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Understanding self-managed super fund performance

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Executive summary

This report presents findings from a joint research venture between the SMSF Association and the University of Adelaide's International Centre for Financial Services (ICFS). The underlying work examines the financial performance of a large sample of self-managed superannuation funds (SMSFs) over the period 2017–2019. In total we use data on over 318,000 unique SMSFs, comprising almost 498,000 unique performance observations.

The key findings of the research are outlined below:

- SMSF return on assets (ROA) persistently underestimates actual SMSF performance as measured via rates of return (ROR), with evidence suggesting that this gap is widening over time.
- After correction, annualised median SMSF underperformance relative to APRA funds either significantly reduces or decreases to zero, depending on the period examined.
- SMSFs generate greater variation in fund-level performance relative to APRA funds, a feature of the significant differences in population characteristics between the two cohorts.
- We recommend that superannuation performance summaries include visualisations of fund performance results, such as return distributions, alongside existing numerical measures.
- We recommend that, if superannuation performance summaries include visualisations based on return distributions, Bhattacharyya coefficient values for performance similarity are presented alongside traditional numerical measures to aid end users.
- The notion that SMSFs with balances under $500,000 deliver materially lower returns, on average, than larger SMSFs, is not supported by the evidence we present. Our results suggest that it is more appropriate to calibrate this threshold at $200,000.
- On aggregate, SMSFs with more diversified asset allocations achieve higher returns.
- Larger SMSFs, with net assets in excess of $200,000, that are not concentrated in cash and other fixed income securities, outperform APRA funds in two of the three years between 2017 and 2019.

Section 1: Project overview and objectives

This report is the result of a joint research venture between the SMSF Association (SMSFA) and the University of Adelaide's International Centre for Financial Services (ICFS). The project is targeted at examining the financial performance of self-managed superannuation funds (SMSFs), complementing existing work in this space on SMSF cost efficacy (Rice Warner, 2020), as well as earlier publications from the Productivity Commission (2018a, 2018b). The research represents a key extension, building on the results presented by the Productivity Commission and correcting for the existing incompatibility in investment performance metrics between SMSFs and Australian Prudential Regulation Authority (APRA) regulated funds.

Investment performance comparisons between SMSFs and APRA funds have historically been difficult to make. APRA relies on information collected from financial statements to generate a Rate of Return (ROR) for ARPA funds, whereas SMSFs are regulated by the Australian Taxation Office (ATO), which produces a Return on Assets (ROA) for SMSFs based on their annual tax returns. Direct comparisons between the statistics published by APRA and the ATO should therefore be avoided since ROR and ROA do not benchmark for one another appropriately. Resolving this issue is our first objective and a prohibitive initial step in any investment performance analysis which looks to position SMSFs within the broader context of the Australian superannuation industry. To achieve this, we take anonymised financial statement data for a large sample of SMSFs over a three-year period and generate an annual ROR measure at the level of individual funds.

Our second objective is to provide evidence-based insights that explain how the financial performance of the SMSF sector has evolved over time. This primarily involves looking at the relationship between fund performance and fund size, since this relationship attracts considerable interest from both regulators and industry bodies. We examine the discourse on minimum fund balances and then directly evaluate the size-performance relationship for our sample of SMSFs to see if it fits the existing narrative. Our remaining work addresses (1) analyses which look at fund performance relative to fund diversification levels, (2) analyses which subsample across funds based on their asset allocations, and (3) analyses which examine the overall SMSF sector performance impacts of at-risk sub-cohorts.

Section 2: Calculating SMSF rates of return

2.1 Estimation approach

The ROA methodology applied by the ATO to summarise SMSF performance has been extensively criticised as incompatible with ROR (Productivity Commission, 2018b). Some of the deficiencies previously noted with the methodology include the way it accounts for individual fund items such as contribution tax and insurance premiums (Class Limited, 2018a, 2018b), as well as the way it imputes changes to the asset base in the ROA denominator (Sy, 2009). The direction of influence from each of these differences is to suppress ROA relative to ROR, generating lower performance estimates all else equal.

One additional issue, neither raised in submissions to the Productivity Commission nor by the commission itself, relates to the calculation of ROA as a pooled estimator rather than at the level of individual funds.[1] Pooled estimators are not necessarily always appropriate to use. Generally, they should only be used when combining data of similar orders of magnitude, with similar statistical properties (Mihaylov and Yawson, 2020). Fund returns typically don't meet these requirements because of large variations in size between funds. This applies equally to ROR calculations. For example, the pooled ROR published for APRA funds with more than 4 members as at June 2019 was 7.1% (see Table 2, APRA, 2021a). However, if we look to recreate it at the level of individual funds, both the mean and median rates of return for those same funds during that period are 6.2% (see Table 3, APRA, 2021b). The higher pooled ROR (relative to the median fund-level ROR) is being influenced disproportionately by the financial performance of the largest APRA funds. In any typical year, for any typical level of performance across the superannuation sector, pooled RORs will usually be higher than fund-level median RORs, all else equal.

We take both the ROA-ROR discrepancies and the difference between pooled versus fund-level returns into account when developing our performance estimation approach. Specifically, we replicate the APRA fund ROR calculation for SMSFs at the level of individual funds. All subsequent benchmarking also utilises fund-level returns for APRA funds, ensuring that we

[1] See Appendix A for an example which illustrates what pooled estimators are and the influence of pooling on returns estimates for funds with dissimilar fund sizes.

are as close as possible to making like-for-like comparisons between the two superannuation fund types.

2.2 SMSF ROR

Figure 1 displays APRA ROR (Level 1), detailed at the level of individual line items, and how this original ratio was modified in order to be applied to SMSFs (Level 2). The individual line items are mapped to APRA fund statements of financial position and performance under Appendix B. The SMSF ROR introduces no new line items and remains structurally identical to APRA ROR, with differences between investment income and expense items in the numerator, and cashflow adjusted beginning of period net assets in the denominator. However, there are a number of APRA fund line items which are not included in the SMSF ROR ratio. APRA ROR includes 40 individual line items whereas SMSF ROR only includes 26 individual line items. Table 1 provides a full list of the excluded (14) line items, including a breakdown by whether items are from the ROR numerator or denominator.

Table 1. APRA ROR items which are not included in SMSF ROR

ROR Numerator	ROR Denominator
Operating income	Defined benefit contributions
Investment management performance fee	Successor fund transfers in
Custodian expenses	Other members’ benefits
Investment consultant expenses	Successor fund transfers out
Impairment expense	Employer repatriation payments
Marketing expenses	Other members’ benefits payments
Service provider admin expenses	
Other admin expenses	

Note: This table lists all APRA ROR line items which are found at Level 1, Figure 1, and are subsequently excluded from SMSF ROR at Level 2, Figure 1.

In order to gain confidence over the ROR changes we adopt for SMSFs, we employed two strategies. First, we received data keys from the data providers, BGL Corporate Solutions and Class Limited. The keys outlined data availability and relevance, highlighting that some of the items from Table 1 are not applicable for SMSFs (e.g., Marketing expenses, Successor fund transfers in/ out). Moreover, a number of the items were subsumed under alternative line item labels (e.g., Service provider admin expenses or Other admin expenses classified under Administration expenses). The second step we took to gain assurance over the …

Figure 1. APRA rate of return modified to generate SMSF rate of return

Level 1

(APRA funds)

$$ROR = \frac{\begin{gathered}\textit{Interest revenue} + \textit{Dividend revenue} + \textit{Rental income} + \textit{Trust distributions} + \textit{Other investment income} \\ + \textit{Operating income} + \textit{Unrealised gains/losses} + \textit{Realised gains/losses} - \textit{Investment management base fee} \\ - \textit{Investment management performance fee} - \textit{Custodian expenses} - \textit{Investment consultant expenses} \\ - \textit{Service provider expenses} - \textit{Other investment expenses} - \textit{Impairment expense} - \textit{Administration expenses} \\ - \textit{Marketing expenses} - \textit{Commissions} - \textit{Director/trustee expenses} - \textit{Service provider admin expenses} \\ - \textit{Other admin expenses} - \textit{Advice expenses} - \textit{Income tax expense/benefit}\end{gathered}}{\textit{Net assets at beginning of period} + \frac{1}{2}\left(\begin{gathered}\textit{Employer contributions} + \textit{Member contributions} \\ + \textit{Defined benefit contributions} + \textit{Inward insurance flows} \\ + \textit{Successor fund transfers in} + \textit{Other members' benefits} + \textit{Rollovers in} \\ - \textit{Contribution surcharge} - \textit{Rollovers out} - \textit{Successsor fund transfers out} \\ - \textit{Lump sum benefit payments} - \textit{Pension benefit payments} \\ - \textit{Employer repatriation payments} - \textit{Other members' benefits payments} \\ - \textit{Contribution tax} - \textit{Outward insurance flows}\end{gathered}\right)}$$

Level 2

(SMSFs)

$$ROR = \frac{\begin{gathered}\textit{Interest revenue} + \textit{Dividend revenue} + \textit{Rental income} + \textit{Trust distributions} \\ + \textit{Other investment income} + \textit{Unrealised gains/losses} + \textit{Realised gains/losses} \\ - \textit{Investment management base fee} - \textit{Service provider expenses} \\ - \textit{Other investment expenses} - \textit{Administration expenses} - \textit{Commissions} \\ - \textit{Director/trustee expenses} - \textit{Advice expenses} - \textit{Income tax expense/benefit}\end{gathered}}{\textit{Net assets at beginning of period} + \frac{1}{2}\left(\begin{gathered}\textit{Employer contributions} + \textit{Member contributions} \\ + \textit{Inward insurance flows} + \textit{Rollovers in} \\ - \textit{Contribution surcharge} - \textit{Rollovers out} \\ - \textit{Lump sum benefit payments} - \textit{Pension benefit payments} \\ - \textit{Contribution tax} - \textit{Outward insurance flows}\end{gathered}\right)}$$

Notes: Items highlighted in red are reported by superannuation funds to APRA via their Statement of Financial Position (APRA form SRF 320.0). Items highlighted in blue are reported by superannuation funds to APRA via their Statement of Financial Performance (APRA form SRF 330.0). All SMSF items highlighted in black were specifically collected for this research.

The cashflow adjustment factor of 0.5 on the ROR denominator assumes that net flows over the year are uniformly distributed. APRA acknowledges that there may be certain situations when this is not an appropriate assumption. This factor can be adjusted between 0 and 1 to reflect actual net flows more accurately, where supported by evidence.

… accuracy of line items removed from SMSF ROR was to interview a SMSF specialist. Via the interview we were able to confirm that the amended SMSF ROR which we present at Level 2, Figure 1, is fit for purpose and inclusive of all performance relevant SMSF line items. Overall, we were able to corroborate not only the appropriate exclusion of inapplicable items, but also that subsumed items were correctly accounted for, and therefore entered with correct sign into our modified SMSF ROR.

Section 3: Analyses and results

3.1 Sample

The sample made available for this project, jointly by BGL Corporate Solutions and Class Limited, is a significant point of strength and differentiation for the research we present. The sample covers the three-year period from financial years ending 2017 to 2019. Overall, during the full three years, we observe the financial performance of over 318,000 unique SMSFs for a total of almost 498,000 unique performance observations (comprising our unbalanced panel).[2] We make use of our unbalanced panel for all headline analyses presented here. However, we also extract a balanced panel from this larger data set, containing just shy of 109,000 unique SMSFs, for robustness and to ensure that the headline results we present here are not subject to a selection effect.[3] The data offers entries across all 26 SMSF line items for each fund (see Level 2, Figure 1), in addition to offering a breakdown of fund asset holdings across 7 of the major asset classes (utilised in Section 3.6). Importantly, so that we could obtain accurate net assets as at the beginning of each period, we lagged the fund net assets variable such that it was collected from 2016 to 2018.[4] Table 2 offers a breakdown of the sample size by year, highlighting the sampling proportion as a percentage of the larger SMSF population in each period. On an annual basis, the sampling proportions range from around 18% (in 2017) to almost 37% (in 2019). Cumulatively over the three-year period, the

[2] 'Unbalanced panel' is a technical term which refers to data that offers a cross-section of funds observed over multiple years, but where not all individual funds are necessarily observed in every year of the sample frame. For some funds in our unbalanced panel we only observe ROR for one or two out of the three years 2017-19. This is a common feature of large panels.
[3] That is, our balanced panel contains 108,982 unique SMSFs for which we are able to generate ROR across all 3 years from 2017 to 2019.
[4] For example, the 2016 end of period fund net assets was used as the 2017 beginning of period fund net assets, and so on.

318,761 unique SMSFs in our sample represent 55.8% of the average total size of the SMSF sector.

Table 2. Annualised sample sizes and sampling proportions

	2017	2018	2019
Sampled SMSFs	106,585	178,948	212,382
Sampling proportion	18.7%	31.4%	36.9%

Notes: The sample sizes quoted here are for our unbalanced panel. Sampling proportions are calculated as the ratio between the number of sampled SMSFs and the total number of registered SMSFs listed in APRA's revised Annual superannuation bulletin as of June each year (APRA, 2021a).

3.2 Headline performance results

In Table 3 we calculate ROR, as outlined in Figure 1 (Level 2), for each individual SMSF in our sample (as summarised in Table 2) between 2017 and 2019. We also obtain median ROA for SMSFs during the same period from ATO published statistics and compare the differences between the performance ratios. In Table 4 we calculate median APRA fund ROR using APRA's annual fund-level superannuation statistics back series and compare that against SMSF ROR. We further follow APRA's standard and provide 25th and 75th percentile returns for each cohort. Both tables provide probability values from chi-square tests for statistically significant differences between medians.

Table 3. Headline SMSF performance – ROA versus ROR

	2017	2018	2019
SMSFs			
Median ROR (%)	6.9	6.0	6.2
Median ROA (%)[1]	5.0	4.0	4.3
Median differences (χ^2)[#]			
ROR – ROA (%)	1.9	2.0	1.9
Probability value	0.0000	0.0000	0.0000

Notes: Unbalanced panel data used. Data is not truncated since extreme observations do not influence medians. 2017 N_{SMSF} = 106,585 & N_{APRA} = 155. 2018 N_{SMSF} = 178,948 & N_{APRA} = 150. 2019 N_{SMSF} = 212,382 & N_{APRA} = 140.
1. Median ROA is obtained from the Australian Taxation Office annual SMSF statistical overview publication, available at: https://www.ato.gov.au/Super/Self-managed-super-funds/In-detail/Statistics/Annual-reports/Self-managed-super-funds--A-statistical-overview-2018-19/
#. Median difference tests are calculated using the chi-square statistic from Mood's two sample median test. The probability values evaluate the likelihood that the true population medians are equal.

Table 4. Headline SMSF performance – SMSF ROR versus APRA fund ROR

	2017	2018	2019
SMSFs			
Median ROR (%)	6.9	6.0	6.2
25^{th}/ 75^{th} ROR Percentiles	2.5 – 12.5	2.2 – 11.3	2.1 – 11.3
APRA funds			
Median ROR (%)[1]	7.8	7.6	6.2
25^{th}/ 75^{th} ROR Percentiles	6.3 – 9.6	6.5 – 8.9	5.3 – 7.1
Median differences (χ^2)[#]			
SMSF ROR – APRA ROR (%)	– 0.9	– 1.6	0.0
Probability value	0.0001	0.0000	0.6276

Notes: Unbalanced panel data used. Data is not truncated since extreme observations do not influence medians. 2017 N_{SMSF} = 106,585 & N_{APRA} = 155. 2018 N_{SMSF} = 178,948 & N_{APRA} = 150. 2019 N_{SMSF} = 212,382 & N_{APRA} = 140.
1. Median ROR is constructed at the level of individual APRA funds with data obtained from APRA (2021b).
#. Median difference tests are calculated using the chi-square statistic from Mood's two sample median test. The probability values evaluate the likelihood that the true population medians are equal.

The results in Tables 3 and 4 yield several thought-provoking insights. First, ATO median ROA understates the SMSF median ROR which we calculate, on average, by more than 1.9% over the three-year period from 2017 to 2019 (see Table 3). While this result is not new, the update we provide for 2017-19 demonstrates that ROA-ROR differences are potentially becoming more severe over time relative to what the Productivity Commission considered for the period 2006-16. Their evidence showed that the average annual SMSF ROA-ROR difference between 2006 and 2016 was less than 1.2% (Class, 2018a; Productivity Commission, 2018b). To emphasize, our equivalent ROA-ROR difference result of 1.9% is more than 50% larger than that presented to the Productivity Commission. In our opinion, this suggests a limited market utility for publishing SMSF ROA due to the risk of misinformation for end-users. At the same time, this also presents an opportunity in the marketplace for the publication of more robust performance metrics. We offer a way forward in relation to this in Sections 3.3 and 3.4 of this report.

Finding 1: *SMSF ROA persistently underestimates actual SMSF performance, with evidence suggesting that this gap is widening over time.*

Once we correct for the ROA-ROR discrepancy, we observe a substantially narrower gap in aggregate performance levels between SMSFs and APRA funds (see Table 4). Nevertheless, some differences persist during our sample frame, even when performance is captured using ROR for both fund types. We find that, at the median, APRA funds outperformed SMSFs in both 2017 and 2018, by 0.9% and 1.6%, respectively. These results are both highly statistically significant, generating near-zero p-values for chi-square tests of median differences. However, we observe no performance gap in 2019 (SMSF and APRA fund median RORs both equal to 6.2%). This is confirmed in formal testing, where we show no statistically significant difference between the two medians via a chi-square test with a large p-value (0.6276). Taken together these results show, not only that when performance differences exist, they are of smaller magnitude than previously understood, but also that claims the SMSF sector underperforms the APRA fund sector across all years are highly questionable. Given the performance matching we observe in 2019, an extended sample outside the 2017-19 period could return annualised results where the performance gap flips, consistent with other existing research which has already suggested that SMSFs outperform APRA funds in some years (Mihaylov and Yawson, 2020).

> **Finding 2:** *After adjustments/ corrections, relative to APRA funds, annualised median SMSF underperformance either significantly reduces or decreases to zero, depending on the period examined.*

Our final result in Table 4 illustrates comparative 25th – 75th percentile ranges for the performance of individual SMSFs and APRA funds. We see that SMSFs are spread out over a larger performance range than APRA funds and that this phenomenon is consistent across all years in our sample frame. This is not surprising. On average, we observe just under 166,000 SMSF performance results each year, versus only 148 APRA fund performance results. This size difference plays a critical role in determining the width of the 25th and 75th percentiles for each cohort because the larger population offers more scope for divergent investment decisions, and therefore also greater scope for variation in performance outcomes.[5] Critically, and we look to put significant emphasis on this, the percentile ranges used by APRA indicate an ability and a need to consider other performance dimensions, beyond pooled and summary statistics. While they represent a step in the right direction, if we are interested in presenting a more holistic understanding of SMSF-APRA fund comparisons,

[5] This is separate to the fact that SMSFs inherently offer members broader investment choice than APRA funds, although that only serves to reinforce our logic here. What we mean is simply to point out that a group, like our sample, of 165,000+ entities making investment decisions from an (effectively infinite) investment pool of assets are mathematically bound to generate greater variation in performance (and a whole host of other characteristics) relative to a smaller group of around 150 entities.

we can go further. In Section 3.3 we offer a way forward which can help achieve this by looking at return distributions.

Finding 3: *SMSFs generate greater variation in fund-level performance relative to APRA funds, a feature of the significant difference in population sizes between the two cohorts.*

3.3 Return distributions and the Bhattacharyya coefficient

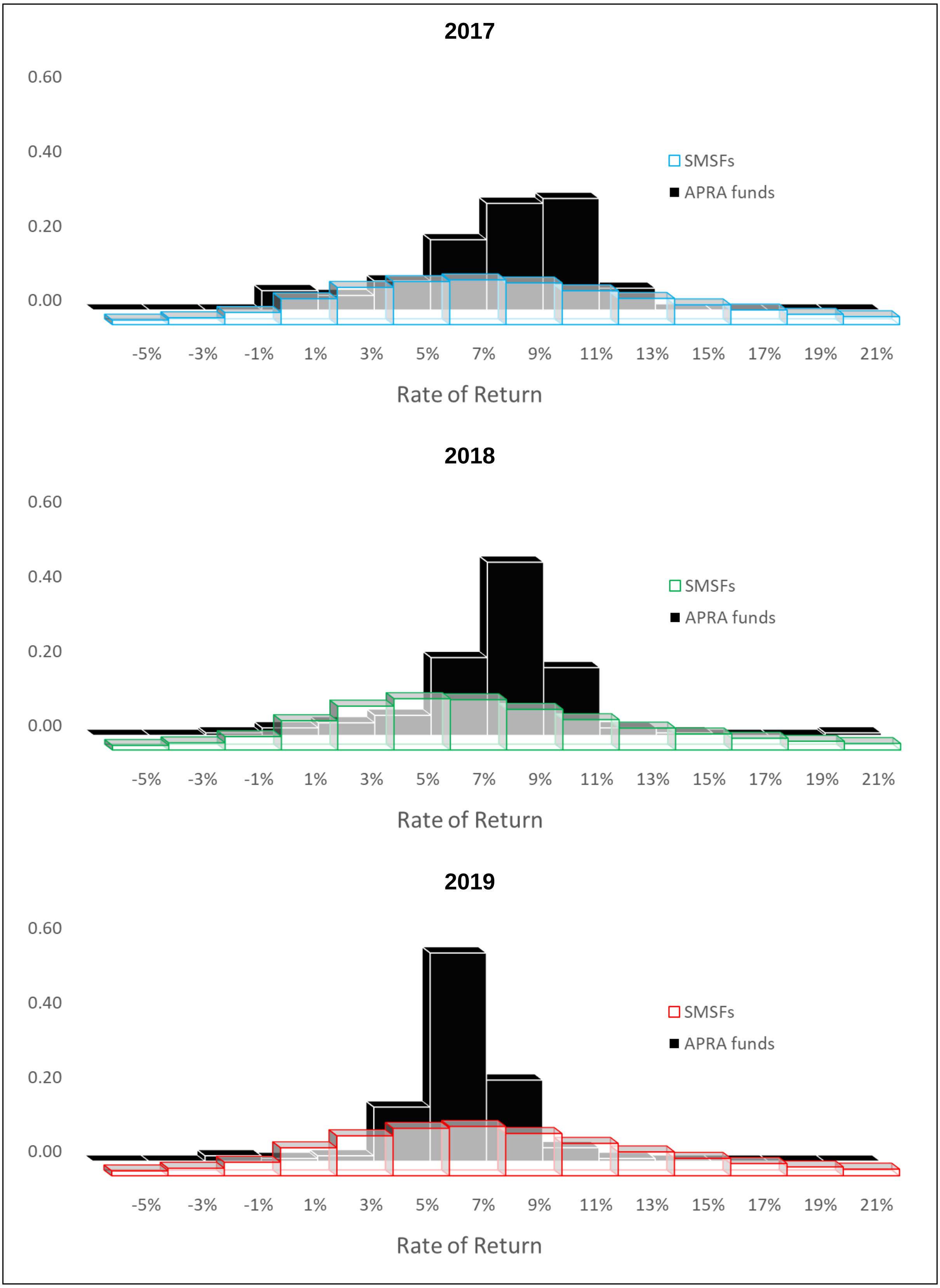
Figure 2 illustrates the return distributions for our sample of SMSFs, benchmarked against the equivalent return distributions for APRA funds, over the period 2017-19. The distributions exclude the lowest and highest 2% of funds (in terms of fund performance) in order to minimise the effects of outliers on the horizontal axes and their scales.[6]

We propose the distributions presented in Figure 2 as a natural complement to summary statistics like pooled ROR, median fund ROR, and return percentiles. The distributions convey the sense that there is significant overlap between the performance of SMSFs and APRA funds, while also illustrating some of the key differences. All regularly published statistics from both the ATO and APRA considered in this report are numerical.[7] In our opinion, visual summaries have the potential to offer greater performance insights because they are more intuitive from the perspective of an average user. Truncated returns distributions, in particular, have the added benefit of accounting for the vast majority of the performance results in any given population, rather than merely the performance level of funds located in the middle of the distribution or the performance level of the sector as a whole. On face value, they are a logical extension of the first order (medians) and second order (percentiles) summaries already provided by APRA for APRA funds. We therefore recommend their inclusion in performance publications issued by both regulators and industry bodies.

[6] That is, the returns distributions presented in Figure 2 are truncated at the 2nd and 98th percentiles. Truncation is an alternative to winzorisation, which revalues outliers outside a specific percentile to equal the largest observation within the percentile.

[7] This also extends to the ATO's *YourSuper Comparison Tool*.

Figure 2. SMSF and APRA fund return distributions 2017-2019



Notes: Unbalanced panel data used. Data truncated at 2% to minimise the influence of extreme observations on the axis scales.
Rate of return bin widths are also set at 2%. Vertical axes denote fund proportions in each bin.
2017 N_{SMSF} = 106,585 & N_{APRA} = 155. 2018 N_{SMSF} = 178,948 & N_{APRA} = 150. 2019 N_{SMSF} = 212,382 & N_{APRA} = 140.

Finding 4: *We recommend that superannuation performance summaries include visualisations of fund performance results, such as return distributions, alongside existing numerical measures.*

The 2017 to 2019 period was relatively stable for both SMSFs and APRA funds with respect to their performance. Both cohorts recorded median returns between 6% and 8% for all 3 years. This stability is accurately reflected in Figure 2, where the annual return distributions, and particularly those for SMSFs, only vary mildly year-on-year. This would not be the case during any period with a significant economic downturn. During an economic downturn, the year-on-year differences between the distributions would be markedly more obvious. In recognition of this, and in order to improve the end-user utility of these distributions, we introduce an innovation – a similarity index based on the Bhattacharyya coefficient.

The Bhattacharyya coefficient (BC henceforth) is not a new concept. In fact, it dates back almost eight decades, and was introduced precisely with the purpose of complementing existing tests of statistical significance (Bhattacharyya, 1943). It is widely used across several fields of research and is regularly incorporated into image processing, phone clustering, and feature extraction studies. The BC offers an intuitive and easy to understand summary statistic which measures the degree of similarity (or overlap) between statistical distributions. BC is equal to zero when there is no overlap, and one when there is complete overlap, between two probability distributions (see Appendix C for details on the BC formula and related illustrations). In this sense, it can be interpreted as a percentage of similarity between distributions, or a similarity index, for all values between its minima (0) and maxima (1). Table 5 summaries the BC calculations for our sample between 2017 and 2019.

Table 5. Bhattacharyya coefficients: SMSF and APRA fund return distributions

	2017	**2018**	**2019**
BC			
SMSFs vs APRA funds	0.775	0.772	0.728
Pooled sample size	102,575	171,939	204,024

Notes: Unbalanced panel data used. Data not truncated.
BC is calculated according to the formula presented in Appendix C with histogram bin width set at 2%.

We actually find the results in Table 5 to be quite remarkable. The BC calculations suggest a high degree of similarity in returns between SMSFs and APRA funds, ranging from around 73% to 77% during the period 2017-19. Interestingly, the BC results show an inverted relationship with median fund performance. That is, BC's are highest when the difference between median SMSF and APRA fund returns is largest, in 2017 and 2018 (see Table 4). Conversely, we observe the lowest overlap in returns distributions for 2019, when median SMSF and APRA fund returns were equal (see Table 4). This suggests that the information content of BC calculations acts to complement that of the summary statistic measures published for superannuation funds (e.g., median returns). BC calculations represent a more holistic perspective on fund performance, accounting for the complete distributions of all funds in any given population. Our results therefore suggest that, even in years where performance levels deviate at the median, significant similarity in returns remains between SMSFs and APRA funds. In our opinion, BC statistics can (1) serve to enhance statistical publications which contain return distributions (such as those we present in Figure 2), (2) are easy to understand and interpret, and (3) add informational value alongside existing performance measure.

Finding 5: *We recommend that, if superannuation performance summaries include visualisations based on return distributions, BC values for performance similarity are presented alongside traditional numerical measures.*

3.4 Fund performance and size

In this section we examine some of the commentary stemming from the Productivity Commission relating to SMSF performance. Finding 2.6 handed down by the Productivity Commission (2018a, p. 52) stipulates that "…many smaller SMSFs (those with balances under $500,000) have delivered materially lower returns on average than larger SMSFs".[8] These comments were written independent of related concerns around the cost efficacy of SMSFs at lower balances,[9] lending themselves particularly easily to various verification tests. Given

[8] Importantly, Finding 2.6 is distinct from the Productivity Commission's related commentary on the cost effectiveness of SMSFs (see Finding 3.8 on page 194, Productivity Commission, 2018a). The issue of SMSF cost efficacy is beyond the scope of this research. However, there is some evidence to suggest that SMSFs with balances above $200,000 are cost competitive with Industry and Retail funds (Rice Warner, 2020).

[9] Although that discussion also suggested that SMSFs with balances below $500,000 were of particular interest (Productivity Commission, 2018a, p. 194).

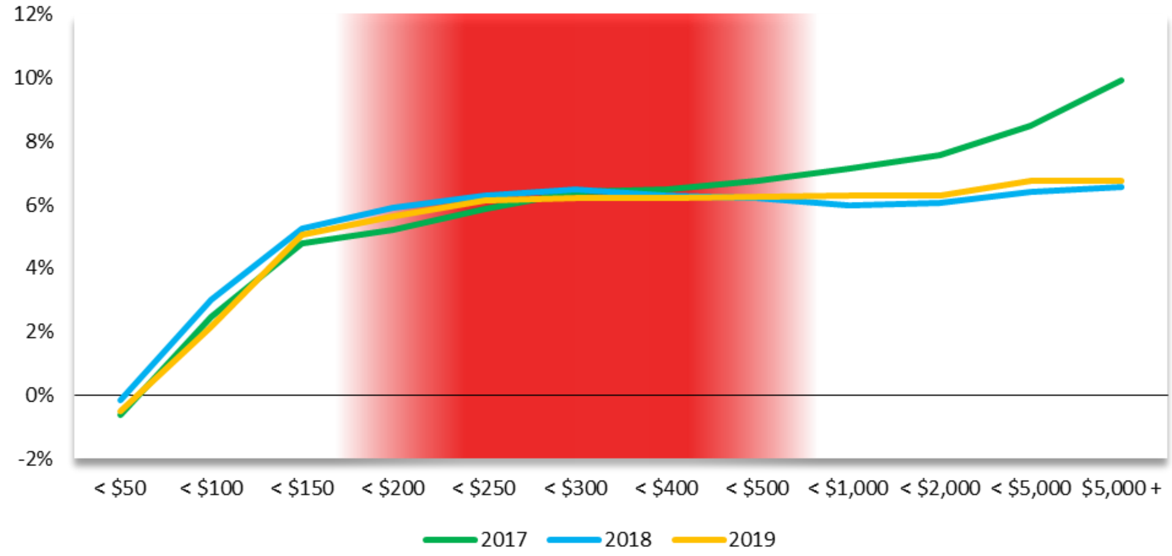
that it was initially set at $1,000,000, and later revised down to $500,000 (SMSFA, 2021), we find the choice of this threshold balance to be somewhat arbitrary. At a minimum, even if we assume that the threshold was appropriately set, we see no reason to assume that it should be stationary over time.

Moreover, this threshold standard is also currently adopted by the Australian Securities and Investments Commission (ASIC). ASIC uses it as guidance for Australian financial services licensees (and their representatives) who provide advice to retail clients about SMSFs. Specifically, ASIC states that "… on average, SMSFs with balances below $500,000 have lower returns after expenses and tax than funds regulated by [the] Australian Prudential Regulation Authority (APRA)" (ASIC, 2021). While ASIC's use of the threshold is likely motivated by both the Productivity Commission's findings around SMSF performance (within scope) and SMSF cost efficacy (outside scope), we question the notion that there are material performance differences between SMSFs at various sizes around the threshold. Even if smaller funds do underperform, it is not immediately apparent that a threshold for this necessarily occurs around funds worth $500,000. Moreover, even if such differences exist, we have seen little to no evidence to suggest that they persist over time.

To this end, we examine the link between the size of SMSFs and their financial performance and offer some simple evidence on how the relationship appears to have changed in recent years. We first stratify our sample by fund size. The bin widths used for this are specifically selected to be consistent with prior research in the area (Rice Warner, 2020).[10] Second, within each bin, we calculate median fund returns for each year in our sample frame. The results are presented in Figure 3 below.

[10] In Appendix D we present sensitivity analyses which examine the robustness of the fund size versus performance relationship when we vary the fund size bin widths. Specifically, we include two replications of Figure 3 with equidistant bins, one in increments of $10,000 and one in increments of $25,000, both up to a maximum fund size of $1,000,000.

Figure 3. SMSF performance versus fund size



Notes: Unbalanced panel data used. Fund size brackets (in '000's of dollars net assets) are on the horizontal axis and increase in lots of $50,000 up to $300,000, and in lots of $100,000 up to $500,000. Median SMSF performance (in percentage points) is on the vertical axis.

The results in Figure 3 yield several important insights. First, there is a strong positive relationship between fund size and fund performance overall (if we consider the full range of fund sizes from funds smaller than $50,000 all the way up to funds larger than $5 million). This relationship is also stable over time, holding for all three years in our sample. However, the strength of this relationship seems substantially driven by the performance outcomes of the most extreme size brackets at both ends of the spectrum (the smallest and largest funds register the most significant deviations). Second, if we focus on those funds whose net asset balances are at around $500,000 and below, we notice that there are two structural breaks in the graph. The first, more severe break, occurs for funds in the range $100,000 to $150,000, and the second, mild break, occurs for funds in the range $200,000 to $250,000. Within the area highlighted in red, beyond net asset balances of $250,000, we see no further structural breaks in the graph, and certainly no noticeable changes in performance pattern as fund sizes approach $500,000. Third, we also see gentle negative partial slopes for the relationship in some years (e.g., in 2018 SMSFs with balances of $250,000 to $300,000 outperformed those with balances between $500,000 and $1 million by 0.5% at the median).

We present sensitivity analyses aimed at providing further detail around our headline fund size results in Appendix D. These results suggest that, when we refine the bin widths used in Figure 3, we observe a relatively (more) precise structural break in the relationship between SMSF size and fund performance at net asset balances closer to $200,000. Figures D1 and D2 in Appendix D fail to differentiate between the performance of typical SMSFs from $200,000 up to $1,000,000 in net assets.

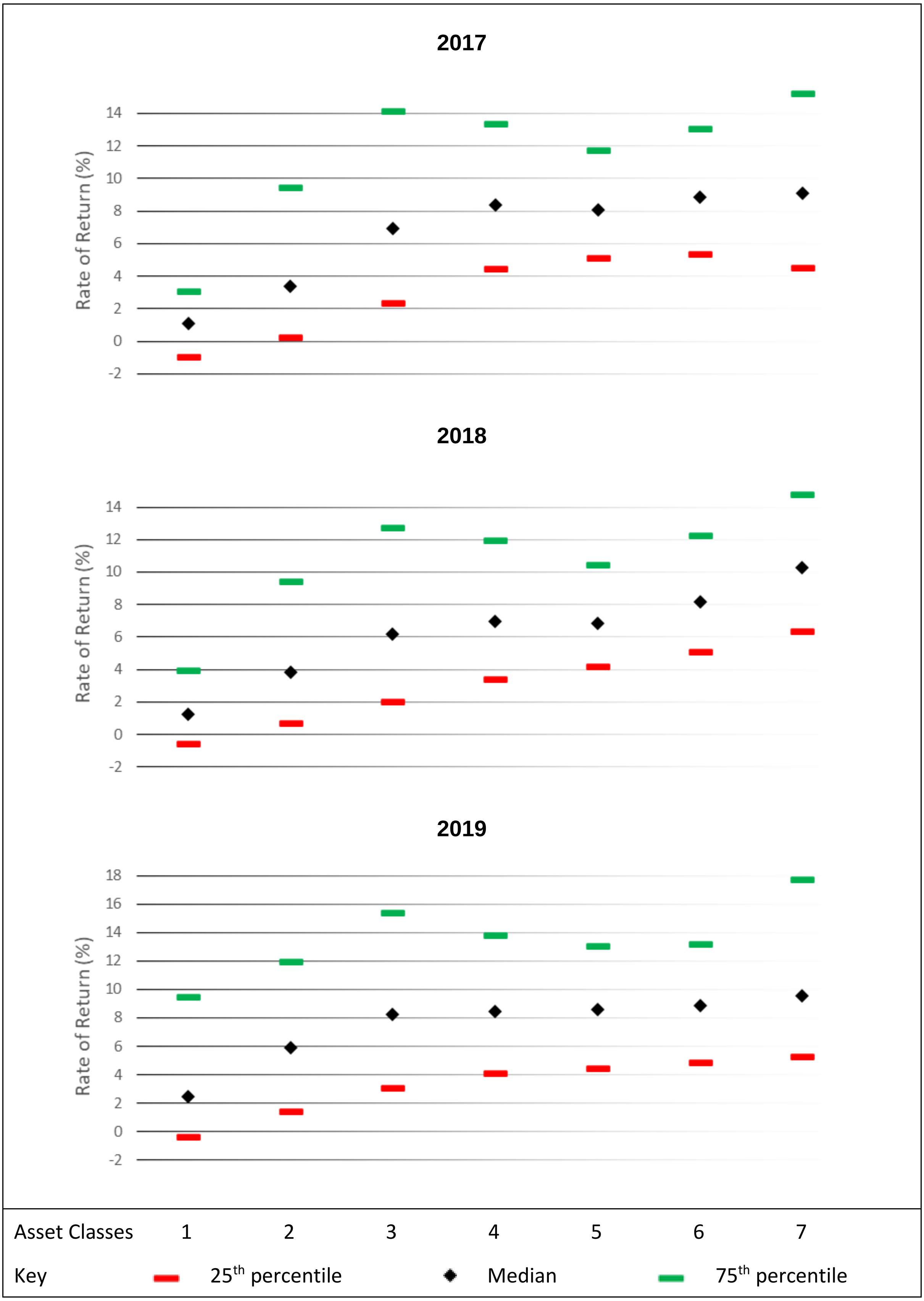
Taken together, these results support the regulatory focus on fund size, but also suggest that current guidelines around minimum SMSF balances might be poorly calibrated. Specifically, we find little to no support for the notion that funds with balances below $500,000 should be singled out as poor performers. Likewise, for people considering the potential to open a new SMSFs (and their advisers), this research allays concerns around the critical mass for opening balances. Our results indicate that, insofar as it relates to fund size, people should have confidence in their performance prospects anywhere upward of $200,000 in net assets.

Finding 6: *The notion that SMSFs with balances under $500,000 deliver materially lower returns, on average, than larger SMSFs, is not supported by the evidence we present. Our results suggest that it is more appropriate to calibrate this threshold at $200,000.*

3.5 Fund performance and diversification

Section 3.5 explores the relationship between fund performance outcomes in the SMSF sector and the degree to which funds pursue diversification across multiple asset classes. Figure 4 presents median and percentile RORs for all SMSFs in our sample, where funds are mapped against a count of their distinct asset classes with non-zero asset holdings. The seven asset classes included are *Cash and term deposits*, *Listed Australian equities*, *Listed international equities*, *Listed trusts*, *Unlisted trusts*, *Limited recourse borrowing arrangements (LRBAs),* and *Other assets*. The most concentrated funds hold their entire superannuation balance in a single asset class, whereas the most diversified funds hold assets in as many as all seven of the recorded asset classes. Figure 4 separates the results for each year between 2017 and 2019 to demonstrate the stability of any pattern(s) or relationship between performance and diversification over time.

Figure 4. SMSF performance versus fund diversification



Notes: Unbalanced pooled 2017-19 data used. Data not truncated.
Vertical axes denote SMSF RORs. Horizontal axes denote the number of asset classes held by SMSFs.
N_{2017} = 105,084, N_{2018} = 176,459, and N_{2019} = 91,162.

The results from Figure 4 are revealing, and mostly in line with what one might expect given standard finance theory. Across all years, the least diversified SMSFs – those holding their entire superannuation balance within a single asset class – recorded the lowest performance outcomes at all points in their return distribution (i.e., had the lowest median as well as the lowest 25th and 75th percentile returns).[11] On aggregate, funds at all other levels of diversification outperform this cohort. The performance benefits of adding a second, third, or fourth asset class are strong and consistent across the period 2017-19. Each incremental increase of an additional asset class (up to 4) appears to be associated with an improvement in median ROR of between 1% to 3%. Diversification beyond 4 asset classes (up to 7) also seems correlated with improved aggregate SMSF performance, although at reduced marginal rates. Funds with extra asset classes above 4 generate anywhere between 0% and 2% in additional median ROR per added class, between 2017 and 2019. These results provide a tangible path forward for meaningful trustee education and can be used by SMSF professionals who are interested in performance uplift across the sector.

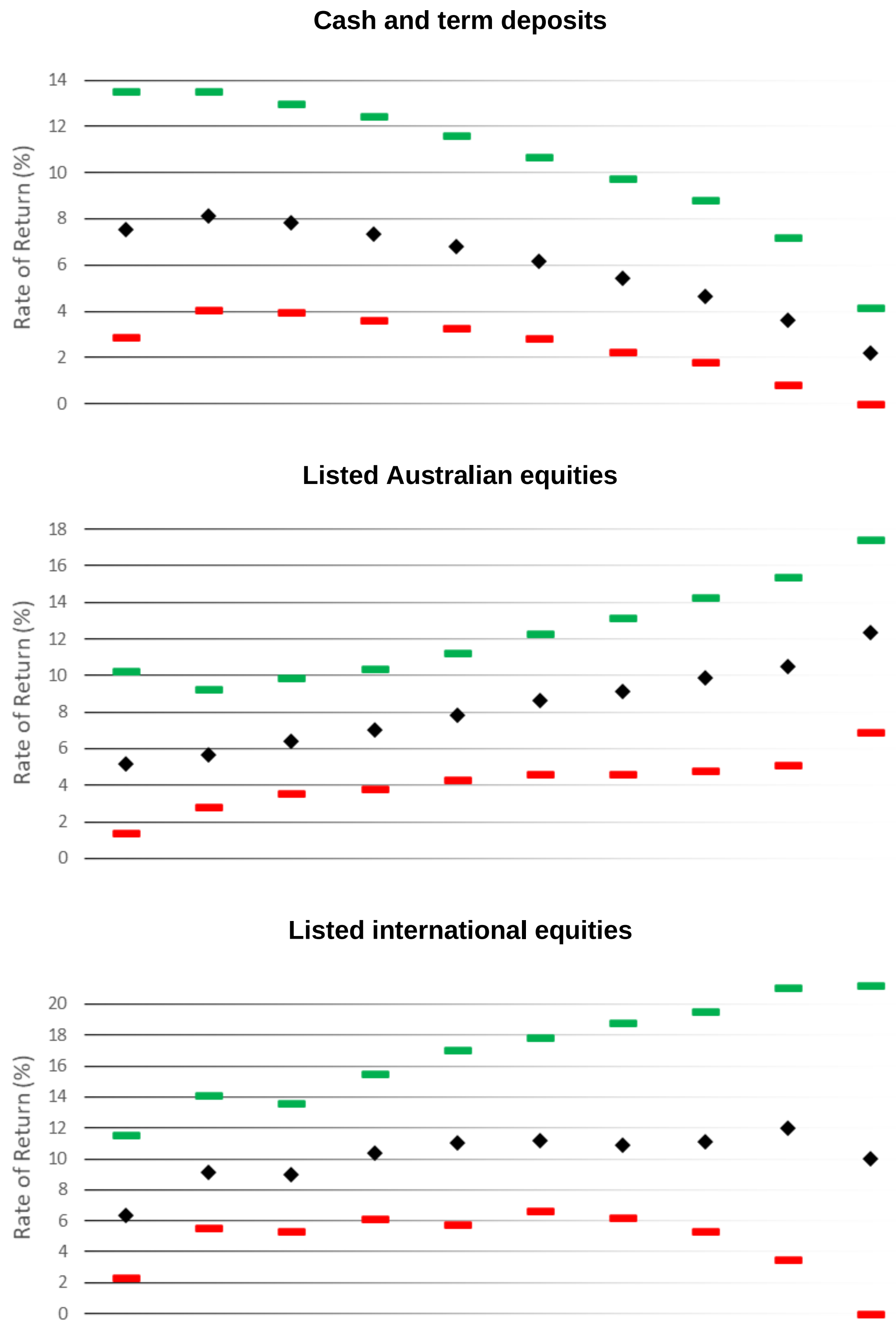
Finding 7: *On aggregate, SMSFs with more diversified asset allocations achieve higher returns.*

3.6 SMSF asset allocations and fund performance

In this section we delve deeper into, and extend, our fund diversification results from Section 3.5. Specifically, we are interested to see how fund performance varies with degrees of concentration within individual asset classes. In Figures 5 and 6 we present SMSF RORs, calculated as described in Figure 1 (Level 2), for all funds in our sample based on pooled differences in their asset allocation proportions over the period 2017-19. Figure 5 includes *Cash and term deposits*, *Listed Australian equities*, and *Listed international equities*. Figure 6 includes *Listed trusts*, *Unlisted trusts*, and *LRBAs*.[12] Each figure contains 10 bins, from funds who allocate 0-10%, up to funds who allocate 90-100%, of their net assets to any given asset class.[13] Median RORs, along with 25th and 75th percentiles, are reported across cohorts.

[11] Our understanding here is that fund lifecycle effects might also play a significant role in identifying sub-cohorts of underperforming funds (e.g., disproportionately more pension phase funds in drawdown). Such effects may overlap with our diversification result here. While this is outside the scope of the research presented here, it remains a point of interest for future research.
[12] LRBAs represent gross assets (primarily real estate) associated with LRBA arrangements.
[13] For LRBAs, funds are instead allocated to bins based on their relative percentile rank.

Figure 5. Asset allocations and SMSF performance (1)

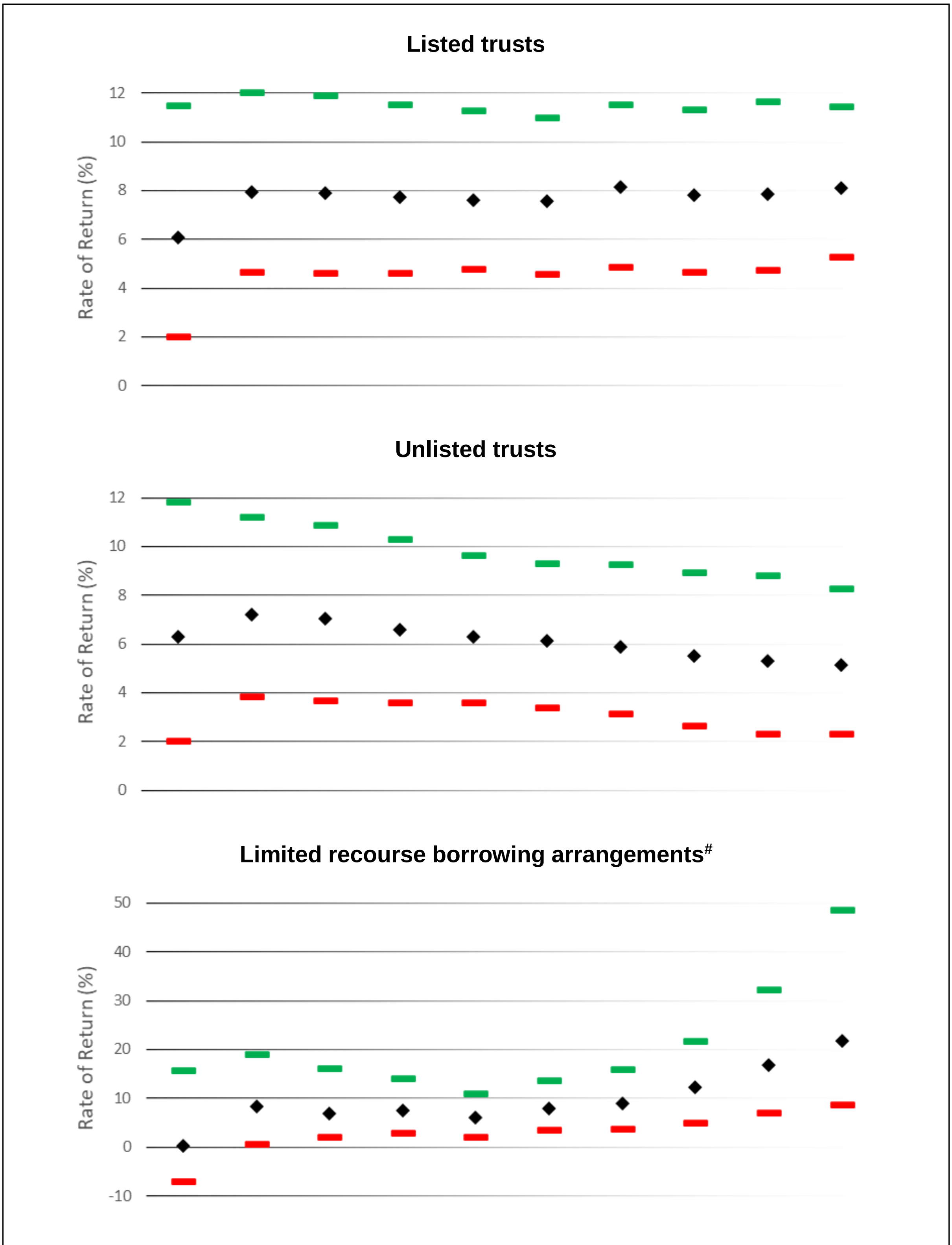


Bin <10% <20% <30% <40% <50% <60% <70% <80% <90% ≤100%

Key 25th percentile ◆ Median 75th percentile

Notes: Unbalanced pooled 2017-19 data used. Data not truncated.
Bin widths set at 10%. Vertical axes denote SMSF RORs for funds in each bin.
$N_{\text{Cash and term deposits}}$ = 453,718, $N_{\text{Listed Australian equities}}$ = 482,914, and $N_{\text{Listed international equities}}$ = 495,537.

Figure 6. Asset allocations and SMSF performance (2)



Bin	<10%	<20%	<30%	<40%	<50%	<60%	<70%	<80%	<90%	≤100%

Key: 25th percentile, Median, 75th percentile

Notes: Unbalanced pooled 2017-19 data used. Data not truncated. # LRBA bins are percentile ranks, not net asset proportions. Bin widths set at 10%. Vertical axes denote SMSF RORs for funds in each bin.
$N_{\text{Listed trusts}}$ = 494,919, $N_{\text{Unlisted trusts}}$ = 489,779, and $N_{\text{Limited recourse borrowing arrangements}}$ = 494,169.

The results in Figures 5 and 6 highlight some interesting, albeit expected patterns for the period between 2017 and 2019 (only).[14] First, there is significant SMSF performance decay as funds allocate greater proportions of their assets to cash and term deposits. This is unremarkable given the known low rates of return on fixed income securities during the 2017-19 period. Interestingly however, typical fund performance doesn't appear to maximise for those SMSFs which minimise their cash and fixed income holdings. Instead, we observe highest median fund performance, at slightly above 8% ROR (see Figure 5), for those SMSFs which allocate between 10% and 20% of their net assets to cash and term deposits for the period 2017-19. This result suggests that funds have an opportunity to optimise their asset allocations with respect to cash and related securities/ assets, but also emphasises that funds with cash holdings concentrated above 20% of net assets are associated with significant performance impairment.

The manner in which fund performance varies with changes in allocations to listed Australian and international equities is intriguing. Median SMSF performance between 2017 and 2019 improves monotonically as funds allocate larger proportions of their assets to Australian equities. The costs associated with this equity risk premium at the sector level appear to be mild, with the 25th-75th percentile spread increasing from a minimum of about 6% to a maximum of around 10% (see Figure 5). In contrast, international equity diversification appears to be less influential for improving returns and, at the same time, is associated with more volatile performance outcomes. SMSFs which invest less than 10% of their net assets in international equities seem to be at a disadvantage however, above this level, median fund performance largely plateaus between 9% and 12% RORs for all other allocation proportions, while the 25th-75th percentile spreads increase substantially.[15] These results suggest a clear role for diversification in domestic equities, and some limited benefits from exposure to international equities, for SMSFs that optimised their overall investment performance during the 2017-19 period.

Figure 6 displays SMSF performance as a function of investments in listed and unlisted trusts. Both graphics demonstrate that the typical (median) fund experiences a marginal

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[14] Our discussion of performance patterns and SMSF asset allocations in Section 3.6 should be read as a retrospective account of aggregated SMSF sector performance during the 2017-19 period. No part of this discussion should be interpreted as a specific financial recommendation for any individual fund, or for any trustee looking to make investment decisions outside of the reference period.

[15] We note that this latter result is subject to a small sample effect since very few SMSFs allocate 70% or more of their net assets to international equities (likely increasing the 25th-75th percentile spreads for the three right-hand side bins at the bottom of Figure 5).

improvement in performance when moving out of the lowest investment band (0-10% of net assets) into the next higher band (10-20% of net assets). This diversification benefit levels out at around 8% median ROR for funds allocating to listed trusts in all higher proportions. In contrast, for unlisted trusts, median fund ROR decays from around 7% for funds with 10-20% of net assets invested, to approximately 5% as that proportion increases up to 90-100%. 25th-75th percentile spreads are relatively stable for both asset classes (see Figure 6).

The final asset class we consider in this section is assets (predominantly real estate purchases) funded with LRBAs.[16] The fund performance impacts of LRBAs are more difficult to disentangle than those of the other asset classes since our data does not differentiate between, on the one hand, loan costs and the effects of leverage, and on the other hand, the performance of the underlying assets. Moreover, we also do not observe data on any (rare) regulatory breaches of the SIS Act and the subsequent ramifications for LRBA investment performance. Despite these limitations to our interpretation, Figure 6 clearly indicates that SMSF performance improves non-monotonically for funds in higher LRBA percentiles. Perhaps the more notable finding here is that LRBAs are also associated with the largest variations in performance of any asset class examined here. This is reflected in the 25th-75th percentile spreads for SMSF ROR at the bottom of Figure 6 which, at the extreme, range above 40% ROR. Both of our observations here are consistent with our understanding of the effects of leverage and the ability for funds to generate excess returns using leverage.

3.7 Subsampling analyses

We conclude by providing analyses that further interrogate two of our main findings. Specifically, we recalculate our headline performance results from Table 4 for subsamples of the SMSFs available for this study. First, we subsample to exclude all SMSFs with net asset balances of less than $200,000. This is consistent with our results under Figure 3 (page 18), our recommendation at Finding 6 (page 19), and with our expectation that SMSFs below this threshold are more likely to lack the critical mass required to keep pace with larger funds. Second, we subsample to exclude all SMSFs with cash and term deposit balances in excess of 80% of underlying fund net assets. Our results in Figure 5 clearly indicate significant

[16] LRBAs effectively enable leverage, so LRBA assets regularly exceed fund size as measured via net assets. We therefore capture LRBA use relative to fund size as a percentile rank, where funds in the 0-10% bin are those which do not use LRBAs or have the smallest LRBAs relative to their net assets and other funds, up to funds in the 90-100% bin that use the largest LRBAs on the same relative basis.

performance decay for cash-heavy funds. Moreover, the proportion of SMSFs with highly concentrated allocations in cash (and related fixed income securities) reduces each year in our sample, suggesting a reduced role for such funds over the short-to-medium term. Finally, we combine these criteria and provide performance results for the subsample of all SMSFs with net assets above $200,000 and with less than 80% invested in cash and term deposits. The results are displayed in Table 6.

Table 6. Subsampled headline SMSF performance

	2017	2018	2019
All SMSFs[1]			
Median ROR (%)	6.9	6.0	6.2
25^{th}/ 75^{th} ROR Percentiles	2.5 – 12.5	2.2 – 11.3	2.1 – 11.3
SMSFs with more than $200,000[2]			
Median ROR (%)	7.4	6.2	6.4
25^{th}/ 75^{th} ROR Percentiles	3.4 – 12.5	2.7 – 10.9	2.7 – 11.0
SMSFs with less than 80% Cash[3]			
Median ROR (%)	7.7	6.5	6.3
25^{th}/ 75^{th} ROR Percentiles	3.4 – 13.1	2.8 – 11.7	2.2 – 11.3
SMSFs meeting both conditions[4]			
Median ROR (%)	8.0	6.6	6.5
25^{th}/ 75^{th} ROR Percentiles	4.0 – 13.1	3.1 – 11.3	2.8 – 11.1
APRA funds			
Median ROR (%)[1]	7.8	7.6	6.2
25^{th}/ 75^{th} ROR Percentiles	6.3 – 9.6	6.5 – 8.9	5.3 – 7.1

Notes: Unbalanced panel data used. Data is not truncated since extreme observations do not influence medians. Rows highlighted in grey are extracted from Table 4 for ease of reference. They do not contain new information.
1. Sample sizes for the full sample of all SMSFs are: N_{2017} = 106,585; N_{2018} = 178,948; and N_{2019} = 212,382.
2. Subsample sizes for SMSFs with net assets above $200,000 are: N_{2017} = 85,827 (80.5% of full sample); N_{2018} = 149,840 (83.7% of full sample); and N_{2019} = 181,101 (85.3% of full sample).
3. Subsample sizes for SMSFs with cash (and term deposit) holdings at less than 80% of net assets are: N_{2017} = 92,373 (86.7% of full sample); N_{2018} = 159,570 (89.2% of full sample); and N_{2019} = 202,161 (95.2% of full sample).
4. ‘Both conditions’ refers to SMSFs that have more than $200,000 in net assets and, at the same time, hold less than 80% of their net assets in cash (and term deposits). Subsample sizes for SMSFs that meet both conditions are: N_{2017} = 77,510 (72.7% of full sample); N_{2018} = 137,985 (77.1% of full sample); and N_{2019} = 174,727 (82.3% of full sample).

The results from Table 6 are in line with our prior expectations. Small funds and funds concentrated in cash (and equivalents) are two of the underperforming sub-cohorts in the SMSF sector. Although each of these cohorts is relatively small as a proportion of the full sample (small funds comprise between 14.7% and 19.5%, and cash-heavy funds comprise between 4.8% and 13.3% of our sample), excluding them from our headline performance calculations increases median RORs and tightens the 25^{th}-75^{th} percentile spreads in all cases. In 2017, when both small and cash-heavy funds are excluded, median SMSF ROR increases by 1.1%, from 6.9% to 8.0% (see Table 6). Likewise, in 2018 and 2019, when both cohorts are excluded, median RORs increase by 0.6% (from 6.0% to 6.6% in 2018) and 0.3% (from 6.2% to 6.5% in 2019), respectively. Taken together, these results show that large SMSFs that are not concentrated in cash and other fixed income securities outperform APRA funds in two of the three years considered in our sample.

Finding 8: *Larger SMSFs, with net assets in excess of $200,000, that are not concentrated in cash and other fixed income securities, outperform APRA funds in two of the three years between 2017 and 2019.*

Based on our results from Section 3.4, we do not check the sensitivity of our results here for alternative choices of fund size cut-off. However, we do check for the performance sensitivity of varying our 80% cash and cash equivalents assumption. Specifically, we recalculate our result from Table 6 while only including SMSFs with less than 50% of their net assets invested in cash and term deposits. Our results remain qualitatively the same. In 2017, median ROR for SMSFs holding less than 50% of their assets in cash is 8.0% (versus 7.7% for SMSFs holding less than 80% cash). Likewise, in 2018 and 2019, median RORs for SMSFs holding less than 50% of their assets in cash were 6.7% (versus 6.5%), and 6.3% (versus 6.3%), respectively. Finally, we note that results from BC estimates for the subsamples in Table 6 also improve over our baseline BCs, by between 2.5% and 3.5% percent across the three-year period 2017-19.

Section 4: Conclusion

Overall, this research supports a reconsideration of the regulatory priorities which govern the SMSF sector. In our opinion, there is sufficient evidence to suggest that SMSF investment performance is largely on par with that of APRA funds. Our results show that ASIC’s existing emphasis on minimum SMSF balances of $500,000 is excessively conservative and can be recalibrated to $200,000. For the SMSF Association, we think there is strong evidence to warrant a focus on trustee education around the risks and limitations of inefficient investment management. Identifying and helping at-risk cohorts, such as small cash-heavy funds or under-diversified funds, offers a promising way forward for lifting standards and improving headline performance outcomes for the SMSF sector overall.

Appendix A: Pooled estimators

This appendix offers an example which illustrates the effect of using pooled estimators, such as the pooled version of ROR, and offers related cautions for the interpretation of subsequent results.

Pooled estimations in statistical (not accounting) analyses combine raw data and/ or elementary sample statistics prior to generating more advanced inferential statistical estimates. Pooled estimates allow for more precise inferential statistics to be generated, but importantly, can only be used under certain conditions. They are primarily appropriate when data is pooled across populations, or is selected from subsamples, which have similar statistical properties. Pooled estimations are generally not appropriate across data sets with dissimilar statistical properties. Table A1 outlines two scenarios which illustrate this in the context of fund performance for funds of different sizes:

Table A1. The relationship between pooled returns and fund sizes

Scenario 1

	Value (t = 1)	Value (t = 2)	Return	Median return	Pooled return
Fund 1	\$100	\$110	\$10 (+10%)	$Med(x_i) = 0\%$	$\frac{\$10 - \$10}{\$100 + \$100} = 0\%$
Fund 2	\$100	\$90	-\$10 (-10%)		

Scenario 2

	Value (t = 1)	Value (t = 2)	Return	Median return	Pooled return
Fund 1	\$1000	\$1100	\$100 (+10%)	$Med(x_i) = 0\%$	$\frac{\$100 - \$10}{\$1000 + \$100} = 8.2\%$
Fund 2	\$100	\$90	-\$10 (-10%)		

Scenario 1 demonstrates that median returns and pooled returns mirror each other when constituent funds are of similar size. Scenario 2 demonstrates that, under identical performance conditions, median and pooled returns diverge when constituent funds are of dissimilar size. More specifically, the pooled return departs from the median fund return toward the individual fund return of the larger fund. This implies that pooled returns are, in effect, value-weighted rather than unweighted like median returns, and therefore, that they are representative of the financial performance of large funds more so than the performance of small funds. Pooled returns should primarily be interpreted as measures of SMSF sector performance, rather than an indication of the individual fund performance levels achieved by a typical SMSF.

Appendix B: ROR line item mapping

This appendix lists all individual line items which contribute to the calculation of ROR (see Figure 1) and maps them to their source reporting forms – the statements of financial performance (SRF 330.0) and position (SRF 320.0) for APRA funds. Items highlighted in red were included in our calculation of SMSF ROR and items highlighted in black were excluded from SMSF ROR.

Table B1. ROR line item mapping

ROR input category	APRA Reporting Reference
Employer contributions	SRF 330.0, Item 1.1
Member contributions	SRF 330.0, Item 1.2
Defined benefit contributions	SRF 330.0, Item 1.3
Contribution tax	SRF 330.0, Item 1.5
Contribution surcharge	SRF 330.0, Item 1.6
Rollovers in	SRF 330.0, Item 1.8
Successor fund transfers in	SRF 330.0, Item 1.9
Other members’ benefits	SRF 330.0, Item 1.11
Lump sum benefit payments	SRF 330.0, Item 2.1.1
Pension benefit payments	SRF 330.0, Item 2.1.2
Rollovers out	SRF 330.0, Item 2.2
Successor fund transfers out	SRF 330.0, Item 2.3
Employer repatriation payments	SRF 330.0, Item 2.4
Other members’ benefits payments	SRF 330.0, Item 2.6
Interest revenue	SRF 330.0, Item 4.1
Dividend revenue	SRF 330.0, Item 4.2
Rental income	SRF 330.0, Item 4.3
Trust distributions	SRF 330.0, Item 4.4
Impairment expense	SRF 330.0, Item 4.6
Unrealised gains/losses	SRF 330.0, Item 5.1
Realised gains/losses	SRF 330.0, Item 5.2
Other investment income	SRF 330.0, Item 6
Operating income	SRF 330.0, Item 8
Investment management base fee	SRF 330.0, Item 9.1
Investment management performance fee	SRF 330.0, Item 9.2
Custodian expenses	SRF 330.0, Item 9.3
Investment consultant expenses	SRF 330.0, Item 9.4
Service provider expenses	SRF 330.0, Item 9.5
Other investment expenses	SRF 330.0, Item 9.6
Administration expenses	SRF 330.0, Item 10.1
Marketing expenses	SRF 330.0, Item 10.2
Commissions	SRF 330.0, Item 10.3
Director/ trustee expenses	SRF 330.0, Item 10.4
Service provider admin expenses	SRF 330.0, Item 10.5
Other admin expenses	SRF 330.0, Item 10.6
Advice expenses	SRF 330.0, Item 11
Inward insurance flows	SRF 330.0, Items 13.1 and 13.2
Outward insurance flows	SRF 330.0, Items 14.1 and 14.2
Income tax expense/benefit	SRF 330.0, Item 17
Net assets at beginning of period	SRF 320.0, Item 21

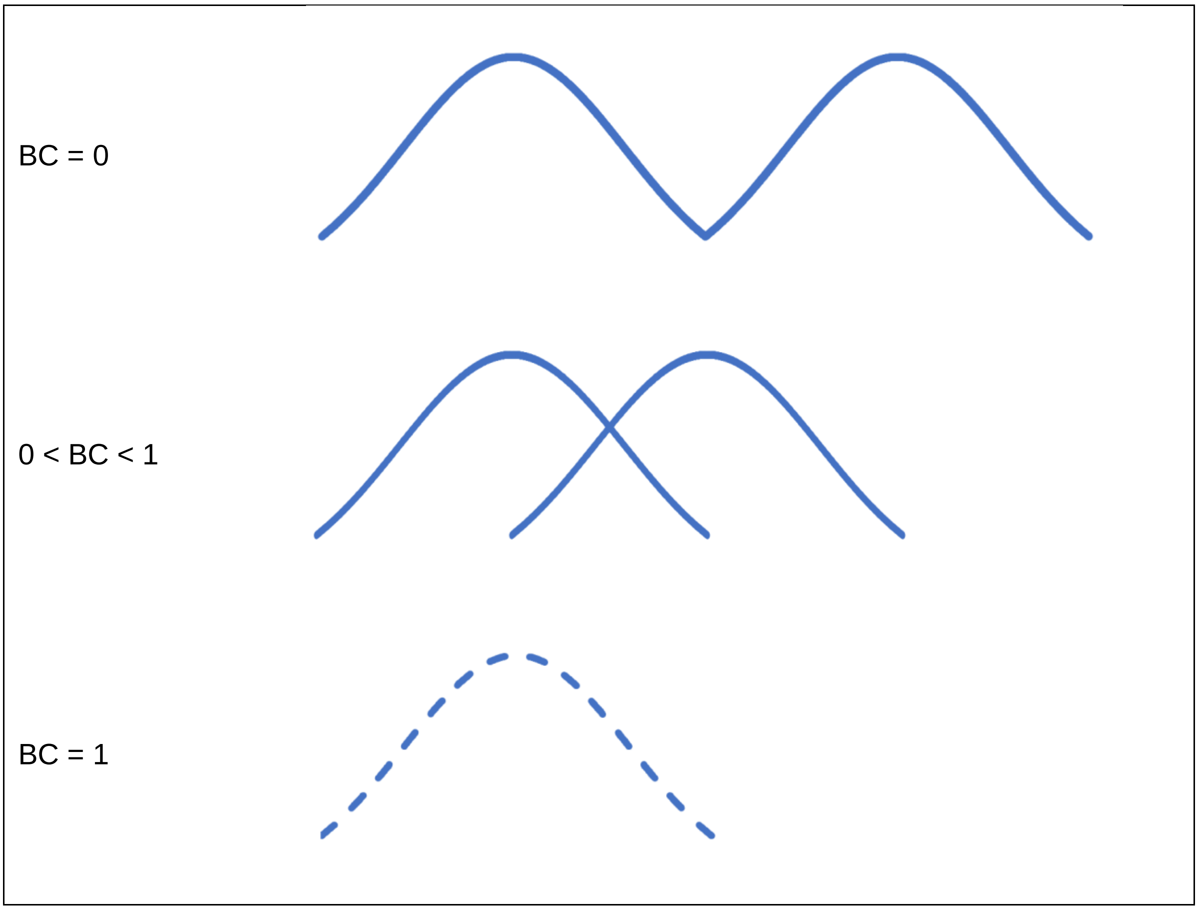
Appendix C: Bhattacharyya coefficient

This appendix contains the BC formula (see below) and basic illustrations of the relationship between the coefficient and distributional overlap (see Figure C1).

BC Formula: $\sum_{x \in X} \sqrt{p(x)q(x)}$

Where *p(x)* and *q(x)* are corresponding relative frequencies at a given *x* from probability distributions *P* and *Q*, and are summed across all *x*.

Figure C1. Bhattacharyya coefficient interpretation

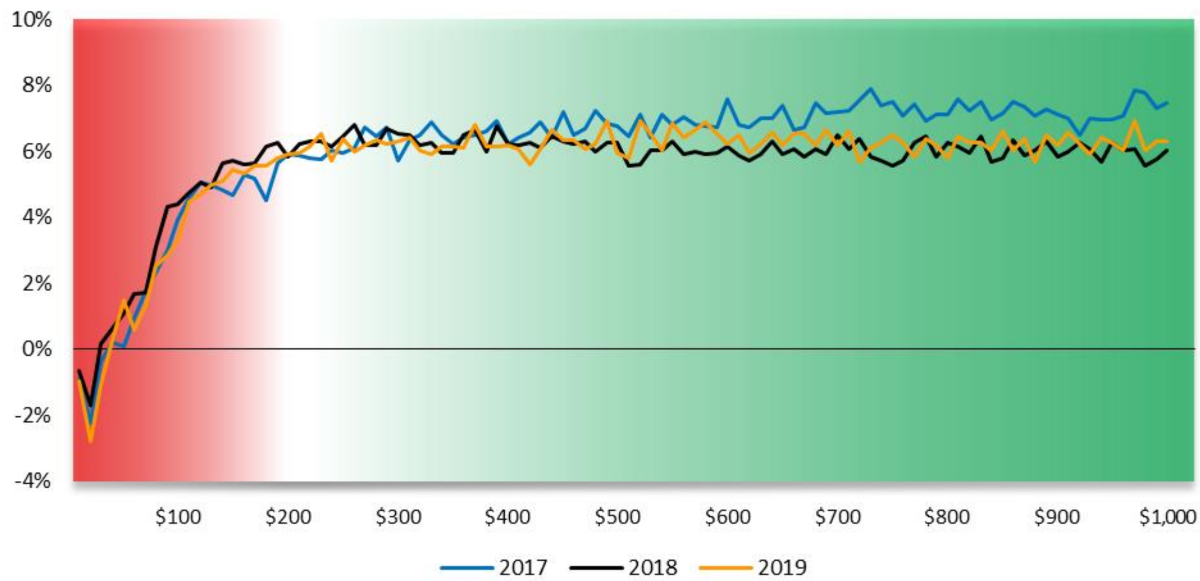


Appendix D: Fund size versus performance – Sensitivity analyses

This appendix presents two figures that vary the fund size bin widths used on the horizontal axis in Figure 3. The headline result bin widths in Figure 3 are consistent with the prior literature examining the role of fund size for fund performance (Rice Warner, 2020). However, the bins in Figure 3 are not equidistant. As a robustness measure, we therefore replicate this analysis using equidistant bins that are $10,000 (Figure D1) and $25,000 (Figure D2) apart, respectively. While Figure 3 includes all SMSFs (up to those which are $5M+ in net assets), the sensitivity analyses below are bounded to SMSFs up to $1M in net assets.

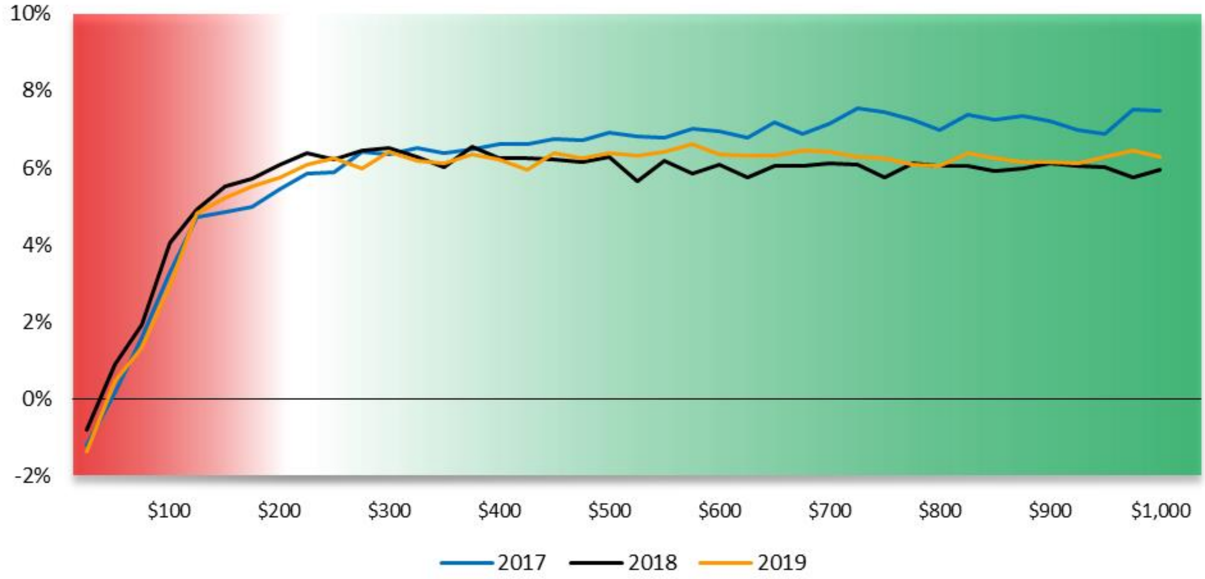
The results in Figures D1 and D2 provide additional detail that complements our headline results from Figure 3. They confirm that there is a strong positive overall relationship between fund size and fund performance and that this relationship was largely stable over the period from 2017 to 2019. Again, this relationship is primarily driven by the performance outcomes of the smallest funds (SMSFs at or below $150,000 in net assets). With respect to structural breaks, Figures D1 and D2 provide clearer insight. Most notably, we can detail our headline result for funds in the range $200,000 to $250,000. That is, our sensitivity analyses demonstrate that the size-performance relationship breaks rather precisely at funds with around $200,000 in net assets (area highlighted in white). Below this point, the typical SMSF can generally be expected to underperform the sector (highlighted in red), whereas the typical SMSF with more than $200,000 in net assets appears to generate comparable performance with that of much larger funds (highlighted in green). We see no systematic deviations in fund performance pattern as fund sizes above $200,000 approach $1,000,000.

Figure D1. SMSF performance versus fund size ($10,000 bin widths)



Notes: Unbalanced panel data used. Fund size brackets (in '000's of dollars net assets) are on the horizontal axis and increase in lots of $10,000 up to $1,000,000. Median SMSF performance in each bin (in percentage points) is on the vertical axis. 2017 N_{SMSF} = 106,585. 2018 N_{SMSF} = 178,948. 2019 N_{SMSF} = 212,382.

Figure D2. SMSF performance versus fund size ($25,000 bin widths)



Notes: Unbalanced panel data used. Fund size brackets (in '000's of dollars net assets) are on the horizontal axis and increase in lots of $25,000 up to $1,000,000. Median SMSF performance in each bin (in percentage points) is on the vertical axis. 2017 N_{SMSF} = 106,585. 2018 N_{SMSF} = 178,948. 2019 N_{SMSF} = 212,382.

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