MEASURING EFFICIENCY OF AUSTRALIAN SUPERANNUATION FUNDS USING DATA ENVELOPMENT ANALYSIS

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Abstract

This research estimates the relative efficiency of Australian superannuation funds using data envelopment analysis (DEA), an operational management model. Data for the research are sourced from the APRA database and financial reports of superannuation funds. The sample comprises 183 superannuation funds. This is approximately 79% of a population of 231 largest APRA-regulated funds as at 30 June 2012. The research covers a seven-year period, from 2005 to 2012. The findings indicate that most Australian superannuation funds are inefficient relative to the efficiency frontier, an internal benchmark established by efficient funds. Consequently, the efficiency targets (such as reduction in expenses and volatility of return) are very challenging for the majority of the funds. The findings emphasize the need for improving efficiency of Australian superannuation funds to narrow the gap in performance between efficient and inefficient funds. While volatility of return can be affected by external circumstances prevailing in the financial markets, expenses are in general more under the control of fund managers. The findings therefore provide a case for mandatory disclosure of fees and expenses in a comparable manner as a means toward accountability and justification of fund performance.

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Glossary and abbreviations

Capital asset pricing model (CAPM): a model that describes the relationship between risk and expected return used in the pricing of risky securities

Constant return to scale (CRS): an increase in inputs will result in the same proportional change in outputs

Efficiency: maximal outputs for a given number of inputs or minimal inputs for a given number of outputs

Decision making unit (DMU): a firm or superannuation fund

Decreasing return to scale (DRS): an increase in inputs will result in a lower proportional change in outputs

Increasing return to scale (IRS): an increase in inputs will result in a higher proportional change in outputs

Managed fund: used in Australian context for *mutual fund*

Mean: used interchangeably with *average*

Mutual fund: used in international context for *managed fund*

Overall technical efficiency (OTE): efficiency assuming constant return to scale, where DMUs are scored regardless of scale

Pension: used in international context for *superannuation*

Pure technical efficiency (PTE): efficiency assuming variable return to scale, where DMUs are scored against other DMUs of similar size

Relative efficiency: efficiency level relative to an efficiency frontier established by efficient DMUs in the sample

Return to scale (RTS) regions: include constant return to scale and variable return to scale (decreasing and increasing)

Scale efficiency (SE) scores: calculated by dividing OTE by PTE scores

Standard deviation (SD): refers to volatility of return

Superannuation: used in Australian context for *pension*

Variable return to scale (VRS): an increase in inputs will result in a different proportional change in outputs

1 Introduction and motivation

Performance of managed funds in general and pension funds in particular is often assessed from an investment return perspective, which may be linked to volatility of return or risk. Important models developed on this approach are Jensen's alpha (1968), Sharpe's index (1966) or Treynor's ratio (1965). These performance measures aim to determine if the activities of a professional fund manager provide additional returns to the fund beyond that of a passive *benchmark*. Despite their popularity over the last four decades, the measures have two major drawbacks.

Firstly, the return and risk relationship, well established in the capital asset pricing model (CAPM), is a controversial benchmark. Researchers argue about the validity of the underlying assumptions of the CAPM model, such as no transaction costs, efficient markets with rational, well informed investors (Galagedera & Silvapulle 2002; Shukla & Trzcinka 1992). The CAPM beta is not a robust benchmark for risk and performance results are sensitive to the choice of benchmark models (Choi & Murthi 2001; Elton et al. 1993; Green 1986; Lehman & Modest 1987; Roll 1978). Secondly, the effect of transaction costs and other operational characteristics have not often been considered in these traditional models. For instance, Sharpe's index only takes into account net returns by subtracting costs from gross returns (Choi & Murthi 2001).

In the mid-1990s, researchers proposed a different approach which addresses some of the limitations of Jensen's, Sharpe's and Treynor's methods for mutual fund performance measurement. This technique is called Data Envelopment Analysis (DEA), often used in service industries to estimate the relative economic efficiency of decision making units (DMUs). DEA is a non-parametric analysis method which does not require any theoretical model as a benchmark (such as the CAPM benchmark). Instead, DEA measures how well a DMU performs relative to the best set of DMUs (Coelli et al. 2006). While investment return is a very useful indicator in fund performance, it lacks insights in regards to the operational activities of the fund and what could be done to improve the quality of these activities. DEA can overcome this disadvantage. DEA is flexible and can evaluate performance of a managed fund by incorporating multiple inputs and outputs *simultaneously*. The inputs and outputs can have *dissimilar* units of measurement. The inputs and outputs that reflect the financial and operational characteristics of the fund under evaluation can be presented in dollar values, percentage terms or other units of measurement (Murthi, Choi & Desai 1997). It is also possible to use DEA to set targets for input reduction (such as costs and expenses) so that if implemented, the fund can operate at an optimal scale (Galagedera & Silvapulle 2002).

The DEA approach in measuring performance of managed funds has been used as an effective alternative to the popular risk-adjusted return methods. For instance, Choi and Murthi (2001) used DEA to measure portfolio management and efficiency of American mutual funds where the relationship between return (output) and expense ratio, turnover and risk (inputs) were tested. Analysis of technical efficiency and economies of scale was conducted for real estate investment trusts in the United States during the period 1992 -1996 (Anderson et al. 2002). In a more recent study, Barros and Garcia (2006) also employed DEA to evaluate Portuguese pension fund management companies using operational and financial variables.

In Australia, the DEA model was used in a study to measure the relative efficiency of mutual funds by Galagedera and Silvapulle (2002). Njie (2006) measured the efficiency of Australia's retirement income system under the effects of financial reforms. Watson, Wickramanayke and Premachandra (2011) investigated the efficiency of domestic Australian equity funds that received Morningstar rating. The DEA method has hardly been used for superannuation funds. This inadequacy is not just confined to Australia. From a global perspective, pension funds generally receive less interest for research due to less transparency and disclosure than other types of mutual funds (Ambachtsheer, Capelle & Lum 2008). Against this backdrop, this research proposes to explore the relative economic efficiency of large APRA-regulated funds using DEA. The research aims to address the question: "***To what extent do Australian superannuation funds operate efficiently?***" This research is the first part of a long-term project which also takes into account governance and reporting practices of Australian superannuation funds.

The research is significant for several reasons. Firstly, legislative changes since the early 1990s have encouraged a significant growth of superannuation assets. When the SIS Act was introduced in 1993, the total superannuation assets were approximately $183 billion (Cooper, J et al. 2010). These assets amounted to $360 billion, nearly 60% of GDP, in 1998. By June 2007, the total assets were over a trillion dollars, about the size of GDP (APRA 2007; APRA 2012). Australia is currently one of the four countries with funds under management approximating annual GDP (Dunn 2012). Despite the importance of superannuation funds from both a macro-economic policy setting and a micro-economic investment management perspective, superannuation research is not as robust as compared to studies on other types of managed funds (Ambachtsheer, Capelle & Lum 2008). The application of DEA has been carried out in very few studies on Australian superannuation funds. This research therefore contributes to superannuation research literature.

Secondly, performance of pension funds worldwide has been in the spotlight due to poor returns and volatility of global financial markets. Members of superannuation funds have arguably been the most vulnerable party. Unlike investors who can liquidate their investments (subject to sufficient liquidity), members of superannuation funds are generally passive and not allowed direct access to their investments until certain times. Members rely on fund managers to manage their money. The importance of ensuring member protection and the efficiency of the superannuation system therefore cannot be overstated (Cooper, J et al. 2010). On that basis, the research contributes useful information to regulators, industry policy makers, members and other market participants.

Lastly, measuring economic efficiency of superannuation funds using a non-parametric benchmark has rarely been done in Australia. Apart from the APRA Annual Superannuation Bulletin which ranks funds according to their investment returns on an on-going basis, there is hardly any other comprehensive approach in evaluating superannuation fund performance. Ranking of superannuation funds tends to be a one-off approach. Therefore, measuring and ranking the performance of superannuation funds has become a pressing issue. The research contributes to this gap in the literature with the aim of setting a foundation for ranking Australian superannuation funds on an on-going basis using the DEA model.

The remainder of this report is organised as follows. Section 2 introduces the theoretical basis for the DEA model. Section 3 discusses the research method. Section 4 analyses the results. Section 5 summarises the findings, discusses the implications and future research areas as an extension to this research.

2 Theoretical background for the research method

2.1 Productivity and efficiency

Productivity is defined as the ratio between outputs (produced goods or services) and inputs (consumed resources) (Coelli et al. 2006). The terms *productivity* and *efficiency* are often used interchangeably, however their concepts are not similar. The term *efficiency*, in the context of this research, refers to economic efficiency. That is the state of being able to produce the maximal output for each given level of input, or the minimal input for each given level of output (Coelli et al. 2006). As per Figure 1, a production frontier (non-linear line OP) represents efficient firms (firm B) in an industry. Any firms (e.g. firm A) that are not operating on the frontier are technically inefficient. Firm A is operating inefficiently because it can increase its output level *y* to point B without requiring more input *x* (Coelli et al. 2006).

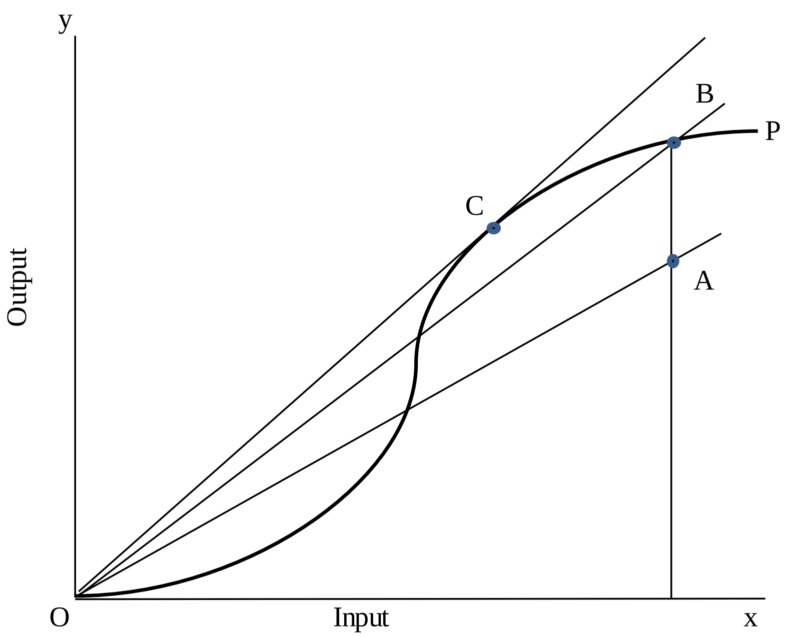

Figure 1. A production frontier with technically and scale efficient firms.
Source: Coelli et al. 2006

Although a firm is technically efficient, it can still improve its productivity by exploiting scale economies. In Figure 1, Firm B is operating efficiently on the production frontier. Firm B however may still improve its productivity by moving to point C. Point C is a tangent between the ray OC and the production frontier OP, which represents maximum possible productivity. This movement is an example of exploiting scale economies. Operation at any other point on the production frontier, albeit demonstrating technical efficiency, results in lower productivity (Coelli et al. 2006).

2.2 Data envelopment analysis (DEA)

The DEA concept was first introduced by Farrell (1957) to estimate the efficiency of the US agricultural industry. The article unfortunately did not generate great interest. For the two decades that followed Farrell's proposal, the DEA concept was considered by only a few researchers (Afriat 1972; Boles 1966; Sheppard 1970). It is only when Charnes, Cooper and Rhodes (1978) proposed a similar model to measure the efficiency of public programs that the DEA concept received full attention and appreciation. The term DEA was first mentioned in Charnes, Cooper and Rhodes' article (Coelli et al. 2006). Since 1978, DEA has been used widely in many industries. Seiford (2005) compiled a bibliography of 2800 articles and research papers on DEA covering the period 1978-2005. The bibliography shows that DEA has been applied in various service industries including transport (railroads, airports), utility (water, electricity, telecommunication), education institutions (tertiary and secondary), agriculture sector, not-for-profit sector, public programs and financial institutions (mainly banks).

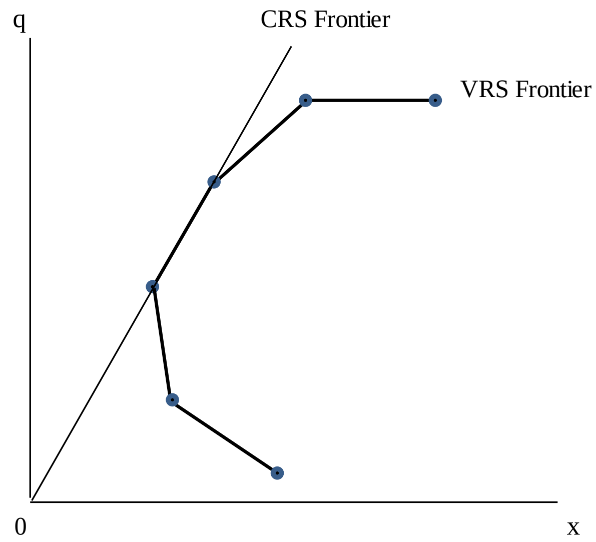

Figure 2: DEA CRS and VRS frontiers.

Source: Cook & Zhu 2008.

DEA "involves the use of linear programming methods to construct a non-parametric piece-wise production frontier over the data" (Coelli et al. 2006, p. 162). See illustrative Figure 2. Efficiency scores are estimated *relative* to this frontier. DEA can handle multiple performance measures (inputs and outputs) under a large number of constraints by using a single integrated programming model. This flexibility makes it easier to deal with complex issues and relations that are normally encountered in many organisational and social contexts (Cooper, WW, Seiford & Tone 2007).

A DEA efficiency frontier can be constructed using a constant return to scale (CRS) model or variable return to scale (VRS) model (see Figure 2). The CRS model generates overall technical efficiency (OTE) scores. The CRS model assumes that all firms are operating at an optimal scale. However, imperfect competition, government regulations, internal constraints and other factors may cause some firms to be operating at a sub-optimal scale. Using CRS specification when not all firms are operating at an optimal scale results in OTE scores confounded by scale inefficiencies. Using variable return to scale (VRS) specification permits the calculation of efficiency scores without the effect of scale efficiencies (SE). The VRS model ensures that an inefficient firm is only benchmarked against firms of a similar size (e.g. using similar levels of inputs and outputs). The VRS model creates a convex hull of intersecting facets that *envelop* data more tightly than the CRS conical hull (see Figure 2). The VRS model provides pure technical efficiency (PTE) scores that are greater or equal the OTE scores generated under the CRS model (Coelli et al. 2006).

SE scores are obtained residually through OTE and PTE scores (Cook & Zhu 2008):

$$Scale\ Efficiency\ (SE) = \frac{Overall\ Technical\ Efficiency\ (OTE)}{Pure\ Technical\ Effiency\ (PTE)}$$

If a firm has a SE score which is smaller than 1, or if there is a difference between the OTE and the PTE score, this indicates that the firm has scale inefficiency and exhibits either increasing return to scale (IRS) or decreasing return to scale (DRS). If a firm is in the IRS region, an increase in inputs will result in a higher proportion of output increase. If a firm is in the DRS region, an increase in inputs will result in a lower proportion of output increase (Cook & Zhu 2008).

2.3 Input-oriented and output-oriented DEA

A DEA model can be used in either direction: input-oriented or output-oriented, depending on the objective of the research. Both input-oriented and output-oriented DEA models estimate the same production frontier and identify the same set of efficient firms in the sample. However, the efficiency targets associated with inefficient firms differ between the two methods. The input-oriented DEA approach identifies efficiency targets (possible reductions) for inputs while holding the outputs constant. By contrast, the output-oriented DEA approach identifies efficiency targets (possible increases) while holding the inputs constant (Cook & Zhu 2008). This is arguably one of the greatest advantages of the DEA model. From a management point of view, efficiency targets are valuable insights which can be used as benchmarks for corrective methods and improvements of operating activities (Anderson et al. 2004; Coelli et al. 2006; Premachandra, Powell & Shi 1998).

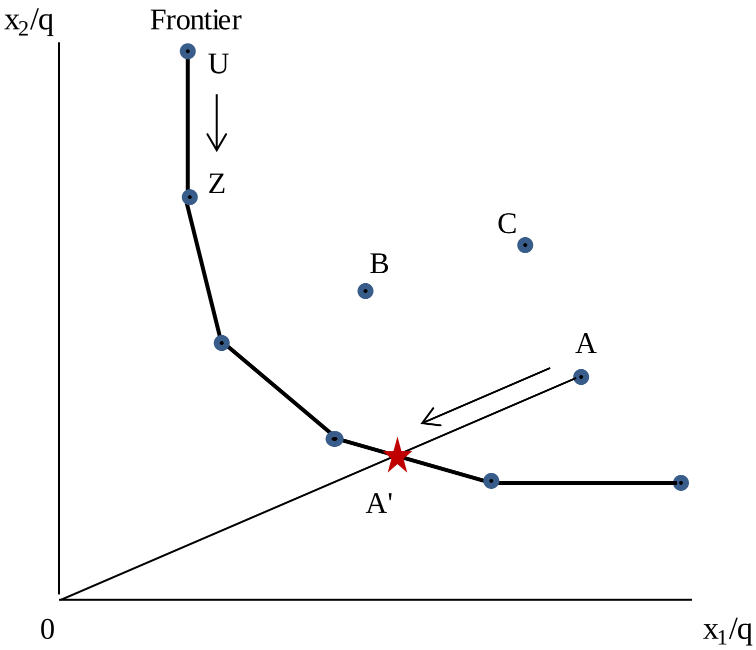

Figure 3. Input-oriented DEA.

Sources: Coelli et al. 2006; Cook & Zhu 2008.

As per Figure 3, the DEA efficiency frontier is constructed by connecting all the points represented by efficient DMUs in the sample. The efficiency frontier *envelops* all DMUs that are deemed to be inefficient, such as A, B or C (Anderson et al. 2004). Fund Z is an efficient fund and scored 1. Fund A is inefficient. Fund A's efficiency score is determined by the rays 0A'/0A, which is approximately 2/3. With the efficiency frontier as a benchmark, it is seen that Fund A could possibly reduce the consumption of all inputs by approximately 1/3 without reducing outputs. This is often referred to as *target efficiency value* in the literature (Anderson et al. 2004).

It is further observed that although lying on the efficiency frontier, Fund U can reduce its input x_2 to a level similar to Fund Z and still produce the same output. This possible input reduction is called input *slack*. Funds which lie on the frontier but can reduce inputs without affecting the output level are *weakly e*fficient (Coelli et al. 2006; Cook & Zhu 2008).

As common with any research method, the DEA model does possess some weaknesses. The DEA model does not take into account the possible influence of measurement errors and other noise in the data (Anderson et al. 2002). Researchers may reduce the possibility of reporting biased results resulting from measurement errors and outliers by plotting outliers and investigating them, or by providing special notes to abnormal results.

3 Research method

3.1 Sample selection

Superannuation fund data were retrieved from the APRA database "Superannuation Fund Level Profile and Performance 2012" and fund financial reports. The total number of funds selected for DEA runs are 183. These funds have been active (see Table 1) and reported to APRA for a period of seven years, from 2005 to 2012. The number of selected funds is lower than the number of fund that reported to APRA as at 30 June 2012 due to missing data across the years and different reporting dates. This period is of significant interest as it covers the global financial crisis (GFC) and includes 4 years of positive return and 3 years of negative return.

Table 1. Number of active* APRA-regulated funds as at 30 June, period 2005-2012.

Year	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12
Number of funds	423	382	351	322	291	254	231

*reported non-zero net assets, contributions and expenses.

Source: APRA 2012b

The sample of 183 funds therefore makes up about 79% of active funds reported to APRA as at 30 June 2012 (APRA 2013b). See Table 1. Compared to global research on mutual funds using the DEA model, mostly done in the US, this sample size is relatively small. Nevertheless, Australia is a smaller market and the sample is sufficiently robust. Several other research studies on Australian managed funds using DEA also had significantly smaller sample sizes.

3.2 Input and output specification

There is no formal selection process agreed among researchers as to what input and output variables should be in included in a DEA model (Callen 1991; Charnes, Cooper & Rhodes 1981; Cholos 1997; Watson, Wickramanayke & Premachandra 2011). Variable selection methods that have been adopted in the past include expert judgement, principal components analysis, a step-wise approach to input-output variable selection or a combination of all the above (Adler & Golany 2001; Norman & Stoker 1991). For this research, variable selection was based on principal components analysis using APRA data (APRA 2013b), current issues identified in the literature and analysis of operating characteristics and performance indicators of superannuation funds (expert judgement). Inputs and outputs are performance measures, and thus, if correctly selected, can provide useful insights to managers and/or regulators. Within the context of the productivity concept and DEA model, efficiency is enhanced by *reducin*g inputs while maintaining the current level of outputs or *increasing* outputs while maintaining the current level of inputs (Galagedera & Silvapulle 2002).

The appropriate number of inputs and outputs are often discussed in the literature. While the DEA model can handle multiple inputs and outputs, it is observed that a very large number of inputs or outputs relative to the number of DMUs may clutter the analysis or result in a large number of efficient DMUs (Adler & Golany 2001; Gregoriou, Sedzro & Zhu 2005). Five inputs and three outputs were selected for this research, which fall into the middle range of inputs and outputs often used for DEA runs. The inputs and outputs cover major financial and operating performance indicators. Rationale for the selection is provided below.

Fees and costs of managed funds in general and superannuation funds in particular have been subject to increased scrutiny since the GFC. Fund managers expect significant cost reductions, as a consequence of lower returns, higher investor expectations and industry consolidation (Main 2011). The number of self-managed superannuation funds has been increasing steadily. Over one million members have decided to manage their own funds due to fees and sub-optimal investment returns from institutional funds (Patten 2012). There have been layers of fees and costs, some directly attributed to the internal management and administration activities, others to third party service providers (see Table 2 and 3). During a year of low return such as 2011-12, expenses are very significant as compared to earnings. Outsourcing activities and related party transactions which are not at an arm's length basis are arguably common practice in many retail superannuation funds (Dunn 2011; Liu & Arnold 2010).

Table 2. Expenses as a Percentage of Earnings before Tax, 2011-2012

Category	Corporate	Industry	Public sector	Retail	Total
Net assets ($m)	54,357	260,640	211,318	370,318	896,633
Earnings before tax ($m)	448	1,290	4,096	-2,982	2,852
Investment expenses ($m)	195	877	480	372	1,924
Operating expenses ($m)	160	1,202	549	2,733	4,644
Total expenses ($m)	355	2,079	1,029	3,105	6,568
Investment expenses (%)	*43.5*	*68.0*	*11.7*	*n/a*	*67.5*
Operating expenses (%)	*35.7*	*93.2*	*13.4*	*n/a*	*162.8*
Total expenses (%)	*79.2*	*161.1*	*25.1*	*n/a*	*230.3*

Source: APRA 2013a

Table 3. Expenses as a Percentage of Earnings before Tax, 2010-2011

Category	Corporate	Industry	Public sector	Retail	Total
Net assets ($m)	57,134	244,762	199,707	368,322	869,926
Earnings before tax ($m)	4,362	20,681	16,193	21,658	62,894
Investment expenses ($m)	159	887	466	388	1,900
Operating expenses ($m)	185	1,164	442	2,732	4,523
Total expenses ($m)	344	2,051	908	3,120	6,423
Investment expenses (%)	*3.7*	*4.3*	*2.9*	*1.6*	*3.0*
Operating expenses (%)	*4.2*	*5.6*	*2.7*	*12.6*	*7.2*
Total expenses (%)	*7.9*	*9.9*	*5.6*	*14.2*	*10.2*

Source: APRA 2012

Given that expenses are important performance indicators, the first set of selected inputs is therefore total expenses, divided into investment, management, administration expenses, director fees and other operating expenses. Another input selected is volatility or standard deviation (SD) of return across the period of study, from 2005-2012. SD of return is, by nature, an undesirable output of investment activities, not an input (see rationale for output specification below). However, to classify SD as an input has several benefits. Firstly, to operate efficiently, funds should attempt to reduce SD of return. SD therefore suits the input profile better than the output profile. Further, the DEA software selected to automate DEA runs for this research allows treating this undesirable output as an input. The DEA software can also calculate input efficiency targets for individual funds while holding outputs constant. Thus, by classifying SD of earnings as an input, SD efficiency targets (possible reductions of SD) for individual funds can be obtained. SD of return has traditionally been included in the input variables (Daraio & Simar 2006).

The size of assets is an important characteristic of any asset management funds. Assets relative to expenses is one of the most common indicators of performance for mutual funds. Researchers on mutual funds often specify assets as an important output variable (Anderson et al. 2004; Davis & Stein 2001). The first output for this analysis is therefore average net assets, which is calculated by the sum of beginning net assets and ending net assets then divided by 2.

The second variable is the number of member accounts. The number of member accounts of APRA-regulated fund during the period of 2005-2012 is very high (see Table 4). Member account relative to operating expense is another important indicator of performance. It is likely that the more member accounts there are, the higher the operating expenses. To be more efficient, fund managers should maximise member numbers while holding operating expenses constant or minimize operating expenses given the same member accounts.

Table 4. Member accounts (million), 2005-2012.

Year	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12
Member account	27.0	28.3	29.8	30.4	31.1	29.7	29.1

Source: APRA 2013b

Table 5. Average rate of return and volatility for APRA-regulated superannuation funds, 2003-2012.

Entities	Average Return %	Volatility %
All entities	4.4	9.4
Corporate	4.8	9.4
Industry	5.1	9.5
Public sector	5.5	9.7
Retail	3.4	9.3

Source: APRA 2013a

Investment return is the most commonly used performance indicator of a mutual fund. The issue of investment return is more pressing during periods of negative returns. As indicated in Table 5, during the 10-year period from 2003-2012 which covers the GFC, APRA-regulated funds delivered low average returns despite high volatility. On this basis, the third variable selected is investment return, represented by annual return and multiple period return. Annual return is required for Phase 1, where efficiency scores are estimated for individual years to identify trends. Multiple-period return is required for Phase 2, when efficiency scores are estimated for the whole period and volatility of return is taken into account. Return is calculated using earnings before tax because this research focuses on fund efficiency and management performance rather than ultimate benefits for members. Using after-tax earnings data where the tax rates might differ across funds could potentially render data poorly comparable and distort the information on management performance. Multiple-period return is calculated using geometric averages. The seven-year period return is computed based on the following formula:

$$[(1+ROR_{t-6})\times(1+ROR_{t-5})\times(1+ROR_{t-4})\times(1+ROR_{t-3})\times(1+ROR_{t-2})\times(1+ROR_{t-1})\times(1+ROR_{t})]^{1/7}-1$$

The DEA model does not recognise negative variables. To deal with the issue of negative returns, an additional step called *translation invariance* is necessary. Returns are adjusted by adding some arbitrarily selected positive constant with the aim of rendering them all positive (Cook & Zhu 2008; Watson, Wickramanayke & Premachandra 2011). This is the approach used in the research to transform negative numbers into positive numbers, for the years where financial markets performed poorly. A new set of positive values is obtained by using an arbitrarily selected translation constant π_r:

$$\hat{y_{rj}} = y_{rj} + \pi_r$$

Where: y_{rj} original output data

π_r translation constant

$\hat{y_{rj}}$ translated output data

In summary, input and output variables selected for the research are presented in Table 6 below.

Table 6. Input and output variables

Measures	Individual years, 2005-2012	Period, 2005-2012
Inputs	- Investment expenses - Operating expenses - Management, administration and director fees - Total expenses	- Investment expenses - Operating expenses - Management, administration and director fees - Total expenses - Volatility/SD of return
Outputs	- Average net assets - Member account - Return before tax	- Average net assets - Member account - Multiple period return

3.3 DEA model

The input-oriented approach is used in this research to obtain efficiency scores for Australian superannuation funds. The input-oriented model is chosen because expenses are areas where managers have more control. This is in comparison to investment return, assets under management and member accounts.

Input-oriented CRS efficiency scores; VRS efficiency scores with slack calculations and efficiency targets; and return to scale regions are computed using the following programming problem:

Constant return to scale:

$$\theta * = min\ \theta \qquad (1)$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} \qquad i = 1,2, \dots, m \qquad (2)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \qquad r = 1,2, \dots, s \qquad (3)$$

$$\lambda_j \geq 0 \qquad j = 1,2,\dots,n$$

Variable return to scale:

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (4)$$

$$\lambda_j \geq 0 \qquad j = 1,2,\dots,n$$

Slack calculations:

$$max \sum_{i=1}^{m} s_i^- + \sum_{i=1}^{r} s_r^+ \qquad (5)$$

subject to:

$$s_i^- = \theta^* x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \qquad i = 1,2, \dots, m \qquad (6)$$

$$s_r^+ = \sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro} \qquad r = 1,2, \dots, s \qquad (7)$$

$$\lambda_j \geq 0 \qquad j = 1,2,\dots,n$$

Efficiency targets:

$$\hat{x_{io}} = \theta^* x_{io} - s_i^{*-} \qquad i = 1,2,\dots,m \qquad (8)$$

$$\hat{y_{io}} = y_{ro} + s_i^{*+} \quad r = 1,2,\dots,s \qquad (9)$$

Return to scale regions (increasing and decreasing):

$$\sum_{j=1}^{n} \lambda_j \leq 1 \qquad (10)$$

$$\sum_{j=1}^{n} \lambda_j \geq 1 \qquad (11)$$

$$\lambda_j \geq 0 \qquad j = 1,2,\dots,n$$

Where:

θ *efficiency score (min. refers to the input-oriented approach)*

ε *optimisation involving slacks*

s_i^- *input slack*

s_r^+ *output slack*

λ *unknown input and output weight*

x *input, denoted as* x_{ij}

y *output, denoted as* y_{rj}

n *total funds under evaluation*

m *total inputs*

s *total outputs*

j *number of fund under evaluation, from 1 to n*

i *number of input, from 1 to m*

r *number of output, from 1 to s*

Sources: Coelli et al. 2006; Cook and Zhu 2008

Efficiency scores with return to scale regions, slack treatments and efficiency targets are obtained through several stages. Firstly, OTE (CRS) and PTE (VRS) scores are calculated. Subsequently, input and output slacks are estimated and efficiency scores are adjusted following slack calculations. Efficiency targets (input oriented) are also estimated in the second step. Efficiency targets indicate to what extent inefficient funds need to reduce all inputs so as to be on the efficiency frontier. Finally, return to scale regions are estimated, where funds are classified under constant return to scale, increasing return to scale or decreasing return to scale.

Efficiency scores are equal or less than 1 but greater than zero. Efficient funds, where minimal inputs are used for a given level of outputs are scored 1 and together form the efficiency frontier. Inefficient funds (deviations from the efficiency frontier) are scored less than 1. The further the inefficient fund is away from the frontier, the smaller the score.

After OTE (CRS) scores and OTE (VRS) scores are obtained, SE scores can be calculated. One shortcoming of this measure is that the SE value does not indicate whether the firm is operating in an area of increasing or decreasing returns to scale. Therefore, return to scale regions (increasing and decreasing) as indicated in problem (10) and (11) need to be determined.

Efficiency scores were estimated in two major phases. Phase 1 calculated the scores for individual years across all funds to identify trends. Phase 2 calculated the scores for a seven-year period, from 2005 to 2012, where volatility of return was taken into account. For individual years, the linear programming problem was repeated for 183 funds by 7 variables by 7 years. For the whole period, the linear programming problem was repeated for 183 funds by 8 variables. Solving these linear programming problems was facilitated with DEA Frontier Software (Zhu 2003).

4 Results

4.1 Descriptive statistics

Descriptive statistics of the 183 sample funds are presented in Table 7 and 8. From 2005 to 2012, total net assets have increased by 79%, member accounts by 19%. The number of member accounts is high which indicates that the same member may have more than one account. This may be a case for consolidation of member accounts (unless members choose to have more than one account to diversify risks or for other reasons). While the average fund size ranges between $2 – 3.6 billion over the period, the smallest fund size is merely between $1.3 – 1.6 million, as compared to the largest fund being $32.5 – 51.6 billion. This may be another case for the consolidation of small superannuation funds.

Table 7. Descriptive statistics of the sample funds

Measure	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12
Total net assets ($mil)	373,691.7	480,813.5	529,053.8	502,717.0	518,205.1	604,908.0	667,731.2
Mean ($mil)	2,042.0	2,627.4	2,891.0	2,747.1	2,831.7	3,305.5	3,648.8
Min ($mil)	1.3	1.4	1.3	1.3	1.5	1.6	1.6
Max ($mil)	32,535.3	40,801.5	43,798.1	40,661.7	40,958.3	47,312.1	51,626.3
Member accounts	23,903,779	23,903,779	25,759,487	26,312,490	26,799,538	26,409,527	26,851,523
Return*(%)	12.37	13.59	-8.90	-12.78	7.85	6.89	-0.44
Total funds	183			Public offer		127	
Corporate	39			Non-public offer		56	
Industry	51			Accumulation		125	
Public sector	15			Hybrid		55	
Retail	78			Defined benefit		2	

* Return over average net assets, unweighted to asset size of individual funds.

4.2 Discussion of results

The objective of this research is to identify efficiency scores of individual superannuation funds in the sample under three models: OTE (CRS), PTE (VRS) and SE (OTE/PTE). The scores were estimated using slightly different sets of input and output (Table 6). The first set was to estimate individual year efficiency scores so as to observe trends and explanation of trends. The second set was to estimate seven-year period efficiency scores where volatility of return was included as an input.

4.2.1 Efficiency scores for individual years, 2005-2012

This section discusses efficiency scores for individual years from several perspectives. These include OTE scores, PTE scores, SE scores, quintile analysis and fund type analysis.

Table 8 presents the OTE scores under the CRS model for individual years. Under this model, all the funds in the sample are scored regardless of size. The number of efficient funds is lowest in 2008-9. Only 6 funds or approximately 3% of the sample funds are efficient. This correlates to the large negative return (-12.78%) in the second year of the GFC (see Table 9). The number of inefficient funds ranges between 169 (2005-2006) to 177 (2008-2009). That is equivalent to 92% to 97% of the funds being inefficient. While the mean score is low, ranging between 0.177 (2007-8) to 0.263 (2006-7), the minimum score is close to zero, ranging from 0.019 (2005-6) to 0.037 (2011-12). This is worsened by the high SD (0.202 to 0.260). This result indicates an extremely wide dispersion of OTE scores among inefficient funds. Most funds are operating far below the optimal level as benchmarked by the efficiency frontier.

Table 8. Overall technical efficiency (OTE) scores, constant return to scale (CRS), individual years

Measure	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12	Average
Efficient funds	14	12	7	6	7	7	9	9
Average asset ($million)	683	954	1,543	974	845	899	5,149	1,578
Inefficient funds	169	171	176	177	176	176	174	174
Average asset ($million)	2,155	2,745	2,945	2,807	2,910	3,401	3,808	2,967
Pearson correlation *r*	-0.0803	-0.0282	-0.0068	0.0291	-0.0503	-0.0462	-0.0569	-0.03
Mean	0.229	0.263	0.177	0.194	0.207	0.212	0.239	0.217
Median	0.140	0.181	0.119	0.117	0.106	0.123	0.156	0.135
SD	0.260	0.248	0.202	0.209	0.229	0.222	0.231	0.229
Min	0.019	0.037	0.024	0.025	0.030	0.022	0.040	0.028
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

There is no correlation between asset size and efficiency score, as indicated by the Pearson correlation *r* which ranges from -0.0803 to 0.0291.

Table 9 presents the PTE scores under the VRS model. There is a significant improvement in efficiency scores when funds are benchmarked against funds of similar size. The results are self-explanatory. The number of efficient funds is lowest in 2007-8 and 2008-9, with 24 funds (13%) being efficient. The number of efficient funds is highest in 2006-7 and 2009-10, with 32 funds (18%) being efficient. Conversely, in 2006-7 and 2009-10, there are 151 inefficient funds (82%). Consistent with the results in Table 8, the number of inefficient funds are highest in the years 2007-8 and 2008-9 at (87%) or with 159 funds, when the average return is significantly negative.

Table 9. Pure technical efficiency (PTE) scores, variable return to scale (VRS), individual years

Measure	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12	Average
Efficient funds	27	32	24	24	32	30	27	28
Average asset ($million)	4,948	5,766	8,502	9,618	8,564	10,059	11,561	8,431
Inefficient funds	156	151	159	159	151	153	156	155
Average asset ($million)	1,539	1,962	2,044	1,710	1,617	1,981	2,279	1,876
Pearson correlation *r*	0.3574	0.3298	0.4363	0.4874	0.4258	0.4104	0.5037	0.422
Mean	0.361	0.412	0.317	0.320	0.392	0.409	0.376	0.370
Median	0.247	0.301	0.174	0.180	0.271	0.265	0.248	0.241
SD	0.315	0.327	0.324	0.324	0.324	0.330	0.316	0.323
Min	0.039	0.049	0.028	0.026	0.033	0.022	0.040	0.034
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

The average asset of efficient funds under the VRS model is in general higher than that of inefficient funds across the seven years. The average asset size of efficient funds ranges from $4.9 billion to $11.6 billion whereas that of inefficient funds ranges from $1.5 billion to $2.3 billion. Pearson correlation between PTE score and asset size is positive, lowest at 0.398 in 2006-7 and highest at 0.5037 in 2011-12. Thus, there is a positive effect of fund size on PTE.

The mean PTE score is nearly double the mean OTE score, lowest at 0.317 and highest at 0.412. Nevertheless, from an overall assessment of efficiency perspective, the mean score is still low, at 0.370. This indicates that the sample funds on average are operating at a sub-optimal level. Compared to the OTE results, there is nearly no improvement in minimum scores which are between 0.022 and 0.040. With very low minimum scores and a high SD (0.315 – 0.330), there is again a wide dispersion of PTE scores among funds.

Table 10 shows the SE scores which is a residual calculation from OTE (CRS) and PTE (VRS) scores. A difference between an OTE score and a PTE score indicates scale inefficiency. In other words, the OTE score has two components: one component indicates pure technical inefficiency and the other component indicates scale inefficiency. Pure technical inefficiency occurs because of the sub-optimal usage of inputs and outputs when compared to funds of similar size. Scale inefficiency occurs because of the sub-optimal scale. Funds of larger size may have scale advantage as compared to funds of smaller size. When a fund is scored 1 for SE, it exhibits scale efficiency and CRS. When a fund is scored less than 1 for SE, it has scale inefficiency and can exhibit either DRS or IRS. Therefore SE scores are more meaningful when presented against individual funds (see Appendix for an example). Aggregated or mean numbers serve the sole purpose of presenting an overall picture of scale efficiency. For instance, the average SE scores of all the funds in the sample range between 0.518 and 0.638 (Table 10). This indicates the funds in the sample exhibit high scale inefficiency.

Table 10. Scale efficiency (SE), individual years

Measure	**2005-6**	**2006-7**	**2007-8**	**2008-9**	**2009-10**	**2010-11**	**2011-12**
Efficient funds	14	12	7	6	7	7	9
Inefficient funds	169	171	176	177	176	176	174
Mean	0.634	0.638	0.558	0.607	0.527	0.518	0.636
Median	0.540	0.698	0.750	0.836	0.580	0.546	0.832
SD	0.250	0.231	0.262	0.257	0.276	0.261	0.277
Min	0.148	0.178	0.127	0.118	0.095	0.071	0.161
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000

In regards to trend, the average OTE scores for individual years over the period are lowest as compared to the PTE scores and the SE scores (0.588) because of both technical inefficiency and scale inefficiency (see Figure 4). OTE and PTE scores are lowest in 2007-8 and 2008-9, due to the effect of the GFC. OTE scores then improve however, PTE scores are down again in 2011-12 due to a slightly negative return in 2011-12 (Table 7).

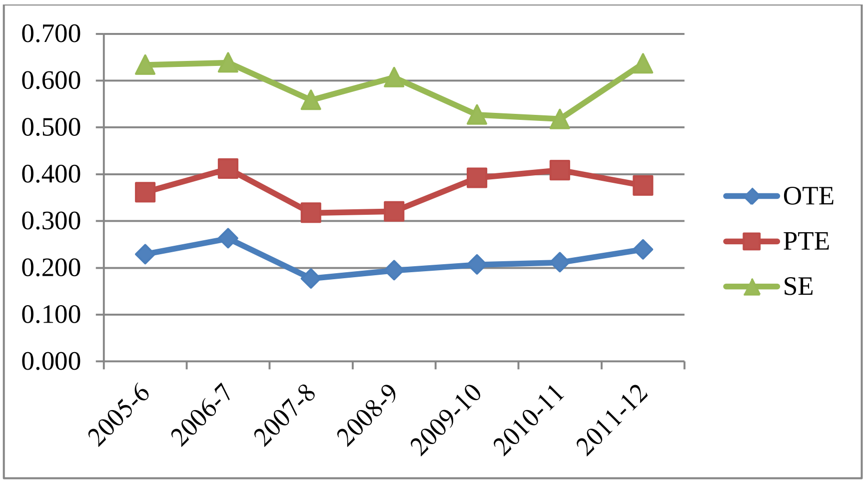

Figure 4. Overall technical efficiency (OTE), pure technical efficiency (PTE) and scale efficiency (SE) scores

Table 11 presents return to scale regions of all funds in the sample. Most funds fall into the DRS region, where an increase in inputs will proportionately result in a smaller increase in outputs, or a decrease in inputs will proportionately result in a smaller decrease in outputs. The number of funds in the DRS region range between 103 (56%) in 2007-8 and 2008-9 to 171 (93%) in 2009-10. The funds in the DRS region should therefore reduce their scale to improve efficiency (to approach CRS region). By contrast, the number of funds in the IRS region is much smaller, ranging from 5 (3%) in 2009-10 to 74 (40%) in 2008-2009. The number of funds in the IRS region appears higher in the years of poor investment returns, and consequently, reduction of net assets, as in 2007-8 and 2008-9. One explanation may be that because of the reduction of net assets, these funds are reduced in size and therefore, an increase in scale may render them more efficient.

Table 11. Return to scale regions, individual years, from 2005 to 2012

Return to scale region	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12
CRS	14	12	7	6	7	9	10
IRS	14	6	73	74	5	8	59
DRS	155	165	103	103	171	166	114

The following tables present the breaking down of PTE scores of inefficient funds into quintiles. A quintile is a statistical data set that represents 20% of the sample. Accordingly, the sample is divided into five equal subsets, from Quintile 1 to Quintile 5, as detailed in Table 12. PTE scores, instead of OTE scores, are selected for the quintile analysis because

PTE scores better reflect the characteristics of the sample funds. The sizes of the sample funds vary widely, from \$1.3 million to \$51.6 billion (Table 7). The PTE model takes into account fund size. That is, funds are only benchmarked against those of similar size. The quintile analysis of PTE scores provides more detailed information on the performance of the inefficient funds when they are classified in their subsets (Table 12).

Table 12. Classification of efficiency scores into quintiles

Measure	**PTE Score**	
	From	**To**
Quintile 1	0.800	0.999
Quintile 2	0.600	0.799
Quintile 3	0.400	0.599
Quintile 4	0.200	0.399
Quintile 5	0.001	0.199

Figure 5 and 6 provide statistical snapshots of the number of inefficient funds and average net assets per quintile. As per Figure 5, the number of inefficient funds is extremely high in the lower quintiles, such as Quintile 4 and 5. In particular, due to the effect of negative returns during the GFC, the number of inefficient funds is much higher in 2007-8 (99 funds) and 2008-9 (100 funds) as compared to the five remaining years. The average net assets are in general higher in Quintiles with high efficiency scores and lower in Quintiles with low efficiency scores. The Pearson correlation coefficient *r* between average net assets and efficiency scores is highly positive, at 0.707. Thus, there is a positive effect of fund size on efficiency.

It is noted that there is no fund classified into Quintile 1 (0.800 – 0.999) for the year 2009-10 (see Table 13). Verification has indicated that there is no error in data recording and processing. The event probably happens randomly and does not conflict with other data. During the year 2009-10, the number of efficient funds is the highest, at 32 funds. Further, Quintile 2 in that year is also the highest. Consequently, efficiency scores are either pushed upward to the efficiency area or downward to Quintile 2, as compared to other years.

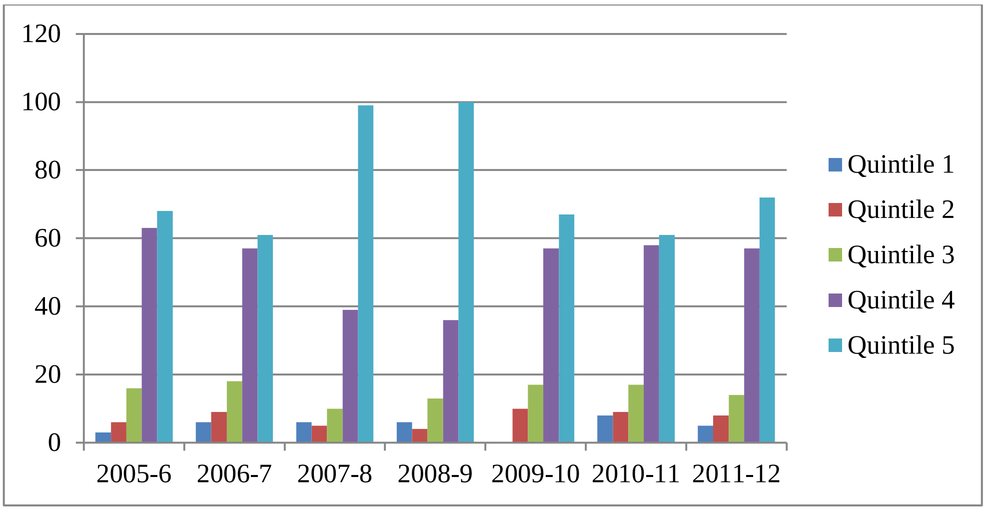

Figure 5. Inefficient funds per quintile, 2005-2012

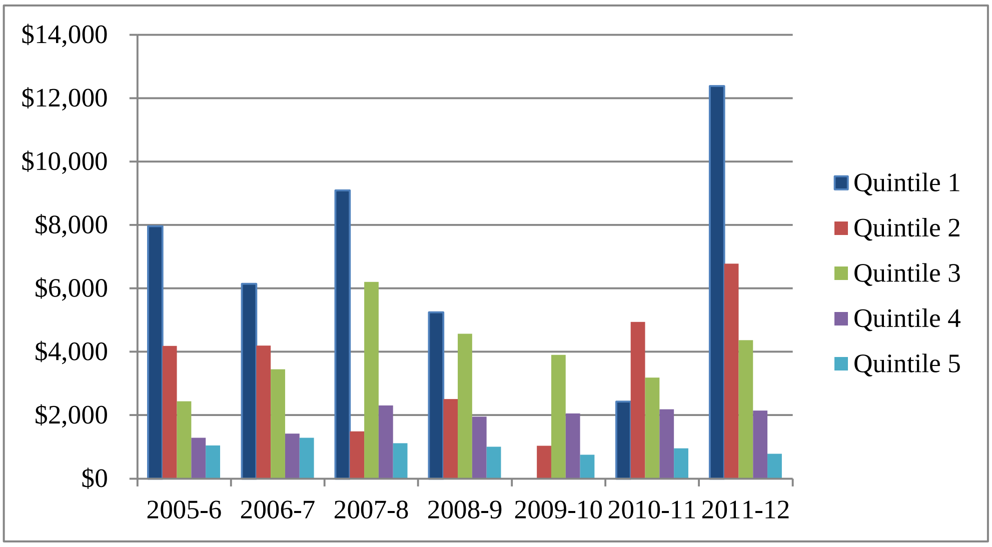

Figure 6. Average net assets ($ million) per quintile, 2005-2012

An important indicator generated by the DEA model is input or output target(s) for inefficient funds. If they achieve these targets, they would be operating on the efficient frontier. This information is probably best interpreted against individual funds for management purposes (see Appendix for an example). Table 13 above provides some highlights in input reduction target for the five quintiles. Quintile 5 which holds the most inefficient funds across the years has a range of total expenses reduction target from 88% to 90%. Quintile 4 holds the second most inefficient funds with a range of total expenses reduction target from 71% to 74%. Quintile 4 and 5 together make up about 65% - 75% of all the funds across the seven years. In brief, the majority of the funds are operating on a very low efficiency level as compared to the benchmark defined by the efficiency frontier. The efficiency targets are consequently very challenging for these funds.

Table 13. Quintile analysis of inefficient funds, 2005-2012

Measure	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12
Quintile 1	3	6	6	6	0	8	5
Average asset ($m)	7,962	6,147	9,094	5,241	n/a	2,431	12,379
Mean	0.904	0.893	0.897	0.906	n/a	0.901	0.847
Min	0.852	0.850	0.812	0.825	n/a	0.803	0.804
Max	0.992	0.941	0.970	0.998	n/a	0.994	0.909
Input target	-0.198	-0.154	-0.207	-0.199	n/a	-0.248	-0.219
Quintile 2	6	9	5	4	10	9	8
Average asset ($m)	4,184	4,200	1,489	2,508	1,037	4,943	6,777
Mean	0.716	0.650	0.648	0.711	0.741	0.708	0.694
Min	0.668	0.601	0.610	0.631	0.647	0.602	0.619
Max	0.777	0.735	0.700	0.763	0.794	0.800	0.790
Input target	-0.348	-0.399	-0.352	-0.289	-0.327	-0.379	-0.308
Quintile 3	16	18	10	13	17	17	14
Average asset ($m)	2,437	3,444	6,202	4,570	3,907	3,183	4,364
Mean	0.473	0.460	0.474	0.469	0.467	0.479	0.490
Min	0.404	0.402	0.416	0.401	0.410	0.415	0.412
Max	0.551	0.570	0.546	0.563	0.571	0.594	0.572
Input target	-0.532	-0.558	-0.537	-0.567	-0.562	-0.547	-0.510
Quintile 4	63	57	39	36	57	58	57
Average asset ($m)	1,291	1,418	2,310	1,958	2,056	2,182	2,144
Mean	0.273	0.293	0.276	0.271	0.291	0.269	0.292
Min	0.201	0.202	0.204	0.203	0.201	0.203	0.203
Max	0.390	0.396	0.390	0.385	0.396	0.393	0.398
Input target	-0.728	-0.709	-0.724	-0.739	-0.724	-0.740	-0.709
Quintile 5	68	61	99	100	67	61	72
Average asset ($m)	1,041	1,292	1,120	1,005	749	959	780
Mean	0.109	0.117	0.100	0.105	0.117	0.123	0.118
Min	0.039	0.049	0.028	0.026	0.033	0.022	0.040
Max	0.195	0.193	0.200	0.198	0.199	0.198	0.195
Input target	-0.891	-0.883	-0.900	-0.897	-0.887	-0.879	-0.882

The last part of this section is dedicated to sector analysis, in particular, how the four fund types, corporate, industry, public sector and retail perform in efficiency. Table 14 presents the average efficiency scores per fund type for individual years. Public sector funds perform the best, followed by corporate and retail. Industry funds perform the worst. Nevertheless, there is no major difference in the average efficiency score between the four fund types. See Table 14.

Table 14. Average PTE scores per sector, individual years, from 2005 to 2012

Sector	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12	Average
Corporate	0.441	0.494	0.267	0.319	0.478	0.511	0.354	0.409
Industry	0.372	0.360	0.249	0.241	0.304	0.312	0.364	0.315
Public sector	0.379	0.531	0.430	0.446	0.450	0.453	0.557	0.464
Retail	0.361	0.381	0.365	0.349	0.399	0.412	0.397	0.381

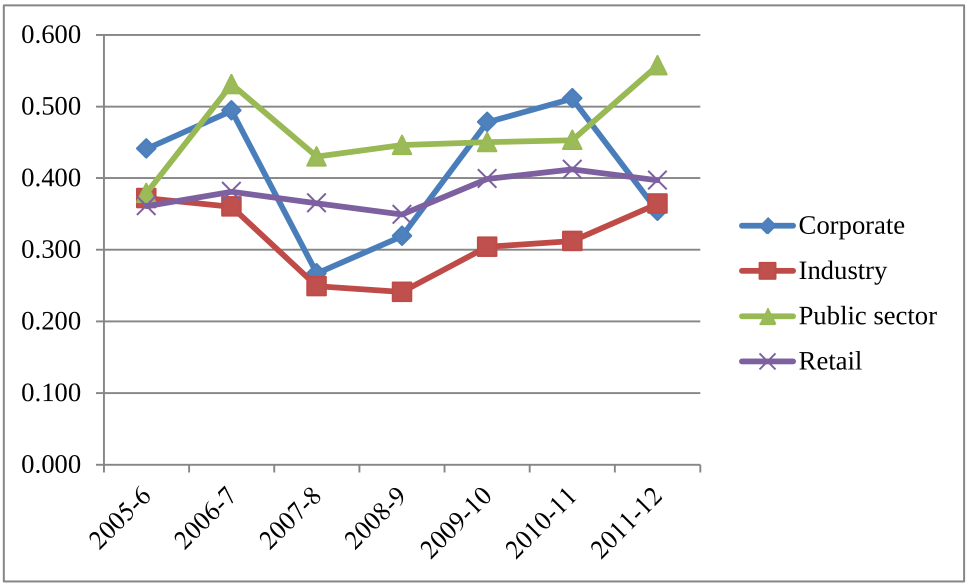

Figure 7. Average efficiency scores per sector, individual years from 2005 to 2012

Figure 7 shows that corporate funds experience the most volatility in efficiency scores, which are down significantly during the GFC (2007-8 and 2008-9). This is possibly because corporate funds are managed by multinational companies which may have more dynamic investment activities. Industry funds appear to be the worst performer. Industry funds are also more negatively affected by the GFC. Retail funds show the least volatility. This is possibly due to more investments in “blue chip” shares and term deposits. Public sector funds are the best performer. Explanations as to why certain sectors perform in certain trends will be sought in the second phase of this research (i.e. correlation between efficiency scores and other fund characteristics).

Table 15 shows the percentage of efficient funds per fund type. On average, 20% of retail funds are efficient as compared to 15% of corporate and public sector. Industry funds perform the worst with 8% of its funds being efficient. One explanation for the high number of retail funds being efficient may be the high member accounts and net assets (net assets and member accounts are two of three outputs selected for the DEA runs). This is by contrast with industry funds which have lower net assets. As for efficient funds per total sample, retail funds are again leading. This is partly due to the highest weight of retail funds in the sample (43%). The number of public sector funds is smallest (8.2%). This is one of the factors that leads to the lowest number of efficient funds. The average number of efficient funds in the sample across the seven years is 15%. This again indicates that the majority of the sample funds are not efficient.

Table 15. Proportion of efficient funds per fund type and total sample, 2005-2012

Measure	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12	Average
Efficient funds per fund type (%)								
Corporate	15.38	23.08	15.38	15.38	15.38	17.95	5.13	15.38
Industry	3.92	7.84	11.76	11.76	7.84	7.84	3.92	7.84
Public sector	6.67	6.67	6.67	6.67	26.67	20.00	33.33	15.24
Retail	23.08	23.08	14.10	14.10	23.08	20.51	23.08	20.15
Efficient funds per sample (%)								
Corporate	3.28	4.92	3.28	3.28	3.28	3.83	1.09	3.28
Industry	1.09	2.19	3.28	3.28	2.19	2.19	1.09	2.19
Public sector	0.55	0.55	0.55	0.55	2.19	1.64	2.73	1.25
Retail	9.84	9.84	6.01	6.01	9.84	8.74	9.84	8.59
Total	14.75	17.49	13.11	13.11	17.49	16.39	14.75	15.30

4.2.2 Efficiency scores for the period, 2005-2012

This section discusses efficiency based on the DEA run using average values of expenses, net assets and member accounts for the whole period of 2005-2012. Multiple-period return is calculated using geometric averages. SD of return is included as an additional input to take into account fluctuation of return over the period.

Table 16 shows the results on PTE scores and input targets for the period 2005-2012. The number of efficient funds is 27 (15%), falling into the result range for individual years. Including SD of return as an additional input does not change the scores dramatically. The average efficiency score is similarly low, at 0.405 for the period. The minimum score of 0.046 is only a little higher as compared to individual years' average (0.034). Apart from total expenses reduction targets, this DEA run also provides risk reduction targets represented by the SD of return. The number of inefficient funds, again, concentrates highly in lower quintiles, such as Quintile 4 and 5. As would be expected, these quintiles have challenging input reduction targets if they wish to be efficient. Higher reduction targets for risk, as compared to expenses, are present in all quintiles except for Quintile 2. For management purposes, input reduction targets are best interpreted against individual funds (see Appendix).

Table 16. PTE scores and input targets for the period of 2005-2012.

Measure	All funds	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Efficient funds	27	0	0	0	0	0
Inefficient funds	156	10	4	26	49	67
Mean	0.405	0.903	0.703	0.494	0.278	0.132
Min	0.046	0.808	0.632	0.402	0.204	0.046
Max	1.000	0.983	0.787	0.578	0.386	0.198
Input targets						
SD of return	n/a	-0.337	-0.484	-0.656	-0.801	-0.894
Total expenses	n/a	-0.162	-0.607	-0.502	-0.754	-0.826

Table 17 and Figure 8 present the mean OTE, PTE and SE scores for individual years and the period. OTE scores for the period improve as compared to OTE scores for individual years. By contrast, there is no noticeable difference between PTE for individual years and the period. PTE model scores funds against funds of similar size, which may create a "smoothing" effect.

Table 17. Efficient funds and efficiency scores, individual years and period

Measure	2005-6	2006-7	2007-8	2008-9	2009-10	2010-11	2011-12	Period
Efficient funds								
OTE	14	12	7	6	7	7	9	13
PTE	27	32	24	24	32	30	27	27
Mean efficiency scores								
OTE	0.229	0.263	0.177	0.194	0.207	0.212	0.239	0.335
PTE	0.361	0.412	0.317	0.320	0.392	0.409	0.376	0.405
SE	0.634	0.638	0.558	0.607	0.527	0.518	0.636	0.827

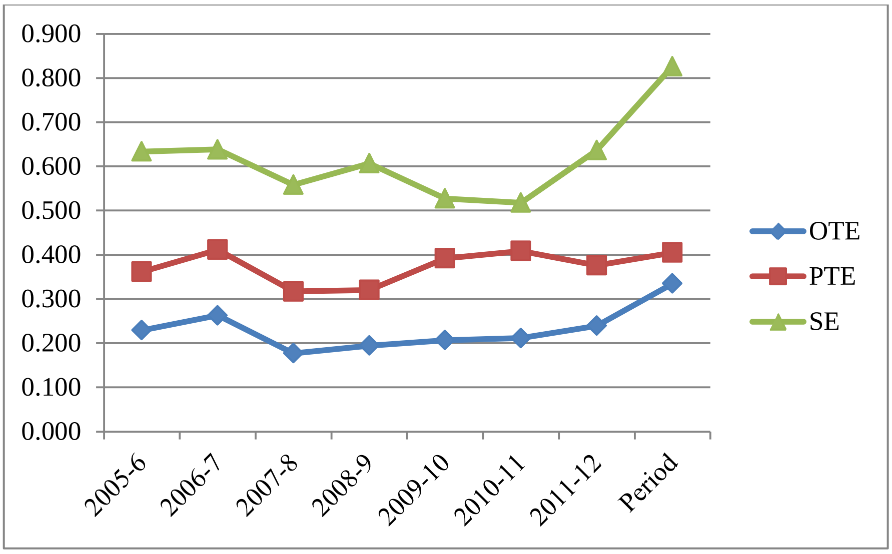

Figure 8. Mean OTE, PTE and SE scores for individual years and the period

Table 18 shows efficiency scores and proportion of efficient funds per fund type. Average scores are low, ranging from 0.326 to 0.504. Consistent with results in individual period DEA runs where SD of return is not taken into account, industry funds have the lowest average efficiency score, and public sector funds have the highest average efficiency score. Retail funds have higher efficiency scores as compared to individual periods. Industry funds, however, have a higher proportion of efficient funds per fund type. These changes warrant a case for further investigation in the second phase of this research.

Table 18. Efficient funds per fund type, period 2005-2012

Sector	Average efficiency score	Number of efficient funds	Efficient funds per sector (%)	Efficient funds per sample (%)
Corporate	0.378	4	10.26	2.19
Industry	0.326	3	20.00	1.64
Public sector	0.504	3	14.29	1.64
Retail	0.451	17	21.79	9.29

5 Summary and conclusions

5.1 Summary of findings

In this report, sample funds are scored in efficiency using the OTE and PTE models. The efficiency scores are estimated for individual years and for the period 2005-2012. Efficient funds, where minimal inputs are used for a given level of outputs, form the efficiency frontier. Inefficient funds are scored relative to this frontier. With individual year’s DEA runs, the inputs are investment expenses; management, administration, trustees' fees; operating expenses and total expenses. The outputs are average net assets, member accounts and return. With the period DEA run, average values across the seven years are used. Similar inputs and outputs are selected except for an additional input, SD of return. This input is included to take into account fluctuation of return over the period. The sample size is 183 funds, covering four fund types: corporate, industry, public sector and retail.

The number of efficient funds is very low using the OTE model – CRS. The average number of efficient funds per year is 9 (5%) under the individual runs. The total efficient funds are 13 (7%) under the period run. This is due to the effect of size and scope on efficiency performance. The scope of expenses, size of net assets and member accounts vary greatly among funds. The OTE model does not take into account scope and size; therefore small funds may be disadvantaged compared to large funds.

The number of efficient funds is much higher using the PTE model – VRS. The average number of efficient funds per year is 28 (15%) under the individual runs. The total efficient funds are 27 (15%) under the period run. The result obtained from the individual runs appears consistent with that obtained from the period run. Therefore, the PTE/VRS approach is probably a better option in this situation, when scope and size vary widely among funds. Based on the PTE model, input reduction targets are then calculated for inefficient funds in quintile analysis. Most of the inefficient funds have very low efficiency scores and concentrate in the lower quintiles such as Quintile 4 (0.200 – 0.399) and 5 (0.001 – 0.199). Consequently, input reduction targets are significantly high for these two quintiles. Similarly, input reduction targets are high under the period run. To be efficient, Quintile 4 funds need to reduce 75% of total expenses (-0.754) and 80% of volatility of return (-0.801). Quintile 5 funds need to reduce on average 83% of total expenses (-0.824) and 89% of volatility of return (-0.894). For management purposes, it is probably best to interpret both efficiency scores and input reduction targets on an individual fund basis (see Appendix).

In regards to performance per fund type, public sector funds have the highest efficiency scores in both individual year runs and period run (0.464 and 0.504 respectively); industry funds have the lowest efficiency scores (0.315 and 0.326 respectively). Corporate funds have a lower average period score (0.378) than individual year score (0.409). This is probably due to the higher SD of return.

The results on efficiency scores indicate that most of the sample funds are inefficient relative to the efficiency frontier established by efficient funds. The efficiency scores vary widely with minimum score of 0.03 as compared to a maximum score of 1. It could be concluded that the efficiency performance of Australian superannuation funds in the sample has very low uniformity.

5.2 Implications

This research looks into the relative economic efficiency of Australian superannuation funds using the DEA model. It is probably one of the very few studies on Australian superannuation funds using an operational management method. This research introduces an effective performance ranking and benchmarking alternative, alongside the more traditional models such as risk-adjusted return commonly used for managed funds and pension funds.

The research findings indicate that performance quality in regards to economic efficiency varies enormously among the sample funds. The number of inefficient funds with low efficiency scores is high. The findings provide important information to superannuation funds regulators and industry practitioners. That is, there is plenty of scope for improvement to low-scored inefficient funds when they are compared to efficient funds. As all the sample funds operate in the same market and under the same regulatory framework, efficient funds could represent achievable benchmarks of performance for inefficient funds. Investigations into efficient funds' operational characteristics can also be done so as to draw information on 'best practices', which could be promoted in the industry.

Expense reduction targets are found to be challenging for the majority of the sample funds. This shows that fees and charges may be excessive. Mandatory disclosure of fees and charges in a comparable manner may be necessary to justify fee payments and to address transparency and accountability issues. There are benefits of scope and size of operation as evidenced by the large difference in efficiency scores when funds are assessed against funds of similar size and when funds are assessed regardless of size. These findings support the argument on the benefits of scale economies in superannuation fund operations. Operating expenses, which represent a very large proportion of total expenses of superannuation funds, could be reduced if very small size superannuation funds were consolidated.

5.3 Limitations of the research

Due the unavailability of data in time to complete the report, liquidity which is calculated from cash and cash equivalents reported in financial reports, has been omitted from the input set. The difficulties in collecting financial reports of the sample funds from publicly available sources provides a case for better regulation of reporting practices in the superannuation industry.

DEA scores generated in this report, despite being useful information, are not linked to fund characteristics, reporting and governance practices, which have been highlighted in recent studies. This gap could be filled by future research.

5.4 Extension of the research

This research is Part 1 of a wider research project that links efficiency scores with fund characteristics which pertain to operating, governance and reporting practices. Governance practices have been identified in some studies as one of the influencing factors on performance of pension funds. Financial reporting practices in the superannuation industry have not been well explored previously. The extension of the research will fill an important literature gap.

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Appendix

Pure Technical Efficiency (PTE), Overall Technical Efficiency (OTE) Scores,
Region to Scale Region and Input Reduction Targets (Expense and Risk of Return)
Period 2005-2012

Inputs:	Investments expenses Operating expenses Management, administration and director fees Total expenses Volatility (SD) of return
Outputs:	Average net asset Member account Multiple period return

No	Fund	PTE (VRS)	OTE (CRS)	SE	RTS	Expense Target	SD Target
1	ACP Retirement Fund	0.247	0.230	0.930	Decreasing	-0.818	-0.927
2	Advance Retirement Savings Account	0.700	0.698	0.997	Increasing	-0.296	0.000
3	Advance Retirement Suite	0.992	0.742	0.748	Decreasing	-0.368	-0.844
4	Alcoa of Australia Retirement Plan	0.528	0.335	0.635	Decreasing	-0.826	-0.891
5	AMG Universal Super	0.154	0.143	0.925	Decreasing	-0.926	-0.935
6	AMP Superannuation Savings Trust	1.000	0.173	0.173	Decreasing	0.000	0.000
7	Aon Eligible Rollover Fund	0.078	0.077	0.998	Increasing	-0.841	-0.689
8	AON Master Trust	0.096	0.047	0.487	Decreasing	-0.923	-0.788
9	ASC Superannuation Fund	0.271	0.259	0.954	Decreasing	-0.835	-0.929
10	ASGARD Independence Plan Division Four	0.050	0.045	0.904	Decreasing	-0.912	-0.906
11	ASGARD Independence Plan Division One	0.042	0.038	0.910	Decreasing	-0.933	-0.827
12	ASGARD Independence Plan Division Two	0.091	0.023	0.255	Decreasing	-0.783	-0.482
13	AusBev Superannuation Fund	0.192	0.133	0.695	Decreasing	-0.855	-0.935
14	Auscoal Superannuation Fund	0.540	0.235	0.436	Decreasing	-0.720	-0.188
15	Australia Post Superannuation Scheme	0.692	0.293	0.424	Decreasing	0.000	0.000
16	Australian Catholic Superannuation and Retirement Fund	0.299	0.134	0.449	Decreasing	-0.836	-0.463
17	Australian Christian Superannuation Fund	0.302	0.301	0.999	Decreasing	-0.918	-0.884
18	Australian Eligible Rollover Fund	1.000	0.219	0.219	Decreasing	-0.069	-0.078
19	Australian Ethical Retail Superannuation Fund	0.065	0.054	0.833	Decreasing	-0.954	-0.925
20	Australian Government Employees Superannuation Trust	0.312	0.156	0.500	Decreasing	-0.734	-0.472
21	Australian Meat Industry Superannuation Trust	0.284	0.156	0.549	Decreasing	-0.827	-0.895
22	Australian Superannuation Savings Employment Trust - Asset Super	0.223	0.106	0.477	Decreasing	-0.830	-0.820
23	Australian YMCA Superannuation Fund	0.220	0.182	0.827	Decreasing	-0.826	-0.863
24	AustralianSuper	1.000	0.255	0.255	Decreasing	0.000	0.000
25	Australia's Unclaimed Super Fund	1.000	0.469	0.469	Decreasing	0.000	0.000
26	Austsafe Superannuation Fund	0.453	0.238	0.526	Decreasing	-0.791	-0.883
27	Avanteos Superannuation Trust	0.064	0.027	0.417	Decreasing	-0.911	-0.743
28	AvSuper Fund	0.224	0.132	0.588	Decreasing	-0.894	-0.918
29	Bankwest Staff Superannuation Plan	0.310	0.159	0.511	Decreasing	-0.729	-0.879
30	Betros Bros Superannuation Fund No 2	1.000	1.000	1.000	Constant	0.000	0.000
31	BHP Billiton Superannuation Fund	0.536	0.263	0.490	Decreasing	-0.683	-0.608
32	Bluescope Steel Superannuation Fund	0.668	0.336	0.503	Decreasing	-0.504	-0.740
33	Boc Gases Superannuation Fund	0.308	0.182	0.592	Decreasing	-0.810	-0.949

34	Bookmakers Superannuation Fund	0.164	0.163	0.993	Decreasing	-0.939	-0.954
35	BT Classic Lifetime	0.059	0.024	0.410	Decreasing	-0.929	-0.873
36	BT Lifetime Super	0.120	0.052	0.438	Decreasing	-0.857	-0.618
37	BT Superannuation Savings Fund	1.000	1.000	1.000	Constant	0.000	0.000
38	Building Unions Superannuation Scheme (Queensland)	0.292	0.136	0.467	Decreasing	-0.738	-0.727
39	Canegrowers Retirement Fund	0.172	0.167	0.971	Decreasing	-0.889	-0.614
40	Care Super	0.285	0.141	0.493	Decreasing	-0.773	-0.295
41	Catholic Superannuation Fund	0.386	0.214	0.554	Decreasing	-0.807	-0.369
42	Christian Super	0.194	0.119	0.614	Decreasing	-0.929	-0.892
43	Clough Superannuation Fund	0.288	0.263	0.913	Decreasing	-0.866	-0.947
44	Club Plus Superannuation Scheme	0.390	0.201	0.517	Decreasing	-0.736	-0.770
45	Club Super	0.161	0.105	0.655	Decreasing	-0.869	-0.926
46	Coal Industry Superannuation Fund	0.274	0.239	0.872	Decreasing	-0.775	-0.935
47	Colonial First State FirstChoice Superannuation Trust	0.260	0.059	0.226	Decreasing	-0.597	-0.026
48	Colonial First State Rollover & Superannuation Fund	0.158	0.041	0.260	Decreasing	-0.870	-0.400
49	Colonial Super Retirement Fund	0.125	0.038	0.305	Decreasing	-0.804	-0.459
50	Commerce Industry Superannuation Fund	0.226	0.206	0.913	Increasing	-0.882	-0.802
51	Commonwealth Life Personal Superannuation Fund	1.000	0.426	0.426	Decreasing	0.000	0.000
52	Concept One Superannuation Plan	0.148	0.125	0.847	Decreasing	-0.888	-0.776
53	Construction & Building Unions Superannuation	0.406	0.100	0.247	Decreasing	-0.574	-0.354
54	DBP Master Superannuation Plan	0.746	0.746	1.000	Increasing	-0.729	-0.923
55	DPM Retirement Service	0.056	0.056	0.988	Increasing	-0.922	-0.899
56	EmPlus Superannuation Fund	0.144	0.099	0.686	Increasing	-0.914	-0.766
57	Energy Industries Superannuation Scheme-Pool A	0.111	0.060	0.536	Decreasing	-0.911	-0.932
58	Energy Industries Superannuation Scheme-Pool B	0.227	0.101	0.446	Decreasing	-0.857	-0.798
59	Energy Super	0.523	0.259	0.495	Decreasing	-0.801	-0.438
60	equipsuper	0.300	0.138	0.458	Decreasing	-0.850	-0.235
61	EquitySuper	0.071	0.038	0.535	Decreasing	-0.919	-0.929
62	ExxonMobil Superannuation Plan	0.201	0.123	0.609	Decreasing	-0.940	-0.950
63	Fiducian Superannuation Fund	0.053	0.023	0.439	Decreasing	-0.957	-0.953
64	Fire and Emergency Services Superannuation Fund	0.404	0.333	0.826	Decreasing	-0.874	-0.872
65	First Quest Retirement Service	0.043	0.024	0.550	Decreasing	-0.940	-0.905
66	First State Superannuation Scheme	0.852	0.210	0.246	Decreasing	0.000	0.000
67	First Super	0.168	0.089	0.528	Decreasing	-0.828	-0.820
68	Freedom of Choice Superannuation Masterfund	0.091	0.070	0.767	Decreasing	-0.939	-0.919
69	General Retirement Plan	0.079	0.069	0.878	Decreasing	-0.659	-0.867
70	Goldman Sachs & JBWere Superannuation Fund	1.000	0.984	0.984	Decreasing	0.000	0.000
71	Greater Staff Superannuation Fund	1.000	1.000	1.000	Constant	0.000	0.000
72	Grosvenor Pirie Master Superannuation Fund Series 2	0.333	0.287	0.860	Decreasing	-0.867	-0.882
73	Grow Super	0.132	0.114	0.863	Decreasing	-0.764	-0.902
74	Guild Retirement Fund	0.052	0.033	0.639	Decreasing	-0.823	-0.820
75	Harwood Superannuation Fund	0.289	0.171	0.590	Decreasing	-0.783	-0.867
76	Health Employees Superannuation Trust Australia	0.714	0.202	0.282	Decreasing	-0.363	-0.317
77	Health Industry Plan	0.167	0.085	0.511	Decreasing	-0.893	-0.942
78	Holden Employees Superannuation Fund	0.307	0.152	0.495	Decreasing	-0.645	-0.830
79	HOSTPLUS Superannuation Fund	0.350	0.117	0.334	Decreasing	-0.643	-0.588
80	IAG & NRMA Superannuation Plan	0.424	0.269	0.634	Decreasing	-0.864	-0.920
81	Intrust Super Fund	0.253	0.128	0.504	Decreasing	-0.848	-0.886
82	IOOF Portfolio Service Superannuation Fund	0.055	0.023	0.422	Decreasing	-0.729	-0.741
83	IRIS Superannuation Fund	0.072	0.035	0.486	Decreasing	-0.886	-0.809
84	Kellogg Retirement Fund	0.184	0.171	0.932	Decreasing	-0.894	-0.784
85	Labour Union Co-Operative Retirement Fund	0.139	0.066	0.473	Decreasing	-0.880	-0.618
86	Law Employees Superannuation Fund	0.214	0.214	0.998	Increasing	-0.892	-0.908
87	legalsuper	0.245	0.138	0.563	Decreasing	-0.837	-0.884
88	Lifefocus Superannuation Fund	0.088	0.088	0.996	Increasing	-0.962	-0.940

89	Lifetime Superannuation Fund	0.217	0.178	0.818	Decreasing	-0.890	-0.955
90	Local Authorities Superannuation Fund	0.232	0.105	0.453	Decreasing	-0.757	-0.261
91	Local Government Superannuation Scheme	0.298	0.161	0.540	Decreasing	-0.609	-0.378
92	Local Government Superannuation Scheme	0.298	0.161	0.540	Decreasing	-0.547	-0.311
93	Local Government Superannuation Scheme - Pool A	0.141	0.067	0.477	Decreasing	-0.875	-0.612
94	Local Government Superannuation Scheme - Pool B	0.251	0.105	0.418	Decreasing	-0.834	-0.634
95	MacMahon Employees Superannuation Fund	0.262	0.248	0.947	Decreasing	-0.912	-0.904
96	Macquarie ADF Superannuation Fund	1.000	1.000	1.000	Constant	0.000	0.000
97	Macquarie Superannuation Plan	0.118	0.055	0.467	Decreasing	-0.720	-0.693
98	Managed Australian Retirement Fund	0.210	0.183	0.874	Decreasing	-0.920	-0.924
99	Map Superannuation Plan	0.088	0.044	0.496	Decreasing	-0.893	-0.893
100	Maritime Super	0.211	0.089	0.423	Decreasing	-0.847	-0.515
101	Meat Industry Employees Superannuation Fund	0.250	0.168	0.671	Decreasing	-0.823	-0.923
102	Media Super	0.287	0.151	0.525	Decreasing	-0.811	-0.709
103	Mercer Portfolio Service Superannuation Plan	0.078	0.033	0.425	Decreasing	-0.916	-0.764
104	Mercer Super Trust	1.000	0.253	0.253	Decreasing	0.000	0.000
105	Mercy Super	0.347	0.185	0.534	Decreasing	-0.845	-0.919
106	Military Superannuation & Benefits Fund No 1	0.462	0.276	0.597	Decreasing	-0.526	-0.162
107	Millennium Master Trust	0.082	0.072	0.882	Decreasing	-0.928	-0.892
108	MLC Superannuation Fund	1.000	1.000	1.000	Constant	-0.245	-0.251
109	MTAA Superannuation Fund	0.312	0.133	0.427	Decreasing	-0.751	-0.516
110	National Australia Bank Group Superannuation Fund A	1.000	0.423	0.423	Decreasing	0.000	0.000
111	National Preservation Trust	1.000	0.231	0.231	Decreasing	0.000	0.000
112	Nationwide Superannuation Fund	0.127	0.077	0.610	Decreasing	-0.857	-0.917
113	Netwealth Superannuation Master Fund	0.054	0.045	0.834	Decreasing	-0.938	-0.818
114	New South Wales Electrical Superannuation Scheme	0.220	0.146	0.666	Decreasing	-0.855	-0.877
115	Newcastle Permanent Superannuation Plan	1.000	1.000	1.000	Constant	0.000	0.000
116	NGS Super	0.274	0.131	0.480	Decreasing	-0.823	-0.470
117	Nufarm Employees Superannuation Trust	0.466	0.384	0.824	Decreasing	-0.552	-0.940
118	Oasis Superannuation Master Trust	0.044	0.019	0.428	Decreasing	-0.864	-0.886
119	O-I Australia Superannuation Fund	0.334	0.279	0.836	Decreasing	-0.799	-0.945
120	OnePath Masterfund	0.867	0.128	0.148	Decreasing	-0.236	0.000
121	Oracle Superannuation Plan	1.000	1.000	1.000	Constant	-0.561	-0.948
122	Perpetual WealthFocus Superannuation Fund	0.344	0.146	0.425	Decreasing	-0.710	-0.775
123	Perpetual's Select Superannuation Fund	0.440	0.198	0.450	Decreasing	-0.836	-0.844
124	Pitcher Retirement Plan	0.222	0.198	0.896	Decreasing	-0.875	-0.912
125	Plan B Eligible Rollover Fund	1.000	1.000	1.000	Constant	0.000	0.000
126	Plan B Superannuation Fund	1.000	1.000	1.000	Constant	-0.607	-0.341
127	Plum Superannuation Fund	0.369	0.114	0.309	Decreasing	-0.500	-0.275
128	Premiumchoice Retirement Service	0.039	0.032	0.830	Decreasing	-0.936	-0.898
129	Prime Superannuation Fund	0.218	0.102	0.467	Decreasing	-0.863	-0.859
130	Professional Associations Superannuation Fund	0.161	0.083	0.515	Decreasing	-0.855	-0.649
131	Public Eligible Rollover Fund	1.000	1.000	1.000	Constant	-0.213	-0.905
132	Qantas Superannuation Plan	1.000	0.498	0.498	Decreasing	-0.434	-0.044
133	Quadrant Superannuation Scheme	0.086	0.039	0.459	Decreasing	-0.938	-0.942
134	Queensland Independent Education & Care Superannuation Trust	0.189	0.099	0.524	Decreasing	-0.866	-0.936
135	Rei Super	0.226	0.114	0.504	Decreasing	-0.836	-0.944
136	Reserve Bank of Australia Officers Superannuation Fund	1.000	1.000	1.000	Constant	0.000	0.000
137	Retail Employees Superannuation Trust	0.777	0.174	0.223	Decreasing	0.000	0.000
138	Retirement Portfolio Service	0.070	0.030	0.435	Decreasing	-0.912	-0.749
139	Rio Tinto Staff Superannuation Fund	0.377	0.194	0.516	Decreasing	-0.793	-0.648
140	Russell Supersolution Master Trust	0.227	0.098	0.432	Decreasing	-0.756	-0.372
141	Smartsave 'Member's Choice' Superannuation Master Plan	0.039	0.036	0.910	Decreasing	-0.952	-0.910
142	SMF Eligible Rollover Fund	0.138	0.133	0.964	Decreasing	0.000	-0.366

143	State Super Fixed Term Pension Plan	0.190	0.187	0.989	Increasing	0.000	0.000
144	State Super Retirement Fund	0.073	0.031	0.419	Decreasing	-0.710	-0.625
145	Statewide Superannuation Trust	0.134	0.068	0.504	Decreasing	-0.878	-0.701
146	Suncorp Master Trust	0.202	0.160	0.794	Decreasing	-0.843	-0.269
147	Sunsuper Superannuation Fund	0.431	0.132	0.306	Decreasing	-0.567	-0.571
148	Super Eligible Rollover Fund	0.142	0.128	0.899	Decreasing	-0.880	-0.736
149	Super Safeguard Fund	1.000	1.000	1.000	Constant	0.000	0.000
150	Super Synergy Fund	0.146	0.145	0.995	Increasing	-0.901	-0.910
151	SuperTrace Eligible Rollover Fund	1.000	1.000	1.000	Constant	0.000	0.000
152	Symetry Personal Retirement Fund	0.052	0.023	0.437	Decreasing	-0.933	-0.747
153	Synergy Superannuation Master Fund	0.052	0.022	0.426	Decreasing	-0.936	-0.785
154	Tasplan Superannuation Fund	0.249	0.118	0.475	Decreasing	-0.813	-0.802
155	Taxi Industry Superannuation Fund	0.139	0.137	0.984	Increasing	-0.907	-0.903
156	Telstra Superannuation Scheme	0.551	0.131	0.238	Decreasing	-0.489	-0.320
157	The Allied Unions Superannuation Trust (Queensland)	0.177	0.130	0.731	Decreasing	-0.888	-0.839
158	The Bendigo Superannuation Plan	0.125	0.081	0.645	Decreasing	-0.786	-0.838
159	The Employees Productivity Award Superannuation Trust	0.251	0.216	0.860	Decreasing	0.000	0.000
160	The Executive Superannuation Fund	0.154	0.085	0.555	Decreasing	-0.870	-0.927
161	The Flexible Benefits Super Fund	0.407	0.204	0.502	Decreasing	-0.612	-0.842
162	The Industry Superannuation Fund	0.115	0.103	0.896	Decreasing	-0.896	-0.766
163	The ISPF Eligible Rollover Fund	0.381	0.380	0.997	Decreasing	-0.471	-0.410
164	The Portfolio Service Retirement Fund	0.056	0.024	0.421	Decreasing	-0.804	-0.771
165	The Retirement Plan	0.061	0.026	0.418	Decreasing	-0.770	-0.826
166	The State Bank Supersafe Approved Deposit Fund	0.078	0.078	0.998	Increasing	0.000	0.000
167	The Super Money Eligible Rollover Fund (SMERF)	1.000	1.000	1.000	Constant	0.000	0.000
168	The Transport Industry Superannuation Fund	0.108	0.100	0.929	Decreasing	-0.929	-0.901
169	The Universal Super Scheme	1.000	0.240	0.240	Decreasing	0.000	0.000
170	Toyota Australia Superannuation Plan	0.195	0.166	0.855	Decreasing	-0.750	-0.925
171	Toyota Employees Superannuation Trust	0.201	0.111	0.552	Decreasing	-0.782	-0.922
172	TWU Superannuation Fund	0.241	0.110	0.456	Decreasing	-0.867	-0.664
173	Unisuper	1.000	0.216	0.216	Decreasing	0.000	0.000
174	United Technologies Corporation Retirement Plan	0.234	0.120	0.512	Decreasing	-0.681	-0.784
175	Victorian Superannuation Fund	0.270	0.120	0.444	Decreasing	-0.637	-0.170
176	Virgin Superannuation	0.201	0.179	0.891	Decreasing	-0.777	-0.903
177	WA Local Government Superannuation Plan	0.213	0.104	0.486	Decreasing	-0.876	-0.872
178	Water Corporation Superannuation Plan	0.367	0.366	0.996	Increasing	-0.744	-0.925
179	Westpac Mastertrust - Superannuation Division	1.000	0.292	0.292	Decreasing	0.000	0.000
180	Westpac Personal Superannuation Fund	0.264	0.140	0.531	Decreasing	-0.531	-0.799
181	William Adams Employees Superannuation Fund	0.445	0.440	0.990	Increasing	-0.782	-0.924
182	Worsley Alumina Superannuation Fund	0.547	0.367	0.670	Decreasing	-0.667	-0.469
183	Zurich Master Superannuation Fund	0.115	0.051	0.441	Decreasing	-0.850	-0.590