	86	**91**

Direct premiums > $25 mill. (46 co.)	5	**48**	**48**	43	**50**	**54**	**50**
	10	59	**67**	**67**	**74**	**78**	59
	15	65	74	**78**	**80**	**83**	74
	20	65	**83**	80	**85**	**83**	76
	25	72	**85**	**85**	85	85	80
	30	72	**87**	85	85	85	85
Direct premiums > $50 mill. (24 co.)	5	**46**	**46**	38	**42**	**50**	**42**
	10	63	63	**67**	**71**	**75**	54
	15	67	75	**78**	**79**	**79**	67
	20	67	**92**	80	**83**	79	71
	25	71	**92**	85	83	79	75
	30	71	**96**	85	83	79	79

Note: Power is the percent of failed insurers in the given sample that would be classified as high risk at the specified Type I error rates (percent of solvent firms that also are classified as high risk). "Troubled" insurers either failed within three years or were classified as high priority for regulatory scrutiny based on regulatory analysis of their data for the data year; "Sound" includes all other insurers. Maximum power for a given sample/Type I error rate for the univariate comparisons is highlighted in bold. Power for multivariate model is highlighted in bold if it exceeds the maximum power for the univariate comparisons.

Table 7

Power to Identify Troubled Companies (in percent): Univariate and Multivariate Comparisons with 1991 Data

				Univariate		Multivariate	
Category of Troubled Co.	Type I Error Rate	P/S	RBC/S	FAST	FAST, RBC/S	FAST, RBC/S components	FAST, RBC/S, Log Assets, Mutual
All (136 co.)	5	44	40	64	64	61	64
	10	61	46	69	69	69	72
	15	69	52	75	79	78	79
	20	74	56	84	85	84	88
	25	77	61	88	89	86	90
	30	81	67	91	91	90	92
Direct premiums < $25 mill. (90 co.)	5	41	40	66	64	61	67
	10	58	47	71	69	72	75
	15	66	53	75	79	78	85
	20	73	56	87	85	86	89
	25	76	60	89	91	87	92
	30	81	63	92	92	93	95

Direct	5	50	42	61	64	61	58
premiums	10	69	44	63	67	64	64
> $25 mill.	15	75	50	75	81	78	67
(46 co.)	20	75	56	78	86	81	83
	25	78	64	86	86	86	86
	30	81	75	89	89	86	86
Direct	5	43	43	48	52	48	48
premiums	10	71	43	52	57	52	52
> $50 mill.	15	71	52	67	71	67	57
(24 co.)	20	71	57	71	81	71	76
	25	76	71	81	81	81	81
	30	76	81	86	86	81	81

Note: Power is the percent of failed insurers in the given sample that would be classified as high risk at the specified Type I error rates (percent of solvent firms that also are classified as high risk). "Troubled" insurers either failed within three years or were classified as high priority for regulatory scrutiny based on regulatory analysis of their data for the data year; "Sound" includes all other insurers. Maximum power for a given sample/Type I error rate for the univariate comparisons is highlighted in bold. Power for multivariate model is highlighted in bold if it exceeds the maximum power for the univariate comparisons.

Table 8

Multivariate Logistic Regression Results for Troubled vs. Sound Companies

Variable	1990 Data			1991 Data		
	(1)	(2)	(3)	(1)	(2)	(3)
FAST Score	0.670	0.687	0.662	0.679	0.695	0.643
	(12.99)	(10.68)	(12.32)	(11.66)	(10.39)	(10.54)
RBC/S	0.730		0.814	1.614		1.943
	(4.56)		(4.81)	(4.30)		(4.91)
Investment RBC/S		-0.805			0.192	
		(0.67)			(0.14)	
Credit RBC/S		-0.594			0.420	
		(0.64)			(0.47)	
Loss Res. RBC/S		0.103			0.417	
		(0.50)			(1.01)	
Written Prem. RBC/S		1.366			1.606	
		(3.96)			(3.37)	
Growth RBC/S		0.955			0.408	
		(1.64)			(0.51)	
Covariance Adj./S		-0.194			-0.614	
		(0.25)			(0.62)	
Log Assets			-0.394			-0.363
			(5.20)			(4.24)
Mutual			-0.481			0.155
			(1.63)			(0.49)
Model χ^2	320.86	343.00	353.10	342.56	350.88	364.38

Note: Absolute t-statistics in parentheses. The models also included an intercept. Coefficients for FAST score multiplied by 100. "Troubled" insurers either failed within three years or were classified as high priority for regulatory scrutiny based on regulatory analysis of their data for the data year; "Sound" includes all other insurers.

On a univariate basis, however, the FAST score again generally has greater power than RBC/S for the full sample of troubled insurers and each size-based subsample for 1991. For 1990, RBC/S has greater power than the FAST score for the subsamples of larger troubled insurers, especially for higher Type I error rates. For the failed versus solvent insurer comparisons for these subsamples, RBC/S fared relatively better in comparison to the FAST score for 1991 rather than 1990. Similar to the failed versus solvent firm comparison results for the subsample of larger failed insurers in 1990, and for the subsample of largest failed insurers in 1991, the power of the P/S ratio to identify larger insurers equals or exceeds the power of the FAST score and RBC/S for intermediate Type I error rates for 1991.

With the exception of the subsample of the largest failed insurers in 1990, the power of the FAST score to identify troubled companies is generally materially greater than its power to identify failed companies for both 1990 (compare Tables 3 and 6) and 1991 (compare Tables 4 and 7). The power of RBC/S to identify troubled companies generally is greater than its power to identify failed companies only for the 1990 data. These increases in power might indicate greater predictive accuracy using a better measure of financial condition. However, they also might be expected if prior regulatory indicators of financial strength were considered in the development of FAST and RBC.

Conclusions

The results of our empirical analysis of the relative power of FAST and RBC to identify financially weak property-liability insurers using data for 1989, 1990, and 1991 indicate that the FAST score generally has greater power to identify insurers that failed within three years of the data year than the ratio of an insurer's RBC to surplus. The FAST score also generally has greater power than the RBC ratio to identify "troubled" insurers, where troubled insurers are defined as those that either failed within three years or which were placed in the highest category for regulatory scrutiny (as part of IRIS) in the year following the data year. The power of the ratio of RBC to surplus to identify failed or troubled insurers improves for subsamples that include failed and troubled insurers with larger premium volume. Nevertheless, our power comparisons for FAST and RBC are largely inconsistent with the hypothesis that a public RBC system should have at least as much power to identify weak insurers as a private screening system. Possible explanations include: (1) that a relatively crude RBC system is somehow beneficial when used in combination with a more accurate private screening system, or (2) that political pressure against increased accuracy led to a relatively crude RBC formula.

We also provide evidence that including both the FAST score and the RBC ratio in a multiple logistic regression model generally does not increase power to identify failed insurers during our sample period, but it leads to some increase in power to identify the broader category of troubled insurers. These findings provide limited support for the hypothesis that the development of RBC produced new information concerning insurer insolvency risk – even though the power of the RBC ratio generally is inferior to the FAST score in univariate comparisons.

We conclude by noting that some observers might regard the overall power of both the RBC ratio and the FAST score as low, especially given the likelihood of material look-ahead bias. They might regard these results as prima facie evidence that the power of both FAST and RBC could easily be improved upon by a better formula or formulas that reflect additional accounting data. Although an analysis of this issue is beyond this paper's scope, an alternative view is that any formula approach that relies primarily on accounting data will be inherently imperfect and have limited accuracy and that potential improvements will likely be modest. An implication of this latter view is that any formula-based assessment of financial strength will need to be supplemented by additional qualitative and quantitative information and expert judgment to achieve meaningful increases in power.

APPENDIX

FAST Variables

The variables included in the FAST scoring system in 1994 are listed below. (The scoring system also includes lagged values for some of the variables). An "I" in parentheses indicates that the variable also is included in IRIS. The variable ranges and associated point values for FAST are not publicly available.

Net premiums written to surplus (I)
Gross premiums written to surplus
Reserves to surplus
Growth in net premiums written (I)
Growth in gross premiums written
Surplus aid to surplus (I)
Investment yield (I)
Growth in surplus (I)
Two-year reserve development to surplus (I)
Change in combined ratio
Gross expenses to gross premiums written
Growth in gross expenses
Growth in liquid assets
Growth in agents' balances
Reinsurance recoverable on paid losses to surplus
Reinsurance recoverable on unpaid losses to surplus
Premiums in long-tailed lines to total premiums
Affiliate investments to surplus
Affiliate receivables to surplus
Miscellaneous recoverables to surplus
Non-investment grade bonds to surplus
Other invested assets to surplus
Managing producer exposure 1
Managing producer exposure 2
Cash outflow test

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