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Style drift, fund flow and fund performance: new cross-sectional evidence

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Abstract

The linkages between style change, fund flows, fund size, and resulting fund performance are complex and not clearly understood. In this paper, we investigate these relationships using a sample of Australian multisector trusts over the sample period 1990 to 1999. We employ a range of fund performance measures of stock selectivity. We find that levels of style drift are positively related to selectivity performance, but are not related to fund flows. We also find that fund size is positively related to fund performance and negatively related to expense ratios. Implications of our findings for investors are identified in the paper. © 2007 Academy of Financial Services. All rights reserved.

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Keywords: Style drift; Fund flows; Managed fund performance; Returns-based style analysis

1. Introduction

The style of many managed funds drift or even change over time (Brown & Goetzmann, 1997; Chan, Chen & Lakonishok, 2002; Kim, Shukla & Thomas, 2000; Swinkels & Van Der Sluis, 2001). Although some style changes might be caused inadvertently because of unrelated manager decisions, there is some evidence that funds might deliberately change styles to attract new fund flow. In a notable recent example, Cooper, Gulen and Rau (2005) find that a style change in a fund's name can attract significantly abnormal flow in the months after the change. They suggest that funds might time 'style' changes to exploit investor

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irrationality. Alternatively, a change in style often occurs after a management change (Gallo & Lockwood, 1999) and as such might not be intended by design.

One factor that is frequently discussed in relation to fund style drift is the degree to which fund flows can influence managerial decisions that subsequently result in style changes. In the current paper, using a sample of Australian multisector managed funds, we examine the links between fund flow and style drift, controlling for other factors that might affect fund performance; for example, fund size, fund category, and management expense ratios (MER).[1] The potential motives for possible style change in the Australian managed fund market are very similar to those put forward in the United States setting. The most potent force is likely to be the way in which many managers receive their compensation: as a percentage of funds under management. In Australia, this practice is most likely to be applicable to domestic equity managers.[2]

Why should individual investors care about style drift and its potential relation to fund performance? One answer to this question relates to the manner in which many investors can practically eliminate from consideration large numbers of funds from the many thousands contained in the fund universe, to reduce their choice to more manageable proportions. Put simply, faced with information overload, the category to which funds are assigned represents an attractive and expedient screening device for investors. By assessing their personal goals and tolerance for risk, individual investors can isolate a smaller group of potentially suitable funds according to the stated objective that each fund makes public via their prospectus (and other publicity or advertising). If fund managers do not strictly comply with their stated objective (whether by design or simply by inferior or slack practices), over time their actual style might be materially different from what it should be. Individual investors could easily be exposed to risk levels or types that are largely incompatible with their own personal situations, thereby creating a less than satisfactory investment experience. In the extreme scenario, this could lead to grossly inferior performance to that which they were expecting based on stated fund objectives. More subtly, even if the performance is not wildly different from (or even superior to) expectations, it may have been achieved with a very different risk profile than investors would prefer. As such, the individual investor should be acutely interested in the general issue of style drift and more particularly how fund performance relates to style drift. Accordingly, our goal is to shed light on this basic research question.

We use a range of fund performance measures of stock selectivity. We begin by estimating alphas using the standard performance models, such as Jensen and Treynor–Mazuy, along with a cubic market model, which allows volatility timing to be considered in the model. Second, as there are suggestions in the literature that the inclusion of public information variables provides a more reliable measure of fund performance (Holmes & Faff, 2004; Sawicki & Ong, 2000), we also incorporate conditional variables in the Treynor–Mazuy model. Third, the standard and conditional models apply restrictions to the level of fund risk. To relax this constraint, we also examine the alpha measures arising from an application of the Kalman filter, allowing fund risk to vary via a random walk.

Our findings can be summarized as follows. Based on rolling returns-based style analysis, we demonstrate a relatively high incidence of style drift, which for some funds in the sample takes on the appearance of major style change. Although we do not find support for a strong link between fund flow and style drift, we do find that style drift is related to fund performance. Specifically, we find evidence that style drift and selectivity are positively related.

The remainder of the paper is organized as follows. In Section 2, we review the literature dealing with fund flow, style drift and fund size, focusing on the relationship of these variables to fund selectivity performance. In Section 3, the research method is detailed, whereas Section 4 briefly describes the data. In Section 5, the results are discussed and conclusions are reached in Section 6.

2. Literature review

2.1. Fund flow

This cyclic relationship between flows, style drift, and performance is problematic to understand. Significant amounts of new flow could cause a manager to trade more frequently, therefore incurring more transaction costs. In addition, fund flows can constrain a fund manager from adhering to an optimal investment strategy, as they might have to hold more cash to allow for erratic flows (Edelen, 1999; Rakowski, 2003). Negative tax implications might also arise from significant fund flows (Shoven, Dickson & Sialm, 2000). In addition, a fund demonstrating style inconsistency could discourage further investment and, therefore, result in fund outflows. Cooper et al. (2005) find that a change in the style of the name of a fund can subsequently attract significant amounts of fund flow.

Many studies have examined the relationship between fund flows and performance (Berk & Green, 2004; Chevalier & Ellison, 1997; Deaves, 2004; DelGuercio & Tkac, 2002; Sirri & Tufano, 1998). Chevalier and Ellison (1997) and Sirri and Tufano (1998) find that mutual fund flows are related to lagged measures of excess returns. This finding implies that successful funds are more likely to attract fund flow in the future. This finding is also reported by DelGuercio and Tkac (2002) for those funds at the top of the distribution. Other literature points to three variables that are important in explaining fund flow: prior period performance, prior period fund flows and the size of the fund (Jain & Wu, 2000; Zeckhauser, Patel & Hendricks, 1991). Deaves (2004), using a sample of Canadian funds, finds that money flows into successful funds, but not out of unsuccessful ones at the same rate. This finding is often referred to as the convex relationship between flow and performance (Brown, Harlow & Starks, 1996; Chevalier & Ellison, 1997). A positive, significant relationship between mutual fund flow and Jensen's alpha is reported by DelGuercio and Tkac (2002), although they find that this is most likely because of a high correlation between published fund ratings and alpha.

2.2. Style drift

There is evidence that funds that adopt inconsistent styles over time might perform at a lower level than style consistent funds, although Brown and Harlow (2004) find that this result is driven by the months in the sample where the overall stock market is rising. In particular, Brown and Harlow (2004) find that when the market benchmark return is negative, low style consistent funds demonstrate relative out performance. They speculate that the reasons for better performance by style consistent funds could be less portfolio turnover and, therefore, lower transaction costs. In addition, style consistent managers are less likely to make asset allocation errors than those that try to time the market. In contrast, however, they consider that there is potential for underperformance with such a propensity to maintain a constant style profile and, therefore, overlook opportunities for market timing.

3. Research method

Various performance measures of selectivity will be used as the dependent variable in a series of cross-sectional linear regressions.[3] The cross-sectional analysis will primarily focus on the role of style drift in the form of a style drift score (SDS) and flows reflected by flow volatility. The control variables included are fund size, management expense ratio and fund category.

3.1. Style drift score

Style analysis (Sharpe, 1992) utilizes a multifactor model generally expressed as follows:

$$R_{it} = w_{il}\, F_{lt} + w_{i2}\, F_{2t} + \cdots \cdots \cdots \cdots + w_{in}\, F_{nt} + e_{it}, \tag{1}$$

where R_{it} is the return on fund i in period t; F_{xt} is the value of the style index return representing the asset class x ($x = 1, 2, \ldots n$); w_{ix} is the style weight of asset class x ($x = 1, 2, \ldots n$) for fund i; and e_{it} is that portion of the fund return that is unexplained by the weighted sum of the style indices. A 'strong' form of returns-based style analysis will be used for this study, whereby the weights estimated with Eq. (1) must be positive and sum to 1.

To ascertain the extent of style variation over time, the model will be applied using a 'rolling window' technique: over an initial time window (36 months), then the window will be moved forward by 1 month and new weights calculated. The goodness of fit of the model is calculated by the associated R^2 value:

$$R^2 = 1 - \frac{\text{var}(e_{it})}{\text{var}(R_{it})}\,. \tag{2}$$

For the rolling window analysis, a series of R^2 values are obtained for each 'window', so we calculate a mean R^2 for each fund.

Idzorek and Bertsch (2004) developed the SDS as a single quantitative measure of the variability of a fund's asset mix over time. The SDS is calculated as the square root of the sum of the variances of the asset class coefficients derived from Eq. (1) as demonstrated by Eq. (3),

$$SDS = \sqrt{var(w_{1t}) + var(w_{2t}) + \cdots\cdots\cdots + var(w_{nt})}\,, \tag{3}$$

where w_{1t}, w_{2t}. . . . . w_{nt} represent the time series style weights obtained from the style analysis process. Idzorek and Bertsch argue that the SDS is an effective, time-efficient way to compare style consistency and eliminates the need to examine rolling window style graphs. A fund with a high SDS will demonstrate greater style inconsistency than a fund with a low SDS. For the cross-analysis, SDS will be used as a measure of style drift as it provides a mean value of the variation in style index coefficients for each fund. SDS is the primary test variable in our analysis.

3.2. Fund flow and flow volatility

Fund flow can be measured as the monthly change in total net assets less fund appreciation:

$$FLOW_{it} = TNA_{it} - TNA_{it-1}(1 + r_{it}), \tag{4}$$

where TNA_{it} is fund i's total net assets at time t, and r_{it} is the fund's excess return for month t. To adjust for scale, the $FLOW_{it}$ value can be divided by $FLOW_{it-1}$ to give a percentage measure of fund flow, relative to the size of the fund (Jain & Wu, 2000).

$$RFLOW_{it} = FLOW_{it} / FLOW_{it-1}. \tag{5}$$

For the current study, we will use the cross-sectional measure of fund flow volatility. Following Rakowski (2003), we use the variance of fund flow as a measure of flow volatility.

3.3. Control variables

The literature points to a relationship between fund flow, performance and size; therefore, fund size is included as a variable in the cross-sectional analysis as the natural log of the mean fund size. There is also a documented relationship between the expense ratio of a fund, fund size, and performance, and as a result, the median MER for the sample period is included as an explanatory variable. We also include dummy variables for each fund category.

3.4. Fund performance variables

Various performance metrics measuring selectivity will be used as the dependent variable. Initially, Jensen's model (Jensen, 1968) will be used to find an overall average measure of fund performance for each fund:

$$r_{it} = \alpha_i + \beta_i r_{mt} + e_{it}, \tag{6}$$

where r_{it} is the excess return of fund i in month t, α_i is a measure of the abnormal return of the fund, β_i is a measure of the fund's systematic risk in relation to the benchmark portfolio and r_{mt} is the excess return on the benchmark portfolio.

A selectivity alpha will also be estimated by the Treynor–Mazuy (1966) model;

$$r_{it} = \alpha_i + \beta_i r_{mt} + \gamma_i r_{mt}^{2} + e_{it}. \tag{7}$$

In addition to market timing, the construct of volatility timing will be included. Specifically, by application of a cubic market model (Holmes & Faff, 2004), a third measure of alpha performance will be generated:

$$r_{it} = \alpha_i + \beta_i\, r_{mt} + \gamma_i\, r_{mt}^{\;2} + \delta_i r_{mt}^{\;3} + e_{it}. \tag{8}$$

Furthermore, the Treynor–Mazuy model can be converted to a conditional performance model through the incorporation of lagged public information variables. Following Sawicki and Ong (2000) and Holmes and Faff (2004), we use the following set of variables: the 30-day Treasury bill yields p.a. observed at $t-1$ (TBY_{t-1}), the dividend yield calculated as average market dividend yield for the past 12 months to $t-1$ (DY_{t-1}), the term structure of interest rates calculated as 10-year Treasury bond yield minus 3-month Treasury bill yield (TS_{t-1}), and a January (July) dummy that takes the value of unity if the month is January (July) and zero otherwise (D_{Jan}, D_{Jul}). When the conditional variables are included, the Treynor–Mazuy model can be expressed as follows:

$$\begin{aligned} r_{it} = \alpha_i + [\beta_i + \beta_{TBi}\, TBY_{t-1} + \beta_{DYi}\, DY_{t-1} + \beta_{TSi}\, TS_i + \beta_{Jani}\, D_{Jan} \\ + \beta_{Juli}\, D_{Jul}]\, r_{mt} + \gamma_{it}\, r_{mt}^{\;2} + e_{it}. \end{aligned} \tag{9}$$

Finally, in addition to including conditional variables, the Jensen and Treynor–Mazuy models are modified to allow for time variation in risk levels, via the application of a Kalman Filter (see, e.g., Black, Fraser & Power, 1992).

3.5. Cross-sectional regressions

As stated earlier, the cross-sectional regressions will aim to capture any relationships between fund performance measures (y_i = estimated alpha values) and our primary cross-sectional explanatory variables: SDS and flow volatility.

$$\begin{aligned} y_i = \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4 + a_5 D_5 + \alpha_6 D_6 + \alpha_7 D_7 + \alpha_8 D_8 + \alpha_{10} SDS_i \\ + \alpha_{11} SIZE_i + \alpha_{12} FLOWVOL_i + \alpha_{13} MER_i + error, \end{aligned} \tag{10}$$

where $D_1 = 1$ for a multisector trust and 0 otherwise; $D_2 = 1$ for a multisector pension and 0 otherwise; $D_3 = 1$ for a balanced super fund and 0 otherwise;[4] $D_4 = 1$ for a defensive super fund and 0 otherwise; $D_5 = 1$ for a growth super fund and 0 otherwise; $D_6 = 1$ for a moderate super fund and 0 otherwise; $D_7 = 1$ for a wholesale non-tax paying (NTP) fund and 0 otherwise;[5] $D_8 = 1$ for a wholesale pooled superannuation trust (PST) fund and 0 otherwise;[6] SDS_i = style drift score; $SIZE_i$ = fund size (equal to the natural log of mean funds under management for the sample period); $FLOWVOL_i$ = flow volatility (equal to the variance of the flow during the sample period); MER_i = management expense ratio (equal to the median expense ratio for the sample period).

Weighted least squares (WLS) estimation is used in the cross-sectional regressions, whereby the weights assigned are the inverse of the standard errors of the respective estimated performance measures. WLS is chosen over ordinary least squares because it recognizes that the dependent variables in our regressions are not observed: they are

Table 1 Sample descriptive statistics

Fund category	Sample size (n = 198)	Mean monthly return	Standard deviation monthly return
Multisector trusts	31	0.0014	0.0283
Multisector pension funds	7	0.0007	0.0136
Multisector superannuation fund: aggressive	4	0.0011	0.0279
Multisector superannuation fund: balanced	20	0.0004	0.0189
Multisector superannuation fund: defensive	7	−0.0001	0.0085
Multisector superannuation fund: growth	73	0.0011	0.0254
Multisector superannuation fund: moderate	21	0.0003	0.0107
Multisector wholesale funds: non-tax paying	6	0.0025	0.0251
Multisector wholesale funds: pooled superannuation trust	29	0.0021	0.0199

estimated in a set of first stage regressions and, hence, are heterogeneous in the degree of precision attached to them.[7]

4. Data

4.1. Fund sample, fund flow, and market index data

This study uses a sample of 198 Australian multisector trusts supplied by MorningStar Downunder. The funds have a minimum of 114 monthly returns over the period January 1990 to June 1999.[8] The sample can be separated into nine fund categories: multisector trusts (n = 31), multisector pension funds (n = 7), superannuation aggressive funds (n = 4), superannuation balanced funds (n = 20), superannuation defensive funds (n = 7), superannuation growth funds (n = 73), superannuation moderate funds (n = 21), wholesale funds (non-tax paying) (n = 6), and wholesale funds (pooled super trusts) (n = 29). Descriptive statistics for the sample are displayed in Table 1. The All Ordinaries Accumulation Index was used as a proxy for the market and the Reserve Bank 3-month Treasury Bill rate was used as a proxy for the risk-free rate. The data for the lagged public information variables (TBY_{t-1}, DY_{t-1}, and TS_{t-1}) were obtained from DataStream International.

There is a potential survivorship issue in our study: approximately 100 funds are excluded because of insufficient data. The issue of survivorship bias has been considered previously with this dataset (Holmes & Faff, 2004) and there is some minor evidence that the selectivity performance measures might be higher when only surviving funds are used. Specifically, two tailed tests of equality of population proportion were conducted and it was found that when the alpha values calculated by the cubic model are considered, there are significantly more positive cases (67.2%) when only surviving funds are used, in comparison to 58.2% of cases when non-surviving funds are included. In contrast, there was no significant difference in the alpha values obtained from the Jensen and Treynor–Mazuy models between the two samples of funds. Although our sample for this study only contains surviving funds, the impact of ignoring the non-surviving funds appears to be minimal.[9]

Table 2 Style drift score per fund category: 36 month rolling window style analysis

Fund categories	Number of funds	Mean	Standard deviation	Maximum	Minimum	Upper quartile	Median	Lower quartile
Multisector trusts	31	0.2044	0.0807	0.4333	0.0981	0.2386	0.1940	0.1435
Multisector pension	7	0.1630	0.0580	0.2423	0.0621	0.1943	0.1713	0.1382
Super aggressive	4	0.1396	0.0086	0.1511	0.1310	0.1433	0.1381	0.1344
Super balanced	20	0.1551	0.0525	0.2949	0.1013	0.1903	0.1351	0.1175
Super defensive	7	0.1565	0.1141	0.3894	0.0527	0.1709	0.1503	0.0806
Super growth	73	0.1544	0.0419	0.2670	0.0782	0.1698	0.1432	0.1256
Super moderate	21	0.1428	0.0702	0.3256	0.0141	0.1852	0.1363	0.1238
Wholesale non-tax paying	6	0.1959	0.0702	0.3198	0.1357	0.2202	0.1662	0.1535
Wholesale pooled superannuation trust	29	0.1350	0.0550	0.2710	0.0736	0.1524	0.1210	0.0951
Total (all fund categories)	198	0.1601	0.0627	0.4333	0.0141	0.19300	0.1450	0.1236

4.2. Style analysis indices

Meaningful style analysis relies heavily on the choice of style indices. Sharpe (1992) specifies that the set of indices should be as exhaustive as possible, mutually exclusive and that their returns should differ. In addressing these issues, we choose the following six indices: (1) Australian Equity (AEQ): Australian DataStream (DS) Market Index; (2) Australian Fixed Interest (AFI): UBS Composite All Maturities Index; (3) International Equity (IEQ): MSCI World Ex Australian Index; (4) Listed Property (LP): ASX Property Trust Index; (5) Overseas Fixed Interest (OFI): WD Citigroup G7 All Maturities Index; and (6) Cash: Reserve Bank of Australia 90 day BAB Index.[10]

5. Results

5.1. Style drift

To determine the degree to which funds maintain style consistency over time, the SDS was estimated for each fund. Those funds with a high SDS can be considered to be more style inconsistent than those with a relatively low SDS. Table 2 displays the SDS summary statistics for each fund category. It can be seen that, on average, funds in the multisector trust category are the least style consistent (mean SDS = 0.2044), followed by the wholesale NTP category (mean SDS = 0.1959). The most style consistent categories, as determined by their mean SDS score were from the wholesale PST category (mean SDS = 0.1350) and the superannuation aggressive fund category (mean SDS = 0.1396). Overall, the highest SDS for the entire sample of funds was found for Fund 12 from the multisector trust category (SDS = 0.4333), whereas the lowest was for Fund 151 from the superannuation moderate funds category (SDS = 0.0141). The statistics in Table 2 also reveal that generally, there is a positive skew in the distribution of SDS in each fund category, as for all but one category, the median value is lower than the mean value.

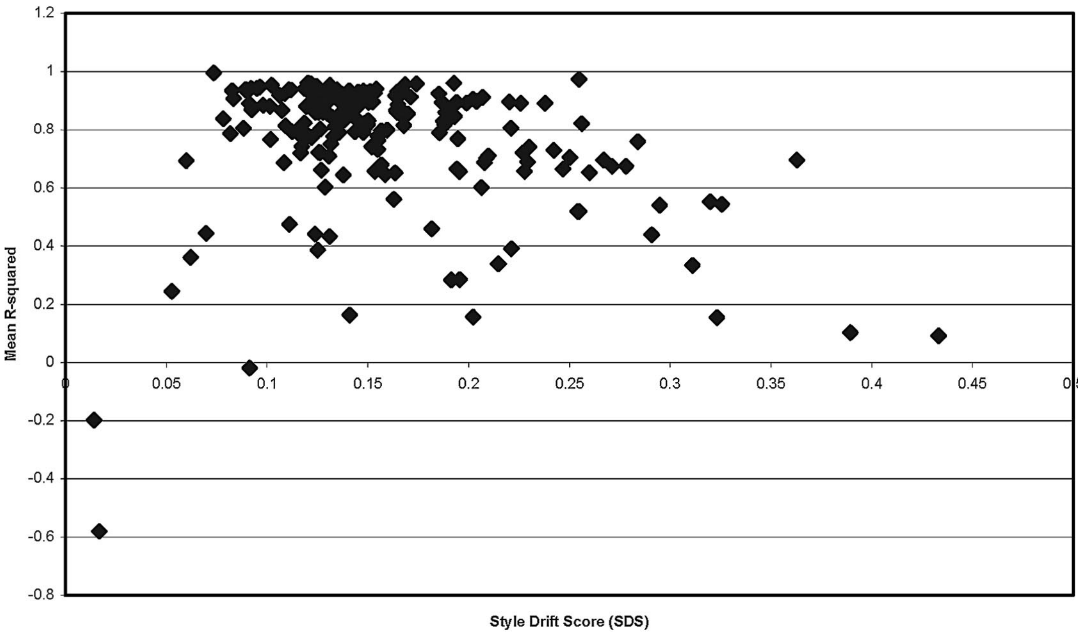

Fig. 1. Relationship between style drift score and mean R^2 values for 36 month rolling window analysis.

The SDS is a measure of style consistency derived from the variability of the style weightings determined through application of a rolling window style analysis process. The style analysis optimization regression aims to maximize the 'goodness of fit' of the model, so that fund return can be expressed as a linear combination of the style indices. The degree to which the linear model can explain the excess fund return is given by the associated R^2 value for each fund. Fig. 1 displays the relationship of the R^2 value to the associated SDS for each fund. There is a significant negative correlation between the two measures (-0.2151, $p = 0.002$), indicating that the amount of variation within the style weightings tends to increase as the 'goodness of fit' of the model decreases.

Following Brown and Harlow's (2004) line of reasoning, it could be that funds with a low R^2 value are basically operating 'outside of the square'. In other words, their return series cannot be explained by the linear combination of six style indices. If this is the case, then it follows that they may have a higher degree of style inconsistency, as the manager charts his/her own course. However, the case could also be made that the choice of passive benchmarks used in the style analysis process were not representative of the fund's actual style and, therefore, the associated low R^2 value was more indicative of ineffectual modeling rather than manager skill. Again, this could result in a higher degree of style inconsistency, because of the difficulty in estimating meaningful style weights. For this study, the style indices were carefully chosen to avoid significant collinearity that has been found to reduce the effectiveness of style analysis (Agudo & Gimeno, 2005).

To provide a visual representation and appreciation of style consistency and inconsistency, the style weightings for three funds from each of two main fund categories are displayed in

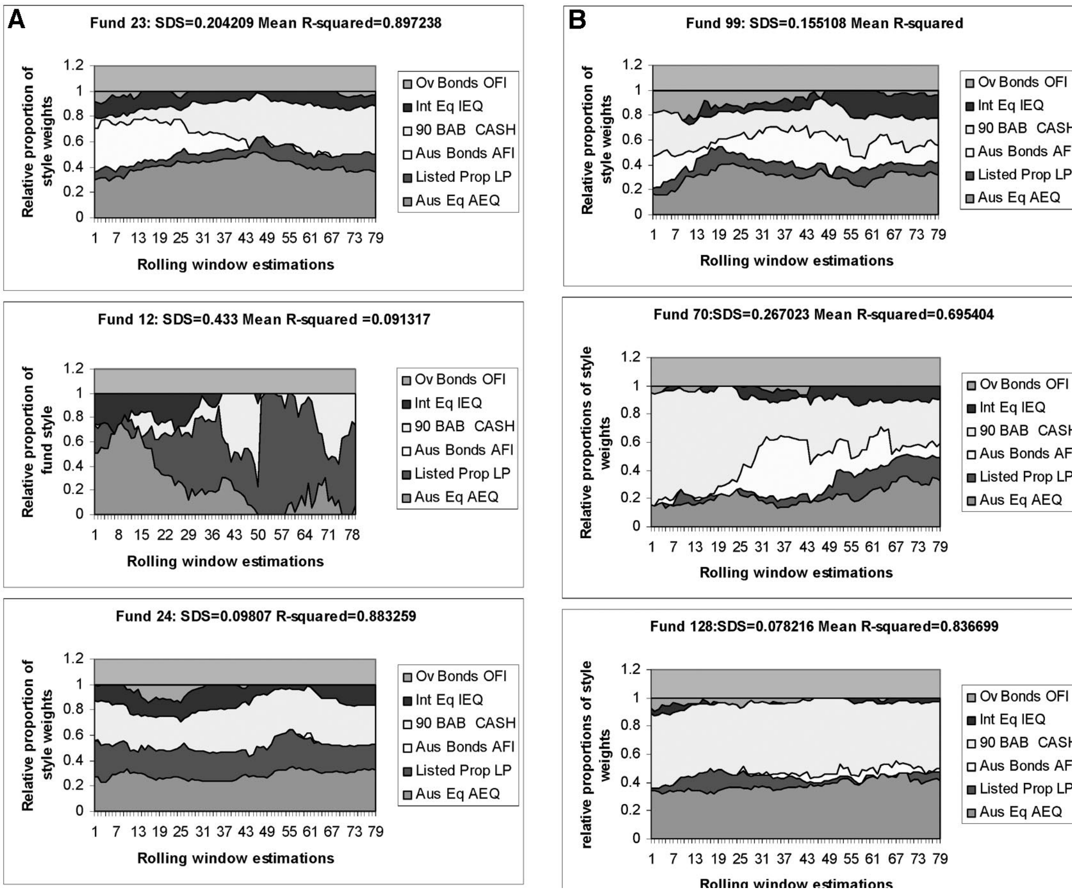

Fig. 2. Change in style weights over time for illustrative multisector funds. Panel A, multisector trusts; Panel B: superannuation growth funds.

Fig. 2. In each panel, the first fund shown has an SDS very close to the mean SDS for that category, the second fund has the highest SDS for that category, whereas the third fund has the lowest SDS for funds in that category. Funds from the multisector trust category are displayed in Panel A. Fund 23 has an SDS of 0.2042, which is just below the mean SDS (0.2044) for all multisector trusts in the sample. It can be seen that although the weighting for the AFI style index is substantial at the start of the sample period, there is a gradual decrease in this style, and it is replaced primarily by the CASH index towards the end of the sample period. The second fund (#12) displayed in Panel A is the multisector trust fund with the highest SDS. It is apparent that the gradual change that occurred in the first fund is not evident for Fund 12 and that the changes in the style weightings are far more volatile. In contrast, the third fund in Panel A, Fund 24, has the lowest SDS of 0.0981. Relative to both Funds 23 and 12, the changes in the style weightings over time are stable, and a high degree of style consistency is observed.

The largest fund category (superannuation growth) is represented in Panel B. For this category the mean SDS (0.1544) is similar to that of the balanced super funds, although Fund

Table 3 Correlations between cross-sectional variables

	Jensen alpha	TM alpha	Cond TM alpha	TM Kalman alpha	Cond TM Kalman alpha	Cubic alpha	Fund size	Flow volatility	MER
TM	**0.833**	1.000							
	(0.000)								
Conditional TM alpha	**0.210**	**0.413**	1.000						
	(0.003)	**(0.000)**							
TM Kalman alpha	**0.906**	**0.853**	**0.215**	1.000					
	(0.000)	**(0.000)**	**(0.000)**						
Conditional TM Kalman alpha	**0.925**	**0.838**	**0.279**	**0.895**	1.000				
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**					
Cubic alpha	**0.499**	**0.433**	**0.505**	**0.460**	**0.440**	1.000			
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**				
Fund size	**0.246**	**0.355**	**0.353**	**0.377**	**0.327**	**0.379**	1.000		
	(0.001)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**			
Flow volatility	−0.009	0.012	0.023	0.008	−0.015	0.020	−0.081	1.000	
	(0.906)	(0.879)	(0.759)	(0.920)	(0.843)	(0.791)	(0.280)		
Management expense ratios	−0.250	−0.161	**−0.227**	**−0.335**	**−0.298**	−0.183	**−0.368**	0.156	1.000
	(0.012)	(0.109)	**(0.023)**	**(0.001)**	**(0.003)**	(0.068)	**(0.000)**	(0.122)	
Style drift score	−0.025	0.109	**0.170**	−0.042	0.031	0.020	−0.130	0.007	0.128
	(0.731)	(0.128)	**(0.016)**	(0.555)	(0.666)	(0.780)	(0.078)	(0.929)	(0.204)

Note: Pearson correlation coefficient is displayed with p-value in parentheses below. Significant correlations (at the 5% level) are bolded.

70 with the highest SDS (0.2670) is more style consistent than its counterpart in the balanced fund grouping. Similarly, the super growth fund with the lowest SDS (Fund 128; SDS = 0.0782) is more style consistent than the corresponding super balanced fund.

5.2. Cross-sectional analysis

5.2.1. Style drift score and performance

There is evidence that style consistent funds perform better than funds that demonstrate inconsistent style (Brown & Harlow, 2004). In this study, we use the SDS as a measure of the variability of fund style over time. In Table 3, the correlation coefficients between the SDS for each fund and various fund selectivity performance measures are presented. There is considerable variation in the correlation coefficients depending on the performance model used. The only significant correlation occurs when alpha is obtained from the Treynor–Mazuy market model with conditional variables included. In this case a positive correlation ($r = 0.170$, $p = 0.016$) is found, indicating that superior selectivity is related to greater levels of style drift.

The regression coefficients presented in Table 4 more formally reveal the impact of the degree of style variability (as measured by the SDS) on fund selectivity measures. Generally, we find that the SDS tends to be positively related to selectivity skill, except in the case of

Table 4 Cross-sectional regression results investigating the potential determinants of alpha performance of Australian multi-sector managed funds

	Dependent variable: alpha coefficients					
Independent variables	Unconditional Jensen model	Unconditional Treynor-Mazuy model	Conditional Treynor-mazuy model	Unconditional Treynor-Mazuy Kalman filter model	Conditional Treynor-Mazuy Kalman filter model	Cubic market model
Multisector trusts	0.0014	0.0012	0.0016	0.012	**0.0025**	0.0014
	(1.89)	(1.22)	(1.79)	(1.51)	**(3.14)**	(1.43)
Multisector pens	0.0001	−0.0002	0.0004	0.0003	0.0010	−0.0001
	(0.097)	(−0.17)	(0.40)	(0.42)	(1.25)	(−0.13)
Super-balanced	0.0009	0.0008	0.0012	0.0007	0.0013	0.0097
	(1.30)	(0.86)	(1.41)	(0.94)	(1.79)	(1.08)
Super-defensive	−0.0004	−0.0006	−0.0002	0.0003	0.0006	−0.0006
	(−0.64)	(−0.84)	(−0.30)	(0.41)	(0.94)	(−0.80)
Super-growth	0.0009	0.0007	0.0010	0.0003	0.0009	0.0010
	(1.46)	(0.86)	(1.28)	(0.42)	(1.43)	(1.14)
Super-moderate	0.0002	−0.0003	0.0003	0.0002	0.0011	−0.0004
	(0.38)	(−0.34)	(0.40)	(0.27)	(1.46)	(−0.052)
Wholesale non-tax paying	**0.0020**	0.0003	0.0008	0.0008	0.0013	0.0005
	(3.27)	(0.29)	(0.90)	(1.01)	(1.65)	(0.59)
Wholesale pooled superannuation trust	**0.0010**	0.0001	0.0005	0.0002	0.0007	0.0004
	(2.10)	(0.16)	(0.91)	(0.33)	(1.27)	(0.55)
Style drift score	−0.0022	0.0011	0.0003	**0.0049**	0.0027	0.0013
	(−1.22)	(0.46)	(0.12)	**(2.59)**	(1.14)	(0.52)
Size	0.0000	**0.0002**	**0.0002**	**0.0001**	**0.0001**	**0.0002**
	(0.23)	**(3.30)**	**(3.13)**	**(2.22)**	**(2.63)**	**(2.91)**
Flow volatility	0.0004	0.0024	0.0018	−0.0002	0.0006	0.0016
	(0.28)	(1.20)	(0.92)	(−0.094)	(0.27)	(0.76)
Management expense ratios	−0.0005	−0.0006	**−0.0008**	**−0.0010**	**−0.0012**	−0.0006
	(−1.66)	(−1.54)	**(−2.1975)**	**(−3.13)**	**(−3.58)**	(−1.52)
R^2	0.611	0.366	0.425	0.530	0.492	0.399

Note: $y_i = a_1D_1 + a_2D_2 + \alpha_3D_3 + a_4D_4 + a_5D_5 + \alpha_6D_6 + a_7D_7 + a_8D_8 + a_{10}SDS_i + a_{11}SIZE_i + a_{12}FLOWVOL_i + a_{13}MER_i + error$, where: $D_1 = 1$ for a multi-sector trust and 0 otherwise; $D_2 = 1$ for a multi-sector pension and 0 otherwise; $D_3 = 1$ for a balanced super fund and 0 otherwise; $D_4 = 1$ for a defensive super fund and 0 otherwise; $D_5 = 1$ for a growth super fund and 0 otherwise; $D_6 = 1$ for a moderate super fund and 0 otherwise; $D_7 = 1$ for a wholesale non-tax paying fund and 0 otherwise; $D_8 = 1$ for a Wholesale PST fund and 0 otherwise; SDS_i = style drift score; $SIZE_i$ = Fund size (equal to the natural log of mean funds under management for the sample period); $FLOWVOL_i$ = Flow Volatility (equal to the variance of the flow during the sample period); MER_i = Management Expense Ratio (equal to the median expense ratio for the sample period). The t-statistic is recorded in parentheses under the estimated coefficient (coefficients significant at the 5% level are bolded).

the Jensen model. In particular, when the alpha derived from the Kalman Filter unconditional Treynor–Mazuy model is used as the dependent variable, there is a significant (5% level) positive coefficient found (0.0049).

Overall, we find evidence that style drift is related to selectivity skill, although this conclusion is dependent on the fund performance model. There is some support of a positive relationship between alpha values and style drift, but the evidence is not consistent across all performance models.

5.2.2. Flow volatility and fund performance

There is evidence in the literature of a relationship between fund performance and the degree of variability in fund flow (Edelen, 1999; Rakowski, 2003; Shoven et al., 2000). To assess this link in our sample, we initially look at the correlation between flow volatility and various measures of fund selectivity performance (Table 3) and find no evidence of a statistically significant correlation. Regardless of the performance model used, we find no significant correlation coefficients between any measure of alpha values and flow volatility, as measured by the variance of the fund flow. This result is confirmed in Table 4, which contains the cross-sectional regression results, where flow volatility is one of the independent variables and various measures of fund selectivity skill are used as dependent variables. In Table 4, it can be seen that the regression coefficient for flow volatility is generally positive (except for the alpha value from the Kalman Filter specification for the Treynor–Mazuy model; -0.000183), but not significant at the 5% level.

5.2.3. Control variables and performance

The literature pertaining to the association between fund size and performance finds either no relationship or an inverse relation (Chan et al., 2002; Chen, Hong, Huang & Kubik, 2004; Gallagher & Martin, 2005; Sawicki & Finn, 2002). Generally, larger funds are not associated with superior performance. The correlation coefficients between fund size and all performance variables used in the present study are presented in Table 3. Interestingly, regardless of the performance model used, we find a significant positive correlation between fund size and all alpha coefficients. When fund size is used as an independent variable against measures of selectivity (Table 4), we find that there is a significant positive relationship, except in the case of the Jensen model.

The literature documents an inverse relationship between MER and fund size (Dowen & Mann, 2004; Geranio & Zanotti, 2005); therefore, we have included MER as a cross-sectional variable in the present study, and we find similar evidence. In particular, we report a significant negative correlation ($r = -0.368$, $p = 0.000$) between fund size and MER, suggesting that for funds in our sample there are economies of scale associated with the fee structure of larger funds. With regard to fund performance, we find that MER is significantly negatively correlated with alpha values from three of the performance models used (correlations vary from -0.335, $p = 0.001$ to -0.227, $p = 0.023$), implying that higher expense ratios do not lead to associated superior selection skills (see Table 3). This result is repeated in the cross-sectional regression results shown in Table 4. Specifically, the estimated MER coefficient is consistently negative, and is statistically significant when alpha is derived from the conditional Treynor–Mazuy model and the conditional and unconditional versions of the Kalman filter Treynor–Mazuy model.

6. Conclusions

Using a sample of Australian multisector managed funds, our primary goal was to investigate the complex links between style drift, fund flow, and alpha performance. To evaluate the degree of style drift over the sample period, we use Sharpe's (1992) style technique in the form of a rolling window analysis to produce a series of style weights for each fund. The variance of these style weights can be interpreted in the form of an SDS, which provides a single quantitative measure of style drift over the sample period (Idzorek & Bertsch, 2004). We provide graphical evidence that the SDS is a meaningful measure of style consistency using our data, and we use the SDS as a key cross-sectional variable along with flow volatility (controlling for fund category, fund size and management expense ratio) to determine their influence over fund performance measures.

We find some evidence that SDS is related to fund performance. In particular, when conditional performance models are used, we find that style drift and selectivity skill are positively related, indicating that managers that are more successful at stock selection tend to be less consistent with respect to style. With regard to fund flow, we find that it is unrelated to fund size, style drift, and performance. In secondary findings, we observe that fund size is related to fund performance as all alpha values (except for the Jensen model) are positively influenced by size. In addition, fund size is found to be negatively related to management expense ratios, which, in turn, are negatively related to alpha values.

This paper has highlighted the tenuous links between fund flow, style drift, and fund performance. We have found evidence that successful stock pickers tend to be more variable in style, but that this variability is unrelated to fund flow volatility. Cooper et al. (2005) find that 'cosmetic' style changes, in the form of a name change, can induce substantial fund inflows. In contrast, we find no relationship between the degree of style variability and flow volatility. However, like us, they find that the fund inflows are unrelated to fund performance.

From an individual investor's perspective, this research has several implications. First, many funds appear to suffer from at least moderate cases of style drift and investors should therefore, assess (or gain professional advice on) the extent to which this phenomenon might be exposing them to risks with which they would not normally be comfortable. The challenge of doing this in a reliable fashion means that the onus will increasingly fall on the shoulders of professionals. As such, financial planners and investment advisers need to become increasingly aware of the possibility of style drift in funds and seek out mechanisms by which they can monitor style changes and trends.

Second, investors need to look below the surface when investing in a particular fund. Although funds with variable style can suggest managers' inability to maintain a stable style profile over time, style drift can also be indicative of superior selectivity skills. Again, financial advisers will need to play a key role in helping to make reliable assessments of this for their clients. Third, there might be little to gain by 'following the pack' when choosing investment vehicles, as we find no evidence that fund flow is related to abnormal fund performance. That said, investors and advisers will be wise not to become overly confident about their abilities to do better than 'the pack,' particularly, as is likely, they acknowledge that their information and skill sets are not superior to many others in the market.

Notes

1. Similar to the United States, a significant change in style of Australian funds will become apparent to investors ex post when the fund issues an amended prospectus. In Australia, new prospectus's tend to be issued every six months or so. We thank an anonymous referee for raising our awareness of this issue.
2. The Reserve Bank of Australia Bulletin, February 2003, cites statistics based in February 2001 showing that half of the Australian equities funds offered such performance based fees.
3. Similar analysis was also conducted on timing measures of performance, but no clear findings emerged. Accordingly, these results are suppressed to conserve space; they are available upon request from the authors.
4. A superannuation fund is an unlisted investment vehicle where investor's contributions and earnings are redeemed (in total or as a pension) at retirement from the workforce. Australian superannuation funds are, broadly speaking, equivalent to 401(k) plans in the United States. The 'super' industry in Australia has experienced sustained growth for many years because of a range of government policy initiatives over the past two decades. Indeed, superannuation dominates the domestic managed funds sector.
5. Wholesale funds in Australia target professional investors and are typified by having quite large minimum investment thresholds. Moreover, wholesale fund transactions tend to be of lower frequency and thus fees charged are lower than 'retail' funds. In contrast, Australian retail funds are targeted at 'less sophisticated' investors who wish to transact much more frequently and at lower values (see Morningstar, 2005, p. 11).
6. PST funds pay tax at the fund level. For NTP funds, the tax is paid in the hands of the investor.
7. As a robustness check, OLS was also used. Because these results are qualitatively the same, they are not reported to conserve space.
8. The index series reflects changes in the value of an investment in a fund over time, and is based on a notional $10,000 investment in the fund. Monthly index values are calculated by reference to the month-end exit price of the fund, which is net of management fees and assumes reinvestment of all cash and bonus unit distributions. The index series therefore gives representative returns which an actual investor may have achieved and measures the monthly performance of the fund.
9. In any case, the rolling window analysis that we employ is infeasible or pointless for funds that do not meet the data requirements imposed. This represents one of the implicit costs in adopting a particular research design, unavoidable when it comes to weighing up all the research design tradeoffs.
10. Initially eleven style indices were considered, but five (ASX Small Ordinaries; ASX SE Russell All Value Index; ASX SE Russell All Value Growth; SandP/ASX 50 DS Index; SandP/ASX 100 DS Index) were discarded after significant return correlations were found between the indices and the AEQ index. In addition to the correlations, tests of equality of variances were conducted between the AEQ index and each of the

five indices and no significant differences in variance were found. On this basis only the six indices mentioned above were included in the style analysis process.

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