Discovering Style Consistency and Drift in Australian Equity Funds and Hedge Funds

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1. Background and aims of project:

A fund manager’s style can be described as the effective asset mix or method of asset allocation (Cummisford & Lummer, 1996). As a result, the style of a fund drives the choice of risk factors that determine the return generating process. Investors will form expectations of returns and risk based on the style and in so doing will use fund styles as the basis for performance measurement and manager compensation. Sometimes, managers have incentives to mis-classify themselves (Donnelley, 1992). Therefore, it is not surprising that increasing emphasis is being placed on correctly identifying a fund’s style. It is an agency problem: a difference exists between how funds are invested and what their stated objectives suggest which may unfairly benefit the manager. Fund managers throw out poor performers and or change the apparent strategy of the fund at the end-of-period to improve their relative historical rankings. Such ‘window-dressing’ of a fund is empirically explored by Brown & Goetzmann (1997). Such behavior has led to the demand for classification that is independent of the originating fund manager and preferably based on past returns.

The Generalized Style Classification (GSC) approach of Brown and Goetzmann (1997, 2003) employs statistical clustering to group funds into a pre-determined number of styles based on past returns. The rationale is that managers that follow similar investment behavior, irrespective of their objectives, will have similar returns and hence will be placed in one group when statistically clustered on the basis of past performance. This is done by attempting to minimize within-style sum of squares between each return and the relevant style mean for all time periods. The algorithm of GSC is similar to k-means clustering developed by Hartigan (1975) except that GSC compensates for heteroskedasticity by considering time-varying and cross-sectional variances. Empirical evidence suggests that this technique is superior to traditional classifications in predicting cross-sectional future and past performances (Brown & Goetzmann, 1997).

Although a number of papers have been published on mutual funds over the past 50 years or so it’s only been since the late nineties that attention has been given to hedge funds. It is important to note that little, if any, work has been published on estimating the number of styles in mutual funds and hedge funds. This is because the industry employs a self-classification system to define styles. For instance, leading data providers such as Lipper Tass, and CSFB Tremont classify funds from anywhere between 10 to 30 different styles. However, empirical studies such as Fung and Hsieh (1997) estimate five hedge fund styles while Brown and Goetzmann (2003) employ the GSC approach and estimate eight investment styles for US mutual funds. To date nothing has been published from markets outside the United States. The proposed study is the first to apply the GSC approach of Brown and Goetzmann (2003) and the GAP statistic of Tibshirani et. al, (2001) to Australian mutual and hedge funds data.

In summary, the aims of the project are as follows:

1. To discover the appropriate number of return-based styles for Australian Equity Funds and Hedge Funds.
2. Classify funds based on ‘soft’ clustering to identify the degree to which each fund belongs to each style.
3. Identify the composition of each style by fund membership values.
4. Tabulate and compare existing industry classifications to return-based styles.
5. Calculate and plot style drift diagnostics of each fund over time.
6. Perform out-of-sample testing to test the explanatory power of the ‘soft’ classifications vs. industry classifications.

2. **Significance and Innovation:**

The GSC places a fund in a single style. Brown & Goetzmann (1997) show that investment actions of the mutual fund managers in the US could be explained by eight different investment styles. Each style was formed using the GSC technology. Such classification of funds into rigid boundaries occurs across all the traditional approaches to identify fund style. Given the wide body of evidence confirming style drift, ‘hard’ clustering may not be providing an accurate picture.

Soft clustering is particularly appealing because the style categories have continuous instead of rigid boundaries. A breakdown of a fund manager’s investment pattern is given by membership values that identify how closely the fund belongs to each of the pre-defined styles. The set of membership values indicate the closeness of fit the fund has to each style, thereby recognizing that fund managers are not restricted to a single style and innately incorporating the possibility of style drift. The membership values are a relative measure of closeness of fit. The information imparted by soft clustering is quite different to that generated by hard clustering. Hence, the membership values also indicate the extent of fund diversification across the styles by showing the closeness of fit to other styles not just the one it fits most closely too.

Soft clustering is based on the concept of ‘fuzziness’ by Zadeh (1965) who is a major contributor to information theory. The most popular algorithm of Fuzzy clustering, Fuzzy C-means was developed by Bezdek (1981). Soft clustering was empirically tested against GSC in classifying mutual fund styles and demonstrated superior explanation of out-of-sample returns (Yahya & Lajbcygier, 2003). This demonstrates the worth of soft clustering compared to the traditional approaches to style. Choo & Lajbcygier (2005) constructed a number of drift diagnostic tools based on fuzzy memberships of mutual funds to identify style consistency of US Mutual Fund Data.

It is important to note that none of the above research in soft clustering for fund style analysis has been applied in the Australian context. Our work is significant as (a) it will determine if Australian mutual and hedge funds are diversified and drift; and, (b) it will provide comparisons with similar studies of US mutual and hedge funds.

3. **Description of Approach:**

1. Obtain Australian equity funds and hedge funds returns and the corresponding industry styles.
2. Establish the appropriate number of styles by applying the GSC and GAP statistic to the data set of Australian equity fund and hedge fund returns. The GAP statistic is a statistical tool that derives the appropriate number of clusters in a data set.
3. Apply the Fuzzy C-means algorithm to the data sets to generate the membership values of each fund to each style.
4. Cross-tabulate industry based styles to the return-endogenous styles for comparison.
5. After breaking up the data into smaller 24 month windows, regress, the membership values generated by soft clustering applied in each window to out-of-sample returns. This will indicate the explanatory power of the soft clustered styles.
6. Regress the industry based classifications via dummy variables to out-of-sample returns to compare the explanatory power to that provided by soft clustering.
7. Construct drift diagnostics as per Choo & Lajbcygier (2005) to identify style consistency and drift for Australian equity and hedge funds on an annual basis.