

Demand for Reinsurance: Evidence from Australian Insurers [★]

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Abstract

Reinsurance is widely recognised as important in insurer risk and capital management. This paper examines the factors that determine insurer demand for reinsurance using Australian data. The Australian situation is interesting because of the tax imputation system and the prudential regulations that were in force during the period of the study. As far as we are aware, this is the first paper to empirically analyse the demand for reinsurance in Australia. A panel-data set (1996-2001) is used, which provides 543 observations. We provide a careful approach to econometric diagnostic testing and the choice of the most appropriate panel-data model and we show how failure to do so may generate misleading results. Based on a robust estimation procedure, we find strong evidence of a positive relationship between company leverage and the demand for reinsurance. The impact of size, taxes, return on investments and company structure are not statistically significant. This reinforces the important role of reinsurance in insurer risk management and the link between capital structure and reinsurance.

Keywords: insurer risk management, reinsurance demand, panel-data estimation.
JEL classification: C13, C52, G22, N27

1 Introduction

Corporate risk management theory that has been developed in recent years has identified the circumstances under which risk management strategies add value to a firm. Hommel (2005[20]) and Gleisner (2005[16]) provide a concise coverage of the value based motivations for corporate risk management. The circumstances generally arise from market imperfections including frictional costs such as taxes, agency costs, financial distress and bankruptcy costs. Insurer risk management will add value from the use of capital and reinsurance strategies that reduce frictional costs including insolvency costs to policyholders and shareholders.

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Mayers and Smith (1990 [31]) were the first to empirically test the theoretical hypotheses underlying the demand for reinsurance. While much attention has been paid to collecting data and defining good proxies, limited attention has been paid to ensuring robust estimation. For example, the first empirical studies do not mention the type of estimator used nor do they give the results of econometric diagnostics. Also, the most recent empirical studies have been using panel-data models instead of cross-sectional models. However, diagnostics are specially important for panel-data models because of the many assumptions required for their error structure.

This paper provides important contributions to empirical methodology as well as to insurer risk management. It is the first article, as far as we are aware, to empirically test the demand for reinsurance using Australian data. The number of insurers in Australia is not as large as in countries used in previous studies, but a larger data set (543 observations) and robust inference were made possible with the use of a panel-data methodology. This article emphasizes the importance of econometric diagnostics, especially in panel-data sets. Many data sets of this type will reasonably be expected to have panel heteroskedasticity, correlation across panels and serial (auto) correlation. Based on our diagnostics, we show that failure to choose the correct panel-data model may generate very misleading results.

We find significant evidence that reinsurance demand is positively related to leverage. This highlights the role of reinsurance in capital management for insurers. The impacts of company size, taxes, investment return and company structure are not statistically significant. In the Australian case, some of these results are less surprising given the tax imputation system.

The structure of this paper is as follows. The next section provides an overview of the theory of corporate risk management and how this impacts insurer risk and capital management including the demand for reinsurance. Section 3 discusses the econometric methodologies and empirical results obtained in previous studies. Section 4 describes the Australian data set used. Section 5 describes the econometric diagnostics and give reasons for the choice of OLS with Panel Corrected Standard Errors (PCSEs) to be the most appropriate model in this case. Section 6 gives the estimated results with this model and compares them with those obtained with OLS, random-effects and fixed-effects estimators. Finally, section 7 concludes.

2 Reinsurance and the Theory of Insurer Risk Management

2.1 Conditions for Risk Management and Reinsurance to be Irrelevant

For perfect, frictionless and complete market assumptions (re-)insurance decisions have been shown to be irrelevant to the shareholders of the firm that cedes the risk. However the theoretical assumptions under which reinsurance is irrelevant do not hold in practice and real world (re-)insurance decisions add value

to a firm under more realistic market assumptions. By relaxing the theoretical assumptions reinsurance becomes important in the risk and capital management of the firm.

The classic paper of Modigliani and Miller (1958 [33]) showed that under conditions of perfect capital markets², the financial decisions of a firm are irrelevant in the sense that they do not change the total value of the firm. This follows from the fact that shareholders can reverse engineer the financing decisions of the firm on their own account at fair market prices.

Fama (1978 [11]) extended the Modigliani-Miller theorem and showed that propositions about the irrelevance of the financing decisions of firms can be built either on the assumption that investors and firms have equal access to the capital market or on the assumption that no company issues securities for which there are not perfect substitutes from other firms (no firm produces any security monopolistically). With either approach it was shown that if the capital market is perfect, then a firm's financing decisions have no effect on its market value, and its financing decisions are of no consequence to its security holders.

The Modigliani and Miller argument implies that if a firm changes its financing structure through the use of any financial instruments, then investors who hold claims issued by the firm can change their holdings of risky assets to offset the change in the firm's financing policy, leaving the distribution of their future wealth unaffected. This applies to the use of any risk management strategy including derivatives and insurance contracts.

The Capital Asset Pricing Model (CAPM) developed by Sharpe (1964 [41]), Lintner (1965 [25]), and Mossin (1966 [36]) has influenced the modern understanding of corporate risk management. The CAPM includes two mutually exclusive types of risk: unsystematic risk, or specific risk to the corporations, and systematic risk, or risk common to all economic agents.

Cummins (1976 [7]) and Main (1982 [27] and 1983 [28]) developed the implications of the CAPM for the corporate demand for insurance³. It was shown that, under the CAPM's ideal assumptions⁴, investors optimally hold a fully diversified portfolio and by doing this they costlessly self-insure against any unsystematic (pure) risks faced by the firms in which they invest. Thus, the firms' market value would not increase if firms contracted insurance for their unsystematic risks. Additionally, in this setting, firms are not better-off either if they buy insurance against systematic risks⁵. On the supply side, insurers writing policies to cover a firms' systematic risk would end up holding a portfolio whose return is exactly correlated with the market return. Thus, if insurers used CAPM in their pricing then the premium they would charge would account not only for

² The model's assumptions are: perfect capital markets (no transaction costs, no bankruptcy costs, no taxes, no managerial agency costs); individuals have equal access to the capital market; homogeneous expectations and information is costless to both investors and firms; and investment strategies of firms are given.

³ In their setting they consider the demand for insurance by noninsurance firms.

⁴ The basic CAPM's assumptions are: perfect capital markets; consumer risk aversion; symmetric stable distributions of returns on all portfolios; riskless borrowing and lending; and homogeneous expectations.

⁵ The systematic risk is defined to be the firm's risk which is correlated with the market return.

the actuarial odds but also for holding this systematic (undiversifiable) risk. Therefore, a firm insuring its systematic risk would not increase its market value because the premium paid is loaded with a compensation for the insurer to hold the ceded systematic risk. Thus, under the CAPM assumptions, the value of risk is the same for the insurance company and for the risk managing firm, so that the firm will not contract insurance because any economic gains would be offset by the premium.

Thus, the CAPM provides an ideal setting under which corporations will have no motivation to insure against specific risks, and insurance premiums charged for any available insurance against systematic risks will be high enough to deter corporate purchases.

Doherty and Tinic (1981 [8]) also use the CAPM to show the conditions under which reinsurance does not increase the value of the insurer's common stock, which is assumed to be traded in an efficient financial market. Their setting differs from the previous setting used by Cummins (1976 [7]) and Main (1982 [27] and 1983 [28]) because it has three types of market players: the reinsurers, the insurers and the insureds. The direct insurance market is assumed to be perfectly competitive. It is assumed that the insureds are neutral to risk, so that the price they are willing to pay for insurance does not depend on the insurer's probability of ruin. In efficient financial markets, the value of the insurer's common stock reflects the values of assets and contingent liabilities. The insurer may contract reinsurance to reduce the systematic (and total) risk of its common stock. However, the value of the insurer's common stock will remain unchanged because efficient financial markets imply that reinsurance transactions, as well as direct transactions, are consummated at market clearing prices, which include an additional charge for the reinsurer to bear systematic risk. In fact, this explanation is the same as the one given by Cummins and Main, but adapted to the reinsurance market. The key point made by Doherty and Tinic is that if insurance demand is not sensitive to the insurer's ruin probability, then exchanging assets and liabilities at market clearing prices does not offer any gains to the shareholders of the ceding and the reinsurance companies.

2.2 When Do Risk Management and Reinsurance Really Matter

Doherty and Tinic (1981[8]) discuss how if one relaxes the assumption that insurance demand is perfectly inelastic with respect to the insurer's ruin probability, then the value of the insurance company can be increased through the use of reinsurance at market prices. In fact, assuming that prospective insurance buyers are risk averse and incompletely diversified, the premium they would be willing to pay for policies from an insurer with higher ruin probability would be lower to account for the risk of default on the policies. Thus, reinsurance at market prices allows the ceding insurer to charge higher premiums and increase the expected return to its shareholders above the equilibrium required rate.

Blazenko (1986 [4]) relaxes the assumption of a perfectly competitive direct in-

insurance market. He allows the possibility that insurable risks are not completely diversifiable in the immediate transaction with an insurer. Such a possibility happens when the insurance market is imperfectly competitive and reinsurance can create value by providing additional capacity to the market in facilitating the spread of risk.

Froot, Scharfstein and Stein (1993[13]) provide a framework for corporate risk management incorporating frictional costs and considering both investment and financing decisions. They discuss the impact on risk management strategies of capital market imperfections and the impact of differing costs of internal versus external financing. Mello and Parsons (2000[32]) discuss how internal capital, which is less costly than external capital because of lower transaction and agency/monitoring costs, impacts investment decisions.

In line with developments in corporate financial theory, frictional costs and other market imperfections are important factors that create a demand for reinsurance. Mayers and Smith (1982[29]) state that if the firm's financing policy is important it is so because of (1) taxes, (2) contracting costs (including agency costs), or (3) the impact of the financing policy on the firm's investment decisions. They examine these costs and their impact on corporate insurance purchases. Analogously, this same theoretical setting was used in the literature to explain hedging demand in large widely-held corporations, whose owners hold diversified portfolios of securities. Because hedging is defined in broad terms, which may include insurance and reinsurance, the results from the hedging literature are also applicable to the reinsurance case. One example is given by Smith and Stulz (1985 [42]), who show that a value-maximizing firm will hedge because of taxes, costs of financial distress and managerial risk aversion. A more detailed description of the effects of frictional costs on the demand for reinsurance is considered in the next section.

2.2.1 Taxes

Mayers and Smith (1982 [29]) identify provisions in the American tax code that can lead to a change in the firm's effective marginal tax bracket so that the purchase of insurance is favored.

First, there are carry-back and carry-forward provisions so that the uninsured loss either cannot be fully deducted from taxable income or has to be carried forward for some years. With this, the expected tax liability of a self-insured firm can be higher than that of a firm with insurance.

Second, the progressivity in the corporate profits tax reduces the expected tax shield of the self-insured company. This happens because the uninsured loss can move pre-tax profits to a lower marginal tax bracket and thus reduce the tax shield that would be obtained with any additional losses.

Smith and Stulz (1985[42]) also provide a tax rationale for hedging. They state that if effective marginal tax rates of corporations are an increasing function of

the corporation's pre-tax value, then the after-tax value of the firm is a concave function of its pre-tax value. Thus, as a consequence of Jensen's inequality, if hedging reduces the variability of pre-tax firm values, then the expected corporate tax liability is reduced and the expected post-tax value of the firm is increased, even in the case of incomplete hedging. However, this is only true as long as the cost of hedging is not larger than the reduction of the corporate tax liability. Graham and Rogers (2002 [17]) find evidence to reject the tax motive for hedging but find that hedging does support higher debt levels.

Third, in the case of property insurance, the present value of the tax reduction from increasing depreciation (since the depreciation basis will be greater with the replaced asset in the case of loss) can exceed the taxes from immediately realizing the gain from indemnity and then the firm's tax liability is reduced. Thus, the rationale is that firms with large expected casualty losses relative to their taxable income have an incentive to insure.

In the Australian taxation system, the imputation system reduces the impact of taxation as a factor in risk management strategies at the corporate level. Individual domestic shareholders receive a credit for corporate taxation to be offset against their personal taxation.

2.2.2 Agency Costs of Debt

Reinsurance purchases can become economically feasible when agency costs are present. Jensen and Meckling (1976 [22]) and Myers (1977 [37]) both show that the firm faces two types of contracting costs associated with principal-agent problems: 1) agency costs of equity and 2) agency costs of debt.

Jensen and Meckling (1976 [22]) define an agency relationship as a contract under which one or more persons (the principal(s)) engage another person (the agent) to perform a service on their behalf which involves delegating decision making authority to the agent. It is assumed that the principal and the agent both maximize their own utility functions, so that they will almost always incur some cost in order to ensure that the agent will make optimal decisions in the sense of maximizing the principal's welfare.

Agency costs are either the costs of inducing the agent to behave as if he were maximizing the principal's welfare or the costs incurred by the firm when the principal-agent problem is not fully avoided. The relationship between the stockholder and the manager of a corporation fits the definition of the principal-agent relationship. The same is true for the relationship between bondholders and managers acting on the shareholder's behalf.

2.2.3 The Underinvestment Problem

Myers (1977 [37]) develops a model to explain that agency costs of risky debt are a reason why rational firms limit borrowing, even when there is a tax advantage

to corporate borrowing and capital markets are strictly perfect, efficient and complete. He shows that leveraged firms can forgo taking a positive present value project because shareholders' value can be reduced if gains from the project accrue primarily to the debtholders. Thus, this underinvestment problem is an agency cost resulting from risky debt.

Mello and Parsons (2000[32]) discuss how internal capital, as opposed to external capital, reduces underinvestment in valuable projects. Risk management strategies can be used to reduce the reliance on external financing and the costs of equity through lower transaction and agency costs, thus mitigating the underinvestment problem. On the other hand, Tufano (1996[44] and 1998[45]) discusses how free cash flow can destroy value.

Mayers and Smith (1987 [30]) provide a first discussion of the role played by insurance in bonding the corporate investment decision. In their model, the firm is assumed to be financed with risky debt and the only source of uncertainty is the possibility of casualty loss. Underinvestment occurs in the sense that, in certain states of nature, shareholders of the levered firm choose to forego a positive net present value investment that, in the absence of risky debt, would be undertaken. Shareholders may decide to underinvest because the benefits of investment in some states of nature would accrue primarily to bondholders. Therefore, a potential conflict of interests exists between shareholders and bondholders. However, the firm can mitigate this conflict by including a covenant in the bond contract requiring insurance coverage. In fact, in their model insurance premiums are actuarially fair and contracting insurance is optimal whenever there is any amount of risky debt. Schnabel and Roumi (1989 [43]) extended the model to account for the effects of a premium loading. They showed that there must be a minimal level of risky debt above which it is optimal to insure and below which it is not.

In MacMinn (1987 [26]), the existence of previously issued risky debt was shown to motivate an underinvestment problem. The analysis showed that, if the previously issued bonds had been issued with an insurance covenant, then the underinvestment problem could be eliminated and the stock and bond values could be increased relative to the case with no covenant. Although the analysis shows that stock value increases, it does not show if stockholders benefit from all the gains from solving the underinvestment problem.

Garven and MacMinn (1993 [15]) show that an insurance covenant can be designed that allows current shareholders to capture the gain in value and that the gain in value equals the agency costs of the underinvestment problem. It is shown that the insurance covenant not only increases current shareholder value but also eliminates the agency costs of underinvestment. In the presence of premium loadings, the corporation demands insurance if the agency cost of the underinvestment problem exceeds the premium loading. In fact, for a sufficiently small agency cost there is no demand for insurance. Therefore, the insurance covenant implied in their model allows shareholders to increase their value by the difference between the agency cost and the premium loading whenever it is positive.

2.2.4 The Asset Substitution Problem

The arbitrage argument of Modigliani and Miller (1958 [33], 1963 [34]) assumes that investment decisions will be independent of the capital structure. The optimal amount of debt should balance the tax deductions provided by interest payments against the external costs of potential default.

Jensen and Meckling (1976 [22]) challenge this argument and argue that there are some incentive effects associated with investment decisions in highly leveraged firms. They state that under some circumstances the owner-manager has an incentive to increase investment risk after debt is issued so that wealth is transferred from bondholder to equity holders, including himself.

For example, it can be that the owner-manager is not indifferent between a low risk investment and a high risk investment. In fact, the riskier investment will be preferable if the owner has the opportunity to first issue debt, then decide which of the investments to take, and then sell all or part of his remaining equity claim on the market. Therefore, he can transfer wealth from the bondholders to the equity holders by promising to take the low risk investment, selling bonds and then taking the high risk investment.

The literature refers to this effect as the Asset Substitution problem. However, assuming rational expectations, the potential bondholders will accurately perceive the motivation of the equity owning manager and his opportunity to take the riskier project. Therefore, potential bondholders will discount the price that they will be willing to pay for new debt issued to account for the asset substitution problem. This discount on the bond price is an agency cost engendered by the issuance of debt and it is entirely borne by the owner-manager of the firm.

Leland (1998 [24]) develops a model which measures agency costs from asset substitution and the benefits of hedging to the value of the firm. However, he also finds that hedging benefits are not necessarily related to environments with greater agency costs. He argues that equity holders may voluntarily agree to hedge after debt is issued, even though it benefits debt holders: the tax advantage of greater leverage allowed by risk reduction more than offsets the value transfer to bondholders.

Morellec and Smith (2004 [35]) use an intertemporal version of the basic model used by Leland (1998 [24]) to examine the firm's ability to commit to a specific hedging policy. They show that cashflow volatility is costly for shareholders since it induces distortions in investment policy. Therefore, shareholders have incentives to maintain the firm's hedging policy once debt has been issued.

2.2.5 Expected Bankruptcy Costs

Until the mid 1980s there was a great deal of controversy about the relevance of bankruptcy costs (or costs of financial distress) to the capital structure and to the value of the firm. In fact, if bankruptcy costs are relatively significant then it

may be argued that at some point the expected values of these costs outweighs the tax benefit derived from increasing leverage and the firm will have reached its optimum capital structure. Furthermore, one aspect of these costs that affects the firm's value and its cost of capital is the fact that payments must be made to third parties other than bondholders and owners. In fact, all expenses from the liquidation process are deducted from the net asset value of the bankrupted firm.

Warner (1977 [46]) was the first to show some evidence on bankruptcy costs in large firms. His empirical work was based on bankruptcy costs for 11 bankrupt railroads. It was emphasized that not all of these costs are measurable. In fact the literature refers to two types of bankruptcy costs: 1) direct costs, which include lawyer's and accountant's fees, other professional fees, and the value of the managerial time spent in administering the bankruptcy; and 2) indirect costs, which include lost sales, lost profits, lost investment opportunities and possibly the inability of the firm to obtain credit or to issue securities except under special terms.

Warner (1977 [46]) shows that the ratio of direct bankruptcy costs to the market value of the firm appears to fall as the value of the firm increases. Also, he finds that the direct cost of bankruptcy is on average about only one percent of the market value of the firm prior to bankruptcy. However, his work was based on a very specific sample of firms and also he was also unable to present a good measure for indirect bankruptcy costs.

Altman (1984 [1]) develops a methodology to estimate expected bankruptcy costs, including both direct and indirect costs. He uses a sample of 19 industrial firms and a second sample of seven large bankrupt companies. He finds that bankruptcy costs in many cases exceed 20% of the value of the firm measured just prior to bankruptcy and even in some cases measured several years prior. His results also show that bankrupt costs ranged from 11% to 17% of firm value up to three years prior to bankruptcy.

Altman (1984 [1]) calls attention to the important fact that indirect bankruptcy costs are not limited to firms which actually fail. In fact, firms which have higher probabilities of bankruptcy, whether they fail or not, can still incur these costs. Thus, whenever bankruptcy costs are present, protecting the firm through insurance and/or derivatives can help to reduce these costs and increase the value of the firm. Of course, the net benefit of this protection will depend on the cost of insurance and hedging.

Following this reasoning, Smith and Stulz (1985 [42]) show that transaction costs of bankruptcy can induce widely held corporations to implement risk management strategies. Their model shows that the value of the levered firm equals the value of the unlevered firm minus the present value of bankruptcy plus the present value of the tax shield from interest payments. They also find that hedging decreases the present value of bankruptcy costs and increases the present value of the tax shield of debt.

Regarding empirical implications, it is argued that even small bankruptcy costs can be sufficient to induce large firms to hedge, if the reduction in expected bankruptcy costs exceeds the costs of hedging. In fact, Warner (1977 [46]) finds that bankruptcy costs are less than proportional to firm size, so that the reductions in expected bankruptcy costs is greater for small firms, which are then more likely to hedge. Also, Nance et al. (1993 [38]) argue that smaller US firms are more likely to have taxable income in the progressive region of the tax schedule, again implying that they are more likely to hedge. However, on the other side, Block and Gallagher (1986 [5]) and Booth, Smith and Stolz (1984 [6]) argue that hedging programs exhibit informational scale economies and that larger firms are more likely to hedge. Also, in the case of derivative markets, there are significant scale economies in the structure of transaction costs, implying that large firms are more likely to hedge with these instruments. Thus, it is argued that the relationship between hedge and firm size is theoretically undetermined.

3 Empirical Studies

We review the results and empirical methodologies of six major previous studies on the demand for (re-)insurance. More specifically, this section shows how the most recent studies use a panel data methodology (instead of cross-sectional regressions) but that little attention has been given to diagnostic tests on panel heteroskedasticity, correlation across panels and serial correlation.

Table 2 shows the empirical results from previous studies on the corporate demand for insurance or reinsurance. The far left-hand side column shows the proxies used for variables that could explain this demand. The abbreviations S(+), S(-) and NS mean: significant positive relationship; significant negative relationship; and not significant relationship, respectively. The blanks mean that the relationships were not tested.

Mayers and Smith (1990 [31]) and Garven and Lamm-Tenant (2003 [14]) investigate the demand for re-insurance. Yamori (1999 [49]) investigates the demand for general insurance in non-financial corporations. Hoyt and Khang (2000 [21]), Aunon and Ehling (2005 [2]) and Zou et al. (2003 [50]) investigate the corporate demand for property insurance.

Regarding the statistical methodology, Mayers and Smith (1990 [31]), Yamori (1999 [49]) and Hoyt and Khang (2000 [21]) based their studies on cross-section regression analysis. These three articles use data sets from 1981, 1986 and 1990, respectively. However, only Khang (2000 [21]) reported the econometric model used, which was Ordinary Least Squares. This last article was also the only one to report some data diagnostics.

Garven and Lamm-Tenant (2003 [14]), Zou et al. (2003 [50]), and Aunon-Nerin and Ehling (2005 [2]) used panel data analysis based on data sets from 1980-1987, 1997-1999 and 1991-2002, respectively. Regarding the model choice and data diagnostics, Garven and Lamm-Tenant (2003 [14]) do not provide any information and only report the estimated results. On the other hand, Zou et al. (2003 [50])

Table 1
Empirical Results: Corporate Demand for (Re-)Insurance

Proxy \ Article	Mayers - Smith (1990 [31])	Yamori - (1999 [49])	Hoyt - Khang (2000 [21])	Aunon - Ehling (2004 [2])	Garven- L.Tennant (2003 [14])	Zou, Adams and Buckle (2003 [50])
Mg. Tax Rate		NS		NS		
Tax Shields			S(+)		NS	
Depreciation\ Assets			S(+)			
Managerial Ownership		NS	S(-)	NS		
Closely Held	S(+)				NS	
Market-to- -Book Ratio			S(+)	S(-)		
Debt Ratio			S(+)	NS	S(+)	S(-)
Credit Rating	S(-)	S(-)	NS			
Size	S(-)	S(+)	S(-)	S(-)	S(-)	S(-)
Regulation		S(+)	S(-)			
Line of Bus. Conc.	S(-)				S(-)	
Geographic Concentration	S(-)				S(-)	
Time Controls					NS	
Asset Volat.					S(+)	
Length of Tail					S(+)	
Correl. Invest. Rets. vs. Claims					S(-)	
Systematic Risk						S(+)
Unsystematic Risk						S(-)

give detailed information not only about their choice of probit and fixed-effects models, but also about data diagnostics ⁶. However, their data diagnostics did not include tests for correlation across panel and for temporal dependency of errors.

Aunon-Nerin and Ehling (2005 [2]) use OLS regressions in which p-values are White's heteroskedasticity consistent. They also provide information about the absence of multicollinearity. However, they contrast their OLS results with those of a fixed-effects model, but they do not provide any diagnostic tests to determine if a fixed-effects model is appropriate. In their fixed effects model they find statistically insignificant estimates for most variables. When commenting their fixed-effects results they mention that "many of the variables which appear in the OLS regressions with significant estimates turn into insignificant results. We suspect that the size of our sample is not suited for the relatively data

⁶ A probit model was used to analyse the decision to reinsure, the fixed-effect model analyses the volume of reinsurance contracted.

extensive fixed effects analysis”. In fact, they do not provide diagnostics for panel heteroskedasticity, correlation across panels, or serial correlation. Sample size is an important issue, but it could be that their data violates many of the fixed-effects assumptions, so that the fixed-effects model is not appropriate.

It can be seen in Table 1 that none of the articles were able to test all proxy variables. Also, it can be noticed that, for proxy variables tested in more than one article, almost all variables present ambiguous results among the articles (with the exception of “Line of Business Concentration” and “Geographic Concentration”). Among all the ambiguous results, the most contradictory one was the negative relationship between insurance purchases and leverage (debt ratio) found by Zou et al. (2003 [50]) for China. To explain this result, the authors argue that “in China, neither creditors nor company managers seem to be able to use property insurance to effectively reduce the risk for financial distress associated with high financial leverage” (p.307). However, it could be possible that their data set violates the random-effects assumption of no correlation between panels and no auto-correlation so that the use of a fixed-effects specification could generate misleading results. We provide a detailed explanation of why this could be the case in Section 5 - Panel Data Analysis.

4 The Data

The data set is based on the annual reports of Australian insurers collected from APRA (Australian Prudential Regulatory Authority) for the period from 1996 to 2001⁷. Therefore, we have a panel (or longitudinal) data set, which is a combination of cross-section and time-series data sets. We observe a number of insurers and their relevant annual variables for six years. Only general insurers and reinsurers are included in the data set. Life insurers are not included because the reports do not provide information about “reinsurance expense” in the life insurance business.

The original data set consisted of 163 insurers, but the final data set was reduced to 98 insurers⁸. Among these 98 insurers, 71 insurers have available information for the period between 1996 and 2001, 9 insurers have available information for the period between 1997 and 2001 and, finally, 18 insurers have available information for the period between 1998 and 2001. Therefore, the final data set has 543 observations. The asset value of the 98 insurers in the final data set represents 70% of all asset value of insurers in 2001.

The reinsurance demand is measured here by the ratio of reinsurance expense to total premium revenue (*REINS*), hereafter “reinsurance ratio”, which rep-

⁷ APRA introduced a new reporting regime to General Insurers from July 2002. Under this new reporting regime, APRA has yet to determine what data will be published. Therefore, data after July 2002 is currently not available.

⁸ Some insurers were excluded because of the following reasons: 1) zero premiums in all years; 2) the insurer was not active in 2001; 3) in 2001 the insurer had been active for a period of three years or less.

Table 2
SUMMARY STATISTICS

	MAX.	MIN.	MEAN	MEDIAN	STD. DEV.	SKEWNESS
REINSURANCE						
RATIO (<i>REINS</i>)	1	0	0.28238	0.19051	0.26753	0.98934
LEVERAGE						
(<i>LEV</i>)	2.07632	0.03371	0.66837	0.71367	0.25553	0.04916
SIZE						
(<i>LnSIZE</i>)	15.90520	6.04500	11.36361	11.37034	1.85927	-0.13819
TAX RATIO						
(<i>TAX</i>)	6.9625	-2.05180	0.10153	0.01834	0.47182	8.52413
RETURN ON						
INVESTMENT (<i>INVEST</i>)	0.97782	-0.20990	0.08428	0.06781	0.10275	5.13779

resents the proportion of total premium ceded⁹. This is the dependent variable in the econometric model. With the available data set it is possible to obtain the following explanatory variables as proxies for the factors that are expected to influence reinsurance demand: a) the ratio of total liabilities to total assets (*LEV*); b) logarithm of total asset value (*LnSIZE*); c) the ratio of tax expense to total premiums (*TAX*); d) the ratio of investment revenue to total investment (*INVEST*); e) a dummy variable for companies that are part of a group of companies (*Dgroup*)¹⁰; f) year dummy variables: D1997 to D2000; and g) a dummy variable for reinsurance companies (*Dreinsurer*).

Table 2 provides the summary statistics for these variables (except for the dummy variables). The reinsurance ratio (*REINS*) is on average 28.23%, which means that, on average, Australian insurers cede about 28.23% of their total premiums. However, the median reinsurance ratio is 19.05%, which means that most reinsurance ratios are less than the average reinsurance ratio¹¹. Regarding the explanatory variables, leverage (*LEV*) and size (*LnSIZE*) present skewness very close to zero, implying that their distributions are quite symmetric¹². The average leverage is 66.83%, but the distribution is only slightly skewed to the right. On the other hand, the other two explanatory variables present high positive skewness: the tax ratio (*TAX*) and investment return (*INVEST*)¹³.

⁹ One limitation of the data set is that it does not allow us to control for the different types of reinsurance contracted.

¹⁰ 51 insurers (150 observations), out of the 98 insurers in the data set, are part of a group of companies.

¹¹ Mayers and Smith(1990[31]) determine an average reinsurance ratio of 38% and a median reinsurance ratio of 31% for American insurers in 1981.

¹² The original value-of-assets distribution is highly skewed to the right. The mean is (in AUD\$000) 388,596, the median is 86,711 and skewness is 5.3.

¹³ Hoyt and Khang (2000[21]) transform highly skewed empirical distributions by taking natural logarithm to reduce potential heteroskedasticity and impact of extreme values. Garven and Lamm Tennant (2003[14]) and Aunon-Nerin and Ehling (2005[2]) also use the natural logarithm of asset value.

Fig. 1. Reinsurance Ratio per Insurer - 1996-2001

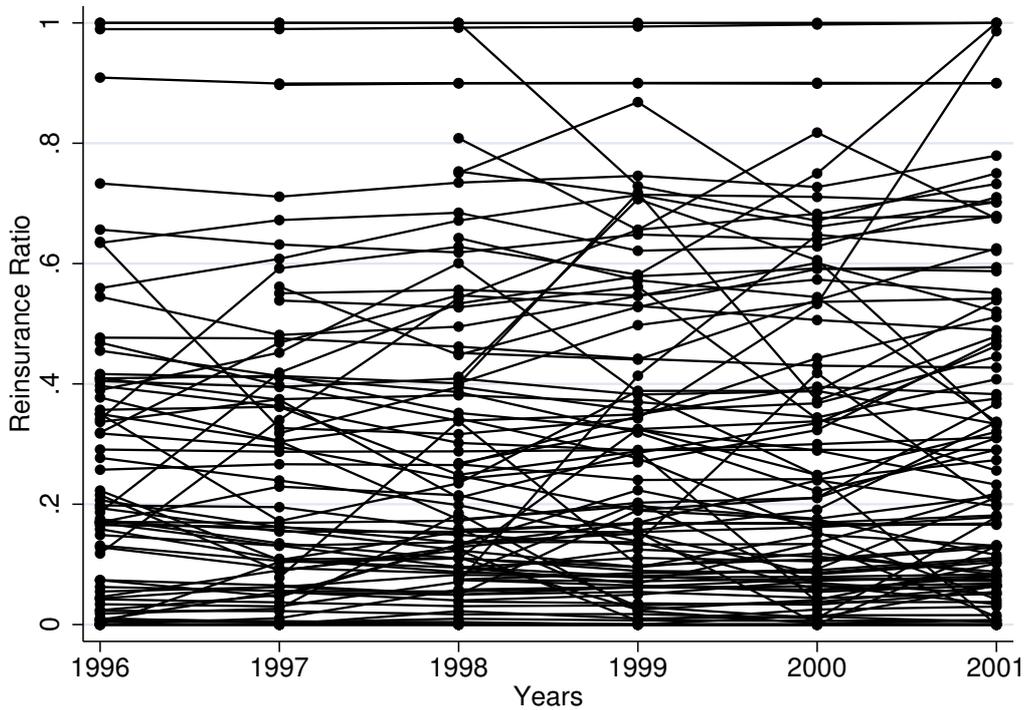


Figure 1 shows the ratio of reinsurance to premiums from the Australian insurers from 1996 to 2001¹⁴. It can be seen that this ratio varies a lot among insurers, despite the fact it is more concentrated between zero and 0.4. The major objective of this study is to determine the factors that explain why different insurers have such different reinsurance ratios. Also, we are interested in determining if the reinsurance ratio varies a lot within each insurer across time and why. In fact, this analysis is only possible with a panel data set. The data set used provides variables that both theory and past empirical studies have determined to be relevant to explain the reinsurance demand.

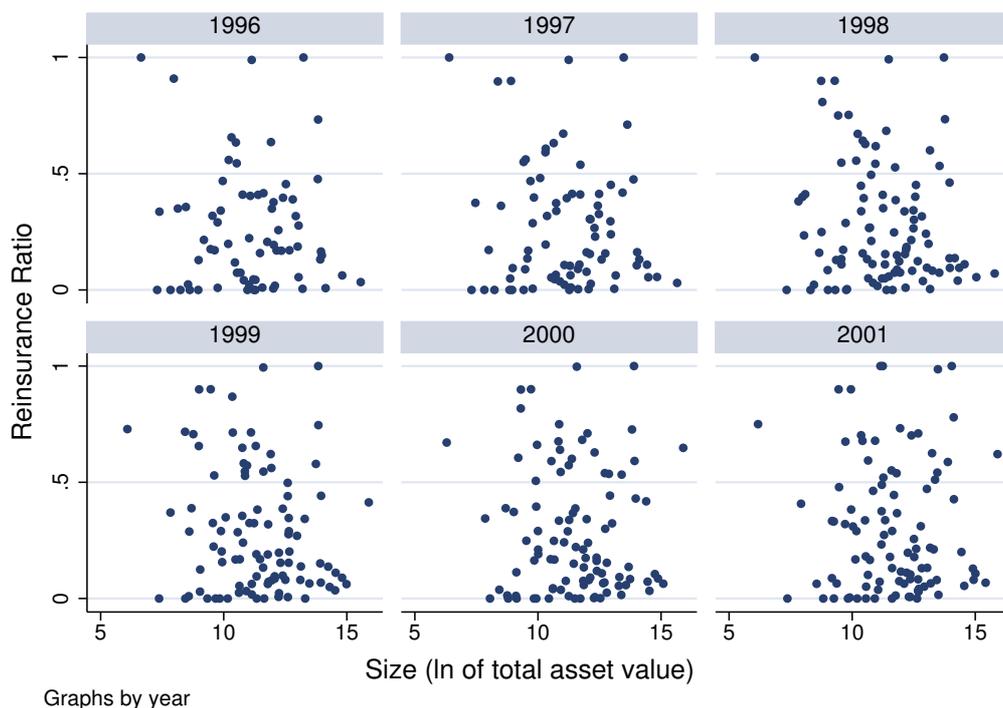
Plots of the reinsurance ratio for each insurer separately (not shown here) indicated that, for most insurers, this variable does not vary a lot from year to year. This suggests that reinsurance demand might be related to company characteristics, which also vary little from year to year.

Prior to econometric analysis, the first company explanatory variable that we are tempted to check is “size”, measured by the logarithm of the total value of assets. Figure 2 shows six annual plots of the reinsurance ratio against company size for each year of the study.

The plots in Figure 2 show again that the reinsurance ratio varies a lot among insurers but that this variation does not appear to be related to company size. We

¹⁴ The STATA econometric package was used to run all data and statistical analysis.

Fig. 2. Reinsurance Ratio vs. Company Size - 1996-2001



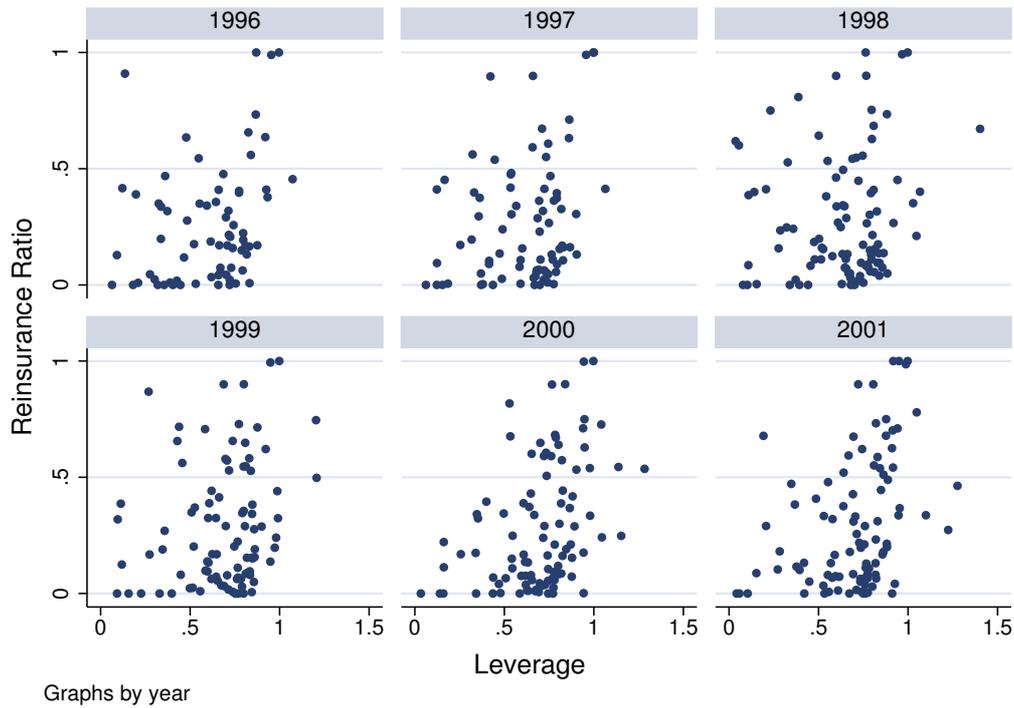
can notice a concentration of points between the reinsurance ratios of zero and 0.5, but there is no indication that the reinsurance ratio increases or decreases with the increase of company size. The six different plots, from 1996 to 2001, show us the same pattern, which help us to reject the possibility of sampling error. However, it could be that company size has an impact on the reinsurance ratio for each insurer over time in the period of analysis. This effect is not easy to determine visually from the graphs. It can be captured in a panel-data model ¹⁵.

Figure 3 shows plots of the reinsurance ratio against the ratio of total liabilities to total assets, which measures financial gearing and also indicates the capital strength of the company. It shows a positive relationship between these two variables. Again, this visual inspection could be misleading, since company relationships between these two variables could be negative when examined across time. Therefore, it would be optimal to use a panel data model that accounts for both company and time variation from explanatory variables.

Figure 4 shows the plots of reinsurance ratio against the tax ratio (tax expense on premium). The plots suggest no relationship between the variables. This is largely expected since the Australian company income tax structure is not progressive and an imputation system reduces the importance of taxation as a factor in risk and capital management for Australian insurers. Theory and evidence from the US insurance market show that there is an incentive to contract

¹⁵ See Frees (2004 [12]) for more examples of this.

Fig. 3. Reinsurance Ratio vs. Leverage - 1996-2001



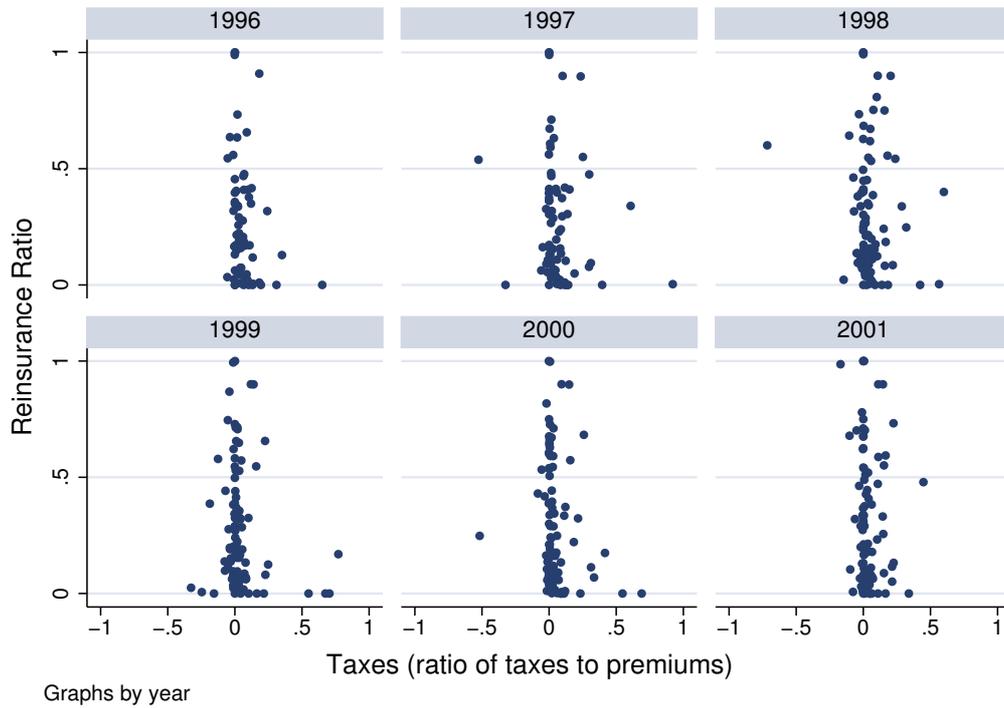
reinsurance in the presence of a convex tax schedule, which is not the case in Australia, where corporate income tax is fixed at 30%.

Figure 5 shows plots of the reinsurance ratio against investment return (ratio of investment return to investments). It indicates no strong relationship between these two variables. A high investment return can be both an indicator of financial sophistication of management and of the investment risk of the insurer. It is not clear that if this were true then this would lead to a higher demand for reinsurance.

5 Panel Data Analysis

This section gives a careful description of regression diagnostics and the choice of the most appropriate panel data estimator. It will be shown that this type of data set is expected to present some characteristics such as groupwise heteroscedasticity, correlation across panels and autocorrelation. Therefore, an appropriate econometric model must be used in order to account for all these factors. The next section of this paper shows how failure to choose the appropriate econometric model can generate very misleading results. Given the sample size and the results of diagnostics, we can evaluate the most appropriate panel data estimator for our data set.

Fig. 4. Reinsurance Ratio vs. Tax Ratio - 1996-2001



5.1 Regression Diagnostics

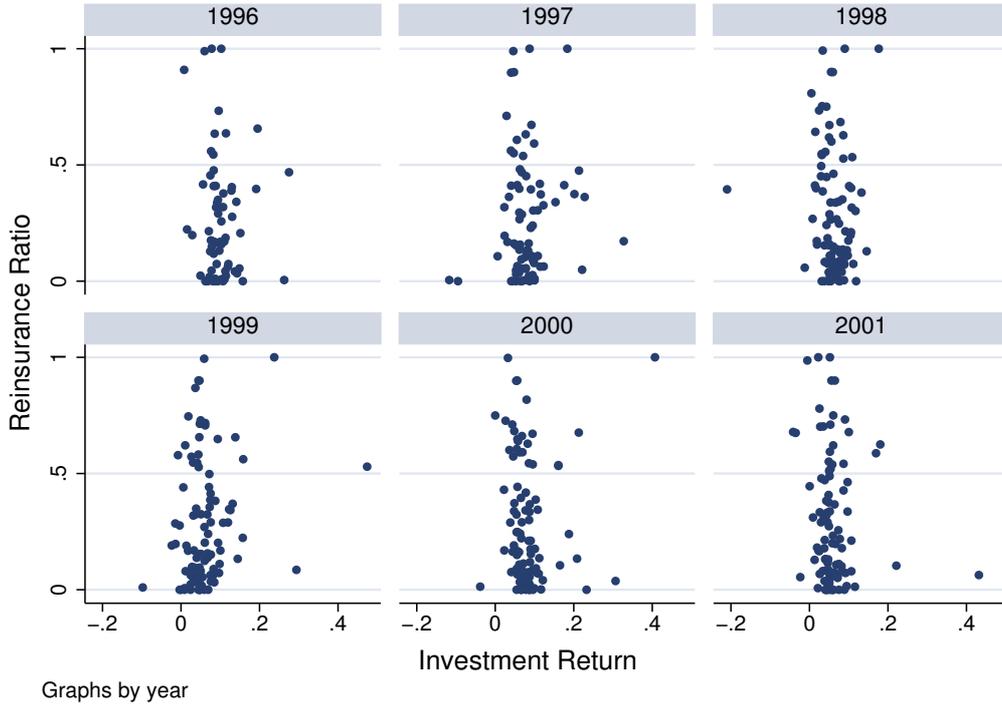
The first step in the econometric analysis is to run an OLS regression and examine its results. This is done here primarily to obtain some diagnostics from STATA (not displayed). A “residual versus fitted” plot shows that heteroskedasticity may be an issue, but this has to be properly tested with a groupwise heteroskedasticity test. Also, a correlation matrix for the regressors shows us that multicollinearity is not present.

Panel data diagnostics for groupwise heteroskedasticity, correlation across panels and autocorrelation are provide by STATA after we run a “random effects” (GLS) regression. However, it will be explained why the random effects regression, or other GLS regression models are not appropriate for our data. The section below gives the reasons why OLS with Panel-Corrected Standard Errors (PCSE) is the most appropriate model.

5.2 The Choice of Regression Model

Beck and Katz (1995 [3]) use Monte Carlo analysis to show that OLS with panel-corrected standard errors (PCSE) gives much better results than pure Ordinary Least Squares (OLS) or Feasible General Least Squares (FGLS) in a

Fig. 5. Reinsurance Demand vs. Investment Return



panel data set with contemporaneously correlated and/or panel-heteroscedastic error structures, and also with serial correlation.

Models for panel data often allow for temporally and spatially correlated errors, as well as for heteroscedasticity. Parks (1967[39]) proposed to treat these problems with a FGLS methodology. However, Beck and Katz show that the use of FGLS in a panel-data set with these characteristics may lead to “dramatic” underestimates of parameter variability in common research situations.

The problem is that, while GLS has optimal properties for panel data, it assumes that we have knowledge about the error process that, in practice, we never have. Thus, instead of using GLS, an option is to use Feasible GLS (FGLS), which uses an estimate of the error structure. However, Beck and Katz point out that FGLS formula for standard errors assumes that the error process is known, not estimated.

For example, assume our panel data model to be estimated is

$$y_{i,t} = \beta_1 x_{it,1} + \beta_2 x_{it,2} + \dots + \beta_K x_{it,K} + \epsilon_{i,t} \quad (1)$$

where $i = 1, 2, \dots, N$ are the number of observation units, $t = 1, 2, \dots, T$ are the number of time periods, and $k = 1, \dots, K$ are the number of explanatory variables, which may include a constant.

A more compact representation can be obtained by using matrix notation. Grouping all time periods $t = 1, 2, \dots, T$ we get

$$\mathbf{y}_i = \mathbf{X}_i \boldsymbol{\beta} + \boldsymbol{\epsilon}_i \quad (2)$$

where \mathbf{y}_i is a $T \times 1$ vector of the dependent variable for the i th subject, $\mathbf{y}_i = (y_{i1}, y_{i2}, \dots, y_{iT})'$. $\boldsymbol{\beta}$ is a $K \times 1$ vector of parameters to be estimated and \mathbf{X}_i is a $T \times K$ matrix of explanatory variables.

$$\mathbf{X}_i = \begin{pmatrix} x_{i1,1} & x_{i1,2} & \dots & x_{i1,K} \\ x_{i2,1} & x_{i2,2} & \dots & x_{i2,K} \\ \vdots & \vdots & \ddots & \vdots \\ x_{iT,1} & x_{iT,2} & \dots & x_{iT,K} \end{pmatrix} = \begin{pmatrix} \mathbf{x}'_{i1} \\ \mathbf{x}'_{i2} \\ \vdots \\ \mathbf{x}'_{iT} \end{pmatrix} \quad (3)$$

This can also be written as $\mathbf{X}_i = (\mathbf{x}_{i1}, \mathbf{x}_{i2}, \dots, \mathbf{x}_{iT})'$. $\boldsymbol{\epsilon}_i$ is a $T \times 1$ vector of error terms for the i th subject. Therefore, we have a $T \times T$ covariance matrix of the errors $\boldsymbol{\Omega} \equiv E(\boldsymbol{\epsilon}_i \boldsymbol{\epsilon}'_i)$, $i = 1, 2, \dots, N$.

Estimation of equation 2 by OLS is optimal only if the error processes are homoskedastic and independent of each other¹⁶. Regardless of any structure in the error process, we can still estimate equation 2 by Generalised Least Squares (GLS)¹⁷ if we know the covariance matrix $\boldsymbol{\Omega}$. The GLS estimates of $\boldsymbol{\beta}$ are

$$\boldsymbol{\beta}^* = \left(\sum_{i=1}^N \mathbf{X}'_i \boldsymbol{\Omega}^{-1} \mathbf{X}_i \right)^{-1} \left(\sum_{i=1}^N \mathbf{X}'_i \boldsymbol{\Omega}^{-1} \mathbf{y}_i \right) \quad (4)$$

Because most times the the covariance matrix of errors, $\boldsymbol{\Omega}$, is not known it is necessary to use an estimate, $\hat{\boldsymbol{\Omega}}$. In Feasible GLS (FGLS) estimation we replace the unknown matrix $\boldsymbol{\Omega}$ with a consistent estimator. The asymptotic properties of the FGLS estimator are easily established as $N \rightarrow \infty$ because its first-order asymptotic properties are identical to those of the GLS estimator under basic assumptions. However, deriving finite sample properties of FGLS is generally difficult and therefore it is difficult to assess the performance of FGLS in finite samples [see Wooldridge (2002 [48] p.157)].

In many applications the FGLS methodology is not a problem because the error process may have few enough parameters that can be estimated with some degree

¹⁶ Pooled OLS assumptions are: 1) there are no contemporaneous relationships between the regressors and the error term, i.e., $E(\mathbf{x}'_{it} \boldsymbol{\epsilon}_{it}) = 0$ for $t = 1, 2, \dots, T$ and $i = 1, 2, \dots, N$; 2) there is no perfect linear dependencies among the explanatory variables, i.e., the matrix $\mathbf{X}'_i \mathbf{X}_i$ has full rank (so that it is invertible); 3) errors are homoskedastic, i.e., $E(\boldsymbol{\epsilon}'_{it} \mathbf{x}'_{it} \boldsymbol{\epsilon}_{it}) = \sigma^2 E(\mathbf{x}'_{it} \boldsymbol{\epsilon}_{it})$, $t = 1, 2, \dots, T$, and $i = 1, 2, \dots, N$, where $\sigma^2 E(\boldsymbol{\epsilon}'_{it} \boldsymbol{\epsilon}_{it})$ for all t ; and 4) the conditional covariances of the errors across different time periods are zero, i.e., $E(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}'_s \mathbf{x}'_t \mathbf{x}_s) = 0$, $t \neq s$, $t, s = 1, 2, \dots, T$ and $i = 1, 2, \dots, N$.

¹⁷ Assumptions for GLS estimation are: 1) each element of $\boldsymbol{\epsilon}_i$ is uncorrelated with each element of \mathbf{X}_i , i.e., $E(\mathbf{X}_i \otimes \boldsymbol{\epsilon}_i) = 0$, and 2) $\boldsymbol{\Omega}$ is positive definite and $E(\mathbf{X}'_i \boldsymbol{\Omega}^{-1} \mathbf{X}_i)$ is non singular.

of reliability. However, this is not the case for panel data models, where the error process has a large number of parameters. Therefore, this oversight may cause estimates of the standard errors of estimated coefficients to understate their true variability.

To clarify, let $\Sigma = E[\epsilon_{it}\epsilon_{jt}]$, so that for each time period $t = 1, 2, \dots, T$ we have

$$\Sigma = \begin{pmatrix} E[\epsilon_{1t}\epsilon_{1t}] & E[\epsilon_{1t}\epsilon_{2t}] & \dots & E[\epsilon_{1t}\epsilon_{Nt}] \\ E[\epsilon_{2t}\epsilon_{1t}] & E[\epsilon_{2t}\epsilon_{2t}] & \dots & E[\epsilon_{2t}\epsilon_{Nt}] \\ \vdots & \vdots & \ddots & \vdots \\ E[\epsilon_{Nt}\epsilon_{1t}] & E[\epsilon_{Nt}\epsilon_{2t}] & \dots & E[\epsilon_{Nt}\epsilon_{Nt}] \end{pmatrix} \quad (5)$$

If we have *panel heteroscedasticity* then $E[\epsilon_{it}^2] \neq E[\epsilon_{jt}^2]$ but $E[\epsilon_{it}^2] = E[\epsilon_{is}^2]$, so that $E[\epsilon_{it}^2] = \sigma_i^2$. This means that the error variances are different across units, but that they are the same for each unit for all time periods.

If we have *contemporaneously correlated errors*, then $E[\epsilon_{it}\epsilon_{jt}] = E[\epsilon_{is}\epsilon_{js}] \neq 0$, but $E[\epsilon_{it}\epsilon_{js}] = 0$, so that $E[\epsilon_{it}\epsilon_{jt}] = \sigma_{it}$. That means that errors from different units are correlated only they are contemporaneous, and that this correlation is the same for all time periods.

With panel heteroscedasticity and contemporaneously correlated errors, the $N \times N$ matrix Σ is

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1N}^2 \\ \sigma_{21} & \sigma_2^2 & \dots & \sigma_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{N1} & \sigma_{N2} & \dots & \sigma_N^2 \end{pmatrix} \quad (6)$$

Therefore, the error covariance matrix for the full NT observations is

$$\Omega = \mathbf{I}_T \otimes \Sigma = \begin{pmatrix} \Sigma & 0 & \dots & 0 \\ 0 & \Sigma & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \Sigma \end{pmatrix} \quad (7)$$

This is a $NT \times NT$ variance covariance matrix of the errors having zeros for all noncontemporaneous observations and free parameters allowing for contemporaneous pairwise correlation of the errors and heteroscedasticity. Because Σ is a $N \times N$ matrix there are $[N \times (N + 1)]/2$ covariances to be estimated by using NT observations each.

The problem is that, in order for Feasible GLS to be used, the estimate of the $N \times N$ matrix Σ has to be invertible, but its rank is the minimum of N or T . Hence, T has to be at least as large as N . However, some studies have shown that even when T is greater than N , FGLS can generate misleading results. For example, Parks (1967[39]) developed a FGLS method for panel data models where the errors show panel heteroscedasticity, contemporaneous correlation, and unit specific serial correlation. However, Kmenta and Gilbert (1970[23]) show in a Monte Carlo study that the estimated standard errors of the Parks estimator appear to be biased when compared with the true variability of the estimates, even in samples as large as 100. Similarly, Beck and Katz (1995[3]) show that the estimated standard errors for the Parks estimator have severe downward bias with pooled cross-section. Additionally, they show that the actual coverage probabilities for confidence intervals could be far below their nominal levels.

In their study, Beck and Katz provide a measure of how much the FGLS standard errors understate true sampling variability, that is, how much the FGLS method falsely inflates confidence in the findings of some previous panel data studies.

They therefore propose to retain OLS parameter estimates but replace the OLS standard errors with panel-corrected standard errors (PCSEs)[see Greene (2000[18], p.594]. Monte Carlo analysis shows that these new estimates of sampling variability are very accurate, even in the presence of complicated error structures.

Beck and Katz find that PCSEs dominate OLS standard errors; when PCSEs are not necessary, they perform as well as the OLS standard errors, and when OLS perform poorly, PCSEs perform well. Also, they find that PCSEs are more accurate than FGLS standard errors.

Beck and Katz were able to replicate a previous study by Hicks and Swank (1992[19]) and found that PCSEs were roughly three times the standard error obtained by these authors. Most importantly, Beck and Katz showed that the Hicks and Swank data, when estimated with corrected standard errors, were not consistent with many conclusions obtained by the authors. For some of the coefficient estimates, not only were the standard errors very different, but in some cases the coefficient signs were the opposite (see Beck and Katz (1995[3], p. 643).

5.3 *Random Effects and Fixed Effects*

Another possible way of solving the problem of estimating the variance covariance matrix Σ is to impose some structure on the errors. We show below how this is done in the random-effects and fixed-effects models.

Assume the following model specification:

$$y_{it} = \mathbf{x}_{it} + c_i + u_{it} \quad t = 1, 2, \dots, T \tag{8}$$

where \mathbf{x}_{it} is a $1 \times K$ vector of observable variables. c_i is a unit-specific unobservable effect and u_{it} are called the *idiosyncratic errors*, because they change across t as well as across i . The random-effects model assumes that c_i is not correlated with the regressors \mathbf{x}_{it} . Therefore, c_i can be treated as part of the error term, so that we have a composite error term $v_{it} = c_i + u_{it}$.

The key is that the random-effects model's assumptions¹⁸ made on the error structure generate the following variance covariance matrix:

$$\mathbf{\Omega} = E(\mathbf{v}_i \mathbf{v}_i') = \begin{pmatrix} \sigma_c^2 + \sigma_u^2 & \sigma_c^2 & \dots & \sigma_c^2 \\ \sigma_c^2 & \sigma_c^2 + \sigma_u^2 & \dots & \sigma_c^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_c^2 & \sigma_c^2 & \dots & \sigma_c^2 + \sigma_u^2 \end{pmatrix} \quad (9)$$

Therefore, in the random effects model $\mathbf{\Omega}$ depends only on *two* parameters, σ_c^2 σ_u^2 , regardless of the size of T . Looking at the matrix $\mathbf{\Omega}$ above it is straightforward to see that the random-effects model assumes no panel heteroskedasticity. Also, the correlation between the noncontemporaneous composite errors v_{it} and v_{is} does not depend on the difference between t and s , i.e., $\text{Corr}(v_{is}v_{it}) = \sigma_c^2/(\sigma_c^2 + \sigma_u^2)$, $s \neq t$. However, the idiosyncratic errors u_{it} are assumed not to be serially correlated.

Analogously, the fixed-effects model also make assumptions on the error structure, so that $\mathbf{\Omega}$ can be estimated in an efficient way. The fixed-effects model assumes the same specification given by equation 8. However, the difference is that the individual effects c_i are assumed not correlated with the regressors \mathbf{x}_{it} , so that they work out as a group-specific constant term in the regression model. The term “fixed” means that c_i does not vary over time, not that it is non-stochastic. In the random-effects model, on the other hand, c_i a group specific random element, similar to u_{it} except that for each group there is a single draw that enters the regression identically in each period.

One advantage of the fixed-effects model is that it consistently estimates partial effects in the presence of time-constant omitted variables, which are captured by the term c_i . However, the fixed-effects model has the drawback that we cannot include time-constant factors in \mathbf{x}_{it} , such as group dummy variables. In fact, if c_i can be arbitrarily correlated with each element of \mathbf{x}_{it} , then there is no way to distinguish the effects of time-constant observables from the time-constant unobservable c_i .

In what concerns the assumed error structure, the fixed-effects model also assumes that idiosyncratic errors u_{it} have constant variance across t and are serially uncorrelated¹⁹.

¹⁸ Assumptions are: 1.a) $E(u_{it}|\mathbf{x}_i, c_i) = 0$, $t = 1, \dots, T$; 1.b) $E(c_i|\mathbf{x}_i) = E(c_i) = 0$; 2) rank of $E(\mathbf{X}_i' \mathbf{\Omega}^{-1} \mathbf{X}_i) = K$;

3.a) $E(\mathbf{u}_i \mathbf{u}_i' | \mathbf{x}_i, c_i) = \sigma_u^2 \mathbf{I}_T$; and 3.b) $E(c_i^2 | \mathbf{x}_i) = \sigma_c^2$

¹⁹ Fixed effects assumptions are: 1) $E(u_{it}|\mathbf{x}_i, c_i) = 0$, $t = 1, 2, \dots, T$; 2) rank $(\sum_{t=1}^T E(\ddot{\mathbf{x}}_{it}' \ddot{\mathbf{x}}_{it})) = \text{rank}[E(\ddot{\mathbf{X}}_{it}' \ddot{\mathbf{X}}_{it})] = K$, where $\ddot{\mathbf{x}}_{it} = \mathbf{x}_{it} - \bar{\mathbf{x}}_{it}$; and 3) $E(\mathbf{u}_i \mathbf{u}_i' | \mathbf{x}_i, c_i) = \sigma_u^2 \mathbf{I}_T$.

Appropriate diagnostics should be run on the error structure in order to check if random-effects or fixed-effects models can be used. In practice, many data sets may present panel heteroskedasticity and serially correlation, so that random-effects or fixed-effects are not the appropriate choice. In addition, data set may be not large enough to enable the use of Feasible GLS. We will show that the data set to be used in this paper presents panel heteroskedasticity, contemporaneous correlation across panels and serial correlation. A preferable approach in this case is to use pooled OLS and make the appropriate correction to the asymptotic covariance matrix, i.e., to use panel-corrected standard errors (PCSE)²⁰.

5.4 Correcting the OLS Standard Errors

The PCSE methodology takes into account that if the errors in equation 2 meet one or more of the panel error assumptions²¹, then OLS estimates of β will be consistent but inefficient. Therefore, the OLS standard errors will be inaccurate, but they can be corrected so that they provide accurate estimates of the variability of the OLS estimates of β .

However, this correction is only for the contemporaneous correlation of the errors (and perforce heteroscedasticity). Any serial correlation of the errors must be eliminated before the panel-corrected standard errors are calculated. Additionally, this correction works only in the panel data context, since the correction for contemporaneous correlation of the errors is only possible because we have repeated information on the contemporaneous correlation of errors.

The sampling variability of the OLS estimates is given by the square roots of the diagonal terms of

$$Cov(\hat{\beta}) = (X'X)^{-1}\{X'\Omega X\}(X'X)^{-1} \quad (10)$$

In the case that the errors are homoscedastic and uncorrelated, this equation simplifies to the usual OLS formula, where the OLS standard errors are the square roots of the diagonal terms of $\widehat{\sigma}^2 (X'X)^{-1}$, where $\widehat{\sigma}^2$ is the OLS estimator of the common error variance, σ^2 . However, if the errors do not meet standard distributional assumptions, then equation 10 provides incorrect standard errors. However, this equation can still be used in combination with the panel structure of the errors to provide accurate panel-corrected standard errors (PCSEs).

In the case of panel data models with contemporaneously correlated and panel heteroscedastic errors, Ω is an $NT \times NT$ block diagonal matrix with an $N \times N$ matrix of contemporaneous covariances, Σ , along the diagonal.

²⁰ See Greene(2000[18]. p.333)

²¹ Panel error assumptions are panel heretoskedasticity, contemporaneously correlated errors, and serial correlation.

Therefore, to estimate equation 10, we need to estimate Σ . Since the OLS estimates in equation 2 are consistent, we can use the OLS residuals from that estimation to provide a consistent estimate of Σ .

Let $e_{i,t}$ the OLS residual for unit i at time t . An element of Σ can now be estimated by

$$\hat{\Sigma}_{i,j} = \frac{\sum_{t=1}^T e_{i,t}e_{j,t}}{T} \quad (11)$$

where the estimate $\hat{\Sigma}$ is formed with all these elements. Finally, we can use this to find the estimator $\hat{\Omega}$ by creating a block diagonal matrix with the $\hat{\Sigma}$ matrices along the diagonal.

6 Empirical Results from Australian Insurers

The Australian reinsurance data set shows error structures with characteristics such as heteroscedasticity, correlation across panels and serial (auto) correlation. The table below summarizes the diagnostic results.

Table 3
REGRESSION DIAGNOSTICS

-
- 1) A modified Wald test for groupwise heteroskedasticity resulted in $\chi^2_{(98)} = 2.2e^{+07}$, significant at the 0.01 level (one-tailed), suggesting the presence of heteroskedasticity in the error term.
 - 2) A Breuch-Pagan LM test of independence resulted in $\chi^2_{(4753)} = 7937.8$, significant at the 0.01 level (one-tailed), suggesting dependence among the panels.
 - 3) A Wooldridge test for autocorrelation in panel data, testing the null hypothesis of no first-order autocorrelation, resulted in $F(1, 97) = 21.573$, significant at the 0.01 level (one-tailed), suggesting the presence of first-order autocorrelation in the error term.
-

Heteroscedasticity is explained by the fact of heterogeneity among the units (insurers), so that their σ_i^2 s are different. However, it is still assumed that error variances within each unit do not differ over time. We ran a Wald test²², under the null hypothesis that $\sigma_i^2 = \sigma^2$ for all i . The null hypothesis is rejected at the 1% level.

²² See Greene(2000[18]. p.598)

Correlation across panels, which is the contemporaneous correlation among the variables from different companies, is explained by the fact that exogenous shocks might affect all companies in a similar way. However, we continue to assume that observations are uncorrelated across time. We use the Breush-Pagan LM test to test if there is no correlation across firms²³. The null hypothesis of no cross-section correlation is rejected at the 1% confidence level.

Finally, it is possible that the errors may show temporal dependence. This is possibly the case since the value of observations in one specific year are quite dependent on the value of observations past years. The most typical assumption is that the errors show first-order serial correlation. We implement a test for serial correlation in the idiosyncratic errors of a linear panel-data model discussed by Wooldridge (2002[48], p.274). We reject the null hypothesis of no first-order serial correlation at the 1% confidence level.

Table 4
CORRELATION MATRIX

Variable	<i>LEV</i>	<i>LnSIZE</i>	<i>TAX</i>	<i>INVEST</i>	<i>D_group</i>	<i>D_reinsurer</i>
<i>LEV</i>	1.000					
<i>LnSIZE</i>	0.316	1.000				
<i>TAX</i>	-0.247	-0.057	1.000			
<i>INVEST</i>	-0.012	-0.096	0.017	1.000		
<i>D_group</i>	0.175	0.576	-0.072	-0.081	1.000	
<i>D_reinsurer</i>	0.072	0.270	-0.035	-0.040	0.375	1.000

Table 4 depicts the correlations among regressors and shows that multicollinearity is not present. Table 5 gives the OLS results from regressing the Reinsurance Ratio (*REINS*) on the explanatory variables.

Because our data set violates most OLS assumptions, Table 5 provides a good example of spurious regression. OLS requires some weak hypothesis for its consistency, but heteroscedasticity and serial correlation are enough to rule out the asymptotically validity of OLS standard errors, *t* statistics, and *F* statistics. For this reason, the *t* statistic for *LEV* (leverage) is inflated and the *pvalue* is zero. The same occurs with the variable for size (*LnSize*).

Table 6 shows the results for a “random effects” regression. As we showed before, the random-effects model assumes a more sophisticated structure than the OLS model, since the error structure has a *composite error term*. However, our data violates many of the random-effects model’s assumption.

The random-effects estimates differ from those from OLS estimation because now coefficient estimates for *LEV* (leverage) are statistically insignificant.

²³ see Greene (2000[18], p.601)

Table 5
OLS REGRESSION RESULTS

Variable	Coefficient Estimates	Standard Errors	t-statistic	p-value ^a
<i>LEV</i>	0.373	0.046	8.00	0.000***
<i>LnSIZE</i>	-0.027	0.007	-3.65	0.000***
<i>TAX</i>	0.005	0.023	0.22	0.829
<i>INVEST</i>	0.082	0.108	0.76	0.448
<i>D_group</i>	-0.006	0.033	-0.18	0.858
<i>D_reinsurer</i>	0.009	0.041	0.23	0.821
<i>D_1997</i>	0.018	0.039	0.46	0.643
<i>D_1998</i>	0.004	0.040	0.11	0.915
<i>D_1999</i>	-0.002	0.039	-0.07	0.948
<i>D_2000</i>	0.019	0.040	0.49	0.623
<i>D_2001</i>	0.336	0.080	4.16	0.000***
<i>Const</i>	0.336	0.080	4.16	0.000

^a The symbols *, ** and *** mean, respectively, statistical significance at the 10%, 5% and 1% level.

Table 6
RANDOM EFFECTS REGRESSION RESULTS

Variable	Coefficient Estimates	Standard Errors	t-statistic	p-value
<i>LEV</i>	0.030	0.031	0.97	0.334
<i>LnSIZE</i>	0.031	0.010	3.06	0.002***
<i>TAX</i>	0.010	0.009	1.08	0.278
<i>INVEST</i>	0.035	0.052	0.67	0.503
<i>D_group</i>	-0.130	0.058	-2.23	0.026
<i>D_reinsurer</i>	-0.014	0.079	-0.18	0.858
<i>D_1997</i>	-0.004	0.014	-0.30	0.762
<i>D_1998</i>	0.002	0.014	0.16	0.877
<i>D_1999</i>	0.001	0.014	0.09	0.926
<i>D_2000</i>	-0.007	0.014	-0.53	0.600
<i>D_2001</i>	0.004	0.015	0.29	0.773
<i>Const</i>	-0.028	0.107	-0.26	0.791

Table 7 shows the estimation results from the fixed-effects model. As already discussed, because of the model assumptions, any time invariant regressors are incorporated in the intercept. That is why Table 7 does not show any estimated coefficients for the dummy variables *D_group* and *D_reinsurer*. Like the random-effects estimated results, the fixed-effects estimates are insignificant for the variable *LEV* (leverage) and still significant at the 1% level for the variable *LnSize* (size). Again, fixed-effects estimates will be misleading since our data

Table 7
FIXED EFFECTS REGRESSION RESULTS

Variable	Coefficient Estimates	Standard Errors	t-statistic	p-value
<i>LEV</i>	-0.007	0.032	-0.24	0.809
<i>LnSIZE</i>	0.060	0.012	4.83	0.000***
<i>TAX</i>	0.010	0.009	1.13	0.258
<i>INVEST</i>	0.026	0.052	0.51	0.609
<i>D_group</i>	-	-	-	-
<i>D_reinsurer</i>	-	-	-	-
<i>D_1997</i>	-0.007	0.014	-0.50	0.618
<i>D_1998</i>	-0.002	0.013	-0.17	0.866
<i>D_1999</i>	-0.005	0.014	-0.36	0.720
<i>D_2000</i>	-0.017	0.014	-1.15	0.253
<i>D_2001</i>	-0.009	0.015	-0.59	0.556
<i>Const</i>	-0.394	0.136	-2.90	0.004***

set violates most fixed-effects assumptions.

It is worth mentioning that, since the data set characteristics violate many OLS, fixed-effects and random-effects assumptions, there is no point in showing diagnostic tests to evaluate which of them is superior. The fact is that none of them are appropriate for this data set. It is also worth highlighting the different conclusions that could be drawn from the analysis if the correct model is not used.

Table 8
OLS WITH PCSE REGRESSION RESULTS

Variable	Coefficient Estimates	Standard Errors	t-statistic	p-value
<i>LEV</i>	0.100	0.051	1.96	0.050**
<i>LnSIZE</i>	-0.004	0.010	-0.47	0.641
<i>TAX</i>	-0.001	0.007	-0.16	0.872
<i>INVEST</i>	0.026	0.049	0.55	0.585
<i>D_group</i>	-0.058	0.038	-1.52	0.129
<i>D_reinsurer</i>	-0.016	0.049	-0.34	0.733
<i>D_1997</i>	-0.000	0.005	-0.11	0.912
<i>D_1998</i>	0.004	0.006	0.79	0.427
<i>D_1999</i>	0.005	0.008	0.60	0.551
<i>D_2000</i>	0.000	0.009	0.03	0.975
<i>D_2001</i>	0.017	0.010	1.61	0.108
<i>Const</i>	0.298	0.103	2.89	0.004***

Table 8 shows the PCSE regression. The previous OLS, random-effects and fixed-effects results show artificially significant estimates for the coefficients of

LnSIZE. Comparing these results with the results of the PCSE regression we can see how those estimates are misleading. In fact, the PCSE results do not give statistically significant estimates for the coefficient of *LnSIZE*. However, like OLS and random-effects regressions, the PCSE estimated coefficients for “taxes”, “investment return” and “group structure” are not significant. These results confirm what we suspected from previous plots.

The most interesting result is that “size” is not an important variable for the demand for reinsurance in Australia. Some previous studies for the U.S. reinsurance market show evidence that “size” is negatively related to reinsurance purchases²⁴. On the other hand, Yamory (1999[49]) has found evidence that company size has a positive relationship with reinsurance purchases in Japan.

Regarding the impact of taxes, our results are consistent with the results found by Yamori for the Japanese market. Like in Japan, Australian companies are not subject to a convex tax schedule and for this reason corporate taxes do not have an impact on the demand for reinsurance.

Mayers and Smith (1990[31], p. 33) find evidence that group membership is generally associated with larger apparent usage of reinsurance. However, our results for the impact of group membership show no statistical significance.

Regarding “investment return”, the hypothesis is that companies with higher investment returns have better risk management practices and therefore should also reinsure more than companies with lower investment returns. However, we find no significant evidence of this relationship.

The results for the impact of “leverage” are also consistent with results from previous studies²⁵, except for the unusual result found found by Zou et al. (2003 [50]) based on Chinese data. In fact, leverage is the major explanation for reinsurance purchases in this study. Since leverage reflects the amount of capital on the insurer balance sheet, this confirms the important role of risk management strategies in the effective management of capital for an insurer.

7 Conclusion

The results of this study assess the factors determining reinsurance and demonstrate a relationship between capital and risk management decisions in the financial management of an insurer. We provide an empirical analysis of reinsurance demand in Australia which is the first study to do this as far as we are aware. A panel-data methodology is used, which provides efficient and reliable estimates of the impact of factors on reinsurance demand.

We find strong evidence of a positive relationship between company leverage and the demand for reinsurance. We find that the impact of size, taxes, return

²⁴ See Mayers and Smith(1990[31], Hoyt and Khang(2000[21], Aunon-Nerin and Ehling(20035[2]) and Garven and Lamm-Tennant (2003[14])

²⁵ See table 1.

of investments and company structure are not statistically significant. The study results highlight how reinsurance is an important component of the capital management strategy of an insurer.

We discuss how many previous studies may not have considered econometric diagnostics or choice of an appropriate estimator carefully enough. We give reasons why OLS with Panel-Corrected Standard Errors (PCSEs) is the most appropriate model for this Australian data set. We compare our results obtained using the OLS with PCSEs estimator with those obtained from OLS, random-effects and fixed-effects estimators and demonstrate how a wrong choice of estimator will produce misleading and spurious results.

OLS with PCSEs is an appropriate choice of panel data estimator when the data set presents heteroskedasticity, correlation across panels and autocorrelation. Despite the fact that no probit (or logit) models are used in this paper, it is worth emphasizing that autocorrelation makes probit (logit) estimates inefficient, and heteroskedasticity leads to inconsistent estimates. Therefore, studies using probit (logit) models should also be careful in identifying and treating these issues²⁶.

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²⁶ For models dealing with these issues, see Estrella and Rodrigues (1998 [9]), Poirier and Ruud (1988 [40]) and Wooldridge (1994 [47])

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