Return Dispersion and Fund Performance: Australia - the Land of Opportunity?

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Abstract

We examine the relation between cross-sectional stock return dispersion and active fund performance in Australia, drawing on the concept that higher return dispersion indicates greater opportunity for skilled managers to generate value. Australian active funds earn positive active returns when return dispersion is moderate-to-high, but not when it is low. We find meaningful differences between large-cap and small-cap funds. For large-caps, outperformance is modest in magnitude, and significant only when return dispersion is high for the most active funds. For small-caps, active returns are larger in magnitude and do not depend greatly on fund activeness. Applying a switching strategy between active funds and passive investment reveals that investors are better off retaining exposure to Australian active funds in all but low return dispersion environments. These results contrast with US findings that outperformance occurs only for the most active funds in the highest return dispersion environments.

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1. Introduction

The active fund industry hinges on the ability to add value relative to passive alternatives. In this study, we explore whether the ability of active managers to create value for investors is conditional on market conditions. Specifically, we examine the relation between active returns and the cross-sectional dispersion of stock returns (return dispersion) within the market, also known as cross-sectional volatility. von Reibnitz (2017) examines this relation for US mutual funds. She finds that the most active of active funds are able to earn significantly positive alpha only when return dispersion is high. Active funds fail to create value for their investors outside of this limited set of circumstances. Nevertheless, von Reibnitz (2017) shows that the observed relation can be exploited to earn significant risk-adjusted returns through a strategy that takes exposure to the most active managers only when return dispersion is high during the prior month, and investing passively in the index otherwise.

The underlying intuition for a relation between return dispersion and alpha is that active bets are likely to deliver greater outperformance when return dispersion is higher, provided that managers have skill. When stock returns are similar, tilting towards better performing stocks offers limited advantage as it becomes more difficult to significantly outperform the market before fees, and even harder after fees. As return dispersion increases, so does the opportunity for a skilled manager to generate alpha as the payoff from being exposed to outperforming stocks increases. Further, the relation between performance and return dispersion should be amplified by the level of fund activeness, particularly if activeness is correlated with skill as suggested by Cremers and Petajitso (2009) and Amihud and Goyenko (2013). von Reibnitz (2017) provides evidence that these forces are in operation within the US equity market.

We extend the analysis of von Reibnitz (2017) to the Australian equity market. This affords an opportunity to conduct an out-of-sample test of the US findings in the context of a market that differs from the US market in notable ways. In particular, Australia is a smaller yet welldeveloped market where active management has been considerably more successful. Pinnuck (2003) and Bennett et al. (2016) find that the holdings[1] and trades of active Australian equity funds are associated with significant active returns, while Bennett et al. (2018) uncover evidence of performance persistence. Chen et al. (2010) find that active Australian small-cap managers generate substantial alpha of 60-68 basis points per month using four-factor and five-factor models. There are also structural differences to the US equity market that might impact on opportunities for active managers. These include a less rich information environment, especially with regard to smaller companies, and substantial involvement from international institutional investors. The Australian market also demonstrates greater concentration than the US market towards larger stocks and certain sectors (e.g. financials and resources).

This study provides further evidence that outperformance by active managers is a function of opportunity as well as skill, and that opportunity varies over time along with return dispersion. Under our preferred performance measure of the 3-factor model of Fama and French (FF) (1993), we find that the average active Australian equity fund generates significantly positive alpha net of fees when return dispersion is in the top two quintiles 4 and 5. Meanwhile, active returns are insignificant in quintiles 2 and 3; and significantly negative in quintile 1 when opportunity is limited for managers to outperform through their active positions. Examining fund segments, a key distinction emerges between funds that invest in large stocks (large-cap funds) and those that invest in small stocks (small-cap funds). The positive active returns we observe largely derive from small-cap funds, which generate significant FF alpha in moderate-to-high return dispersion environments, i.e. quintiles 3 through 5. Meanwhile, large-cap funds generate insignificant active returns on average, as well as in all dispersion quintiles. These findings are consistent with skill being more widely available among small-cap than large-cap funds in Australia. We also divide our fund sample by style. No clear trends emerge along this

[1] Excess returns are estimated using the characteristic-based benchmark method of Daniel et al. (1997).

dimension other than a tendency for positive returns to occur in moderate-to-high return dispersion environments across all styles.

To confirm these findings, we conduct analysis using the 4-factor model by including momentum, and then a 5-factor model by further including an illiquidity factor. Under these models, alphas for the overall fund sample lose their significance in return dispersion quintiles 4 and 5, but the core findings for small-cap funds are confirmed. Applying the MR test for monotonicity proposed by Patton and Timmerman (2010) confirms there exists a significantly positive relation between return dispersion and alpha both for the overall fund sample and for small-cap funds, irrespective of the performance measure.

We further drill down by applying a 5*5 double-sort by return dispersion and fund activeness, where the latter is measured using the R-squared based selectivity measure of Amihud and Goyenko (2013). This analysis uncovers evidence of a relation between fund activeness and active returns. Again, important differences emerge between large-cap and small-cap funds. For large-caps, the most active funds (those allocated to the highest selectivity quintile 5) tend to perform better than less active funds, and generate significantly positive FF alpha when return dispersion is in the highest quintile 5. For small-caps, active returns do not depend greatly on fund activeness, with small-cap funds of varying activeness generating positive FF alpha of broadly comparable magnitude provided that return dispersion is not in the lowest quintile 1. These results accord with the notion that skill is concentrated in the most active funds within the large-cap segment, while being more widespread among small-cap funds.

We gauge the significance of these results for investors by applying a switching strategy that invests in active funds when return dispersion sits above various thresholds, and invests passively otherwise. The key finding is that investors are better off retaining exposure to active funds as long as return dispersion remains moderate-to-high, and switching to a passive alternative only when return dispersion is low. This result emerges because active funds perform relatively well in Australia across a wide range of return dispersion environments, implying that passive investment can have an opportunity cost. The optimal strategy entails remaining exposed to active funds when return dispersion in the previous month sits within either quintiles 2-5 or quintiles 3-5, depending on the fund segment. For example, investing in small-caps in moderate-to-high dispersion environments, and otherwise investing passively, produces significant FF alpha in the range of 2.75%-3% per annum, depending on whether the market index or an actual indexed fund is used as the passive alternative. Limiting active fund investment to only high dispersion environments generates lower returns, as this incurs the opportunity cost of missing out on positive active returns when return dispersion is moderate.

Various messages emerge from our analysis. In Australia, it appears better to remain exposed to active funds over a majority of periods, only switching to passive alternatives when return dispersion is low enough to signal that active opportunity is quite limited. Further, applying such a strategy in fund segments where skill appears more pronounced – such as highly active large-cap funds and small-cap funds – can produce strong outperformance. This suggests that when meaningful skill is present, fund managers only need a moderate level of return dispersion to generate substantial value for investors. Further, active management appears to have been successful across a wider bandwidth than in the US, where von Reibnitz (2017) finds that a combination of high fund activeness and high return dispersion is required to make active investing worthwhile.

The findings of this study and von Reibnitz (2017) have important implications for investors and researchers. Both studies highlight the value of focusing on whether the market environment may deliver opportunities for active managers. This can be useful both ex ante and ex post. Ex ante, considering the market environment can help investors to decide whether to invest in active funds at a given time, by highlighting when active funds are more likely to deliver outperformance. Combining such knowledge with evidence of how fund segment and activeness relate to manager skill can further help identify the potential for active returns, while ensuring that they are captured when the market environment is conducive. Ex post, information on return dispersion can be useful in evaluating manager performance. Knowing that alpha may depend on market conditions can guard against mistakenly concluding that a manager lacks skill because they fail to deliver in an environment of low return dispersion, and consequently, low active opportunity.

Our study contributes to a broader body of research into the relation between active performance and market conditions. With regard to return dispersion, the majority of studies apart from von Reibnitz (2017) focus on its relation with the dispersion of mutual fund performance, e.g. de Silva et al. (2001); Ankrim and Ding (2002); Gorman et al. (2010); Bouchey et al. (2011). Meanwhile, the link between return dispersion and alpha generation has gained more attention among practitioners. For example, Russell Investments partnered with Parametric Portfolio Associates to create the Russell-Parametric Cross-Sectional Volatility Indexes ("CrossVol") in 2010, as a guide to investors on the impact and risk of active strategies through time. Another notable strand of research considers the relation between active fund performance and economic conditions, including Moskowitz (2000); Kosowski (2011); Glode (2011); and Kacperczyk et al. (2014; 2016). This literature provides mixed evidence that active managers may provide insurance by outperforming during downturns; while Kacperczyk et al. (2016) further find that the sources of performance vary with the economic state.

Our study also relates to the literature showing that performance increases with fund activeness. This relation is found to hold when using return-based measures of activeness such as tracking error (Wermers, 2003; Huij and Derwall, 2011) and R-squared (Amihud and Goyenko, 2013); as well as using fund portfolio holdings, such as Kacperczyk et al. (2005), Brands et al. (2005), Cremers and Petajisto (2009) and Doshi et al. (2015). We confirm the existence of a positive relation between activeness and fund alpha for the Australian market, using the R-squared based selectivity measure of Amihud and Goyenko (2013).

One paper that is closely related to both the current study and von Reibnitz (2017) is Petajisto (2013), which finds that return dispersion positively predicts the subsequent average returns of US funds classified as 'active stock pickers' based on active share. Our work extends the findings of both Petajisto (2013) and von Reibnitz (2017) into another market with differentiating characteristics. In doing so, we show that the positive relation between return dispersion and subsequent fund alpha is also evident outside of the US. The differences in alpha opportunity between the two markets, however, hold important implications for how this relation can be exploited by investors for maximum gain.

This paper is arranged as follows. Section 2 outlines the experimental design, while Section 3 describes the data sources and preparation of our sample. Section 4 presents the results, including the robustness tests. Section 5 concludes.

2. Experimental design

This study undertakes an empirical analysis to establish the relation between cross-sectional return dispersion and fund performance, and then investigate whether this relation may be exploited by investors through a strategy that switches between active funds and passive investment. We analyze Australian active funds, and consider fund 'segments' comprising both the overall sample and funds stratified by the size of stocks in which they invest (large-cap and small-cap), fund style (value, growth and blend) and relative activeness. Our measures of return dispersion and fund activeness are outlined in the Section 2.1 and Section 2.2 respectively. Section 2.3 sets out construction of factor returns, while Section 2.4 details the performance measures. Section 2.5 outlines the switching strategy.

2.1. Cross-sectional return dispersion

We estimate return dispersion over a calendar month t (RD_t) as an equally-weighted standard deviation of stock returns versus the market index using equation (1):

$$\textit{Return Dispersion:}\ RD_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(R_{it} - R_{mt}\right)^2} \quad (1)$$

where n is the number of stocks in the sample universe, R_{it} is the return on stock i in month t, and R_{mt} is the equally weighted average return on stocks in the sample universe during month t. To facilitate our tests, we rank months according to return dispersion and assign them into quintiles. Q1 is the low RD quintile, comprising the 20% of months with the lowest RD over the sample period. Q5 is the high RD quintile, comprising the 20% of months in which RD is highest.

2.2. Fund activeness

We employ the method of Amihud and Goyenko (2013) to determine fund activeness, which the authors term 'selectivity'. The measure is described by equation (2). It is implemented by estimating R^2 from regressing fund returns on a set of benchmark factors, providing a measure of the proportion of variation in fund returns that is not explained by variation in the factors. We are unable to examine the active share measure of Cremers and Petajisto (2009) due to lack of access to sufficient portfolio holdings data for Australian equity funds.[2]

$$Selectivity\colon S_j = 1 - R_j^2 = \frac{Var(Error_j)}{Var(Total_j)} \quad (2)$$

$$= \frac{Var(Error_j)}{Var\left(Systemtatic\ Risk_j\right) + Var(Error_j)}$$

[2] The research cited in Section 1 that analyses holding data for Australian equity funds had access to private databases that are unavailable to us. Morningstar is now collecting holdings data for Australian funds, but the history and breadth of funds is limited. In the US, portfolio holdings data are disclosed under the 13(f) forms.

where $Var(Total_j)$ is the overall variance in a fund j's returns, $Var(Systematic\ Risk_j)$ is the portion of total variance due to variation in the benchmark factors under the performance model, and $Var(Error_j)$ is the variance of the error term of the regression. Selectivity is effectively a relative, or scaled, measure of idiosyncratic volatility. Its value increases with the portion of fund return variance that is explained by idiosyncratic sources, as opposed to factors. Our estimates of R^2 are generated from rolling regressions of the Fama and French (1993) three-factor model using 24 months of data, as per equation (3):

$$\text{FF model regressions: } R_{jt} - R_{ft} = a_j + \beta_{jt}(R_{mt} - R_{ft}) + s_{jt}(SMB_t) + h_{jt}(HML_t) + e_{jt} \quad (3)$$

where R_{jt} is the return to fund j in month t; R_{ft} is the monthly periodic rate on three-month bank accepted bills;[3] R_{mt} is the month t return on the market benchmark; SMB_t is the month t return on the small-large size factor benchmark; HML_t is the month t return on the value-growth factor benchmark; β_{jt} is the estimated market beta for fund j; s_{jt} is the estimated factor loading on the small-large size factor for fund j; and h_{jt} is the estimated factor loading on the value-growth factor for fund j. A fund must have data for at least 18 of the 24 months to be included.

We rank funds in each month t according to their level of selectivity (S), and sort funds into five quintile portfolios of differing activeness. Quintile S1 represents the 20% of funds with lowest selectivity, and quintile S5 represents the 20% of funds with highest selectivity. This ranking facilitates the examination of how activeness is related to fund performance, as well how it interacts with RD.

2.3. Market and factor returns

The market return proxy and factor benchmarks under the FF model are constructed using the S&P Broad Market Index (BMI) series[4] for Australia. The BMI offers the advantage of being

[3] Three-month bank accepted bills are selected as the risk-free proxy and converted to the equivalent monthly rate, as the Reserve Bank of Australia does not report data for one-month rates spanning our sample period.
[4] See https://au.spindices.com/index-family/global-equity/global-bmi.

designed to capture the investible universe for institutional investors, including full adjustment for free-float and limits on minimum market capitalization. This makes it particularly suitable for use in the context of evaluating the performance of institutionally-managed funds. Of note is that the BMI delivers higher returns over the sample period than the more commonly cited S&P/ASX indices, outperforming the S&P/ASX300 Index by 4.8 basis points per month (0.59% per annum) since June 1997. Benchmarking against the BMI universe should hence deliver relatively conservative estimates of active returns.

The size (*SMB*) and value (*HML*) factor proxies are formed using the S&P Australia size and value-growth sub-components of the BMI through applying equations (4) and (5).

$$\textit{Size factor: } SMB_t = \frac{RSV_t + RSG_t}{2} - \frac{RLV_t + RLG_t}{2} \tag{4}$$

$$\textit{Value factor: } HML_t = \frac{RLV_t + RSV_t}{2} - \frac{RLG_t + RSG_t}{2} \tag{5}$$

where RLV_t is the month t return on the S&P Australia Large Value Index; RLG_t is the month t return on the S&P Australia Large Growth Index; RSV_t is the month t return on the S&P Australia Mid/Small Value Index; and RSG_t is the month t return on the S&P Australia Mid/Small Growth Index.

We also evaluate fund performance using a 4-factor model that includes momentum (MOM) factor (Carhart, 1997), as well as a 5-factor model in which a fifth illiquidity (IML) factor is added to account for any illiquidity premium (Amihud, 2019). The inclusion of IML is motivated by the relatively low liquidity of small capitalization stocks in Australia. Given the absence of indices replicating the MOM and IML factors for Australia, we construct these factors ourselves.

We generate MOM factor returns using an approach similar to that described in the Ken French data library. For each month t, we calculate the cumulative prior return for each stock over months t-12 to t-2. Stocks are then ranked by market capitalization at the end of month t-1, and the universe restricted to the largest 300 stocks for consistency with the investment universe that we consider. We then determine monthly prior return breakpoints as the 30th and 70th percentiles for the top 300 stocks. From this, we form four value-weighted portfolios: a big (small) winner portfolio comprising stocks ranked 1-100 (101-300) by market capitalization with prior returns at or above the 70th percentile; and a big (small) loser portfolio comprising stocks ranked 1-100 (101-300) by market capitalization with prior returns at or below the 30th percentile. The MOM factor return is calculated for each month *t* as the average return on the big and small winner portfolios less the average return of the big and small loser portfolios, as described in equation (6).

$$\textit{Momentum factor: } MOM_t = \frac{RLW_t + RSW_t}{2} - \frac{RLL_t + RSL_t}{2} \tag{6}$$

where RLW_t is the month *t* return on the large-cap winner portfolio; RSW_t is the month *t* return on the small-cap winner portfolio; RLL_t is the month *t* return on the large-cap loser portfolio; and RSL_t is the month *t* return on the small-cap loser portfolio.

To construct the IML factor, we follow the approach of Amihud (2019) with one notable exception – we include stocks in the price range of $1 to $1000, whereas Amihud (2019) includes stocks with prices between $5 and $1000. In Australia, some of the largest and most heavily traded stocks have prices below $5. Applying this minimum price threshold at the time of writing would exclude approximately 25% of the constituents of the S&P/ASX100 Index. The procedure involves forming 15 (i.e. 5*3) stock portfolios through double-sorting by the illiquidity measure (ILLIQ) introduced in Amihud (2002) and the standard deviation of daily stock returns. IML is calculated as the average return of the highest illiquidity quintiles less the average return of the lowest illiquidity quintiles across three standard deviation rankings, as described by equation (7).

$$\textit{Illiquidity factor: } IML_t = \frac{RHI(SD,1)_t + RHI(SD,2)_t + RHI(SD,3)_t}{3} - \frac{RLI(SD,1)_t + RLI(SD,2)_t + RLI(SD,3)_t}{3} \tag{7}$$

where $RHI(SD,x)_t$ is the month t return on the portfolio with the highest quintile by *ILLIQ* and ranked in tercile x by standard deviation, $RLI(SD,x)_t$ is the month t return on the portfolio with the lowest quintile by *ILLIQ* and ranked in tercile x by standard deviation, with $x = 1$, 2 or 3.

The use of indices to form factor benchmarks under the FF model follows Faff (2001), and has certain advantages. Indices more closely align with the benchmarks used by investors in practice, and are becoming even more relevant given the increasing availability of products that passively replicate indices. Further, Cremers et al. (2013) raise questions over the appropriateness of multi-factor models such as those of Fama and French (1993) and Carhart (1997) as benchmarks for fund performance evaluation, arguing that benchmarks based on indices are superior. One of the prime reasons is that factor models embed alpha due to their construction, specifically related to a tendency to overweight small value stocks. Such construction issues are potentially even more acute in the case of Australia, where both market capitalization and liquidity are concentrated in a more limited number of larger companies, and stocks outside the top 300 are thinly traded and rarely held by institutional investors. A benchmarking approach based around indices thus better captures the realities of the Australian equity market. The construction of the MOM and IML factor returns departs from using indices by necessity. Questions over whether factor-mimicking portfolios are replicable and hence operate as fair benchmarks are more acute for MOM and IML, given that both factors imply higher turnover and implementation costs. For these reasons, we focus on the FF model as our primary evaluation method, and use the 4-factor and 5-factor models to check whether the core results might have been influenced by the omission of momentum and illiquidity factors.

2.4. Performance measurement

We consider four performance measures – excess return, FF alpha, 4-factor alpha and 5-factor alpha (including IML) – but focus on results under the FF model. Excess return is estimated relative to the benchmark index that is applicable to each fund j using equation (8). The benchmark indices are detailed in Table 3 (see Section 3.2); but largely involve benchmarking against the appropriate size and style benchmark for each fund. For instance, large-cap growth funds are benchmarked against the large-cap growth index for the purpose of estimating excess return. To estimate FF alpha, 4-factor alpha and 5-factor alpha, for each fund j we first estimate factor loadings by regressing fund returns on the market and the factor returns over the 24-months prior to month t. Equation (3) describes this regression for the FF model. An equivalent regression is run for the 4-factor and 5-factor models by adding MOM and then IML factors. We then apply equation (9), equation (10) or equation (11) to arrive at an alpha estimate for each fund j at month t. This effectively entails estimating alpha as a residual after deducting factor contributions from fund returns in excess of the risk-free rate proxy:

$$\textit{Excess return:} \quad XR_{jt} = R_{jt} - B_{jt} \tag{8}$$

$$\textit{FF alpha:} \quad FF\alpha_{jt} = R_{jt} - R_{ft} - \beta_{jt\text{-}1}(R_{mt} - R_{ft}) - s_{jt\text{-}1}(SMB_t) - h_{jt\text{-}1}(HML_t) \tag{9}$$

$$\textit{4-factor alpha:} \quad 4F\alpha_{jt} = R_{jt} - R_{ft} - \beta_{jt\text{-}1}(R_{mt} - R_{ft}) - s_{jt\text{-}1}(SMB_t) - h_{jt\text{-}1}(HML_t) - m_{jt\text{-}1}(MOM_t) \tag{10}$$

$$\textit{5-factor alpha:} \quad 5F\alpha_{jt} = R_{jt} - R_{ft} - \beta_{jt\text{-}1}(R_{mt} - R_{ft}) - s_{jt\text{-}1}(SMB_t) - h_{jt\text{-}1}(HML_t) - m_{jt\text{-}1}(MOM_t) - i_{jt\text{-}1}(IML_t) \tag{11}$$

where $m_{jt\text{-}1}$ is the estimated MOM factor loading for fund j at month t-1, $i_{jt\text{-}1}$ is the estimated IML factor loading for fund j at month t-1, with all other variables as defined in equation (3).

The excess return estimates account for fund-specific benchmarks. It might be considered the performance measure that is more closely aligned to how an investor views the value added by the manager versus their style index benchmark. The FF, 4-factor and 5-factor models control for factor loadings in addition to broad systematic risk, and are more closely aligned with how active returns are measured in much of the academic literature. All four performance measures help to control for fund style,[5] either through the use of fund-specific index benchmarks, or adjusting for factor exposures that are aligned with fund styles. We prefer the FF model in part because it adjusts for factors that accord with the most widely accepted concepts of fund style, i.e. small-cap versus large-cap and value versus growth exposure.

For the purpose of statistical testing, we average the performance measures across all funds in a segment of interest during a month, then average the monthly averages across time. This provides a measure of performance to a notional strategy that is exposed to all available funds in the segment during each month. Evaluating a time series of monthly averages is more appropriate in the context than examining a pooled average. The latter is not representative of a strategy that can be practically implemented, and would be implicitly weighted towards the latter half of the sample when a larger number of funds are available. This is particularly important given that we examine the relative performance of funds in different RD environments that are spread through time. For example, times of high RD are concentrated in the early 1990s (during which the sample comprises approximately 70 funds per month), 1998-2002 (a range of 121-206 funds per month), 2008-2009 (362-402 funds) and 2013 (381-391 funds). It is important to prescribe all months in each RD quintile an equal weighting. This is facilitated by our approach, and would be disrupted under pooled averages.

2.5. Switching strategy

In order to establish the practical implications of any relation between RD and fund performance, we simulate a strategy that switches between active equity funds and passive investment. The strategy involves taking a position during month t conditional on a signal arising from observing RD_{t-1}. This analysis builds on von Reibnitz (2017), who tested a strategy based on investing in a portfolio of highly active US funds (those in the top selectivity quintile

[5] We contend that the single-factor CAPM is less appropriate in the context where it is important to adjust for factors and style. Nevertheless, we also estimate CAPM alphas, and discuss the results in Section 4.4.

5) only when RD_{t-1} was in the highest quintile 5, and investing passively otherwise. We extend this test through examining a set of strategies spanning the range of RD quintiles. Specifically, exposure to active funds is taken when RD_{t-1} is observed in: (a) Q2, Q3, Q4 or Q5, (b) Q3, Q4 or Q5, (c) Q4 or Q5, and (d) Q5 only. We also report for comparison the alpha arising from a constant holding in both active funds and the passive investment across all months. For the switching strategy, we estimate RD quintile cut-offs based on an expanding window of RD estimates, thus avoiding look-ahead bias. The initial window spans 10-years prior to the commencement of the strategy on July 1997 (i.e. July 1987 to June 1997), with each additional month added to the estimation window as the strategy moves forward in time.

Spanning the full range of combinations across *RD* quintiles provides a comprehensive test. It also recognizes that active management appears to have been more successful in Australia, as discussed in Section 1. von Reibnitz (2017) tests a strategy based on investing in active funds when RD_{t-1} sits in Q5 because her analysis reveals that the alpha delivered by the most active US managers arises only when RD is in the highest quintile, suggesting a need to be selective about when to take active exposure. Australian active managers appear to add value on a more consistent basis, raising the question of whether an investor might want to retain active exposure across a wider range of RD environments.

Our test is implemented by switching between an equally-weighted investment in all funds in a segment of interest and one of two passive alternatives: a notional investment in the BMI, and the Vanguard Australian Share Index Fund which replicates the S&P/ASX300 Index. The BMI provides a zero alpha benchmark by construction. However, it does not allow for the management fee and transaction costs incurred when investing passively, whereas these costs are incorporated in active fund returns. It also generates a higher return than the S&P/ASX300 that is tracked by the Vanguard index fund, as noted in Section 2.3. The BMI test hence sets a higher bar for generating alpha from active funds, thus providing a conservative test of the value that might be added through the active strategy. As returns on the Vanguard index fund commence in July 1997, we begin the switching strategy at that date. The test does not allow for the costs of switching between active funds and passive investments. These are difficult to estimate, but unlikely to significantly change the results.

3. Data and sample preparation

The fund sample covers the period September 1989 to July 2018, and is coupled with stock data extending back to July 1987 in order to estimate RD over the 10 years prior to the start of the switching strategy. The data support an initial analysis of fund returns spanning 27-years from August 1991 to July 2018, noting the need for 24 months of prior returns for the calculation of fund factor loadings. The tests of the switching strategy span just over 21-years from July 1997 to July 2018, which aligns with the availability of returns for the Vanguard index fund. This section describes the data collection and sample preparation for stocks in Section 3.1, and for funds in Section 3.2.

3.1. Stock data and return dispersion series

Stock total return indices and market capitalization for all dead and live stocks listed on the Australian Stock Exchange (ASX) are downloaded from Datastream as of the last day of each month. The sample is filtered to remove stocks delisted or suspended at month-end, as well as those with missing data. To avoid the RD measure being distorted by outliers and possible data errors, we further trim stocks with the largest and smallest 2.5% of returns during each month.[6] The filtered and trimmed sample is then ranked based on market capitalization at the end of the prior month, and three stock universes created: all stocks ranking in the top 300, large-cap stocks ranking in the top 100, and small-cap stocks ranked 101-300. This categorisation is

[6] Three trims of the top and bottom tails were considered: 1%, 1.5% and 2.5%. The 2.5% trim was preferred as the maximum monthly return exceeded 100% in only 1% of months. In contrast, 20% (9%) of months had maximum returns exceeding 100% under the 1% (1.5%) trim. The 1% and 1.5% trims were retained for robustness testing, and produce qualitatively consistent results.

chosen to align with how the Australian fund management industry is structured, where the top 100 companies are considered as large-caps, and those outside of the top 100 as small-caps. RD is calculated for all three universes using equation (1).

Summary statistics for the RD measures appear in Table 1. A time-series plot of the three RD series is shown in Figure 1. As expected, RD is greater and more volatile among small-caps. Autocorrelation is relatively high at around 0.65, indicating that RD is persistent. The high persistence in RD is relevant for the potential success of the switching strategy. It implies that investors may be able to exploit any relation between RD and active performance by observing the current level of RD and acting accordingly, on the basis that high persistence means that a similar RD environment is likely to continue. We further explore RD persistence below using transition matrices. Examining Figure 1 reveals that RD tends to spike in periods of market upheaval, including during the recovery from the recession of the early-1990s, the Fed tightening of 1993 (the 'taper tantrum'), the technology collapse of the early-2000s, and the financial crisis of 2008-2009.[7]

INSERT TABLE 1

INSERT FIGURE 1

Table 2 reports monthly transition matrices across RD quintiles for the three stock universes. The estimates confirm that RD is relatively persistent. The highest RD quintile (Q5) demonstrates the greatest persistence, such that if month *t*-1 belongs to Q5, there is a 55% to 60% probability (depending on the stock universe) of remaining in Q5 in month *t*, and a 20% to 26% probability of transitioning to Q4. In only about 10% of cases does dispersion drop from Q5 in month *t*-1 to Q2 or Q1 combined. The transition matrices are broadly similar for all three stock universes. There is a bit more movement between the higher RD quintiles in Australia

[7] von Reibnitz (2017) observes a similar pattern in the US, and demonstrates that the positive relation between dispersion and performance is robust to controlling for fluctuations in the business cycle.

compared to US results, where von Reibnitz (2017) reports that for 67% of the months in which RD is in Q5, RD remains in Q5 for the following month.

INSERT TABLE 2

3.2. Equity fund data

Data for Australian funds are extracted from Morningstar Direct, including monthly returns, total net assets (TNA), fees and expenses, and fund summary information for each share class. The sample includes both live and dead funds, and is therefore free from survivorship bias. The data are first filtered to remove funds in base currencies other than Australian dollars or not marked as having 'equity' mandates. Data are then retained only for funds that match one of the seven Morningstar categories appearing in Table 3. This yields 1,373 fund share classes, corresponding to 984 funds of which 240 comprise multiple share classes. For these 240 funds, an average return is estimated through weighting share class returns by their beginning-of-month TNA.[8] To protect against incubation bias (Evans, 2010), our sample only includes return observations after a fund's inception date as reported by Morningstar, which signifies the date on which the fund was first offered to the public for investment. A manual examination of fund names, prospectuses and benchmarks is performed to identify and exclude index funds, sector funds, long-short equity funds, absolute return funds, and funds aiming to achieve outperformance through investments outside of Australia. Finally, the sample is restricted to only include funds with at least 18 months of observations in order to support the estimation of the factor models. The final sample includes 718 funds, with a breakdown by Morningstar category contained in Table 3.

INSERT TABLE 3

[8] A check of share class returns for the same fund reveal them to be very similar, with the variation appearing to be largely attributable to fee differences. Share class weights are also manually checked, and adjustments made for missing TNA observations with reference to the last available TNA observation.

4. Results

We commence in Section 4.1 by reporting results on the relation between fund performance and RD across six fund segments: all funds, large-cap funds, small-cap funds and the three style categories of value, growth and blend. Section 4.2 then examines the relation between RD and fund performance with funds sorted by activeness. Section 4.3 present results for the switching strategy. Section 4.4 provides an overview of the robustness tests.

4.1. Return dispersion and fund performance

Table 4 reports fund performance across RD quintiles for the six segments. Excess returns are presented in Panel A, FF alpha in Panel B, 4-factor alpha in Panel C and 5-factor alpha in Panel D. Figure 2 plots the FF alpha estimates, which are our primary performance measure. Consistent with von Reibnitz (2017), we focus on the lagged relation between RD_{t-1} and subsequent fund performance in period t. Examining a lagged relation envisages that managers can implement active bets in response to an increase in RD. We discuss this matter and report on FF alpha estimates for the coincident relation in Section 4.4.

Four key findings emerge from the results presented in Table 4 and Figure 2. The first is that there is a positive relation between RD and average fund performance. However, this relation is concentrated in small-cap funds, while being largely absent for large-cap funds. This is suggestive of skill differences across the two segments. In our sample, small-cap funds generate significant outperformance on average, with excess return of 2.61% per annum, FF alpha of 4.26% per annum, 4-factor alpha of 3.59% per annum and 5-factor alpha of 4.01% per annum. Meanwhile, average large-cap excess return and alphas are all modestly negative but insignificant. The significant outperformance observed for small-cap funds is concentrated in RD quintiles Q3 and Q5 based on excess returns, and spread across Q3, Q4 and Q5 based on FF alpha, 4-factor alpha and 5-factor alpha. In the highest RD quintile (Q5), the average small-cap fund generates excess returns of 7.68% per annum, FF alpha of 10.76% per annum, 4-factor alpha of 10.11% per annum and 5-factor alpha of 10.59% per annum. By contrast, there is no clear relation between RD and fund performance in the large-cap segment. The relatively stronger performance for small-cap funds is broadly consistent with the Australian studies discussed in Section 1 (e.g. Chen et al, 2010; Bennett et al. 2016).

Second, the fund style results are mixed, providing no evidence of clear differences in the relation between RD and active fund performance across styles. Nevertheless, the style analysis generates a few interesting findings. While all three styles deliver outperformance when RD sits in Q3 to Q5, the manner in which this occurs differs. Value funds tend to deliver their greatest risk-adjusted outperformance when RD is highest, with significant FF alpha of 5.89% per annum in Q5. Meanwhile, growth funds deliver their greatest outperformance in Q4, with insignificant alpha in Q5. This result is consistent with the concept that the highest RD environments deliver mispricing, which is in turn more readily exploited by value managers who seek out mean reversion to fair value. Meanwhile, to the extent that growth funds are more inclined to seek trending behavior rather than mean revision, they may only require more moderate RD environments to generate active returns.

Third, every fund segment generates negative alpha in RD Q1, which is sometimes significantly negative, e.g. for all funds combined, and for the growth and blend categories. Performance in Q2 is insignificant across all segments for all performance measures. This suggests that low RD environments adversely impact the ability of active managers to generate sufficient returns to cover their fees. It is consistent with lack of active opportunity when RD is low.

Fourth, adding the momentum and illiquidity factors makes no substantial difference to the core findings. In general, 4-factor alphas are of modestly lower magnitude than the FF alphas, with 5-factor alphas sitting in between the FF and 4-factor estimates. The patterns and significance levels are very similar. The only instances where the 4-factor and 5-factor models result in alpha dropping below significance are for the all fund segment in RD Q4 and Q5, and for growth funds in Q5 under the 5-factor model. Meanwhile, significance does not change in any other segment, which is more pertinent given that our main findings relate to how performance varies across size segments. Also of note is that adding MOM boosts alpha for value funds (except in RD Q5), while it reduces alpha for growth and blend funds. This is consistent with value funds loading negatively on MOM, with the converse holding for growth and blend. The robustness of our results to the inclusion of IML indicates that the outperformance achieved by small-cap managers is not merely due to harvesting an illiquidity premium during high RD environments.

To evaluate the significance of the conditional relation between alpha and RD, we apply the MR test for monoticity proposed by Patton and Timmermann (2010). The estimated p-values appear in the bottom row in each panel. They indicate a positive relation that is significant at the 5% level for all funds and small-caps funds under all four performance measures, but provide no evidence of a significant positive relation for large-cap funds. This confirms that the positive relation between RD and alpha largely arises from small-caps. The monoticity tests are mixed across fund styles and performance measures. Under our preferred measure of FF alpha, there is a significantly positive relation for value and blend funds, but not growth funds.

INSERT TABLE 4

INSERT FIGURE 2

An important point in comparing our results with prior literature is that we analyze after-fee returns for pooled funds as reported by Morningstar, whereas the more recent research into Australian equity funds draws on institutional mandates and excludes management fees. This provides scope for the level of fund performance we report to vary from previous studies due to differences between institutional and retail funds, including the impact of differing fees. In general, our measures of fund performance are more conservative than the prior studies based around institutional mandates. We examine gross fund performance excluding fees under robustness testing, which is reported in Section 4.4.

In summary, the results reported in this sub-section are consistent with the concept that higher RD environments provide opportunities to generate active returns that can be exploited by skilled active managers. Fund performance increases with RD in a broadly monotonic manner, although the extent to which this holds varies with fund segment. Not only does performance tend to be superior when RD is higher, but this appears to align with skill, noting that it is clearest for small-cap funds where prior evidence of skill is strongest (Chen et al, 2010). The fact that value managers produce greater FF alpha in the highest RD quintile when large mispricings are more likely is also consistent with skill-based elements being at play.

4.2. Return dispersion, fund activeness and performance

We now delve deeper into the findings, focusing on FF alpha as our primary performance measure. This section investigates the interaction between the market environment, fund activeness and performance. We conduct a double sort by RD and fund selectivity (S) at the end of month *t*-1, then calculate FF alpha within each RD/S quintile. The results are reported in Table 5 and plotted in Figure 3. They reveal a tendency for outperformance within the higher RD quintiles to be concentrated among funds in the higher S quintiles. This is visually evident in Figure 3. Both the most (S5) and second most (S4) active fund portfolios achieve their greatest FF alphas during the top dispersion quintile (Q5). Funds in S5 and S4 also produce significantly positive alphas in Q3 and Q4, respectively. The largest average FF alpha of 7.76%. per annum occurs in Q5/S5, with FF alpha declining progressively as activeness declines towards S1. The relation between FF alpha and activeness is monotonic across S quintiles within the highest RD Q5 (p-value of 4%). Performance is negative (often significantly so) across S portfolios within RD Q1, with the exception that FF alpha is positive but insignificant for Q1/S5.

A number of points arise from the RD/S double-sorts. While the estimates are not always statistically significant and monotonic, there is an evident tendency for more active funds to deliver better performance. This is can be readily seen in the 'All S | RD' results near the bottom of Table 5, where the MR test for monoticity generates a p-value of 4%. Further, the more active funds generate their performance when RD is moderate to high, rather than low, with the MR test being significant across S3, S4 and S5. These findings are broadly consistent with the literature highlighting a relation between fund activeness and performance as discussed in Section 1, as well as von Reibnitz (2017) who finds that the outperformance by the most active US funds occurs when RD is highest. The key difference is that the outperformance by the more active funds occurs across a wider range in Australia, where it emerges for funds in S4 and S5 when RD sits in Q3 through Q5. In contrast, von Reibnitz (2017) finds outperformance to be concentrated only in Q5/S5 in the US. The implication is that scope for active management to add value for investors is broader in Australia, spanning more funds and moderate-to-high RD environments.

INSERT TABLE 5

INSERT FIGURE 3

Given the differences between large-cap and small-cap funds, we undertake RD/S double-sorts within each of these two segments. The estimated FF alphas are plotted in Figure 4. For large-caps, a tendency emerges for meaningful alpha to be generated only by the most active funds (S5), particularly in Q5/S5 where they produce significant FF alpha of 3.08% per annum. The Australian large-cap results thus broadly accord with von Reibnitz (2017), who finds that only the most active US funds generate significant alpha and only when RD is highest. In addition, the large-cap funds ranked in S5 deliver greater FF alpha than funds ranked in all other S quintiles within each RD quintile. That is, the most active large-cap funds do persistently better. In small-caps, the role of fund activeness is less clear. While small-cap funds ranked in S5 generate higher FF alpha than funds in other S quintiles within RD Q1 and Q4, this is not the case for other RD quintiles. Indeed, the small-cap FF alpha patterns are mixed and variable across RD/S quintiles. The rule that emerges is that small-cap funds tend to perform better in RD Q3, Q4 and most notably Q5 (where FF alpha is significant in all but one of the S quintiles), and worst in Q1, almost regardless of activeness. This suggests that the RD environment matters more than fund activeness for alpha generation in the small-cap segment.

INSERT FIGURE 4

The findings in this section are consistent with skill being less widely available and concentrated in the most active funds in the large-cap segment, but being more broadly spread across small-cap funds. It is worth noting that small-cap funds tend to be more active than large-cap funds across the sample. In small-caps, the average R-squared from regressing fund returns on the factors ranges from 0.86 in S1 to 0.45 in S5. In large-caps, the range goes from 0.98 in S1 to 0.74 in S5. This implies that conditioning on activeness may matter more in large-caps due to a larger portion of funds that are closet indexers.

4.3. Switching strategy

We now present the results for the switching strategy, under which an investment is made in active funds when RD is within specified quintiles at the beginning of the month, and a passive investment made otherwise. Table 6 displays the FF alpha where the BMI is used for the passive alternative. Table 7 reports equivalent results for the Vanguard index fund. Each panel displays results where the active leg of the strategy involves a notional equally-weighted portfolio across four active fund segments. These include: all active funds (Panel A); the most active (S5) funds within the full sample (Panel B); the most active (S5) funds within the large-cap sample (Panel C); and all small-cap funds (Panel D). The latter three fund segments are chosen with reference to the tests reported in Sections 4.1 and 4.2 indicating that they offer the greatest performance, suggesting that testing other segments would generate little additional insight.

The columns in Table 6 and Table 7 are arranged from left to right in decreasing degree of exposure to active funds across the RD states. The first column of results displays the FF alpha from investing in the active funds within each segment throughout the sample period, without switching.[9] The second, third, fourth, and fifth columns report FF alphas to the strategy of investing in the active funds when RD is in Q2-Q5, Q3-Q5, Q4-Q5 and Q5; and investing passively otherwise. Alpha for the passive alternative is reported in the final column.

As discussed in Section 2.5, the FF alpha of the BMI is zero by construction. However, the Vanguard index fund has negative alpha of -0.60% per annum. This is mostly attributable to its management fee of 0.18% per annum,[10] and the fact that the S&P/ASX300 underperformed the BMI[11] over the analysis period, as noted in Section 2.3. The key issue is how the return patterns arising from the switching strategy vary across the various combinations of active and passive. In this regard, the test using the Vanguard index fund places both active and passive on the same footing in terms by accounting for costs and measuring against a common performance benchmark. This provides a more practical test than comparing active funds against the BMI, which investors could not directly access over the period.

[9] The FF alphas in Table 6 and Table 7 for the always active strategy do not match those reported in Table 4 due to differences in sample period and model design. In particular, the sample in Table 6 starts in 1997, rather than 1991, due to the availability of the Vanguard index fund. Further, to avoid look-ahead bias when assessing performance across RD quintiles, the FF alphas in Table 4 are calculated using 24 month rolling regressions. For Table 6 and Table 7, we evaluate the switching strategy based on the return it delivers over the sample period as a whole, generating a single FF alpha estimate. We also calculate the FF alphas for the switching strategy using rolling regressions in the manner outlined in Table 4, and find the results to be qualitatively consistent.

[10] Vanguard reduced the management fee to 0.16% as of 1 July 2019. For further details on the fund, see https://www.vanguardinvestments.com.au/retail/ret/investments/product.html#/fundDetail/wholesale/portId=8100/assetCode=equity/?overview.

[11] The Vanguard index fund has a correlation with the BMI of 0.995; and the loadings suggest that the return difference relates to the constituents and/or stock weights rather than factor exposures. The fund has a beta on the BMI of 0.97 (t = 180.01), a loading on SMB of 0.01 (t = 0.82), and a loading on the HML of 0.00 (t = -0.07).

The strategies may be viewed as switching between a market investment without any factor exposure, and an investment in active funds that may contain factor exposures. Benchmarking against the FF model implicitly adjusts alpha for returns arising from factor exposures under the active fund leg of the strategy. For instance, the small-cap fund portfolio will load on the size factor under the FF model. This facilitates adjustment of fund returns for the relative performance of small-cap versus large-cap stocks, via the product of the (positive) size beta for the small-cap funds and returns to the size factor during the period.

INSERT TABLE 6

INSERT TABLE 7

The results reported in Table 6 and Table 7 suggest that the switching strategy enhances FF alpha relative to both a constant active and constant passive investment. FF alpha is maximized by taking active exposure when RD is either in Q2-Q5 or Q3-Q5, depending on the active fund segment and the passive alternative. Further, performance worsens notably in moving from taking active exposure during RD Q3-Q5 to the columns sitting to the right, under which the passive investment is held over an increasingly larger number of periods. The lowest FF alpha is generated by a constant passive investment in the Vanguard index fund. Instances where FF alpha is both significant and at its greatest magnitude occur in RD Q2-Q5 for the most active funds (Panel B), and either RD Q2-Q5 or Q3-Q5 for small-cap funds (Panel D). The most active large-cap funds (Panel C) generate significant FF alpha in RD Q3-Q5 with the BMI as the passive alternative, but not with the Vanguard index fund as its negative alpha drags down the overall returns to the strategy.

Three observations help interpret the switching strategy results. First, being exposed to active funds in the Australian market can generate positive FF alpha, consistent with findings in the literature discussed in Section 1. As a consequence, going passive can miss out on active alpha. Second, results reported in prior sub-sections indicate that this alpha is generated across a wide range of RD environments, with the exception of Q1 and perhaps Q2. This implies that it pays to remain exposed to active funds unless RD is in Q1 or Q2, explaining why peak FF alpha appears in Q2-Q5 or Q3-Q5. Third, FF alpha is greater for more active funds and small-cap funds. This is consistent with the literature, as well as the results reported earlier. The return-enhancing impact of activeness can be seen by comparing Panel A with Panel B and Panel C in Table 6 and Table 7; while the impact of small-cap exposure is evident from Panel D.

The Australian switching strategy results may be interpreted through the lens that alpha is maximized where the opportunity cost associated with investing passively is minimized. This gives rise to an optimal strategy that entails remaining exposed to active funds when RD is within either Q2-Q5 or Q3-Q5 for all the fund segments examined, and going passive only when RD is low. In contrast, investing in active funds only during (say) Q5 generates relatively low alpha. This is because returns are diluted by the opportunity cost associated with failing to capture the value created by active funds during the moderate RD quintiles. Indeed, investing in active funds only in Q5 generates negative FF alpha in Table 7 due to the return drag from the Vanguard index fund in other RD quintiles, given that it delivers negative alpha under the BMI benchmark and with fees included. These dilutive effects are lessened but still apparent if the investment in active funds is retained across RD Q4-Q5. The US switching strategy results can also be interpreted through the opportunity cost lens. von Reibnitz (2017) finds that active funds fail to add value, and indeed often destroy it, outside of the highest RD quintile. That is, there is no opportunity cost for switching to passive outside of high RD environments. Investors can hence afford to be more selective about when they invest in US active funds.

Two messages are embedded within these results. First, in Australia it is better to remain exposed to active funds over a majority of periods, only switching to passive alternatives when RD is low enough to significantly limit the opportunity for active managers to generate alpha. This stands in contrast to the US, where the question seems to be when to go active, rather than when to go passive. Second, outperformance from the switching strategy can be maximized by focusing active investment in segments where skill appears to be higher – such as more active funds and small-cap funds. When skill is present, managers have greater capacity to generate alpha even when RD is moderate, and moving to passive alternatives is more likely to entail a larger opportunity cost.

4.4 Robustness tests

We run a number of carefully targeted tests to confirm the robustness of our findings. To conserve space, the results are described and interpreted rather than tabulated.

4.4.1. Coincident relation between RD and performance

It is worth reflecting on the choice between analyzing the lagged versus coincident relation between fund performance and RD. This choice might be viewed in two ways. The first is that managers put stock bets in place independently of the RD environment, but these bets have a greater propensity to pay off once a high RD state occurs. This interpretation would imply a coincident relation. The second possibility is that an increase in RD itself provides a source of active opportunity because it delivers mispricing, which skilled managers then move to exploit. This interpretation is suggestive of a lagged relation, as managers react to opportunities that emerge as a consequence of higher RD. In addition, the lagged results are more meaningful from a practical perspective, as they imply scope for investors to exploit the observed relation. Specifically, it does not require investors to predict higher RD before it occurs, but rather enables them to observe a shift in the RD environment before reallocating their investments in the subsequent month. The ability of investors to observe RD and then react is a key feature of our switching strategy as presented in Section 4.3.

Against this background, we also examine the coincident relation between RD_t and fund performance in month t. FF alphas for the coincident relation follow a similar pattern to the lagged relation, although mainly are smaller in magnitude. For example, the coincident relation between RD and FF alpha for small-cap funds is still monotonically increasing in the RD quintiles, but the average alpha in the highest RD Q5 is 9.27% versus 10.76% under the lagged relation as reported in Table 4. Across fund styles, the FF alphas in the lower RD quintiles of Q1 and Q2 are either insignificant or significantly negative, while the FF alphas in the RD Q3-Q5 are either insignificant or significantly positive. Overall, the coincident results are broadly in line with the lagged results.

4.4.2. Gross alpha, adjusting for fees

Our primary focus has been net returns, allowing us to examine whether investors gain residual value from investing in active funds after fees. Tests of gross returns provide an alternative perspective on manager skill. Specifically, they offer a more direct measure of skill by separating out what managers are charging for their purported skill. Gross return analysis also provides insight into whether our net return findings might be altered by differences in the fees charged across fund segments, or to different investors. In particular, Morningstar states that they deduct the maximum fee quoted in the fund prospectus in arriving at net returns. This will reflect the fee charged to investors in pooled funds, who will often be retail investors, while the fee paid by institutional investors may be much lower. Our core results may hence be most applicable to retail investors.

The analysis underpinning Table 4 is repeated using gross returns, estimated by adding one-twelve of maximum annual management fee reported by Morningstar to the monthly net return figures. As expected, FF alpha increases for all fund segments across all RD quintiles. All fund categories now produce positive and significant gross FF alpha for the period as a whole. Meanwhile, FF alpha remains negative in RD Q1 for all fund segments except value funds. This suggests that the switching strategy would still add value at the gross return level. Significantly positive gross FF alpha is generated by the all, growth and blend fund segments in RD Q2-Q5; value funds in Q3-Q5; large-cap funds in Q2 and Q4; and small-cap funds in Q3-Q5. The relative performance between fund segments mirrors the net return analysis, confirming that our findings are largely driven by cross-sectional differences in active returns rather than fees. Small-cap funds remain the top performers, earning peak gross FF alpha in RD Q5 of 12.79% per annum, versus 11.14% per annum under net returns.

The difference between gross and net FF alpha of 1.33% per annum provides an estimate of the average fee that Morningstar is subtracting from the active fund returns. In contrast, the Mercer Global Manager Fee Survey (2014) quotes an indicative fee on a US$100 million segregated mandate of 0.42% per annum for Australian active equities, and 0.20% per annum for Australian passive (although we understand that lower fees may be negotiated on the latter). This highlights that the difference in fees paid by retail and institutional investors may be of the order of 0.50%-1% per annum. This confirms that the alpha available from investing actively can vary substantially across investors, and may be meaningfully larger for institutions than under our core results. The implication is that exposure to Australian active funds may add value for institutional investors across an even broader range of RD environments than is portrayed under our core analysis.

4.4.3. Factor loadings estimated within each RD quintile

One possibility is that alpha estimates might be distorted if fund factor loadings vary with the RD environment. Where this occurs, factor loadings estimated from rolling regressions based on 24 months of prior data may not reflect the factor exposure held by the funds in a particular RD quintile. There are reasons why fund factor exposures and RD might be related. RD has been shown to be positively correlated with the subsequent value premium (Stivers and Sun, 2010), as well as countercyclical to the stock market (e.g. Loungani et al., 1990; Gomes et al., 2003; Stivers, 2003; Zhang, 2005). It is therefore possible that active managers alter their factor exposures depending on expected payoffs that vary though time. To account for this possibility, we follow von Reibnitz (2017) and conduct in-sample regressions within each RD quintile. After sorting the sample months into five sub-periods according to the RD quintile, we regress fund excess returns on the FF factors for the panel of all months within each sub-period. This generates FF alphas that are specific to each RD quintile. The results are similar to those reported in Table 4, although there is a tendency for the FF alphas to reduce in magnitude. The absence of any meaningful changes leads us to conclude that the findings are robust to the possibility of a relation between fund factor exposures and the RD environment.

4.4.4. Alternative size factor

We also generate results using an alternative size factor return series, constructed from the difference between the Small All Ordinaries Index and the S&P/ASX100. The ASX indices accord with the conventional breakpoint between large-caps and small-caps used by the Australian investment industry, against which there may be some slippage under the S&P Australia BMI-based indices due to differing construction rules. Data availability for the S&P/ASX100 restricts the analysis using this alternative size factor to the period June 1994 to July 2018, which are compared with the baseline results over this more limited sample period. We find that the FF alpha estimates under the alternative size factor are similar to the baseline estimates for most segments, differing by 0.20% per annum or less. The notable exception is the small-cap fund segment, where FF alpha declines to 1.95% per annum using the alternative size factor versus 2.62% under the baseline results over the 1994 to 2018 period.[12] The reduction in small-cap FF alpha is spread across Q2 through to Q5, with Q3 losing significance. Thus the size factor benchmark choice appears to make some difference to the magnitude of small-cap alpha. Nevertheless, the general tenor of the findings remains unchanged.

[12] As a further check of the sensitivity of our small-cap results to the size factor employed, we conduct a variation of the test under which both size factors are included in the model simultaneously. The significance of the alphas and their relation with RD remains intact, with FF alpha estimates in fact increasing above those generated when either of the size factors are included on their own.

4.4.5. CAPM alpha

We estimate CAPM alphas, with market betas generated by regressing fund excess returns on the BMI. The results are qualitatively consistent, but appear to be influenced by returns arising from unrecognized factor exposures. This is consistent with the contention that the single-factor CAPM is less appropriate for evaluating fund performance than factor models in the context where it is important to adjust for factors and/or style. We conclude that CAPM alphas provide little additional insight.

4.4.6. Other

Finally, we trim stock returns for the top and bottom 1% and 1.5% during any month (originally 2.5%) for the purpose of estimating the RD measure. We also run the analysis using RD terciles rather than quintiles. In both cases, no substantial changes to the findings emerge.

5. Conclusions

Our examination of the relation between cross-sectional RD and active fund performance in Australia generates results that differ considerably from those found in the US by von Reibnitz (2017). In Australia, active managers add value for investors provided that RD is not too low. In the US, exposure to active managers is justified only when RD is high, and then only in the most active managers. We also find that the Australian results are primarily driven by small-cap managers. Results for Australian large-cap managers show a similar pattern, but are much more modest in magnitude. Similar to the US, alpha in large-caps only attains significance for the most active large-cap managers in the highest RD quintile. Applying a switching strategy confirms that investors are better off remaining exposed to active funds in Australia *excep*t when RD is low. In contrast, US investors are better off staying passive *unless* RD is high.

While the Australian and US results may seem somewhat at odds, they actually tell a consistent story. In both countries, a positive relation exists between RD and fund performance. The common driver is manager ‘skill’, or ability to generate alpha, and how it interacts with the market environment as indicated by RD. The greater the skill, the less the need for a high RD environment in order for a manager to deliver alpha. Skill is rarer in the US but appears to align with activeness, resulting in significant alpha being available only from the most active US funds in the highest RD environments. Within the Australian small-cap fund segment, skill seems to be more widely available. Hence significant alpha can be generated by investing actively across a much broader range of RD environments. Australian small-cap managers apparently only need a moderate amount of RD to capitalize on active opportunities. For this segment, switching to a passive approach only seems worth considering when return RD is very low, and can entail a significant opportunity cost otherwise. The results for Australian large-cap managers sit somewhere in-between, but are closer to those for US mutual funds than Australian small-cap funds. In summary, our study finds that active management can be worthwhile. However, when and where it is likely to pay off is conditional on both the market environment and fund segment being considered.

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Table 1: Summary Statistics for Return Dispersion

Universe	Total Sample Top 300	Large-caps Top 100	Small-caps Bottom 101-300
Mean	8.57%	7.01%	9.18%
Median	8.07%	6.59%	8.68%
Standard Deviation	2.04%	1.94%	2.23%
Autocorrelation	0.686	0.627	0.667

The mean, median, standard deviation and single-period autocorrelation are reported for the monthly time-series of return dispersion for Australian stocks over the test period of August 1991 to July 2018. Return dispersion is estimated as an equally-weighted standard deviation of returns versus the market index, using equation (1) appearing in Section 2.1. Estimates are generated for the top 300 stocks by market capitalization, and sub-samples comprising the top 100 large-cap stocks and the bottom 101-300 small-cap stocks.

Table 2: Transition Matrices for Return Dispersion Quintiles (%)

Panel A: Total Sample (Top 300)

	RD Quintile *t*				
RD Quintile *t*-1	Q1	Q2	Q3	Q4	Q5
Q1	35.38	33.85	23.08	6.15	1.54
Q2	33.85	29.23	20.00	9.23	7.69
Q3	21.88	18.75	23.44	25.00	10.94
Q4	7.69	7.69	26.15	33.85	24.62
Q5	1.54	10.77	6.15	26.15	55.38

Panel B: Large-caps (Top 100)

	RD Quintile *t*				
RD Quintile *t*-1	Q1	Q2	Q3	Q4	Q5
Q1	32.31	27.69	21.54	15.38	3.08
Q2	23.08	24.62	30.77	15.38	6.15
Q3	26.56	21.88	20.31	20.31	10.94
Q4	16.92	18.46	18.46	24.62	21.54
Q5	1.54	7.69	7.69	24.62	58.46

Panel C: Small-caps (101-300)

	RD Quintile *t*				
RD Quintile *t*-1	Q1	Q2	Q3	Q4	Q5
Q1	32.31	35.38	20.00	10.77	1.54
Q2	38.46	21.54	21.54	12.31	6.15
Q3	18.75	23.44	23.44	25.00	9.38
Q4	7.69	12.31	24.62	32.31	23.08
Q5	3.08	7.69	9.23	20.00	60.00

The transition matrices are formed by allocating the monthly return dispersion estimates into five quintiles, with Q1 (Q5) representing low (high) return dispersion. The estimates reflect the percentage of times that return dispersion is observed in each quintile in month t (shown horizontally) after being observed in each quintile during the previous month t-1 (shown vertically). Panel A reports percentages for the total sample of top 300 stocks; while Panel B and Panel C report percentages for the top 100 large-cap and bottom 101-300 small-cap sub-samples, respectively.

Table 3: Fund Sample

Morningstar Category	Number	Percentage	Benchmark Index
Australia Fund Equity Australia Large Blend	318	44.3%	S&P Australia Large
Australia Fund Equity Australia Large Growth	87	12.1%	S&P Australia Large Growth
Australia Fund Equity Australia Large Value	72	10.0%	S&P Australia Large Value
Total Large	*477*	*66.4%*	
Australia Fund Equity Australia Mid/Small Blend	91	12.7%	S&P Australia Mid/Small
Australia Fund Equity Australia Mid/Small Growth	41	5.7%	S&P Australia Mid/Small Growth
Australia Fund Equity Australia Mid/Small Value	33	4.6%	S&P Australia Mid/Small Value
Total Small/Medium	*165*	*23.0%*	
Australia Fund Equity Australia Other	76	10.6%	S&P Australia Broad Market (BMI)
Total Sample	**718**	**100%**	
By Style			
Blend	409	57.0%	
Growth	128	17.8%	
Value	105	14.6%	
Other	76	10.6%	
Total Sample	**718**	**100%**	

This table details the structure of the final sample of Australian active funds by fund category and style. The benchmark index used in the estimation of excess returns is also shown in the final column. The sample covers the period September 1989 to July 2018. To form the fund sample, data for all Australian domiciled funds, both live and dead, is downloaded from Morningstar. The data is filtered to remove funds that: have base currencies other than Australian dollars, or invest overseas; are non-equity mandates; do not match one of the seven Morningstar categories; are index, sector, long-short and absolute return funds; or have insufficient data. Funds with multiple share classes are combined, with an average return estimated by weighting by total net assets in each class.

Table 4: Active Performance by Segment Across Return Dispersion Quintiles

Panel A: Excess Return vs. Fund-Specific Benchmark Index

RD_{t-1}	All	Large-cap	Small-cap	Value	Growth	Blend
Q1 (low)	-2.00	0.00	-2.50	-1.11	-2.41	-2.30**
(t-stat)	(-1.61)	(0.00)	(-1.33)	(-0.49)	(-1.57)	(-1.97)
Q2	-0.79	0.21	0.73	-1.98	1.19	-0.61
(t-stat)	(-0.62)	(0.18)	(0.33)	(-1.00)	(0.74)	(-0.49)
Q3	1.19	-1.32	4.79**	2.35	1.54	1.29
(t-stat)	(1.20)	(-1.18)	(2.02)	(1.64)	(1.04)	(1.35)
Q4	1.05	1.82	2.63	-0.64	4.20***	0.85
(t-stat)	(0.99)	(1.42)	(1.25)	(-0.30)	(2.72)	(0.74)
Q5 (high)	1.37	-1.58	7.68**	1.91	2.19	0.61
(t-stat)	(0.90)	(-1.03)	(2.13)	(0.79)	(0.91)	(0.41)
Overall	0.15	-0.18	2.61**	0.09	1.32*	-0.04
(t-stat)	(0.28)	(-0.32)	(2.32)	(0.09)	(1.68)	(-0.08)
Monotonicity: MR test (p-value)	0.04**	0.81	0.04**	0.15	0.09*	0.11

Panel B: Fama-French Alpha

RD_{t-1}	All	Large-cap	Small-cap	Value	Growth	Blend
Q1 (low)	-1.32*	-0.34	-2.24	-0.10	-2.05**	-1.67**
(t-stat)	(-1.83)	(-0.54)	(-1.12)	(-0.08)	(-2.55)	(-2.37)
Q2	-0.03	-0.36	0.30	-0.99	1.27	0.40
(t-stat)	(-0.04)	(-0.58)	(0.15)	(-0.76)	(1.27)	(0.53)
Q3	0.66	-0.56	6.76***	2.90***	0.52	0.59
(t-stat)	(0.76)	(-0.94)	(2.75)	(2.74)	(0.49)	(0.74)
Q4	1.61*	1.06	6.23***	1.03	4.20***	1.59*
(t-stat)	(1.74)	(1.38)	(2.85)	(0.70)	(3.24)	(1.66)
Q5 (high)	2.49*	-0.31	10.76***	5.89***	1.62	1.65
(t-stat)	(1.81)	(-0.27)	(3.01)	(3.42)	(0.87)	(1.24)
Overall	0.67	-0.10	4.26***	1.72***	1.10*	0.51
(t-stat)	(1.55)	(-0.30)	(3.74)	(2.75)	(1.92)	(1.20)
Monotonicity: MR test (p-value)	0.03**	0.36	0.04**	0.08*	0.13	0.04**

Table 4 *(continued)*

Panel C: 4-Factor Alpha

RD_{t-1}	All	Large-cap	Small-cap	Value	Growth	Blend
Q1 (low)	-1.36*	-0.39	-2.93	0.83	-2.00**	-1.69**
(t-stat)	(-1.78)	(-0.64)	(-1.42)	(0.70)	(-2.34)	(-2.34)
Q2	-0.57	-0.35	-0.53	-0.98	0.44	-0.46
(t-stat)	(-0.69)	(-0.54)	(-0.26)	(-0.69)	(0.44)	(-0.61)
Q3	0.76	-0.76	6.28**	3.22***	0.66	0.64
(t-stat)	(0.83)	(-1.27)	(2.28)	(2.84)	(0.59)	(0.77)
Q4	1.19	0.52	5.57**	1.94	2.79**	0.92
(t-stat)	(1.14)	(0.66)	(2.42)	(1.32)	(2.00)	(0.89)
Q5 (high)	1.97	-0.71	10.11**	5.49***	1.03	1.42
(t-stat)	(1.28)	(-0.61)	(2.53)	(2.96)	(0.51)	(1.01)
Overall	0.39	-0.34	3.59***	2.08***	0.57	0.16
(t-stat)	(0.83)	(-0.96)	(2.93)	(3.2)	(0.95)	(0.36)
Monotonicity: MR test (p-value)	0.04**	0.73	0.04**	0.08*	0.09*	0.01***

Panel D: 5-Factor Alpha

RD_{t-1}	All	Large-cap	Small-cap	Value	Growth	Blend
Q1 (low)	-0.95	-0.01	-2.24	1.32	-1.50*	-1.32*
(t-stat)	(-1.27)	(-0.02)	(-1.06)	(1.14)	(-1.74)	(-1.79)
Q2	-0.30	-0.63	0.75	-0.53	0.80	-0.14
(t-stat)	(-0.35)	(-1.01)	(0.37)	(-0.35)	(0.79)	(-0.17)
Q3	0.95	-0.52	6.24**	3.61***	0.89	0.79
(t-stat)	(1.05)	(-0.78)	(2.24)	(2.99)	(0.82)	(0.99)
Q4	0.95	1.06	5.18**	1.20	2.57	0.65
(t-stat)	(0.83)	(1.28)	(1.99)	(0.77)	(1.62)	(0.58)
Q5 (high)	2.42	-0.65	10.59***	6.42***	1.61	1.80
(t-stat)	(1.60)	(-0.54)	(2.76)	(3.38)	(0.83)	(1.32)
Overall	0.61	-0.15	4.01***	2.37***	0.87	0.35
(t-stat)	(1.26)	(-0.41)	(3.25)	(3.52)	(1.42)	(0.79)
Monotonicity: MR test (p-value)	0.04**	0.81	0.04**	0.11	0.09*	0.04***

This table reports annualized average fund performance for six segments, both overall and during the months within each return dispersion quintile, over the period August 1991 to July 2018. Panel A presents estimates of average excess return relative to the benchmark index assigned to the fund category, as identified in Table 3. Panel B presents estimates of average Fama-French alpha; Panel C presents estimates of average 4-factor alpha; and Panel D presents estimates of average 5-factor alpha, where the fifth factor is the illiquidity factor of Amihud (2019). t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level. Monotonicity p-values are estimated by applying the MR test of Patton and Timmermann (2010) across the return dispersion quintiles for each fund segment.

Table 5: FF Alpha Across Return Dispersion and Selectivity Quintiles

RD_{t-1}	S1 (low)	S2	S3	S4	S5 (high)	MR test: RD (p-value)	All S | RD
Q1 (low)	-1.19**	-2.36***	-2.68***	-1.57	1.44	0.17	-1.28*
(t-stat)	(-2.32)	(-4.16)	(-3.05)	(-1.35)	(0.84)		(-1.78)
Q2	-0.86*	0.17	0.55	-0.22	0.13	0.09*	-0.05
(t-stat)	(-1.74)	(0.28)	(0.56)	(-0.16)	(0.07)		(-0.06)
Q3	-0.80*	-0.74	0.16	1.19	3.57*	0.03**	0.66
(t-stat)	(-1.87)	(-1.20)	(0.18)	(0.83)	(1.81)		(0.77)
Q4	1.11	0.61	0.89	2.46*	2.92	0.16	1.59*
(t-stat)	(1.27)	(0.72)	(0.96)	(1.82)	(1.46)		(1.72)
Q5 (high)	-1.05	-0.17	1.17	5.04**	7.76***	0.04**	2.50*
(t-stat)	(-1.42)	(-0.17)	(1.02)	(2.52)	(2.63)		(1.81)
MR test: S (p-value)	0.37	0.13	0.04**	0.04**	0.08*		0.03**
All RD | S	-0.56**	-0.50	0.01	1.36**	3.13***	0.04**	0.68
(t-stat)	(-1.98)	(-1.48)	(0.02)	(2.03)	(3.28)		(1.55)

Annualized average Fama-French alpha for all funds over the period August 1991 to July 2018 is reported under a double sort by return dispersion quintile (Q1 to Q5, shown vertically) and fund activeness quintile (S1 to S5, shown horizontally). Overall averages along the RD dimension are shown as 'All S | RD', and averages along the activeness dimension as 'All RD | S'. Funds are ranked by activeness using the R-squared based selectivity measure of Amihud and Goyenko (2013). t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level. p-values under the MR test for monoticity of Patton and Timmermann (2010) are also reported.

Table 6: FF Alpha for Switching Strategy with BMI as the Passive Alternative

Panel A: All Funds						
Active months	***RD Q1-Q5 (Always active)***	***RD Q2-Q5***	***RD Q3-Q5***	***RD Q4-Q5***	***RD Q5***	***Always passive***
FF alpha	0.16	0.54	0.74*	0.46	0.01	0.00
(t-stat)	(0.37)	(1.31)	(1.85)	(1.31)	(0.02)	n.a.
R^2	0.98	0.98	0.98	0.98	0.99	1.00

Panel B: Most Active Funds, Ranked in S5						
Active months	***RD Q1-Q5 (Always active)***	***RD Q2-Q5***	***RD Q3-Q5***	***RD Q4-Q5***	***RD Q5***	***Always passive***
FF alpha	1.40	1.88*	1.79*	1.38*	0.02	0.00
(t-stat)	(1.42)	(1.95)	(1.92)	(1.75)	(0.03)	n.a.
R^2	0.88	0.89	0.90	0.93	0.95	1.00

Panel C: Most Active Large-Cap Funds, Ranked in S5						
Active months	***RD Q1-Q5 (Always active)***	***RD Q2-Q5***	***RD Q3-Q5***	***RD Q4-Q5***	***RD Q5***	***Always passive***
FF alpha	0.46	0.90	0.92*	0.62	0.15	0.00
(t-stat)	(0.8)	(1.6)	(1.67)	(1.29)	(0.37)	n.a.
R^2	0.95	0.96	0.96	0.97	0.98	1.00

Panel D: Small-Cap Funds						
Active months	***RD Q1-Q5 (Always active)***	***RD Q2-Q5***	***RD Q3-Q5***	***RD Q4-Q5***	***RD Q5***	***Always passive***
FF alpha	2.41**	2.86**	2.98***	1.90*	-0.11	0.00
(t-stat)	(2.18)	(2.56)	(2.72)	(1.92)	(-0.13)	n.a.
R^2	0.88	0.87	0.88	0.90	0.93	1.00

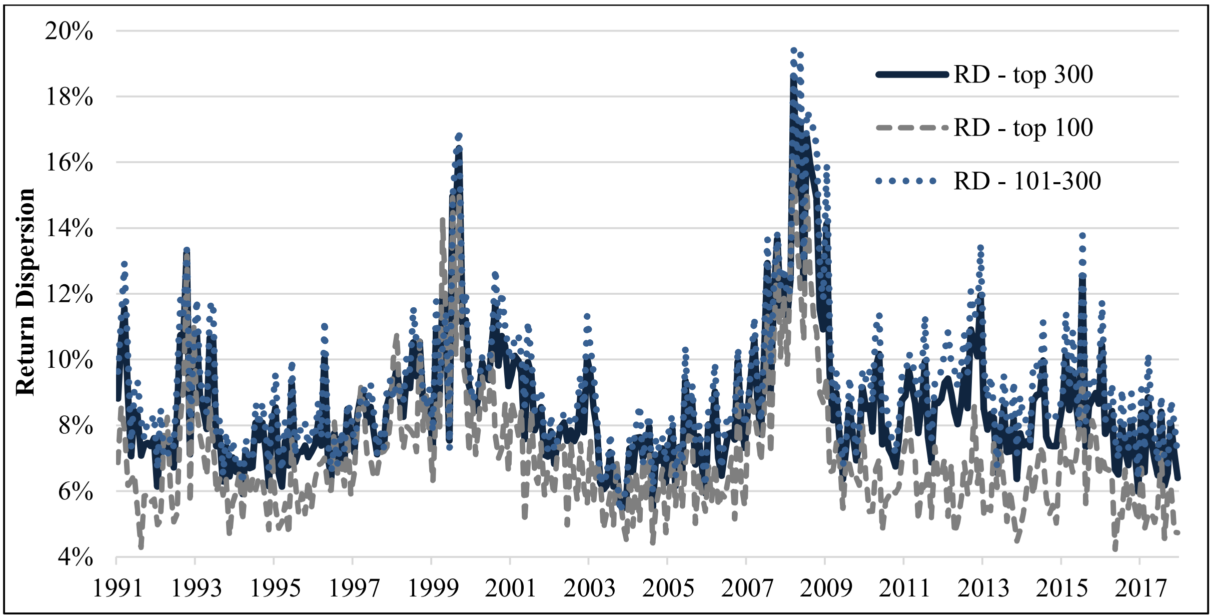
Annualized average Fama-French alpha is reported for a switching strategy applied over the period July 1997 to July 2018, under which an investment is made in active funds when return dispersion is within specified quintiles at the beginning of the month, and a notional passive investment in the Broad Market Index (BMI) otherwise. The table is arranged so that exposure to active funds conditional on return dispersion decreases from left to right. The first column of results reports FF alpha from a constant exposure to active funds in all months; followed by active exposure when return dispersion is observed in Q2-Q5, Q3-Q5, Q4-Q5 and Q5; with the far right column reporting the Fama-French alpha from a constant passive exposure in all months. R-squared from the regression of fund excess returns on the Fama-French factors is shown to indicate the portion of fund return variance explained by factor exposure. t-statistics are reported in brackets. ***, ** and * denote significance at the 1%, 5% and 10% level.

Table 7: FF Alpha for Switching Strategy with Vanguard Index Fund as the Passive Alternative

Panel A: All Funds						
Active months	***RD Q1-Q5 (Always active)***	***RD Q2-Q5***	***RD Q3-Q5***	***RD Q4-Q5***	***RD Q5***	***Always passive***
FF alpha	0.16	0.44	0.52	0.22	-0.35	-0.60
(t-stat)	(0.37)	(1.06)	(1.27)	(0.57)	(-1.01)	(-2.23)
R^2	0.98	0.98	0.98	0.98	0.98	0.99
Panel B: Most Active Funds, Ranked in S5						
Active months	***RD Q1-Q5 (Always active)***	***RD Q2-Q5***	***RD Q3-Q5***	***RD Q4-Q5***	***RD Q5***	***Always passive***
FF alpha	1.40	1.78*	1.57*	1.14	-0.34	-0.60
(t-stat)	(1.42)	(1.85)	(1.68)	(1.42)	(-0.5)	(-2.23)
R^2	0.88	0.89	0.90	0.92	0.94	0.99
Panel C: Most Active Large-Cap Funds, Ranked in S5						
Active months	***RD Q1-Q5 (Always active)***	***RD Q2-Q5***	***RD Q3-Q5***	***RD Q4-Q5***	***RD Q5***	***Always passive***
FF alpha	0.46	0.80	0.70	0.38	-0.20	-0.60
(t-stat)	(0.80)	(1.43)	(1.25)	(0.75)	(-0.46)	(-2.23)
R^2	0.95	0.95	0.96	0.97	0.97	0.99
Panel D: Small-Cap Funds						
Active months	***RD Q1-Q5 (Always active)***	***RD Q2-Q5***	***RD Q3-Q5***	***RD Q4-Q5***	***RD Q5***	***Always passive***
FF alpha	2.41**	2.76**	2.76**	1.66*	-0.47	-0.60
(t-stat)	(2.18)	(2.47)	(2.52)	(1.66)	(-0.56)	(-2.23)
R^2	0.88	0.87	0.87	0.90	0.93	0.99

Annualized average Fama-French alpha is reported for a switching strategy applied over the period July 1997 to July 2018, under which an investment is made in active funds when return dispersion is within specified quintiles at the beginning of the month, and a notional passive investment in the Vanguard Australian Share Index Fund otherwise. The table is arranged so that exposure to active funds conditional on return dispersion decreases from left to right. The first column of results reports FF alpha from a constant exposure to active funds in all months; followed by active exposure when return dispersion is observed in Q2-Q5, Q3-Q5, Q4-Q5 and Q5; with the far right column reporting the Fama-French alpha from a constant passive exposure in all months. R-squared from the regression of fund excess returns on the Fama-French factors is shown to indicate the portion of fund return variance explained by factor exposure. t-statistics are reported in brackets. ***, ** and * denote significance at the 1%, 5% and 10% level.

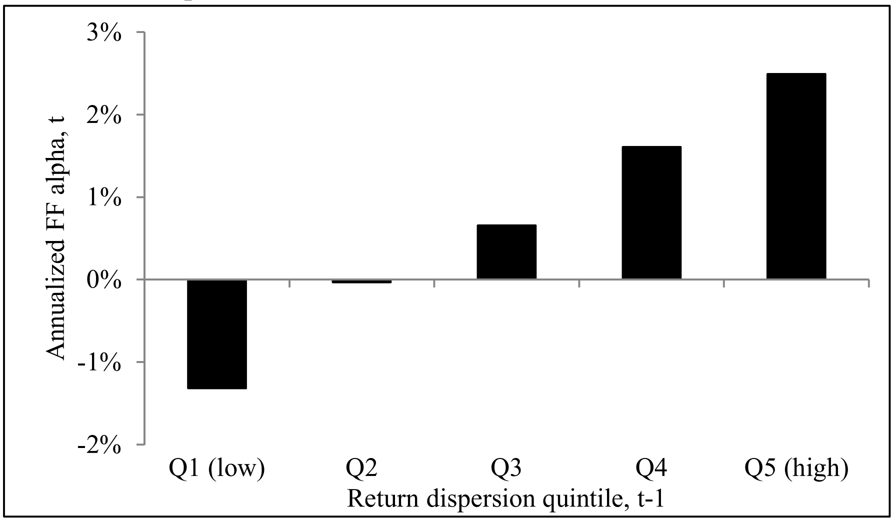
Figure 1: Times Series of Return Dispersion



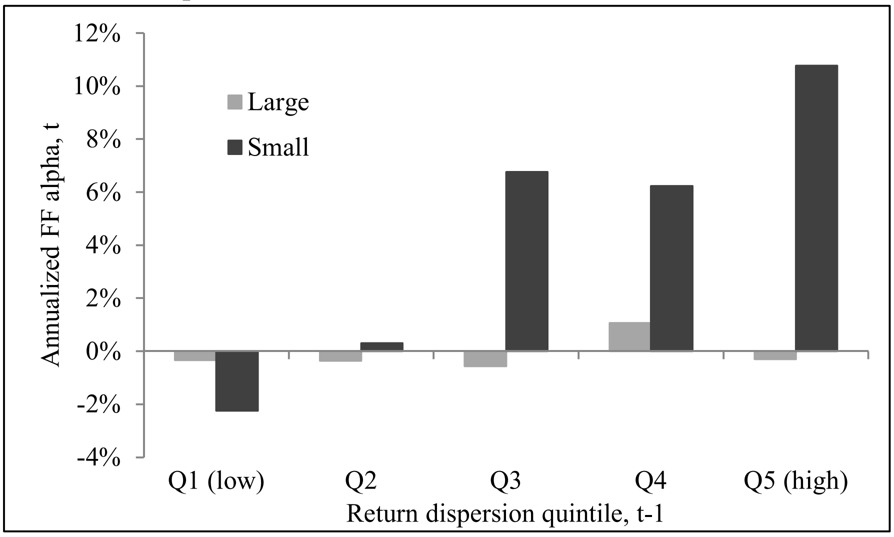
This figure is a time series plot of the equally-weighted monthly return dispersion estimates over the period August 1991 to July 2018. Series are shown for the 300 largest Australian stocks by market capitalization, as well as sub-samples comprising the top 100 large-caps and the bottom 101-300 small-caps.

Figure 2: Performance by Segment Across Return Dispersion Quintiles

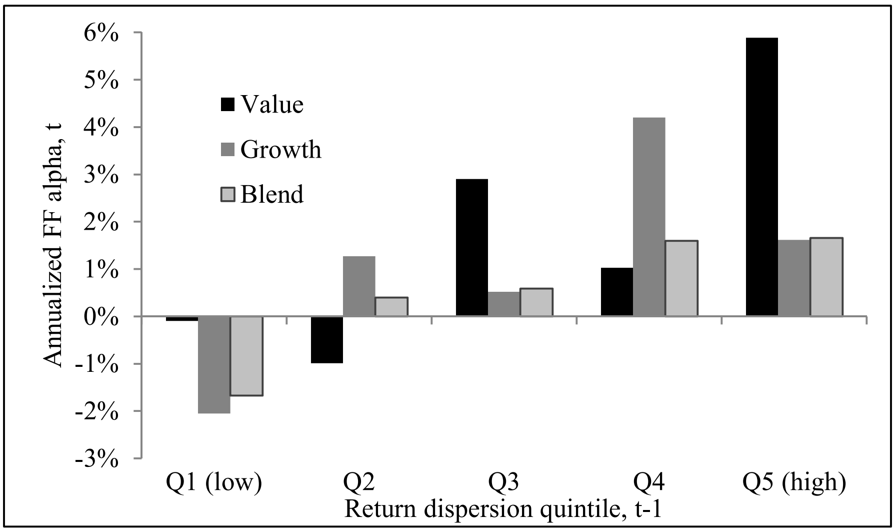
Panel A: FF Alpha, All Funds



Panel B: FF Alpha, Size

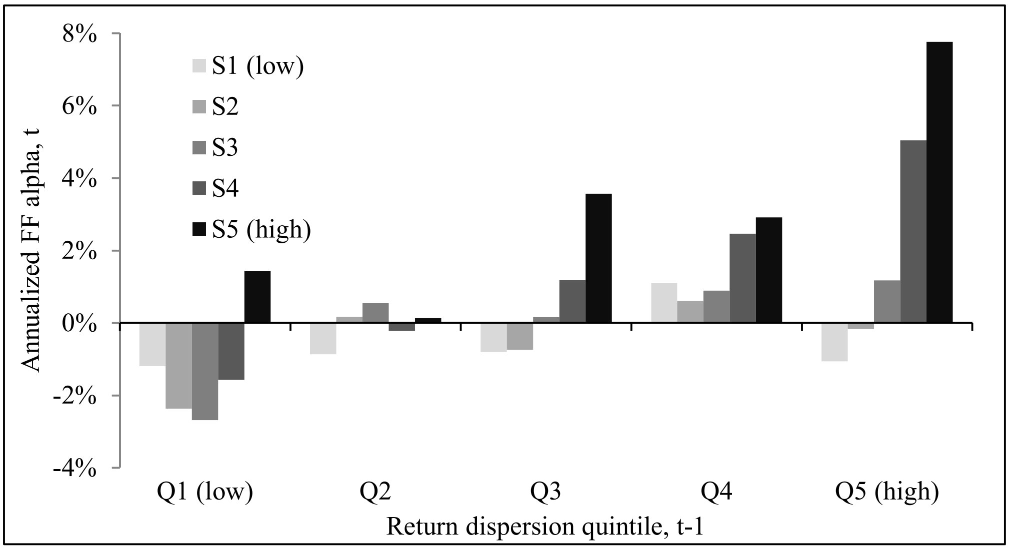


Panel C: FF Alpha, Style



Annualized average Fama-French alpha estimates within each return dispersion quintile over the period August 1991 to July 2018 are plotted for all funds in Panel A, by size segment in Panel B, and by fund style category in Panel C.

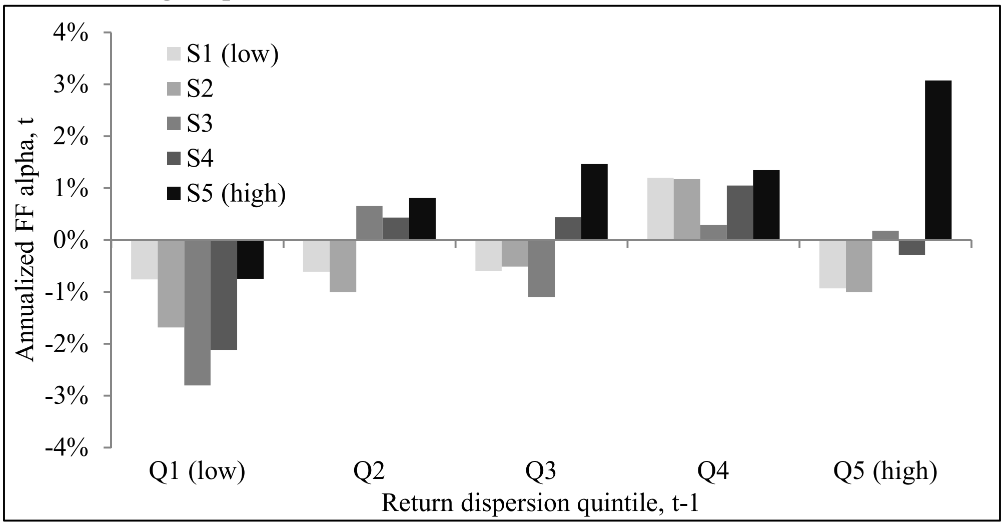
Figure 3: FF Alpha Across Return Dispersion and Selectivity Quintiles



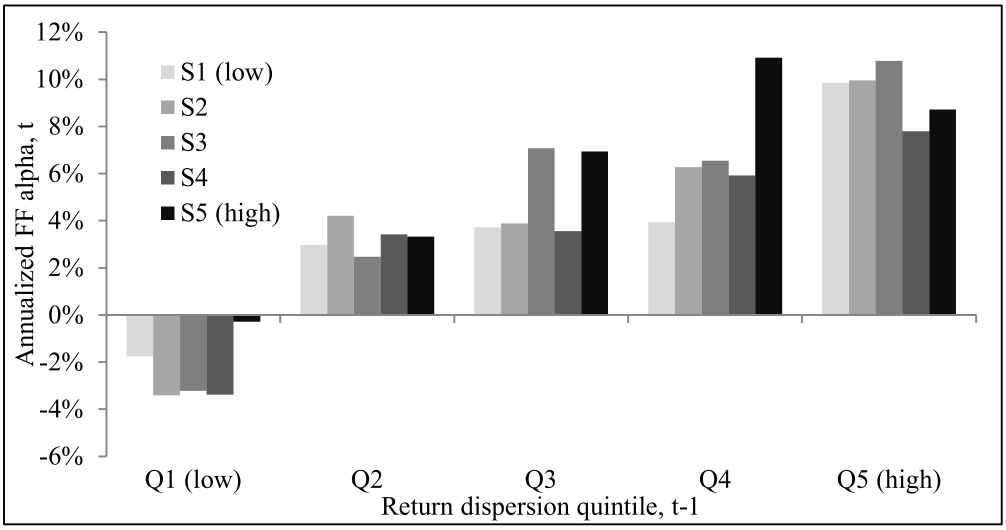
Annualized average Fama-French alpha across all funds over the period August 1991 to July 2018 is plotted based on a double sort by return dispersion quintile (Q1 to Q5), and fund activeness quintile (S1 to S5) according to the R-squared based selectivity measure of Amihud and Goyenko (2013).

Figure 4: FF Alpha Across Return Dispersion and Selectivity Quintiles by Size

Panel A: Large-caps



Panel B: Small-caps



Annualized average Fama-French alpha for large-cap funds (Panel A) and small-cap funds (Panel B) over the period August 1991 to July 2018 are plotted based on a double sort by return dispersion quintile (Q1 to Q5), and fund activeness quintile (S1 to S5) according to the R-squared based selectivity measure of Amihud and Goyenko (2013).