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Financial Distress in Australian General Insurers

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Abstract

We develop and test a statistical model to identify Australian general insurers experiencing financial distress over the 1999–2001 period. Using a logit model and two measures of financial distress we are able to predict, with reasonable confidence, the insurers more likely to be distressed. They are generally small and have low return on assets and cession ratios. Relative to holdings of liquid assets they have high levels of property and reinsurance assets, and low levels of equity holdings. They also write more overseas business, and less motor insurance and long-tailed insurance lines, relative to fire and household insurance.

Introduction

The rapid pace of financial innovation, globalization, and deregulation of the financial system over the past decade has made the operations of financial intermediaries (FIs) more complex and potentially more risky. These developments, in turn, have led prudential supervisors to design new processes for monitoring and identifying FIs experiencing deteriorating financial conditions (Sahajwala and Van den Berg, 2000). These processes include on-site examination systems, statistical early warning systems, and market based measures of FI risk.[1]

Although these techniques have their broadest application in banking, a number of insurer failures in the United States in the mid 1980s and early 1990s led to a questioning of the effectiveness of insurance regulation and solvency monitoring and the

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[1] Esho et al. (2005) illustrate the use of a market based measure of FI risk in the Australian context.

ability of regulators to identify insurers at risk of insolvency at an early stage of their financial deterioration. The subsequent regulatory reforms led to the adoption of the FAST (Financial Analysis and Surveillance Tracking) solvency monitoring system for insurers and the introduction of risk-based capital requirements. These developments were associated with a number of empirical models that examined the ability of accounting based statistical models to predict the insolvency of life and health insurers and property–liability insurers.[2]

Outside the United States there has, until recently, been little interest in developing and applying solvency prediction models to the insurance industry. In the Australian context, Black (2004) provides an overview of the formation of the Australian Prudential Regulation Authority (APRA) in 1998 and its move toward a risk-based prudential approach. The failure and appointment of provisional liquidators in March 2001 to HIH, a large insurance company, led to concerns relating to the adequacy of APRA's approach to prudential regulation and supervision and to the appointment of a Royal Commission to investigate the collapse of HIH. The Commission was critical of APRA, reporting that "the manner in which APRA exercised its powers and discharged its responsibilities under the *Insurance Act* fell short of that which the community was entitled to expect from the prudential regulator" (HIH Royal Commission, 2003). In April 2001, APRA's board concluded that it should have had a mechanism for identifying institutions at risk, and that it should require more explicit and timely information about those institutions (Black, 2004, p. 33).

Drawing on the Canadian and U.K. approaches, APRA's response was to develop a risk-based approach within the Probability and Impact Rating System (PAIRS) and Supervisory Oversight and Response System (SOARS) frameworks. Although numerically scored, the approach is largely qualitative relying on assessments provided by APRA's supervisory staff. There has been little effort within APRA or the Australian academic or professional community to develop or assess quantitatively based systems to identify financial institutions in financial distress.[3]

We address this gap in the literature by developing a model to identify Australian general insurance companies (GIs) in financial distress. As general insurance includes any insurance that is not life insurance, it is also referred to as nonlife insurance. GIs provide cover against loss from a particular financial event including workers compensation, public liability, product liability, automobile and homeowners' policies, pet insurance, mortgage and creditor insurance, and others. In the United States, GIs are known as property and casualty insurers or property–liability insurers.

There is an extensive body of U.S. literature that develops and tests static and/or dynamic insolvency prediction models for property–liability and life–health insurers (Chen and Wong, 2004). The dynamic approach involves deterministic or stochastic cash flow modeling (Ceccarelli, 2003; Cummins, Grace, and Phillips, 1999). It is assumed that the insurer collects premiums for the next 1 or 2 years, after which time it goes into "run-off." The principal cash flows for each insurance line are then modeled

[2] Chen and Wong (2004, Table I) provide a listing of U.S. insolvency studies classified by the technique used.

[3] There are however a number of papers examining financial distress in Australian nonfinancial firms. See, for example, Jones and Hensher (2004).

for a horizon of 20+ years, adopting a set of assumptions for investment returns, loss (claims) development factors for each line, expenses, etc. The net worth of the insurer is then determined at the 20+ year time horizon and the insurer is classified as insolvent if its projected net worth is zero or negative.

Data limitations currently preclude an application of the cash flow simulation approach to Australian GIs. Moreover, because detailed data on an insurer's claims experience are typically not in the public domain,[4] it can be argued that good dynamic modeling is best undertaken by insurance companies as part of APRA's dynamic simulation modeling and stress testing of large financial institutions. The static approach may then be viewed as complementary to the dynamic internal stress testing approach. In this respect, Cummins, Grace, and Phillips (1999) find that the cash flow simulation model adds significant discriminatory power to the risk-based capital and FAST early warning models used in the United States.

The static approach, which we adopt in this article, utilizes financial ratios and a variety of statistical techniques to identify factors that discriminate between samples of solvent and insolvent insurers. The techniques include multiple discriminant analysis, recursive partitioning, neural networks, and logit and probit analysis.

There is, however, a difficulty in applying this approach outside the United States because most countries have limited experience with failing insurers and lack the number of insurer insolvencies to be able to estimate the models. Hence, our focus is on financial distress, rather than insolvency, of insurers. The costs of financial distress borne by stakeholders of a troubled insurer, although less than the costs of insolvency or regulatory takeover, are significant. They include reductions in the market value of the insurer's debt and equity, additional supervisory costs incurred by the prudential regulator, and disruption to policyholders and insurance markets with increased uncertainty as to the value of the insurer's policy reserves.

In the following section, we critically review two approaches to defining financial distress that have been used in studies of Asian and Dutch insurers where the limited number of insurer insolvencies precludes a study of insolvencies. The approaches suffer from a number of problems including subjectivity, a focus on supervisor's assessments, and/or explaining "financially unstable" insurers using financial ratio regressors similar to those used in the classification system to determine whether the insurer was financially unstable. We avoid these problems by developing an alternative regulatory based measure of financial distress derived from the Solvency Condition in the *Insurance Act* applying to Australian GIs.

After defining financial distress, we specify a model of the determinants of financial distress, describe the data used in estimating the model, summarize the results, and conclude with a summary and suggestions for further research. From a regulatory perspective, our objective is to identify GIs likely to experience financial distress so that prompt and appropriate corrective action can be implemented.[5]

[4] The data for liability products are available on an industrywide basis in the National Claims and Policies Database (NCPD).

[5] Statistical models may be viewed as complements to, rather than substitutes for, expert judgment based models such as PAIRS.

DEFINING FINANCIAL DISTRESS

In the absence of a significant number of insurer insolvencies in Australia, we focus on predicting "financial instability or weakness" as an indicator of financial distress. There are two approaches in the literature for handling this problem. Kramer (1996) evaluates the financial solidity of Dutch nonlife insurance companies using a three-way subjective classification system of whether the company is "strong," "moderate," or "weak" as the dependent variable. In the Netherlands, supervisors provide a written assessment of the insurer following an examination process. "The major weak and strong points of a company are described in that text as value statements, criticisms, or indications of negative or positive trends" (Kramer, 1996, p. 81). The researcher's classification is then based on the number and severity of the weak and strong points in the assessment.

This approach raises several issues. First, there is considerable subjectivity involved in applying the classification from the written assessments. Second, the approach is really a study of how supervisors assess the financial solidity of insurers and thus is more appropriate for studies of determinants of examiner ratings when a precise rating is not available.

The second approach is used by Chen and Wong (2004) in a study of the financial health of Asian insurance companies. They adopt different classification approaches for general and life insurers. For general insurers they use a variant of the Insurance Regulatory Information System (IRIS) as implemented by the National Association of Insurance Commissioners (NAIC) in the United States in the 1970s and 1980s. They examine 14 financial ratios under three categories: liquidity, profitability, and capacity. Each of the ratios for an insurer is compared to an industry norm and the insurer is classified as "financially unstable" if it fails to meet the industry standard in five or more of the 14 ratios. They then run a logit regression to explain "financially unstable" insurers using similar financial ratios to those in the classification system.

For life insurers Chen and Wong use the HHM model (see Hollman, Hayes, and Murrey, 1993). This model computes an index of financial solidity based on the relative change in a set of financial ratios over the period. The implicit assumption is that companies in financial distress make larger changes in key financial statement ratios than those that are not distressed. The solidity index for individual insurers is averaged and insurers with an index value worse than the average are classified as financially unstable. The dichotomous stability variable is then used as the dependent variable in a logit regression.

A weakness of the Chen and Wong approach lies in the regressions which, in effect, explain dichotomous dependent variables derived from financial ratios by independent variables which are almost identical to the financial ratios used in the classification system. However, the problem may not be quite as severe for the application of the HHM model where the classification criteria are based on relative changes, rather than absolute levels, of the financial ratios.

Our approach differs from this prior research and reflects the Australian regulatory environment during our sample period. We report results for two definitions of "distress."[6] The first, which we refer to as *Distress 1*, uses the pre-July 2002 Solvency Condition in the *Insurance Act*. This required net assets[7] (*NA*) to be (i) greater than AUD2m, (ii) greater than 20 percent of net premium revenue (*NPR*) during the preceding financial year, and (iii) greater than 15 percent of net outstanding claims (*NOC*) at the end of the preceding financial year. This was mandatory on both an inside Australia basis and on a total (both inside and outside Australia) business basis. In addition direct insurers were required to meet APRA reinsurance guidelines as set out in a mandatory circular. This required direct insurers, on a total business basis, to have net assets: (iv) greater than 20 times its highest risk retention (*HRR*) defined as the biggest loss under a single insurance policy, net of reinsurance recoveries, and (v) greater than the solvency requirement as above (the maximum of (i), (ii), and (iii) on a total business basis) plus its maximum event retention (*MER*) defined as the biggest loss exposure due to a concentration of policies, net of reinsurance recoveries. Thus *Distress 1* is an indicator variable of financial distress which takes the value of unity if one or more of the solvency or reinsurance conditions are *not* met and zero otherwise.

The second measure of financial distress strengthens the solvency requirement relative to *Distress 1*. In July 2002 the solvency condition was changed, increasing the minimum capital requirement. Thus *Distress 2* takes the value of unity if the insurer's net assets on either an Australian or total business basis are (i) less than AUD5m, (ii) less than 30 percent of net premium revenue in the preceding year, and (iii) less than 22.5 percent of net outstanding claims at the end of the preceding financial year. The *HRR* and *MER* requirements are as for *Distress 1*.

An analysis of the five distress criteria is provided in Table 1. It shows the number of insurers classified as distressed by each of the individual criteria and by jointly applying the criteria. The final row of the table shows the number of insurers classified as distressed in one or more of the individual criterion and thus corresponds to the definition of *Distress 1* and *Distress 2* used in this article. Almost a quarter (21–23 percent) of the insurers are financially distressed using the *Distress 1* measure, whereas 39–47 percent are distressed using the strengthened *Distress 2* measure. With *Distress 2* requiring higher capital than *Distress 1*, the number of distressed insurers as classified by criteria (i) to (iii) is higher for *Distress 2* than for *Distress 1*. The primary difference relates to a number of smaller insurers that are classified as distressed by the *Distress 2* $5m fixed capital requirement.

MODEL SPECIFICATION

The dependent variable in our model is one of the two financial distress indicator variables, as defined above. The probability of financial distress at time t is expected to depend on the insurer's profitability, the underwriting expense ratio, cession ratio, scale, growth, asset composition, and insurance lines at time t.

There is an uncertain relationship between profitability and financial distress. As a measure of operating risk, high profitability may result from taking on greater insurance or investment risk (Borde, Chambliss, and Madura, 1994). On the other hand,

[6] Table 1 has an algebraic summary of the distress conditions.

[7] Net assets are total assets minus total liabilities.

TABLE 1
Analysis of the Distress Criteria

	Distressed Insurers Using *Distress 1*			Distressed Insurers Using *Distress 2*		
Criterion	1999 $N = 69$	2000 $N = 70$	2001 $N = 66$	1999 $N = 69$	2000 $N = 70$	2001 $N = 66$
(i)	8	8	8	20	18	16
(ii)	9	10	8	14	17	15
(iii)	8	10	9	11	13	11
(iv)	7	4	5	7	4	5
(v)	10	9	7	10	9	7
[(i)U(ii)U(iii)]	10	12	12	27	30	25
[(i)U(ii)U(iii)U(iv)]	14	13	14	31	31	26
[(i)U(ii)U(iii)U(v)]	15	15	13	31	33	25
[(i)U(ii)U(iii)U(iv)U(v)]	16	15	14	32	33	26

Note: Denoting Australian and total business with 'A' and 'T' subscripts respectively, the individual criterions for *Distress 1* are:

(i) $\{NA_A < \$2\text{m or } NA_T < \$2\text{m}\}$
(ii) $\{NA_A < 0.2 * NPR_A \text{ or } NA_T < 0.2 * NPR_T\}$
(iii) $\{NA_A < 0.15 * NOC_A \text{ or } NA_T < 0.15 * NOC_T\}$
(iv) $\{NA_T < 20.0 * HRR_T\}$
(v) $\{NA_T < MER_T + \max(\$2\text{m}, 0.2 * NPR_T, 0.15 * NOC_T)\}$

For *Distress 2*:
(i) $\{NA_A < \$5\text{m or } NA_T < \$5\text{m}\}$
(ii) $\{NA_A < 0.3 * NPR_A \text{ or } NA_T < 0.3 * NPR_T\}$
(iii) $\{NA_A < 0.225 * NOC_A \text{ or } NA_T < 0.225 * NOC_T\}$
(iv) $\{NA_T < 20.0 * HRR_T\}$
(v) $\{NA_T < MER_T + \max(\$2\text{m}, 0.2 * NPR_T, 0.15 * NOC_T)\}$

high profitability may signal a more efficient management and lower risk (BarNiv and McDonald, 1992). We proxy profitability by the return on total assets, denoted *ROA*.[8]

Insurers with unfavorable underwriting results have a higher likelihood of experiencing financial distress (Browne and Hoyt, 1995). There are several measures of underwriting performance including the expense ratio, loss ratio, and combined ratio. We focus on the expense ratio, *EXPENSE RATIO*, defined as the ratio of underwriting expenses to net premium revenue (premium revenue less reinsurance expense) and expect it to be directly related to the likelihood of financial distress.[9]

[8] The independent variables are all defined in Table 2. In addition to *ROA*, we also experimented with the return on equity, *ROE*. However, this did not change any of the findings and hence is not reported in the results.

[9] Results are also reported below substituting the *COMBINED RATIO* for the *EXPENSE RATIO*. The combined ratio is the sum of the expense and loss ratios, the latter being the ratio of claims expense less reinsurance and other recoveries revenue to net premium revenue.

TABLE 2
Variable Definitions

Variable	Definition
Distress 1	See Table 1
Distress 2	See Table 1
ROA	$= \frac{\text{Profit after Tax}}{\text{Total Assets}}$
EXPENSE RATIO	$= \frac{\text{Underwriting Expenses}}{\text{Premium Revenue less Reinsurance Expense}}$
CESSION	$= \frac{\text{Reinsurance Expense}}{\text{Premium Revenue}}$
ln*(TOTASSETS)*	= Natural Logarithm of Total Assets
GROWTHPREM	$= \left(\frac{\text{Premium Revenue at Time } t}{\text{Premium Revenue at Time } t-1} - 1\right) * 100$
EQUITY RATIO	$= \frac{\text{Investments in Listed and Unlisted Shares}}{\text{Total Assets}}$
PROPERTY RATIO	$= \frac{\text{Investments in Property and Land}}{\text{Total Assets}}$
LIQUID ASSETS RATIO	$= \frac{\text{Cash and Other Liquid Investments}}{\text{Total Assets}}$
DEBT RATIO	$= \frac{\text{Debt Securities and Loan Investments}}{\text{Total Assets}}$
REINS ASSETS RATIO	$= \frac{\text{Reinsurance Assets}}{\text{Total Assets}}$
OTHER ASSETS RATIO	$= \frac{\text{Other Assets}}{\text{Total Assets}}$
INTLPREM	$= \frac{\text{Premium Revenue from Outside of Australia}}{\text{Total Gross Premium Revenue}}$
MOTORPREM	$= \frac{\text{Motor Vehicle Premium Revenue}}{\text{Total Gross Premium Revenue}}$
LONGTAILPREM	$= \frac{\text{Long-tailed Premium Revenue}}{\text{Total Gross Premium Revenue}}$
CONSCREDITPREM	$= \frac{\text{Consumer Credit Premium Revenue}}{\text{Total Gross Premium Revenue}}$
FIREHOUSEPREM	$= \frac{\text{Fire \& Industrial Special Risk and Householders Premium Revenue}}{\text{Total Gross Premium Revenue}}$
OTHERPREM	$= \frac{\text{Other Australian Short-tailed Premium Revenue}}{\text{Total Gross Premium Revenue}}$

As insurers may transfer risk through reinsurance we include the cession ratio, *CESSION*, defined as the ratio of outward reinsurance expense to premium revenue. However, its relationship to the probability of distress is uncertain. Although the traditional view, referred to as the risk shifting view, suggests an inverse relationship between the cession ratio and the likelihood of financial distress, an alternative view is that reinsurance increases the insurer's dependence on the financial health of the reinsurer which, under some circumstances, may increase the insurer's risk (see Kim et al., 1995; Pottier and Sommer, 1999).

Scale has a number of potential benefits for insurers including diversification and higher franchise values. Claim costs tend to be less volatile for large firms whereas higher franchise values provide greater incentive to limit risk exposure (Cummins, Harrington, and Klein, 1995; Sommer, 1996). This suggests financial distress will be inversely related to the insurer's scale, proxied by the logarithm of total assets ln*(TOTASSETS)*. Moreover, Borde, Chambliss, and Madura (1994) and Chen and Wong (2004) argue that rapid growth of insurance business may be associated with a reduction in underwriting standards and an increase in underwriting risk. Hence we expect financial distress to be directly related to the rate of growth of gross premiums, *GROWTHPREM*.[10]

Typically, studies of insurer risk control for investment and insurance risk by including asset composition and product mix variables.[11] For asset composition we include the ratio of amounts held in each of the primary asset categories to total assets, that is, *EQUITY RATIO*, *PROPERTY RATIO*, *LIQUID ASSETS RATIO*, *DEBT RATIO*, *REINS ASSETS RATIO*,[12] and *OTHER ASSETS RATIO*, respectively. Some aggregation is required to derive these categories. Debt includes fixed and variable rate securities and loans (including amounts owing under Section 30(1) of the Insurance Act to directors, employees, private trading companies, financial enterprises, and fund managers). Equity includes listed and unlisted shares and trusts (but excludes cash and property trusts). Property includes land and buildings and listed and unlisted property trusts while liquid assets include cash, cash management trusts, and deposits held. With *LIQUID ASSETS RATIO* excluded from the regression to avoid singularity, the coefficients on the included asset categories indicate the effect on the probability of distress of increasing the proportion of total assets invested in that category matched by an equal reduction of the proportion of total assets held in liquid assets. Relative to liquid assets, investments in property are generally more illiquid and somewhat higher risk. Moreover, Harrington and Nelson (1986) use the proportion of assets held in equities as a measure of asset risk, noting that equities have greater price volatility.[13] Consequently, we expect the coefficients of *PROPERTY RATIO* and *EQUITY RATIO* to be positive.

We proxy insurance lines by premiums written in six primary product lines, each scaled by total premiums: (i) outside Australia premiums, *INTLPREM*; (ii) Australian short-tailed motor vehicle premiums, *MOTORPREM*; (iii) long-tailed Australian

[10] The growth of gross outstanding claims produced similar results and hence is not reported in the results.

[11] An exception is Cummins and Sommer (1996). They apply a measure from the option model using asset and liability return volatilities and the correlation between the asset and liability processes.

[12] Reinsurance assets include amounts recoverable under reinsurance contracts and deferred reinsurance expense.

[13] An alternative view is that high holdings of liquidity can lead to aggressive investment strategies, and hence higher risk, in later periods (see Borde, Chambliss, and Madura, 1994).

premiums,[14] *LONGTAILPREM*, including premiums for compulsory third party motor vehicle insurance (CTP), professional indemnity, public and product liability, and employers' liability; (iv) Australian consumer credit premiums, *CONSCREDITPREM;* (v) Australian fire and industrial special risk (ISR) premiums and house owners/householders premiums, *FIREHOUSEPREM*; and (vi) other miscellaneous Australian premiums, *OTHERPREM*, including travel and accident premiums. With *FIREHOUSEPREM* excluded from the regression to avoid singularity,[15] the coefficient of an included premium share shows the effect on the probability of distress of increasing the total premiums written in that business line matched by an equal reduction in fire and household premiums. The excluded premium category, *FIREHOUSEPREM*, is a short-tail line with a relatively short period between the claim events and claim payments. In contrast, the long period between claim event and final claim payment for long-tail premium lines results in greater uncertainty of future GI cash flows and higher risk (Sommer, 1996). Hence the coefficient of *LONGTAILPREM* is expected to be positive.

DATA

The data for GIs are drawn from APRA's annual GENESIS 101, 102, and 211 forms for the 1998 to 2001 period. Although, the period chosen for analysis is rather short, two factors influenced this choice. First, the prudential regulator, APRA, was formed in July 1998 and began its annual GENESIS insurance data collection in fiscal year 1998. Second, following the criticism of APRA in the HIH Royal Commission (2003), the GENESIS data collection was replaced by a significantly different and more extensive collection known as D2A (Direct to APRA). As D2A is a quarterly collection and is based on an entirely different set of data definitions to those of GENESIS; APRA has not merged the two databases.

Because of their unique features and missing data, mortgage insurers, captive insurers, and branches of foreign insurers are excluded from our sample, leaving 69 complete observations in 1999, 70 in 2000, and 66 in 2001.[16] Summary statistics of the dependent and independent variables for each year are provided in Table 3. The typical general insurer is small with mean (median) 1999 total assets of AUD572m (AUD110m). Approximately 20–22 percent of its premiums are reinsured, it has an expense ratio of 30–34 percent, and a combined ratio of 109–165 percent. The predominant premium business lines are motor vehicle insurance (21–22 percent), long-tail insurance lines (17–22 percent), fire and householders insurance (21–23 percent), and consumer credit insurance (11–12 percent), though the mean statistics often conceal a concentration of premiums in one or two lines within individual insurers. The asset side of the balance sheet is typically 40–45 percent in liquid assets and loans and debt securities, 11–16

[14] Long-tail insurance lines are those for which claims generally take more than 12 months to be reported and then settled.

[15] We also disaggregate the *FIREHOUSEPREM* variable into fire and ISR premiums and house-owners/householders premiums. This makes little difference to the results, and hence is not reported.

[16] Because of the inclusion of *GROWTHPREM* in the regression model, it is not possible to estimate the model for 1998.

TABLE 3
Summary Statistics of Australian General Insurers

	1999					2000					2001				
Variables	Number of Obs	Mean	Std Dvn	Min	Max	Number of Obs	Mean	Std Dvn	Min	Max	Number of Obs	Mean	Std Dvn	Min	Max
Distress 1	69	0.23	0.43	0.00	1.00	70	0.21	0.41	0.00	1.00	66	0.21	0.41	0.00	1.00
Distress 2	69	0.46	0.50	0.00	1.00	70	0.47	0.50	0.00	1.00	66	0.39	0.49	0.00	1.00
*100 × ROA***	69	1.26	8.86	−27.78	31.94	70	3.70	9.87	−27.78	31.94	66	3.08	7.94	−15.70	28.23
CESSION^^	69	0.2	0.22	0.00	0.99	70	0.22	0.23	0.00	1.00	66	0.22	0.21	0.00	0.82
ln(*TOTASSETS*)	69	11.64	1.93	8.04	15.80	70	11.81	1.90	8.58	15.91	66	11.90	1.88	8.60	15.92
*GROWTHPREM**	69	23.98	59.43	−56.16	208.12	70	17.19	55.23	−56.16	208.12	66	26.97	60.93	−56.16	208.12
EXPENSE RATIO^	69	0.31	0.22	0.00	1.35	70	0.30	0.22	0.00	1.19	66	0.34	0.24	0.00	1.57
COMBINED RATIO^	69	1.09	0.71	0.00	6.11	70	1.56	2.88	0.00	22.24	66	1.65	2.52	0.00	14.81
DEBT RATIO	69	0.27	0.23	0.00	0.90	70	0.27	0.25	0.00	0.96	66	0.27	0.24	0.00	0.76
EQUITY RATIO	69	0.16	0.17	0.00	0.69	70	0.13	0.17	0.00	0.67	66	0.11	0.16	0.00	0.62
PROPERTY RATIO	69	0.03	0.06	0.00	0.29	70	0.02	0.04	0.00	0.18	66	0.02	0.05	0.00	0.24
LIQUID ASSETS RATIO	69	0.16	0.21	0.00	0.99	70	0.17	0.22	0.00	0.98	66	0.20	0.26	0.00	0.98
REINS ASSETS RATIO	69	0.15	0.16	0.00	0.75	70	0.17	0.19	0.00	0.85	66	0.14	0.14	0.00	0.53
OTHER ASSETS RATIO	69	0.23	0.16	0.00	0.78	70	0.24	0.19	0.00	0.88	66	0.25	0.17	0.01	0.90
INTLPREM	69	0.04	0.15	0.00	0.99	70	0.04	0.15	0.00	0.98	66	0.03	0.15	0.00	0.89
MOTORPREM	69	0.22	0.25	0.00	0.98	70	0.22	0.25	0.00	0.98	66	0.21	0.24	0.00	0.80
LONGTAILPREM	69	0.22	0.32	0.00	1.00	70	0.20	0.28	0.00	1.00	66	0.17	0.26	0.00	1.00
FIREHOUSEPREM	69	0.23	0.26	0.00	1.00	70	0.21	0.23	0.00	1.00	66	0.23	0.25	0.00	1.00
CONSCREDITPREM	69	0.12	0.29	0.00	1.00	70	0.12	0.30	0.00	1.00	66	0.11	0.28	0.00	1.00
OTHERPREM	69	0.17	0.28	0.00	1.00	70	0.21	0.30	0.00	1.00	66	0.25	0.32	0.00	1.00
HIGH LIQUIDITY	69	0.04	0.21	0.00	1.00	70	0.04	0.20	0.00	1.00	66	0.06	0.24	0.00	1.00

Notes: *Series are truncated at the 5th and 95th percentiles. **Series are truncated at the 1st and 99th percentiles. ^Series are truncated at the 99th percentile and at 0. ^^Series are truncated at 0 and 1.

percent in equities, 14–17 percent in reinsurance assets, 2–3 percent in property, and the remainder in other miscellaneous assets.

REGRESSION RESULTS

Determinants of Financial Distress

With the dependent variable being a discrete choice variable, we estimate the model using the logit regression technique.[17] We begin with an examination of the explanatory variables influencing financial distress using pooled data, 1999 to 2001.

Distress 1 Measure. The results for the *Distress 1* measure in Table 4 suggest that the model does a reasonable job within-sample in predicting financial distress with an Estrella (1998) pseudo R^2 of 32 to 36 percent. In addition, the regression coefficients are generally consistent in sign with our *a priori* expectations.

In REG 1 we find that the coefficient of the profitability measure, *ROA*, is significantly negative, consistent with more profitable Australian GIs (with higher *ROA*) having lower probability of being financially distressed. This mirrors the results of Lee and Urrutia (1996) for U.S. property–liability insurers and is consistent with high profitability signaling a more efficient management and lower risk (BarNiv and McDonald, 1992). The alternative argument that high profitability may signal the use of a more aggressive investment or insurance underwriting strategy and higher risk is not supported by our data (Borde, Chambliss, and Madura, 1994).

In contrast to the profitability result, there is little evidence that high expense behavior is linked to the likelihood of financial distress. Although the coefficient of the underwriting *EXPENSE RATIO* has a positive sign consistent with our *a priori* expectation, it is not statistically significant. A possible explanation could lie in the expense ratio being an ambiguous measure of operating efficiency in that it cannot distinguish between good and bad (or wasteful) expenditure. For example, expenditures on claim management that increase operating efficiency will reduce risk while overspending on administrative expenditures and/or management perks will reduce efficiency and increase risk.[18]

As an alternative to the specification involving the *EXPENSE RATIO*, in REG 2 of Table 4, we replace it with the *COMBINED RATIO*, noting that the combined ratio is the sum of the expense and loss ratios (the loss ratio is defined as the ratio of claims expense less reinsurance and other recoveries revenue to net premium revenue).[19] Although the substitution of the combined ratio for the expense ratio improves the explanatory power of the regression, with the pseudo R^2 increasing from 0.32 to 0.36, the combined ratio has a negative and statistically significant coefficient at the 95 percent confidence level. Our perverse result contrasts with that of Browne and Hoyt (1995) and Chen and Wong (2004) who find a significant positive relationship between the combined ratio and insolvency for U.S. and Singaporean/Malaysian property–liability insurers, respectively.

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[17] Results using the probit estimator were similar to those reported in this article.

[18] We are grateful to a reviewer for this suggestion.

[19] We also tried the loss ratio as an independent variable but it produced similar results as the combined ratio. For space reasons this result is not reported.

TABLE 4
Financial Distress of Australian General Insurers: Logit Regression Results for Pooled 1999–2001 Data

	Dependent Variable: *Distress 1*				
Independent Variables	REG 1	REG 2	REG 3	REG 4	REG 5
Constant	1.2741	2.3225	1.6033	1.0954	2.1897
	(0.64)	(1.07)	(0.76)	(0.48)	(0.93)
ROA	−11.2689***	−13.7798***	−11.4609***	−16.1655***	−11.4619***
	(−3.42)	(−3.69)	(−3.43)	(−3.42)	(−3.38)
CESSION	−3.3585*	−3.4379*	−3.3481*	−2.4741	−3.3486*
	(−1.77)	(−1.84)	(−1.77)	(−1.15)	(−1.71)
ln(*TOTASSETS*)	−0.0584	−0.0782	−0.0477	−0.0361	−0.1999
	(−0.41)	(−0.53)	(−0.33)	(−0.21)	(−0.85)
SIZE × *LEVERAGE*	–	–	–	–	0.1173
	–	–	–	–	(0.75)
GROWTHPREM	−0.0014	−0.0044	−0.0013	−0.0047	−0.0015
	(−0.34)	(−0.92)	(−0.31)	(−0.94)	(−0.37)
EXPENSE RATIO	0.3672	–	0.2613	−0.7225	0.2601
	(0.29)	–	(0.21)	(−0.45)	(0.20)
COMBINED RATIO	–	−0.3283**	–	–	–
	–	(−2.11)	–	–	–
DEBT RATIO	−2.0284	−2.0873	−2.5119	−0.8079	−2.1099
	(−1.46)	(−1.47)	(−1.49)	(−0.56)	(−1.53)
PROPERTY RATIO	−1.1203	−2.1736	−1.6765	−8.1897	−1.6779
	(−0.26)	(−0.49)	(−0.38)	(−1.28)	(−0.39)
EQUITY RATIO	−3.7362*	−4.2384**	−4.1311**	−4.2235*	−3.5593*
	(−1.91)	(−2.09)	(−1.97)	(−1.72)	(−1.84)
REINS ASSETS RATIO	3.8005	5.1396**	3.3392	6.4444**	2.9380
	(1.49)	(1.97)	(1.24)	(2.06)	(1.04)
OTHER ASSETS RATIO	−3.2104*	−4.3764**	−3.7912*	−2.4342	−3.3561*
	(−1.66)	(−1.98)	(−1.65)	(−1.07)	(−1.72)
INTLPREM	2.5552*	3.1164**	2.4818*	3.4589**	2.6375*
	(1.75)	(2.12)	(1.70)	(2.05)	(1.77)
MOTORPREM	−1.7028	−1.9033	−1.7587	−2.7201	−1.9286
	(−1.06)	(−1.22)	(−1.10)	(−1.56)	(−1.17)
LONGTAILPREM	1.1342	0.9501	1.1493	0.1548	1.0762
	(0.97)	(0.85)	(0.99)	(0.11)	(0.91)
CONSCREDITPREM	−2.4474	−2.2319	−2.1360	−1.5421	−2.4496
	(−1.47)	(−1.28)	(−1.24)	(−0.94)	(−1.46)
OTHERPREM	0.2681	0.3294	0.2992	−1.0922	0.4076
	(0.25)	(0.29)	(0.28)	(−0.80)	(0.37)
HIGH LIQUIDITY	–	–	−0.8170	–	–
	–	–	(−0.48)	–	–
Summary stats					
Number of Obs	205	205	205	189	205
Pseudo R^2 (Estrella, 1998)	0.320	0.359	0.321	0.318	0.323

(Continued)

TABLE 4
(Continued)

	Dependent Variable: *Distress 1*				
Independent Variables	REG 1	REG 2	REG 3	REG 4	REG 5
Type II Error Rate (%)	Type I Error Rate (%)				
5	48.89	48.89	48.89	51.11	51.11
10	42.22	40.00	40.00	42.22	42.22
20	31.11	24.44	31.11	26.67	31.11
30	13.33	8.89	13.33	11.11	13.33
40	6.67	6.67	6.67	4.44	5.93
50	4.44	4.44	4.44	2.22	4.44
60	4.44	2.22	4.44	2.22	4.44
70	3.33	2.22	3.13	2.22	3.33
80	2.22	0.00	2.22	2.22	2.22

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

We also find in REG 1 that financial distress is significantly (at the 90 percent confidence level) and inversely related to the *CESSION* ratio (outward reinsurance expense to premium ratio). This is consistent with the traditional view that outward reinsurance expense is a means of reducing claims exposure. In contrast to our finding, Kim et al. (1995) find that U.S. property–liability insurer insolvencies are positively related to reinsurance recoverable while Kramer (1996) finds that reinsurance is not a significant determinant of financial solidity of Dutch nonlife insurance companies (GIs). The U.S. result is consistent with the alternative view that reinsurance increases the insurer's dependence on the financial health of the reinsurer which, under some circumstances, may increase the insurer's risk.

With respect to product mix, there is some evidence in REG 1 that the mix of insurance lines influences the likelihood of GI financial distress. Relative to the omitted premium category (Australian fire and ISR and house owners/householders insurance premiums, *FIREHOUSEPREM*), overseas insurance business (*INTLPREM*) is associated with a significantly higher probability of general insurer financial distress. However, although the coefficient of *LONGTAILPREM* has the expected positive sign, it is not statistically significant.

Asset composition also plays a role in determining financial distress in REG 1. Relative to holdings of liquid assets (the omitted asset category), equities and "other assets" are associated with significantly lower likelihood of financial distress at the 90 percent confidence level. With liquid assets having low default and liquidity risk, the result for equities is contrary to our *a priori* expectation and is inconsistent with results found in studies of property–liability insurers in the United States and Singapore (see, respectively, Lee and Urrutia, 1996; Chen and Wong, 2004). We consider three explanations for our counterintuitive result. First, if equity returns were high over the sample, GIs with relatively high equity holdings would experience high investment returns and reduced risk of financial distress. Consistent with this explanation, the returns on Australian equities over the 1998–2001 period were relatively high with the S&P/ASX 200 Accumulation Index showing a return of 11 percent over the period.

A second possibility is that the counterintuitive finding may be attributable to extreme holdings of liquid assets in a small number of GIs. Although the mean liquid asset holdings is 16–20 percent of total assets, the portfolios of six insurers in our sample are held predominantly (in excess of 80 percent of total assets) as liquid assets. In REG 3 of Table 4 we include an indicator variable, denoted *HIGH LIQUIDITY*, which takes the value of unity if the liquid assets ratio is greater than 0.8 and zero otherwise. However its coefficient is not statistically significant and its inclusion has little effect on the coefficients of the asset composition variables in the regression. Consequently, the perverse result cannot be explained by extreme values of the liquid assets variable.

A third possibility is that the counterintuitive result could be attributable to the behavior of a small number of insurers that are in runoff (approximately 7 percent of our sample). In REG 4 we exclude insurers in runoff from the regression, reducing the sample from 205 to 189 observations.[20] Although the coefficient of the *EQUITY RATIO* remains negative and significant at the 90 percent confidence level, the exclusion of insurers in runoff alters the significance of several coefficients relative to REG 1. For example, the coefficients of the cession and other asset ratios are no longer significant at the 90 percent confidence level and the coefficient of the share of international premiums increases in significance (now at the 95 percent level vis-à-vis 90 percent previously). Moreover, the coefficient of the reinsurance assets ratio, which was previously insignificant, is now (positive and) statistically significant at the 95 percent level. This is consistent with our *a priori* expectation that a portfolio shift from liquid to reinsurance assets will increase the likelihood of financial distress.

Although Lee and Urrutia (1996) find that financial insolvency of U.S. property–liability insurers is significantly and directly related to the rate of growth of net premiums written, in REG 1 we do not observe a significant relationship for premium growth in the Australian context. Moreover, although Cummins, Harrington, and Klein (1995) and Chen and Wong (2004) find that financial distress is significantly and inversely related to the size of property–liability insurers in the United States, Singapore, and Malaysia, consistent with scale providing diversification benefits, our *Distress 1* measure is not significantly related to insurer size. In REG 5 we consider the possibility that large insurers may be able to sustain greater leverage and modify REG 1 by including the interactive variable ln*(TOTASSETS)* × *LEVERAGE* where *LEVERAGE* is the ratio of *(TOTASSETS – EQUITY)* to *TOTASSETS*. However, both the size proxy and the interactive size term in REG 5 are statistically insignificant.

Distress 2 Measure. Although the regression results for the *Distress 2* measure reported in Table 5 have a higher pseudo R^2 (0.47 to 0.50) than the corresponding regressions for *Distress 1*, this reflects the higher proportion of insurers classified as distressed by the *Distress 2* measure. Moreover, although the regression coefficients are similar in sign to those for *Distress 1*, the estimated coefficients for *Distress 2* are generally more significant than those for *Distress 1*.

[20] Rather than exclude the observations, we also tried including an indicator variable for insurers in runoff but it was not significant and the coefficient of the equity ratio remained negative and statistically significant. For space reasons this result is not included in Table 4.

TABLE 5
Financial Distress of Australian General Insurers: Logit Regression Results for Pooled 1999–2001 Data

	Dependent Variable: *Distress 2*				
Independent Variables	REG 1	REG 2	REG 3	REG 4	REG 5
Constant	9.5465***	8.6658***	8.4119***	10.5640***	12.0319***
	(4.05)	(3.89)	(3.43)	(4.12)	(4.52)
ROA	−19.8724***	−17.9629***	−19.9037***	−19.3094***	−21.2602***
	(−4.41)	(−4.26)	(−4.44)	(−3.98)	(−4.53)
CESSION	−5.4611***	−5.7621***	−5.3409***	−6.8284***	−5.2726**
	(−2.89)	(−3.15)	(−2.81)	(−3.01)	(−2.52)
ln(*TOTASSETS)*	−0.4348***	−0.4306***	−0.4504***	−0.5419***	−0.8988***
	(−2.84)	(−2.86)	(−2.92)	(−3.16)	(−3.72)
SIZE × *LEVERAGE*	–	–	–	–	0.4150**
	–	–	–	–	(2.56)
GROWTHPREM	0.0011	0.0026	0.0020	0.0010	−0.0013
	(0.27)	(0.68)	(0.49)	(0.24)	(−0.31)
EXPENSE RATIO	−2.3719**	–	−2.0922*	−1.5425	−2.232*
	(−1.98)	–	(−1.66)	(−1.23)	(−1.69)
COMBINED RATIO	–	−0.0416	–	–	–
	–	(−0.42)	–	–	–
DEBT RATIO	−1.3454	−1.5260	0.0731	−1.1630	−1.5573
	(−1.29)	(−1.48)	(0.05)	(−1.09)	(−1.44)
PROPERTY RATIO	20.9243***	18.9457***	22.5466***	18.9006***	15.9069***
	(3.54)	(3.33)	(3.72)	(3.08)	(2.64)
EQUITY RATIO	−5.1742***	−6.0047***	−4.0264**	−5.1141***	−4.9838***
	(−3.02)	(−3.59)	(−2.12)	(−2.85)	(−2.93)
REINS ASSETS RATIO	8.1084***	7.9421***	9.123***	10.6736***	5.3849*
	(2.92)	(2.99)	(3.10)	(3.24)	(1.72)
OTHER ASSETS RATIO	−2.8997	−3.9509**	−1.1908	−3.5394*	−3.6148*
	(−1.52)	(−2.24)	(−0.53)	(−1.78)	(−1.78)
INTLPREM	2.6822*	3.4454**	2.8426*	2.2701	3.4094**
	(1.83)	(2.35)	(1.92)	(1.44)	(2.13)
MOTORPREM	−3.8307***	−2.6338**	−3.7873***	−3.6474***	−4.0248***
	(−2.87)	(−2.27)	(−2.80)	(−2.65)	(−2.93)
LONGTAILPREM	−2.5998**	−1.6630	−2.5976**	−2.4710*	−2.6694**
	(−2.15)	(−1.55)	(−2.13)	(−1.94)	(−2.09)
CONSCREDITPREM	−1.3143	−1.7544*	−1.8028	−1.7016	−0.9048
	(−1.19)	(−1.66)	(−1.53)	(−1.49)	(−0.76)
OTHERPREM	−4.1440***	−3.3875***	−4.2773***	−4.2188***	−3.3188**
	(−3.27)	(−2.88)	(−3.34)	(−3.06)	(−2.56)
HIGH LIQUIDITY	–	–	2.2124	–	–
	–	–	(1.45)	–	–
Summary stats					
Number of Obs	205	205	205	189	205
Pseudo R^2 (Estrella, 1998)	0.490	0.473	0.499	0.466	0.520

(Continued)

TABLE 5
(Continued)

	Dependent Variable: *Distress 2*				
Independent Variables	REG 1	REG 2	REG 3	REG 4	REG 5
Type II Error Rate (%)	Type I Error Rate (%)				
5	45.05	43.19	48.68	45.38	43.68
10	34.07	32.75	37.14	37.36	34.29
20	21.98	24.18	17.69	21.10	18.68
30	10.99	12.09	11.87	11.65	12.09
40	5.49	7.36	5.49	5.49	5.93
50	4.40	4.40	3.30	3.30	3.30
60	3.30	3.30	3.30	3.30	1.10
70	1.32	2.20	0.00	1.10	0.00
80	0.00	0.00	0.00	0.00	0.00

***, **, and * denote significance at the 1 percent , 5 percent , and 10 percent levels, respectively.

As for the *Distress 1* measure, the likelihood of GI financial distress as measured by *Distress 2* is significantly and inversely related to GI profitability, *CESSION* ratio (outward reinsurance expense to premium ratio), and equity holdings, and directly related to overseas insurance business (*INTLPREM*). In the following we focus on the primary differences between the Table 4 and Table 5 results.

Whereas there is little evidence of a significant relationship between *Distress 1* and insurer size, in Table 5 we find a significant size relationship for *Distress 2*. Consistent with scale providing risk reducing diversification benefits, we find that financial distress is significantly and inversely related to the size of Australian GIs.[21] As noted above, Cummins, Harrington, and Klein (1995) and Chen and Wong (2004) find a similar result for property–liability insurers in the United States, Singapore, and Malaysia. The difference in the insurer size result across the distress measures may be explained by their different regulatory capital requirement. In effect, *Distress 2* evaluates insurers' capital pre-2002 with a higher capital requirement that was not introduced until July 2002. Although some small insurers may have met the pre-2002 regulatory capital requirement of *Distress 1*, the amount of excess capital held may not have been sufficient to meet that of the *Distress 2* solvency requirement. In other words, small insurers can be viewed as operating with smaller margin above the regulatory requirement ("sailing closer to the wind") than large insurers.

When the size proxy is interacted with the leverage measure in REG 5 the pseudo R^2 improves and both the size and interactive size-leverage variables are significant. Although the negative coefficient on the size variable captures the diversification

[21] Several readers have suggested that the inverse relationship was unexpected given the high profile failures of the large insurers, GIO, HIH, and FAI, during our sample. With the regression analysis weighting individual small insurers equally with large insurers, our result suggests a higher frequency of financial distress in small insurers than large insurers. Moreover, our definition of financial distress does not correspond to failure.

benefits of scale, the positive coefficient of the interactive term is consistent with diversification benefits decreasing with leverage (for a given scale).

Whereas property and reinsurance assets are insignificant determinants of the narrower *Distress 1* measure, for the *Distress 2* measure in Table 5 we find that increased holdings of property and reinsurance assets (and fewer liquid assets) increase the likelihood of financial distress. With direct property and reinsurance assets being relatively illiquid and higher risk than liquid assets, this result is consistent with our *a priori* expectation.

There is also strong evidence from the *Distress 2* results that the mix of insurance lines influences the likelihood of financial distress, whereas the *Distress 1* results were somewhat weak. Relative to the omitted premium category (Australian fire and ISR and house owners/householders insurance premiums) financial distress increases with the proportion of overseas insurance business (as for *Distress 1*) but decreases with the share of motor vehicle insurance premiums, long-tail insurance lines, and other premiums. The unexpected finding that financial distress is inversely related to the share of long-tail insurance lines in the product mix highlights a problem for statistical financial distress models based on accounting data and encompassing relatively short sample periods. It is now widely acknowledged that there were significant problems in many GI long-tail lines in the late 1990s and early 2000s (see HIH Royal Commission, 2003). This involved GIs underestimating the correct premiums on long-tail lines and compounding the problem by not setting aside sufficient reserves for their long-term liabilities. Consequently, the accounting data during our sample "masked" the true financial health of the long-tail insurance exposures, incorrectly signaling in the *Distress 2* results that the long-tail lines involved significantly lower likelihood of financial distress than short-tail lines.

In-Sample Type I and Type II Errors. A Type I error involves incorrectly classifying an insurer as being financially strong when in reality it is financially distressed, whereas a Type II error occurs when a financially strong insurer is incorrectly classified as being distressed. From a regulatory viewpoint, the economic and political cost of failing to identify a distressed insurer (a Type I error) is likely to be significantly greater than the cost of incorrectly identifying a nondistressed insurer as being distressed (a Type II error). The latter costs would be those of intensifying regulatory supervision of an institution not requiring additional supervision.

For each of the regressions, the bottom sections of Table 4 and Table 5 report the in-sample trade-offs between the Type I and Type II error rates for Type II error rates from 5 to 80 percent. For the *Distress 1* measure in Table 4, REG 1 produces a Type I error rate of 4.4 percent at a 50 percent Type II error rate. This suggests that if a regulator was to use the model in-sample predictions so as to identify financially distressed insurers with less than a 5 percent error rate, then it will incorrectly predict that at least half of the sound insurers are financially distressed. Consequently, it is not possible to identify distressed insurers with a high degree of accuracy without incorrectly classifying a large proportion of sound institutions as being distressed.

In comparing the trade-offs for the two distress measures for REG 1 in Table 4 and Table 5, respectively, it is evident for Type II error rates above 30 percent that there is little difference between the models. At a 50 percent Type II error rate the Type I error rate is 4.44 percent for *Distress 1* and 4.40 percent for *Distress 2*. Although the error trade-offs from our financial distress models cannot be compared with those in failure prediction models, a comparison is possible with trade-offs reported in Chen and Wong's (2004) study of financially unstable property–liability insurers from Malaysia, Singapore, and Taiwan. For a 30 percent Type II error, Chen and Wong report Type I 1-year prediction errors of 38 percent, 28 percent, and 15 percent for the respective countries whereas our Australian GI model produces Type I errors of 11 percent to 13 percent for a 30 percent Type II error.[22] Although our error trade-off is superior to those in Chen and Wong (2004), the high Type I error rate for Type II error rates equal or less than 30 percent is unlikely to be acceptable to regulators.

Out-of-Sample Predictions

Although the in-sample trade-off of Type I and Type II error rates provides a useful indication of the model's fit, to be useful as part of an early warning system the model must predict well out-of-sample. We evaluate this feature by (i) estimating the model with 1999 data and predicting distress in each of 2000 and 2001, 1 and 2 years ahead respectively; (ii) estimating the model with 2000 data and predicting distress in 2001, 1 year ahead; and (iii) estimating the model with pooled 1999 and 2000 data and predicting distress in 2001, 1 year ahead. Each of the estimated models and the out-of-sample predictions relate the distress measure at period $t + n + j$ where $j = 1$ or 2 to values of the independent variables at period $t + n$.

With the two distress measures, Table 6 reports four single year regression estimates for 1999 and 2000 and two regression estimates using pooled 1999 and 2000 data. It also includes the in-sample Type I and Type II error trade-off rate analysis at the foot of the table. Although the estimates in Table 6 are broadly similar to the 3 year pooled results reported in Table 4 and Table 5 in terms of signs and significance of the estimated coefficients, there is a considerable improvement in explanatory power reflected in the pseudo R^2 and improved trade-off of in-sample Type I and Type II errors for the single year estimates vis-à-vis the pooled estimates. For the 1999 regressions, the Type 1 error rate is zero at a 30 percent Type II error rate. This implies that the cutoff probability for classifying insurers as financially distressed can be set to achieve a perfect classification of all the distressed insurers while classifying 30 percent of nondistressed insurers incorrectly as being distressed. The in-sample trade-off deteriorates a little for 2000 where the Type I error rate is 6.67 percent for *Distress 1* and 3.33 percent for *Distress 2* at a 30 percent Type II error rate.

The out-of-sample predictions for the solvency distress measures are evaluated in Table 7 in terms of the Type I and Type II error trade-off. Not surprisingly, the out-of-sample trade-offs in Table 7 are inferior to the corresponding trade-offs in the in-sample predictions in Table 6. Relative to the near perfect in-sample predictions (zero Type I error rate) of distressed insurers at the 30 percent Type II error rate for the single year regressions in Table 6, the out-of-sample Type I error rate for the corresponding regression in Table 7 lies in the range of 12 to 40 percent.

[22] Comparable error trade-off statistics are not available in Kramer's (1996) study of nonlife Dutch insurance companies.

TABLE 6
Financial Distress of Australian General Insurers: Logit Regression Results for 1999, 2000, and Pooled Data

	Dependent Variable					
	Distress 1			*Distress 2*		
Independent Variables	1999	2000	1999 & 2000	1999	2000	1999 & 2000
Constant	21.2642	−5.1622	−0.4449	90.4474**	12.8959**	8.0932***
	(1.57)	(−1.2)	(−0.16)	(2.09)	(2.38)	(2.87)
ROA	−56.2985**	−55.8817***	−17.9654***	−259.0029**	−29.244***	−18.5651***
	(−1.97)	(−2.97)	(−3)	(−2.1)	(−2.7)	(−3.19)
CESSION	−25.4827*	−7.2524	−2.9859	−35.0104*	−5.9790	−4.0737
	(−1.70)	(−1.5)	(−1.14)	(−1.76)	(−1.34)	(−1.58)
ln(*TOTASSETS*)	−0.9814	−0.2597	−0.1087	−3.9042**	−0.5280	−0.329*
	(−1.38)	(−0.66)	(−0.56)	(−2.17)	(−1.59)	(−1.72)
GROWTHPREM	−0.0164	0.0194	0.0037	0.0109	0.0148	0.0066
	(−0.60)	(1.24)	(0.55)	(0.63)	(1.46)	(1.15)
EXPENSE RATIO	−9.6255*	13.353**	1.5763	−55.7994*	5.1445	−2.5989
	(−1.68)	(2.2)	(0.77)	(−1.92)	(1.43)	(−1.47)
DEBT	−6.4479	2.5402	0.0116	−30.4793*	−2.5833	−1.5322
	(−0.94)	(0.63)	(0.01)	(−1.8)	(−1.23)	(−1.1)
PROPERTY	−2.2805	7.6352	5.5883	113.4513**	24.2563	24.7879***
	(−0.19)	(0.48)	(0.82)	(2.17)	(1.49)	(2.83)
EQUITY	−8.7651	−8.8385	−2.2874	−37.0474*	−8.4083*	−4.4715**
	(−0.92)	(−1.61)	(−0.91)	(−1.93)	(−1.79)	(−2.02)
REINS ASSETS	23.3422	9.3399	3.7871	28.3415	11.5097*	7.435**
	(1.63)	(1.38)	(1.09)	(1.26)	(1.88)	(1.98)
OTHER ASSETS	−27.5989*	−9.8106*	−5.1102	−10.2043	−11.7345**	−2.9074
	(−1.75)	(−1.65)	(−1.61)	(−0.96)	(−2.15)	(−1.12)
INTLPREM	−2.5627	13.4798**	3.5386	−60.6099**	3.6075	1.1217
	(−0.33)	(2.17)	(1.5)	(−1.99)	(0.95)	(0.6)
MOTORPREM	−0.7273	12.7504**	1.6830	−23.4839*	−4.5624	−4.3685**
	(−0.12)	(2.03)	(0.64)	(−1.84)	(−1.59)	(−2.47)
LONGTAILPREM	0.5690	7.8492*	2.3859	−13.4633	−5.8113*	−2.8224*
	(0.16)	(1.77)	(1.28)	(−1.62)	(−1.92)	(−1.9)
CONSCREDITPREM	−36.6169	−687.4343	−228.0668	21.6593*	−6.4035**	−1.0819
	(−0.85)	(−0.71)	(−0.38)	(1.91)	(−2.13)	(−0.75)
OTHERPREM	8.0853**	3.2735	1.8646	−0.6464	−6.077**	−3.6144**
	(1.99)	(0.79)	(0.98)	(−0.23)	(−2.1)	(−2.25)
Summary stats						
Number of Obs	69	70	139	69	70	139
Pseudo R^2 (Estrella, 1998)	0.687	0.522	0.404	0.865	0.654	0.539
Type II Error Rate (%)	Type I Error Rate (%)					
5	12.50	35.00	45.16	8.13	27.88	51.38
10	12.50	13.33	35.48	0.00	17.88	32.62
20	6.25	13.33	25.81	0.00	6.06	9.85
30	0.00	6.67	12.90	0.00	3.03	4.62
40	0.00	6.67	3.23	0.00	0.00	4.62
50	0.00	0.00	0.00	0.00	0.00	3.08
60	0.00	0.00	0.00	0.00	0.00	1.54
70	0.00	0.00	0.00	0.00	0.00	0.00
80	0.00	0.00	0.00	0.00	0.00	0.00

***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

TABLE 7
Out of Sample Predictions of Financial Distress for Australian General Insurers

	1999 Reg'n 2000 Pred'n (1999 I'Vars)	1999 Reg'n 2001 Pred'n (1999 I'Vars)	2000 Reg'n 2001 Pred'n (2000 I'Vars)	1999–2000 Reg'n 2001 Pred'n (2000 I'Vars)
Distress 1				
Type 2 Error Rate (%)		Type 1 Error Rate (%)		
5	35.71	71.43	80.00	74.00
10	28.57	52.86	62.00	66.67
20	28.57	42.86	21.33	45.33
30	28.57	40.00	20.00	26.67
40	21.43	35.71	6.67	13.33
50	21.43	28.57	6.67	13.33
60	14.29	28.57	6.67	6.67
70	14.29	24.29	6.67	6.67
80	0.00	7.14	6.67	6.67
Distress 2				
Type 2 Error Rate (%)		Type 1 Error Rate (%)		
5	59.38	84.62	61.48	77.78
10	35.00	74.62	55.56	75.19
20	12.50	65.38	33.33	54.81
30	12.50	30.00	21.85	18.15
40	9.38	23.08	15.56	11.11
50	6.25	19.23	14.81	9.26
60	3.13	16.92	7.41	6.67
70	3.13	15.38	7.41	3.70
80	3.13	11.54	3.70	3.70

The first two columns of Table 7 use the 1999 regression coefficients to predict distress in 2000 and 2001, respectively, using data for the independent variables available in 1999. The expectation that the quality of forward predictions deteriorates as the forward time horizon lengthens is strongly supported by the data in these columns. For example, at the 30 percent Type II error rate the Type I error rate for the 1 year forward prediction of the *Distress 2* measure is 12.5 percent compared to 30 percent for the 2 year forward prediction. Although the 1 year ahead forecasts provide a reasonable trade-off of Type I and Type II errors, the deterioration in performance of the 2 year ahead forecasts is of concern. With delays in reporting and processing the annual accounting based GI data, the 1 year ahead predictions may not allow sufficient lead time to identify most problem insurers.

Over time the regression model and estimated coefficients may be updated as new data become available. The second and third columns of Table 7 compare out-of-sample predictions for 2001 based on regression models (and data for independent variables) for 1999 and 2000, respectively. It is expected that the predictions from the more current model (the 2000 model in the third column) will be superior to those from the older model (the 1999 model in the second column). This is the case for both measures. For the *Distress 2* measure, at the 30 percent Type II error rate the Type I error rate for the 2000 model with 1 year forward prediction is 21.9 percent compared to 30 percent for the 2 year forward prediction with the 1999 model and data.

An issue in updating models as new data become available is whether to generate forward predictions from a model estimated with the new data alone or a model estimated with pooled data. A comparison of the results in the third and fourth columns of Table 7 sheds light on this issue. Both columns consider 2001 predictions, with the third column using the 2000 model and the fourth column using the pooled 1999–2000 model (both use 2000 values of the independent variables for the predictions). Although the in-sample predictions from the single year estimates have a superior error trade-off relative to the pooled estimates, the evidence for out-of-sample predictions is somewhat mixed.

SUMMARY AND LIMITATIONS

Although there is an extensive literature modeling the determinants of failure of U.S. property–liability insurers, this approach is not possible in Australia because of the small number of insurer insolvencies. Hence, our focus in this article is the modeling of financial distress, rather than insolvency, of Australian GIs. The significance of the study stems from the considerable costs borne by stakeholders of financially distressed insurers including reductions in the value of the insurer's debt and equity claims, additional supervisory costs of the prudential regulator, and disruption to policyholders and insurance markets because of increased uncertainty of the value of the insurer's policy reserves.

Moreover, we overcome problems in prior studies of financial distress of Dutch and Asian insurers by developing two regulatory measures of financial distress from the Solvency Condition in the Insurance Act applying to Australian GIs. We find that financially distressed insurers are typically small in size, and have low profitability and cession ratios. Relative to liquid asset holdings, they have high holdings of reinsurance assets and property, and low levels of equity and other assets. Finally, relative to fire and household insurance premiums, they derive a relatively high proportion of premium revenue from overseas insurance business and a low proportion from motor vehicle and long-tail insurance business lines.

Our models perform reasonably well in both in- and out-of-sample tests of predictive performance and have superior trade-offs of Type I and Type II errors vis-à-vis an existing study of financial distress in Asian insurers. Typically the predictive performance deteriorates as the time increases between the forward prediction and the sample estimation period. There is also evidence that predictions based on a single year regression model are superior to those using pooled data.

There are, however, a number of shortcomings in our study that need to be addressed in future research. The major shortcomings stem from the limited experience encompassed in our 1999–2001 sample, after accounting for the 1 year lag built into the model. The choice of sample was limited by APRA's formation in 1998 and by its move to a new GI data collection system from September 2002. Our findings that large equity holdings and large exposures to long-tail insurance lines are associated with lower levels of financial distress, contrary to our *a priori* expectation, is likely to be a reflection of the sample period which was characterized by strong equity returns. Moreover pricing practices, and in some instances accounting approaches, relating to long-tail insurance lines "masked" the true financial health of the long-tail insurance exposures, and incorrectly signaled that the long-tail lines involved significantly lower likelihood of financial distress than short-tail lines. The problems subsequently emerged with the failure of HIH and became evident in accounting data beyond our sample period.

Another data based shortcoming of this article is that our out-of-sample predictions are, with one exception, 1 year ahead predictions. In developing models to assist APRA in the early identification of GIs likely to become distressed, models with a 1 year lead time may not be especially useful.

Moreover, APRA's GENESIS data collection is limited in its ability to capture several important dimensions of an insurer's risk exposure. For example, the relationship between a GI's cession ratio (outward reinsurance expense) and financial distress is unclear because the quality of the reinsurance is not evident from the reported GENESIS data. Unlike U.S. insurer financial statements which provide details on the quality and use of reinsurance, as in the reporting of "surplus relief," there is no similar reporting requirement in GENESIS. Nor were GIs required to report the quality of assets beyond asset type. For example, bond holdings are not classified by debt rating or by investment/noninvestment grade.

In September 2002 APRA replaced the annual GENESIS data collection with a significantly different and more extensive quarterly collection known as D2A (Direct to APRA). Although it would be desirable to extend our research by appending the D2A data to GENESIS, this has not been possible because of the very different basis of data collection in D2A.

However, a study based on the post-2002 D2A data may make several useful contributions to the literature. D2A contains more detailed information relating to the quality of reinsurance and debt securities than GENESIS that will enhance future research by providing better measures of GI operating and investment risk. It also encompasses a period when the risks of long-tail lines became more apparent. Finally, it would allow a study of the relationship between the probability of financial distress using the statistical models developed in this article and the largely qualitative risk-based rankings developed by APRA's supervisory staff within the PAIRS and SOARS frameworks which are available from late in 2002.

REFERENCES

BarNiv, R., and J. B. McDonald, 1992, Identifying Financial Distress in the Insurance Industry: A Synthesis of Methodological and Empirical Issues, *Journal of Risk and Insurance*, 59: 543-573.

Black, J., 2004, The Development of Risk Based Regulation in Financial Services: Canada, the UK and Australia, *Research Report*, London School of Economics and Political Science, Centre for the Analysis of Risk and Regulation and the Law Department, September.

Borde, S. F., K. Chambliss, and J. Madura, 1994, Explaining Variation in Risk Across Insurance Companies, *Journal of Financial Services Research*, 8: 177-191.

Browne, M. J., and R. E. Hoyt, 1995, Economic and Market Predictors of Insolvencies in the Property–Liability Insurance Industry, *Journal of Risk and Insurance*, 62: 309-327.

Ceccarelli, S., 2003, Insolvency Risk in the Italian Non-Life Insurance Companies: An Empirical Analysis Based on a Cash Flow Simulation Model, SSRN Working Paper #536763.

Chen, R., and K. A. Wong, 2004, The Determinants of Financial Health of Asian Insurance Companies, *Journal of Risk and Insurance*, 71: 469-499.

Cummins, J. D., M. F. Grace, and R. D. Phillips, 1999, Regulatory Solvency Prediction in Property–Liability Insurance: Risk-Based Capital, Audit Ratios, and Cash Flow Simulation, *Journal of Risk and Insurance*, 66: 417-458.

Cummins, J. D., S. E. Harrington, and R. Klein, 1995, Insolvency Experience, Risk-based Capital, and Prompt Corrective Action in Property–Liability Insurance, *Journal of Banking and Finance*, 19: 511-527.

Cummins, J. D., and D. W. Sommer, 1996, Capital and Risk in Property–Liability Insurance Markets, *Journal of Banking and Finance*, 20: 1069-1092.

Esho, N., P. Kofman, M. G. Kollo, and I. G. Sharpe, 2005, Market Discipline and Subordinated Debt of Australian Banks, Australian Prudential Regulation Authority, Sydney, Working Paper.

Estrella, A., 1998, A New Measure of Fit for Equations with Dichotomous Dependent Variables, *Journal of Business and Economic Statistics*, 16: 198-205.

Harrington, S. E., and J. M. Nelson, 1986, A Regression-Based Methodology for Solvency Surveillance in the Property–Liability Insurance Industry, *Journal of Risk and Insurance*, 53: 583-605.

HIH Royal Commission, 2003, *The Failure of HIH Insurance. Volume 3. Reasons, Circumstances and Responsibilities* (Canberra: Commonwealth of Australia, National Capitol Printing).

Hollman, K. W., R. D. Hayes, and J. H. Murrey, 1993, A Simplified Methodology for Solvency Regulation of Life–Health Insurers, *Journal of Insurance Regulation*, 11: 509-522.

Jones, S., and D. A. Hensher, 2004, Predicting Firm Financial Distress: A Mixed Logit Model, *Accounting Review*, 79: 1011-1038.

Kim, Y., D. R. Anderson, T. L. Amburgey, and J. C. Hickman, 1995, The Use of Event History Analysis to Examine Insurer Insolvencies, *Journal of Risk and Insurance*, 62: 94-110.

Kramer, B., 1996, An Ordered Logit Model for the Evaluation of Dutch Non-Life Insurance Companies, *De Economist*, 144: 79-91.

Lee, S. H., and J. L. Urrutia, 1996, Analysis and Prediction of Insolvency in the Property–Liability Insurance Industry: A Comparison of Logit and Hazard Models, *Journal of Risk and Insurance*, 63: 121-130.

Pottier, S. W., and D. W. Sommer, 1999, Property–Liability Insurer Financial Strength Ratings: Differences Across Rating Agencies, *Journal of Risk and Insurance*, 66: 621-642.

Sahajwala, R., and P. Van den Berg, 2000, Supervisory Risk Assessment and Early Warning Systems, Working Papers 4, Basle Committee on Banking Supervision.

Sommer, D. W., 1996, The Impact of Firm Risk on Property–Liability Insurance Prices, *Journal of Risk and Insurance*, 63: 501-514.