Technical, allocative and cost efficiency in the Australian general insurance industry†

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Abstract

Data envelopment analysis is used to calculate technical, allocative and cost efficiency indices for a sample of fifty-three Australian general insurers. The inputs used are labour, physical capital (in the form of both information technology and plant and equipment) and financial capital. The outputs are net premium revenues for housing-related insurance, transport-related insurance, indemnity-related insurance and other insurance, along with investment revenue. The results indicate that the major source of overall cost inefficiency would appear to be allocative inefficiency, rather than technical inefficiency, and that the largest twenty percent of insurers are significantly more efficient than the remaining firms. A second-stage analysis uses limited dependent variable regression techniques to relate efficiency scores to financial and non-financial information. Cost efficiency appears to be closely related to asset size, the proportion of non-premium income, and participation in compulsory third party (CTP) markets, but not to stock exchange listing or product range.

Key words: Data envelopment analysis; Technical, allocative and cost efficiency; general (non-life) insurance.

JEL classification: C24; C61; D24; G22

1. INTRODUCTION

In December 1997 the World Trade Organisation’s (WTO) negotiations on a revised set of financial services commitments were completed. A total of 56 schedules of commitments representing 70 WTO member governments, including Australia, and 16 lists of most-favoured-nation (MFN) exemptions were annexed to the Fifth Protocol to the General

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Agreement on Trade in Services (GATS). These were opened to acceptance by Members until June 1999 (WTO 2000). With five countries making commitments in financial services for the first time, the number of WTO Members with commitments in financial services will increase to 104 upon entry into force of the Fifth Protocol. These commitments entail significant changes to the way in which financial services, including insurance and insurance-related services, are regulated in Member economies. Key reforms include the elimination or relaxation of limitations governing foreign ownership of local financial institutions, the juridical form of foreign commercial presence (branches, subsidiaries, agencies, etc.), and limits to the expansion of existing operations (WTO 2000).

However, and like most industrialised countries in the WTO, Australia began the process of financial liberalisation long before GATS. In 1981 the Australian Financial System [Campbell] Inquiry (1981) recommended that many of the regulatory controls governing financial institutions be removed in order to increase efficiency and competitiveness. The four main areas of reform included the removal of direct controls on interest rates and portfolio composition, the strengthening of prudential controls to increase the stability of the financial sector, the removal of barriers to entry, and the modification of macroeconomic management controls and policy. Sixteen years after the Campbell Inquiry the Financial System [Wallis] Inquiry (1997) was instigated to review the developments since the Campbell report, as well as making recommendations concerning future directions in the financial system. While the Wallis Inquiry was similar in some respects to earlier financial inquiries, an emphasis was placed on minimising inefficiencies and the removal of restrictions to competition. Overall, more than one hundred recommendations were made with the objective of increasing efficiency and competitiveness in financial services.

A recurrent theme in the almost generational process of financial service reform in Australia has thus been the efficiency of the financial system. For example, in its stocktake of financial system reform, the Wallis Inquiry (1997: 598) concluded:

> Efficiency has improved in several areas since deregulation. Increased pricing efficiency in securities and foreign exchange markets in particular has improved resource allocation. The productivity of finance sector participants has risen in many cases, as has their dynamic efficiency with technological innovation playing a major role in these improvements.

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However, in some sub-sectors of the financial services industry, especially insurance and insurance-related services, post-deregulation efficiency improvements have not been so noticeable. For example, the Wallis Inquiry (1997) found that Australian general (non-life) insurers were still operating at costs well above international best practice. This was despite significant improvements in the expenses to premiums ratio between 1986 and 1995. At the same time, insurers have increasingly been working on a global basis, and competition between banks and insurers in Australia has intensified as regulations delineating the two services have been relaxed. Combined with the need to maximise economies of scale to improve distribution efficiency, reduce costs and spread information technology expenses over a larger base, the industry has become increasingly concentrated in recent years (KPMG 1999). For instance, the five largest private general insurance groups accounted for 47 percent of private sector premium income in 1997, and this share had increased to 63 percent by 1999.

At the same time, continued pressure on premium rates, and the deterioration of claims and expense ratios combined with customer demand for better quality services, have provided a mixed outlook for general insurers. With a large number of firms, strong competition and relatively low barriers to entry, it is generally accepted that there are too many firms in the domestic market for long-run sustainability (KPMG 1999). Furthermore, with the insurance industry being on the agenda for international reform for the first time, it is expected that the convergence of world markets will put increasing amounts of pressure on Australian general insurers to increase efficiency to survive. A thorough examination of cost efficiency would throw light on both future pressures for consolidation, and the ability of domestic general insurance companies to compete in the increasingly globalised insurance business.

Unfortunately, almost no empirical evidence exists concerning the pattern of cost efficiency in Australian general insurers. First, while there have been numerous international efficiency studies conducted in other areas of the financial services industry, especially deposit-taking institutions, only a handful have been concerned with insurance services. Second, most analyses of insurance company efficiency have tended to concentrate on life insurers [examples include Fukuyama (1997) Hardwick (1997), Ward (1998) and Cummins, Tennyson or Weiss (1999)] or single product lines such as property-liability insurance [see, for instance, Doherty (1981) and Weiss (1992)]. Third, many studies have also tended to rely upon simple cost function approaches [see, for example, Bernstein (1992), Grace and Timme (1992) and McIntosh (1998)] with a smaller number of analyses taking advantage of the sizeable
advances in frontier efficiency measurement techniques. Finally, most studies to date have concentrated on technical and/or scale efficiencies, and have generally ignored allocative efficiency. This is important because allocative efficiency is likely to be a major component of overall cost efficiency and is generally accepted to be the area most likely to have improved during the process of financial deregulation.

With these considerations in mind, an attempt is made to examine the cost efficiency of Australian general insurance companies. The purposes of this exercise are twofold. First, we calculate measures of cost efficiency using nonparametric methods. Second, we explain the calculated efficiency scores in terms of the operating characteristics of individual general insurers. This provides insights into the determinants of inefficiencies, and yields useful information about the possible impact of recent deregulation and future pressures for consolidation. The paper itself is divided into five main areas. Section 2 briefly surveys the frontier approach to efficiency measurement in financial services. Section 3 explains the nonparametric technique used in the measurement of general insurer cost efficiency. Section 4 deals with the specification of inputs and outputs in this model. The results are dealt with in Section 5. The paper ends with some brief concluding remarks.

2. FRONTIER APPROACHES TO EFFICIENCY MEASUREMENT

The recent history of microeconomic efficiency measurement begins with Farrell (1957) who defined a simple measure of firm efficiency that could account for multiple inputs. In his approach, Farrell (1957) proposed that the efficiency of any given firm consisted of two components: technical efficiency, or the ability of a firm to maximise output from a given set of inputs, and allocative efficiency, or the ability of a firm to use these inputs in optimal proportions, given the respective prices. Combining the two measures provides a measure of cost or productive efficiency. It is Farrell’s (1957) suggestion that efficiency could be measured empirically in reference to an idealised frontier isoquant – or equivalently, disturbances in an econometric model – which forms the basis of subsequent analysis.

The essence of Farrell’s (1957) argument is contained in Figure 1. Here two inputs, \(x_1\) and \(x_2\), are utilised to produce a single output, \(y\), under an assumption of constant returns to scale. The isoquant of the fully efficient firm \(SS'\) (showing the alternative combinations of inputs which can used to produce a given level of output) permits the measurement of technical efficiency. For a given firm using quantities of inputs defined by point \(P\) to produce a unit of output, the
level of technical efficiency may be defined as the ratio $OQ/OP$. This is the proportional reduction in all inputs (ie. by movement onto the efficient isoquant) that could be theoretically achieved without any reduction in output. The technical efficiency ratio for the firm at point $P$ will then be less than unity.

FIGURE 1. Technical, allocative and cost efficiencies

Point $Q$, on the other hand, is technically efficient since it already lies on the efficient isoquant. The technical efficiency ratio of the firm at $Q$ is $OQ/OQ$ or unity, thereby implying absolute or relative efficiency (depending upon the manner in which the efficient isoquant is constructed). If the input price ratio $AA'$ is known (showing the different combinations of inputs that can be purchased with a given cost outlay), then allocative efficiency at point $P$ is the ratio $OR/OQ$, where the distance $RQ$ is the reduction in production costs which would occur if production occurred at $Q'$ – the allocatively and technically efficient point, rather than $Q$ – the technically efficient, but allocatively inefficient point. Hence, total economic (cost) efficiency is the ratio $OR/OP$, with the cost reduction achievable being the distance $RP$. Note that the cost efficiency ratio $OR/OP$ is the product of the technical efficiency ratio $OQ/OP$ and the allocative efficiency ratio $OR/OQ$.

Of course, these efficiency measures assume the production function of the fully efficient firm is known. As this is usually not the case, the efficient isoquant must be estimated using sample data. Farrell (1957) suggested the use of either: (i) a nonparametric piecewise-linear convex isoquant constructed such that no observed point should lie to the left or below it (known as the mathematical programming approach to the construction of frontiers); or (ii) a
parametric function, such as the Cobb-Douglas form, fitted to the data, again such that no observed point should lie to the left or below it (known as the econometric approach). These approaches use different techniques to envelop the observed data, and therefore make different accommodations for random noise and for flexibility in the structure of the production technology.

First, the econometric approach specifies a production function and normally recognises that deviation away from this given technology (as measured by the error term) is composed of two parts, one representing randomness (or statistical noise) and the other inefficiency. The usual assumption with the two-component error structure is that the inefficiencies follow an asymmetric half-normal distribution and the random errors are normally distributed. The random error term is generally thought to encompass all events outside the control of the organisation, including both uncontrollable factors directly concerned with the ‘actual’ production function (such as differences in operating environments) and econometric errors (such as misspecification of the production function and measurement error). This type of reasoning has primarily led to the development of the ‘stochastic frontier approach’ (SFA) which seeks to take these external factors into account when estimating the efficiency of real-world organisations, and the ‘deterministic frontier approach’ (DFA) which assumes that all deviations from the estimated frontier represent inefficiency. A number of previous studies have used this approach to estimate the efficiency of insurance companies. These include Cummins and Weiss (1993), Gardner and Grace (1993) and Rai (1996).

Second, and in contrast to the econometric approaches which attempt to determine the absolute economic efficiency of organisations against some imposed benchmark, the mathematical programming approach seeks to evaluate the efficiency of an organisation relative to other organisations in the same industry. The most commonly employed version of this approach is a linear programming tool referred to as ‘data envelopment analysis’ (DEA). DEA essentially calculates the economic efficiency of a given organisation relative to the performance of other organisations producing the same good or service, rather than against an idealised standard of performance. A less-constrained alternative to DEA sometimes employed in the analysis of efficiency in financial services is known as ‘free-disposal hull’ (FDH). Both DEA and FDH are nonstochastic methods in that they assume all deviations from the frontier are the result of inefficiency. Fukuyama (1997), Cummins and Zi (1998) and Cummins, Tennyson and Weiss (1999) have applied these approaches to insurance
companies. Suitably detailed surveys of both the mathematical programming and econometric approaches to efficiency measurement may be found in Førsund, Lovell and Schmidt (1980), Seiford and Thrall (1990), Greene (1993), Lovell (1993), Ali and Seiford (1993) and Charnes, Cooper, Lewin and Seiford (1993)

The approach employed in the current paper to empirically construct measures of cost, allocative and technical efficiency is based upon the DEA approach. One obvious problem with DEA is that in contrast to the econometric approaches to efficiency measurement it is both nonparametric and nonstochastic. Thus, no accommodation is made for the types of bias resulting from environmental heterogeneity, external shocks, measurement error, and omitted variables. Consequently, the entire deviation from the frontier is assessed as being the result of inefficiency. This may lead to either an under or over-statement of the level of inefficiency.

However, there a number of benefits of the mathematical programming approach that makes it attractive on a theoretical level. First, given its nonparametric basis it is relatively easy to alter the specification of inputs and outputs and thereby the formulation of the production correspondence relating inputs to outputs. Second, when using either econometric approach considerable structure is imposed upon the data from stringent parametric form and distributional assumptions regarding both inefficiency and, in the case of SFA, statistical noise. These considerations, and the natural emphasis of DEA on the notion of ‘best-practice’ performance, make it an attractive choice from these two separate, though conceptually similar, approaches to the assessment of cost efficiency

3. EMPIRICAL METHODOLOGY

The computational procedure used to implement the DEA approach to cost efficiency measurement consists of two steps. The first step is to obtain measures of technical efficiency as introduced by Charnes et al. (1978). Consider $N$ general insurers each producing $M$ different outputs using $K$ different inputs. The $K \times N$ input matrix, $X$, and the $M \times N$ output matrix, $Y$, represent the data of all $N$ general insurers, while for the individual general insurer these are represented by the vectors $x_i$ and $y_i$.

The purpose of DEA is to construct a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier. The relative efficiency of each general insurer in ratio form (where for each general insurer we obtain a ratio of all outputs over all inputs) is specified as follows:
\[
\begin{align*}
\max_{u,v}(u'y_j/v'x_j) \\
\text{s.t. } u'y_j/v'x_j \leq 1 \\
u,v \geq 0
\end{align*}
\] (1)

where \(y_i\) is the vector of outputs produced by the \(i\)th general insurer, \(x_i\) is the vector of inputs used by the \(i\)th general insurer, \(u\) is a \(M \times 1\) vector of output weights and \(v\) is a \(K \times 1\) vector of input weights (the prime denotes a transposed vector), \(i\) runs from 1 to \(N\), and \(j\) equals 1, 2, ..., \(N\). The first inequality ensures that the efficiency ratios for all general insurers cannot exceed one, whilst the second ensures that the weights are non-negative. The weights are determined such that each general insurer maximises its own efficiency ratio. A problem with this particular ratio formulation is that it has an infinite number of solutions. To avoid this the constraint \(v'x_i = 1\) is imposed. This fractional linear program (1) can then be transformed into the following equivalent linear programming problem:

\[
\begin{align*}
\max_{\mu,\nu}(\mu'y_i) \\
\text{s.t. } \nu'x_i = 1 \\
\mu'y_j - \nu'x_j \leq 0 \\
\mu,\nu \geq 0
\end{align*}
\] (2)

where the notation change from \(u\) and \(v\) to \(\mu\) and \(\nu\) reflects the transformation. Using the duality of linear programming, this multiplier form can then be used to derive an equivalent envelopment form of the problem:

\[
\begin{align*}
\min_{\theta,\lambda} \theta \\
\text{s.t. } -y_i + Y\lambda \geq 0 \\
\theta x_i - X\lambda \geq 0 \\
\lambda \geq 0
\end{align*}
\] (3)

where \(\theta\) is a scalar and \(\lambda\) is a \(N \times 1\) vector of constants. The value of \(\theta\) will be the technical efficiency score for a particular general insurer. It will satisfy \(\theta \leq 1\), with a value of 1 indicating a point on the frontier, and hence a technically efficient general insurer. The value of \(\theta \leq 1\) identifies the amount of any inefficiencies that may be present.

The model specified in (3) has an assumption of constant returns-to-scale (CRS) and is only appropriate where all general insurers are operating at an optimal scale. Where this assumption does not hold, scale effects will confound the measures of technical efficiency. We would normally assume that many general insurers are not operating at an optimal scale.
Following Banker et al. (1984) the linear programming problem can be modified to account for variable returns-to-scale (VRS) (that is, measures of technical efficiency without scale efficiency effects) by adding the convexity constraint $N^1\lambda = 1$ to (3).

The second step is to calculate cost efficiency with respect to this DEA dual reference technology by solving the following linear program (including the convexity constraint):

$$\min_{\lambda, x_i^*} w_i x_i^*$$

subject to:

$$-y_i + Y\lambda \geq 0$$

$$x_i^* - X\lambda \geq 0$$

$$N^1\lambda = 1$$

$$\lambda \geq 0$$

where $w_i$ is a vector of input prices for the $i$th general insurer and $x_i^*$ is the cost-minimising vector of input quantities for the $i$th general insurer given the input price vector $w_i$ and the output vector $y_i$. The ratio $(w_i'x_i^*/w_i'x_i)$ measures the cost (or economic or productive) efficiency ($CE$) of the $i$th general insurer, and $[(w_i'x_i^*/w_i'x_i)^{-1}-1]$ measures the amount by which cost is increased due to both kinds of inefficiency (both technical and allocative): that is, the ratio of minimum to observed cost. Following the earlier discussion, allocative efficiency ($AE$) can then be calculated residually by dividing cost efficiency ($CE$) by technical efficiency ($TE$).

The primary technique used for explaining variation in the various efficiency measures is a regression-based approach. In this model, the calculated measures of technical efficiency ($TE$), allocative efficiency ($AE$) and cost efficiency ($CE$) for all general insurers (both efficient and inefficient) are specified as the dependent variable in three separate regressions. Given that in each case the calculated measure of efficiency is a limited dependent variable, tobit estimation is appropriate. The explanatory variables posited to explain the presence of inefficiency are a set of institutional characteristics and financial measures that characterise each general insurer’s operations.

4. SPECIFICATION OF VARIABLES

Summary statistics of the inputs, input prices and outputs used in the calculation of the nonparametric efficiency measures are detailed in Table 1 (all money amounts are in AUD). All data corresponds to the year ending 31 December 1998 and is obtained from the Australian Prudential Regulatory Authority (APRA). Following recommendations by the
Wallis Inquiry (1997) APRA is now the sole prudential regulator of banks, credit unions, building societies, insurance and superannuation companies, prior to which this function was divided amongst a number of regulatory bodies. The data collected contains information relating to profit and loss and balance sheet information, as well as additional information concerning expenses. At least some part of this data is publicly available information while other parts are confidential releases that have been made available for the first time.

As at 31 December 1998 there were 172 private sector insurers supervised under the Insurance Act 1973. This total was composed of 106 direct underwriters, 15 mortgage insurers, 6 captive insurers, 29 reinsurers, and 16 other insurers. Although all of these insurers fall under the same legislation they have highly differentiated functions. Therefore, the sample was narrowed to those specifically operating as direct underwriters. From this group of 106 firms, the smallest 53 firms were discarded due to lack of sufficient data leaving 53 firms to use for the analysis.

Following most existing work in the area, the outputs (y) in this analysis are specified as net premium income for each insurance line, defined as premium revenue less reinsurance expense [see, for example, Praetz (1980), Gardner and Grace (1993), Rai (1996) and Ward (1998)]. In one sense, defining outputs in this manner has some intuitive appeal in that it is the amount of premium income that is paid to insurers by policyholders (usually annually) in order to ‘buy’ risk protection. Houston and Simon (1970: 856), for example, argued that “premiums paid is used as a proxy for output which is analogous to measuring output as total sales”.

However, and notwithstanding the widespread acceptance of premium income as an indicator of insurance output, it is acknowledged that there are a number of limitations associated with this measure. The main consideration is that premiums actually measure price multiplied by output, and not just output. Therefore any difference in the price of premiums across insurers could lead to misleading inferences concerning relative efficiency (Yuengert, 1993). As an alternative, a number of studies used additions to reserves to measure output. These include Yuengert (1993) and Cummins and Weiss (1993). It is argued that additions to reserves is a more adequate reflection of productive behaviour since it incorporates reserves arranged for new business, new deposit funds and new reserves as established policies age. Nevertheless, defining output in terms of reserves still suffers from the limitation that it is not immune to differences in prices across firms and alternative actuarial practices (Yuengert, 1993).
Regardless, the data collected by APRA does not contain information on additions to reserves. However, the data is rich in information about premium income divided into various lines of insurance and includes figures relating to reinsurance, which is a major influence on the overall net underwriting result. Four categories of insurance product are specified as outputs in Table 1. These are: (i) housing-related insurance (HSE) (mainly home and contents insurance); (ii) transport-related insurance (TRN) (including commercial and domestic motor vehicle insurance, compulsory third party and marine and aviation insurance); (iii) indemnity-related insurance (IND) (including professional indemnity, employer’s liability and public and product liability insurance); and (iv) ‘other’ insurance (OTH) (including relatively minor products such as travel, consumer credit and other miscellaneous insurance). Lastly, and in addition to the four outputs concerning the net underwriting results of general insurers, an additional output is specified in the form of investment revenue (IRP). This is also a well-established choice of output since most general insurance net profit comes from investment revenue rather than premiums [see, for instance, Gardner and Grace (1993) and Grace and Timme (1992)].
The inputs \((x)\) and input prices \((w)\) used in the calculation of the efficiency measures are also presented in Table 1. The four inputs selected are labour expenses \((LAB)\), expenses on information technology \((INF)\), expenses on other physical capital \((PHY)\), and expenses on financial capital \((FIN)\). Justification for specifying insurance inputs in this manner is as follows. First, labour is generally accepted as being one of the most important expenses in the insurance industry accounting for some two-thirds of non-loss expense in Australia. In this study, labour is defined as the sum of expenses on commissions on premiums, salaries, wages and benefits and management fees. This follows the work of Grace and Timme (1992) and Rai (1996), amongst others.

Second, physical capital, which is normally summed together, is divided into two parts. The first part consists of information technology expenses, which includes computers and computer software. The second part includes expenses on items such as furniture, fittings, plant and equipment. Grace and Timme (1992), Gardner and Grace (1993), Rai (1996), Ward (1998), and Cummins and Zi (1998) also specified physical capital as an important insurance service input. Rent, land and buildings expenses are deliberately omitted, for while insurance companies do hold large real estate portfolios, this is usually due to investment rather than operational purposes. The final input comprises an indication of the cost of obtaining financial capital. As an alternative, a number of studies have used equity capital (or equivalent) as a measure of input [see, for example, Cummins and Weiss (1993), Cummins and Zi (1998) and Cummins et al. (1999)]. Unfortunately, many insurance companies in Australia are unlisted and the data collected by APRA does not contain an equivalent measure. Therefore, although it is not the optimal proxy for financial capital, interest expense is used in this study.

The prices \((w)\) for each of these input quantities are assumed to be constant across all firms in the sample given that general insurers purchase their inputs in competitive markets. The average gross weekly earnings of all persons employed in the finance and insurance industry (Australian Bureau of Statistics, Catalogue No. 6302.0) specifies the wage rate (Grace and Timme 1992; Cummins and Zi 1998). The price of information technology \((DEI)\) is the prime cost depreciation rate over 5 years for computers, and the price of furniture, fittings, plant and equipment \((DEP)\) is the prime cost depreciation rate over 15 years. The technique of proxying the price of physical capital (however defined) with a depreciation rate has also been used by Hardwick (1997). Lastly, the price of financial capital \((INT)\) is specified as the long term interest rate (measured by the yield on ten-year Treasury bonds). Hardwick (1997) and Ward
(1998) used a similar proxy for the financial capital input price. All non-labour input price data is obtained from the Treasury Model of the Australian Economy (Australian Bureau of Statistics, Catalogue No. 1364.0).

As a way of explaining variation in efficiency across Australian general insurers, a second-stage procedure is used to relate measures of technical, allocative and cost efficiency to a set of explanatory variables presumed to account for differences in (in)efficiency. These explanatory variables are intended to evaluate several associated hypotheses on the relationships between financial institution inefficiency and firm-specific variables. In this approach, the index measures of efficiency are specified as the dependent variables in a regression-based approach. General insurers with efficiency scores less than one are relatively ‘inefficient’. For example, an insurance company with a cost efficiency score of 0.75 is only three-quarters as cost efficient as the ‘efficient’ insurers that define the best-practice frontier, while one with an efficiency score of 0.90 is only ten percent less cost efficient. A positive estimated coefficient in the regression model is thereby associated with an improvement in efficiency, while a negative coefficient is linked with a reduction in efficiency. Summary statistics for these variables are detailed in Table 1. The explanatory variables include (i) total assets \( AST \), (ii) the investment ratio \( IR/TR \), (iii) the asset to liability ratio \( TA/TL \), (iv) operating expense to asset ratio \( OE/TA \), (v) operating income to operating expenses \( OI/OE \), (vi) a Herfindahl index of market specialisation \( HRF \), (vii) a dummy variable defining whether an insurance company is listed \( LST \) or unlisted company, and (viii) whether the insurance company is a compulsory third party \( CTP \) provider. The first five variables are typical financial measures while the remaining three are more closely related to specific conditions in the Australian insurance industry.

The first group of explanatory variables relates to firm-specific operational characteristics. The first of these is the firm’s book value of assets (squared) \( AST \). Though the measures of cost efficiency calculated exclude the confounding effects of scale economies, it is posited that larger insurers may direct more resources into identifying and resolving inefficiency. A positive coefficient is hypothesised when measures of efficiency are regressed against asset size. The next four variables relate to aspects of insurance company financial management. These are: (i) the proportion of investment revenue to total revenue \( IR/TR \), (ii) ratio of total assets to total liabilities \( TA/TL \), (iii) the ratio of operating expenses to total assets \( OE/TA \), and (iv) the ratio of operating income to operating expense \( OI/OE \). All of these measures are...
traditional indicators of efficiency in financial services, and in all four cases a positive coefficient is hypothesised when specified as an explanatory variable for firm-level efficiency.

The second group of explanatory variables relates to additional non-financial characteristics of Australian general insurers. First, a common explanatory factor for differences in insurance company efficiency is the degree of firm specialisation. In general, cost sub-additivity implies cost savings from one firm producing a set of products as compared to the cost of separate firms producing separate lines. Evidence to date is mixed. In a sample of Canadian insurers, Bernstein (1992) found that significant savings occurred when producing multiple products, while Fields (1988) and Fields and Murphy (1989) found nothing to suggest that scope economies existed in the US industry. Following Hardwick (1997), a Herfindahl index \( (HRF) \) is used to measure the extent to which firms specialise or diversify their production of insurance services (calculated by summing the squared proportions of total revenue for each product class). The index measure of product complexity lies between zero and unity, with a value of one indicating that a firm specialises in a single product line. Following the assumption of cost complementaries, a negative coefficient is hypothesised when efficiency is regressed against this measure of product simplicity.

Second, a dummy variable is included to distinguish between listed stock \( (LST) \) and unlisted stock and mutual forms of general insurers, and is drawn from the well-established principal-agent literature. Work by Weiss (1981), Fields (1988) and Ward (1998) has used a similar approach to quantify the impact of differences of ownership on insurance company efficiency. However, Fields (1988) and Fukuyama (1997) found no differences between the alternative organisational forms, while Cummins and Van Derhei (1979) found stock companies to be more inefficient than mutuals. An important consideration is that in the Australian insurance industry only one major general insurer retains a mutual form (KPMG 1999). However, the majority of stock companies remain unlisted. Hence, this analysis will test for a significant difference between insurers that are listed and those that are not. It is posited that listed companies should be more efficient than unlisted companies because listed companies are exposed to the markets for corporate control and stricter regulatory oversight by the Australian Stock Exchange (ASX).

Finally, a dummy variable is included to indicate whether the insurer is a participant in the compulsory third party \( (CTP) \) insurance market. Only one study has examined the possible impact of CTP markets on insurance company efficiency. Prosperetti (1991) examined the
efficiency of Italian non-life CTP insurers and found that those insurers that dealt with CTP had higher than average costs. Given the compulsory nature of CTP, and the fact only certain general insurers participate, the incentives for efficient behaviour may be lessened in a less competitive market. A negative coefficient is hypothesised when efficiency is regressed against CTP.

5. EMPIRICAL RESULTS

Table 2 provides summary statistics for the DEA measures of Australian general insurance companies technical, allocative and cost efficiency. The inputs used are labour, physical capital (in the form of both information technology and plant and equipment) and financial capital. The outputs are premium revenue less reinsurance expenses for housing-related insurance, transport-related insurance, indemnity-related insurance and other insurance along with investment revenue. The factor prices used are the implied prices of labour, physical capital and the interest rate on long-term borrowings. The measure of overall cost inefficiency therefore incorporates both allocative inefficiencies, which result from failing to react optimally to relative prices of inputs, and technical inefficiencies from employing too much of the inputs to produce the outputs.

The first set of descriptive statistics in Table 2 are those relating to the entire sample (ie. all insurers). As indicated, of the 53 general insurers examined, 23 insurers (or 42 percent) are judged technically efficient (that is, with an efficiency index equal to one), while 13 insurers (some 25 percent) are allocatively efficient. The results for technical efficiency indicate that, on average, inputs could be reduced to 65.5 percent of the current level based upon observable best-practice, whilst the results for allocative efficiency suggest that efficiency losses due to allocative effects account for 48.4 percent of inputs (that is, 1.000-0.516). In general, more insurers are either technically efficient or nearly so, with 75 percent of institutions having an efficiency score greater than 80.7 percent. On the other hand, 50 percent of general insurers are less than 53.7 percent allocatively efficient when compared to best-practice. However, a large number of general insurers have very low efficiency scores. For example, the lowest 25 percent of general insurers have a relative technical efficiency index of 27.5 percent or lower, and a relative allocative efficiency index of 20.4 percent or lower. The conclusion that there is a large number of general insurers with very low efficiency scores is further emphasised when the statistics on ‘inefficient insurers’ (ie. those with scores less than unity) are examined. In
that case, the average technical efficiency is 39 percent, 34.3 percent for allocative efficiency and only 12.6 percent for overall cost efficiency.

The results generally indicate that the larger portion of cost efficiency is the result of allocative, rather than technical, effects. In terms of international comparisons, Cummins and Weiss (1993) measured technical efficiencies of 90 percent in US property-liability insurers, Yeungert (1993) estimated technical inefficiencies from 35 to 50 percent in a sample of US life insurers, and Gardner and Grace (1993) calculated average cost efficiencies of 42 percent in US life insurers. All of these results appear broadly comparable to those obtained in the present analysis.

### Table 2. Technical, allocative and cost efficiency indices

<table>
<thead>
<tr>
<th></th>
<th>Technical efficiency</th>
<th>Allocative efficiency</th>
<th>Cost efficiency</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>All insurers</td>
<td>Inefficient insurers</td>
<td>Without outliers</td>
</tr>
<tr>
<td>Number</td>
<td>53</td>
<td>30</td>
<td>42</td>
</tr>
<tr>
<td>Mean</td>
<td>0.655</td>
<td>0.390</td>
<td>0.669</td>
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<tr>
<td>Std. deviation</td>
<td>0.378</td>
<td>0.298</td>
<td>0.397</td>
</tr>
<tr>
<td>First quartile</td>
<td>1.000</td>
<td>0.996</td>
<td>1.000</td>
</tr>
<tr>
<td>Second quartile</td>
<td>1.000</td>
<td>0.578</td>
<td>1.000</td>
</tr>
<tr>
<td>Third quartile</td>
<td>0.807</td>
<td>0.367</td>
<td>0.807</td>
</tr>
<tr>
<td>Fourth quartile</td>
<td>0.275</td>
<td>0.151</td>
<td>0.275</td>
</tr>
<tr>
<td></td>
<td>All insurers</td>
<td>Inefficient insurers</td>
<td>Without outliers</td>
</tr>
<tr>
<td>Mean</td>
<td>0.516</td>
<td>0.343</td>
<td>0.451</td>
</tr>
<tr>
<td>Std. deviation</td>
<td>0.347</td>
<td>0.219</td>
<td>0.323</td>
</tr>
<tr>
<td>First quartile</td>
<td>1.000</td>
<td>0.765</td>
<td>1.000</td>
</tr>
<tr>
<td>Second quartile</td>
<td>1.000</td>
<td>0.556</td>
<td>1.000</td>
</tr>
<tr>
<td>Third quartile</td>
<td>0.537</td>
<td>0.223</td>
<td>0.537</td>
</tr>
<tr>
<td>Fourth quartile</td>
<td>0.204</td>
<td>0.154</td>
<td>0.204</td>
</tr>
</tbody>
</table>

Notes: Statistics relating to ‘all insurers’ includes entire sample, ‘inefficient insurers’ relates to those with an efficiency index < 1, ‘without outliers’ are general insurers remaining after eleven institutions with significantly higher cost-to-asset ratios were removed.

As a non-stochastic technique, one important consideration in DEA is the role of outliers in the sample. In order to address this concern, each insurer’s ratio of total costs to total assets was examined, eleven firms with exceptionally (high) ratios were removed from the sample, and the DEA calculations redone. The results of this sensitivity analysis indicate that the results are moderately robust with respect to the presence of outliers, with no dramatic changes in the average level of technical, allocative and cost efficiency. Statistics relating to the sub-set of non-outlier insurers are also presented in Table 2.

### Table 3. Tests of efficiency differences by asset size

<table>
<thead>
<tr>
<th></th>
<th>Technical efficiency</th>
<th>Allocative efficiency</th>
<th>Cost efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mann-Whitney U test</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 and 2</td>
<td>36.000</td>
<td>28.000</td>
<td>28.000</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>(0.027)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>2 and 3</td>
<td>54.000</td>
<td>56.500</td>
<td>56.000</td>
</tr>
</tbody>
</table>
The distribution of technical, allocative and cost efficiency across Australian general insurers is further investigated using a number of nonparametric techniques that are used to test for efficiency differences by asset size. It should be emphasised that the sample of 53 insurers used in this analysis comprise the largest (by total assets) 50 percent of all Australian direct underwriters, and therefore excludes many smaller institutions. To construct these tests, the general insurers are divided into five equally sized groups on the basis of the book value of total assets. For example, the first group of insurers grouped on the basis of the book value of total assets consisted of the largest twenty percent of insurance companies by asset size, the second group were the next largest twenty percent, and so on.

### TABLE 4. Determinants of technical, allocative and cost efficiency

<table>
<thead>
<tr>
<th></th>
<th>Original specification</th>
<th>Modified specification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Normalised coefficient</td>
<td>Standard error</td>
</tr>
<tr>
<td>Technical efficiency</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AST</td>
<td>2.13E-41</td>
<td>1.03E-14</td>
</tr>
<tr>
<td>IR/TR</td>
<td>-0.3508</td>
<td>0.1593</td>
</tr>
<tr>
<td>TA/TL</td>
<td>-0.0014</td>
<td>0.0286</td>
</tr>
<tr>
<td>OE/TA</td>
<td>-2.0773</td>
<td>1.5786</td>
</tr>
<tr>
<td>OI/OE</td>
<td>0.0071</td>
<td>0.0044</td>
</tr>
<tr>
<td>HRF</td>
<td>-0.2810</td>
<td>0.2138</td>
</tr>
<tr>
<td>LST</td>
<td>-0.1118</td>
<td>0.1314</td>
</tr>
<tr>
<td>CTP</td>
<td>0.1214</td>
<td>0.1416</td>
</tr>
</tbody>
</table>

Log-likelihood:

AIC: 1.0955; SIC: 1.4672

AIC: 1.0300; SIC: 1.2530

Allocative efficiency

| AST                 | 2.66E-14               | 1.01E-14               | 0.0081                 | 2.69E-14       | 1.01E-14     | 0.0079                 |
IR/TR  -0.0604  0.1483  0.6838  
TA/TL  0.0641  0.0268  0.0169  0.0445  0.0179  0.0128  
OE/TA  -1.3952  1.4712  0.3430  
OI/OE  0.0098  0.0037  0.0097  0.0112  0.0030  0.0002  
HRF    0.1243  0.1990  0.5321  
LST    0.1472  0.1243  0.2362  
CTP    0.2855  0.1320  0.0306  0.2859  0.1219  0.0191  
Log-likelihood: -11.0898; AIC: 0.7958; SIC: 1.1675  
Log-likelihood: -13.0933; AIC: 0.6827; SIC: 1.0576  

Cost efficiency  
AST  2.76E-14  8.85E-15  0.0018  2.89E-14  8.87E-15  0.0011  
IR/TR -0.1388  0.1259  0.2701  
TA/TL  0.0371  0.0225  0.0990  
OE/TA -1.9513  1.2395  0.1154  
OI/OE  0.0134  0.0037  0.0003  0.0164  0.0031  0.0000  
HRF   -0.0822  0.1664  0.6213  
LST   0.0401  0.1056  0.7044  
CTP   0.3916  0.1138  0.0006  0.3965  0.1047  0.0002  

The tests used are the Mann-Whitney and Kolmogorov-Smirnov tests. Test statistics and significance values are detailed in Table 3. The null hypothesis in the first instance is that the efficiency indices are equivalent in location across the selected groups, while in the second the null hypothesis is that the groups are equivalent in the shape and location of the efficiency distribution. To start with, the Mann-Whitney tests indicate that there are significant differences between the largest asset group and the next to largest group across all three measures of efficiency. This finding holds for the efficiency differences between all other combinations except between the second to largest group and the middle-sized group of insurers.

The Kolmogorov-Smirnov test, however, indicates fewer statistically significant differences in the efficiency distributions. For instance, only the largest and smallest twenty percent of insurers have different distributions of allocative efficiency, and only the smallest twenty percent have a statistically different distribution of technical efficiency. Overall, these results would suggest that there are statistically significant differences in cost efficiency across Australian general insurers, and that largest twenty percent of insurers by asset size are considerably more cost efficient than the remainder.

The second stage of the analysis involves regressing the calculated efficiency indexes (technical, allocative and cost) on a vector of explanatory variables. Estimated coefficients, standard errors and $p$-values for the Tobit regressions are summarised in Table 4. The
dependent variables for the three regressions in Table 4 are the DEA measures of technical, allocative and cost efficiency indices. In brief, the explanatory variables are total assets (AST), the proportion of investment revenue (IR/TR), the asset to liability ratio (TA TL), operating expense to asset ratio (OE/TA), operating income to operating expenses ratio (O/0E), a Herfindahl index of product simplicity (HRF), whether the insurer was listed (LST) and whether it participated in the compulsory third party insurance (CTP) market. Initially all eight explanatory variables were included in the Tobit regressions. After testing for redundant variables, a number of variables were omitted using the log likelihood ratio test. The results of the final tobit specifications are also presented in Table 4.

For all three regressions a test of the null hypotheses that all slope coefficients are zero is rejected at the 0.01 percent level using the log likelihood ratio procedure. This statistic is reported in Table 4 along with the Akaike information criterion (AIC) and the Schwartz information criterion (SIC). The latter measures are used for assessing each model’s adequacy and reflect the trade-off between minimising the sum of squared errors and limiting any increase in the number of regressors. In sum, smaller values of these measures indicate a better model. The hypotheses formulated above state that: (i) as assets increase, efficiency should increase, (ii) as the proportion of investment revenue increases relative to total revenue, efficiency should increase, (iii) as the asset to liability ratio improves efficiency should also improve, (iv) as the expense to asset ratio increases so should efficiency, (v) as the income to operating expense ratio increases there should be an improvement in efficiency, (vi) efficiency should increase as the firm becomes more specialised, (vii) if the firm is publicly listed efficiency will be higher, and finally (viii) efficiency may be negatively or positively related if the firm sells CTP. The tobit regression using technical efficiency as the dependent variable yields results that indicate that total assets (AST), the investment ratio (IR/TR) and the assets to liability ratio (TA TL) are all significant at the 0.01 level. Thus, as assets increase, technical efficiency increases and as operating income increases in proportion to operating expenses (O/0E) along with the proportion of investment revenue (IR/TR) it can be expected that technical efficiency will also increase. Although the investment ratio (i.e. the proportion of investment revenue to total revenue) is significant, the sign on the estimated coefficient goes against \textit{a priori} expectations.

The regression results using allocative efficiency as the dependent variable indicate that asset size (AST), the asset to liability ratio (TA TL), the operating income to operating expenses
The sign on the estimated coefficient for CTP (positive) contrasts to that found by Prosperetti (1991), however this result should be treated carefully because it may be due to the fact that those insurers that offer CTP are also the largest insurers. The final cost efficiency regression yields similar results to that of allocative efficiency with the exception that the assets to liabilities ratio (TA/TL) is insignificant. Overall, total asset size, the proportion of investment revenue, the asset-to-liability and operating expense-to-revenue ratio would appear to be financial measures most closely associated with improvement in technical, allocative and cost efficiency. However, the only non-financial factor that is significant is participation in the compulsory third party (CTP) market. A diversified or specialised product base appears to have no influence on relative cost efficiency, nor does public listing. The latter finding differs from that found by Fukuyama (1997) that listing on a stock exchange increased firm-level efficiency. However, this observation should be treated with some caution as many large insurers, while of a stock form, are unlisted.

6. CONCLUDING REMARKS

A number of points emerge from the present study. The cost frontier measures indicate that in 1998 a typical Australian general insurer’s costs were 64.5 percent above what could be considered necessary based on observable best-practice. The main source of this cost inefficiency would appear to be allocative inefficiency, rather than technical inefficiency; that is, the inability of the firm to use inputs in optimal proportions, given the respective prices, rather than the inability of the firm to minimise inputs for a given level of output. Notwithstanding the low average level of efficiency across the industry, the study also indicates that the industry is divided between a smaller number of relatively efficient insurers, and a very large number of relatively inefficient insurers. This would suggest that the gap, in terms of both market share and efficiency, between the largest general insurance groups and the remaining firms that opened with a wave of mergers and joint ventures in the last two years of the twentieth century is likely to continue into the new millennium. Such pressures for consolidation are only likely to intensify with the further liberalisation of trade in insurance-related services negotiated by the WTO.

There are at least three ways in which this research may be extended. First, the approach used in this study could be expanded to include additional influences on general insurance provider efficiency. These may include variables related to regulatory and administrative frameworks,
the degree of competition amongst insurers and other insurance-related services, and additional detail relating to the quantity and quality of services offered. Second, in order to more fully examine the changing patterns of efficiency improvements, technological change and productivity gain since deregulation it may be useful to obtain estimators of general insurer efficiency using pooled time-series, cross-sectional data. This would not only provide consistent estimators of efficiency over time, but would also indicate improvements in efficiency due to deregulation and so on. One method could be the Malmquist index approach used by Cummins, Tennyson and Weiss (1999) to analyse productivity change in U.S life insurance companies. Finally, similar techniques to the present study could be extended to examine the question of merger in Australian general insurance companies. Given that that many large mergers and joint ventures were completed in 1998, a natural question arises as to the role of cost inefficiency in promoting this activity and the cost efficiency consequences of this behaviour.

REFERENCES


