On the characteristics and performance of long-short, market-neutral and bear mutual funds

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ABSTRACT

We evaluate the return performance of long-short, market-neutral and bear mutual funds using multi-factor models and a conditional CAPM that allows for time-varying risk. Differences in the bearish posture of these mutual funds result in different performance characteristics. Returns to long-short mutual funds vary with the market, returns to market-neutral mutual funds are uncorrelated with the market and returns to bear mutual funds are negatively correlated. Using the conditional CAPM we document significant changes in the market-risk exposure of the most bearish of these funds during different economic climates. We then assess the flow-performance relationship for up to 60 months following up and down markets and find that investors direct flows towards market-neutral and bearish funds for several months after down markets. Market-neutral funds provide a down market hedge, but bear funds do not generate the returns that investors hope for.

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1. Introduction

From 1970 to 2007, mutual fund assets have grown at an annual rate of 16% from $43 billion in 1970 to nearly $11 trillion at the end of 2007 with nearly 44% household participants.1 Mutual fund research develops, assesses and improves models to measure fund performance and examines how the behavior of portfolio managers and investors impacts (and is impacted by) that performance. This literature has studied fund subsets such as equity, growth, fixed-income, and other long-oriented fund families. The long orientation of most mutual funds has implied a relative lack of mutual fund products that offer investment opportunities that capitalize upon adverse economic conditions. While mutual funds that offer some short side exposure emerged in the 1990s, they have not been as closely investigated. The primary purpose of this paper is to study the flow and return performance of such mutual funds.

Strategies employing short exposure are however common among many hedge funds. Agarwal et al. (2009a) describe hedge fund strategies and performance using a comprehensive sample of 7535 hedge funds. They identify long-short funds as those which take long (short) positions in undervalued (overvalued) securities. Fung and Hsieh (2004) also observe that some equity long-short hedge funds have a small positive exposure to stocks and tend to be long the small-cap stocks and short the large-cap stocks. In addition to capitalization, this two-sided exposure can be growth specific (long value, short growth), sector specific or expressed by selling call options on stocks owned. Some market-neutral hedge funds attempt to keep their portfolio betas low. However, Patten (2008) documents other forms of market-neutrality – dollar neutral, mean-variance neutral, and VAR-neutral. Indeed, it is reasonable to consider market-neutral portfolio strategies as a specific implementation of a long-short strategy that minimizes exposures along one of these multiple dimensions. Other hedge funds strategies can be described as dedicated short-biased since they take outright short positions in candidate stocks with perceived downside potential. Still others offer direct short bets on narrow and broad-based market indexes, interest rates, sectors, currencies and regions. At times, these positions are leveraged with narrow or wide index put options, index futures positions and swap arrangements.

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1 The numbers we report are from the CRSP Survivor Bias-Free Mutual Fund database and confirm the general trend. Various versions of the Mutual Fund Fact Book (1996–2008) report a range of $47.6 B to $12 trillion invested in mutual funds over this period.

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Retail investors are often unable to take advantage of such hedge fund offerings because of high initial contributions and substantial lock-up periods. Consequently, their clones have appeared in the mutual fund space. In this paper, we consider mutual funds that offer portfolios with substantial amounts of short exposure. Our sample consists of all mutual funds on the 2007 CRSP Survivor Bias-Free Mutual Fund database that pursue the investment objectives of long-short (LS), market-neutral (MN) and bear (BR). These investment objectives are ordered to reflect their position on a continuum of increasing bearishness. Throughout the paper, we refer to these three investment objectives as fund subsets and report results for each individual subset as well as for the entire sample of mutual funds with such objectives. We describe these funds, examine patterns of investor flows, study the returns earned by fund managers, assess their performance both conditionally and unconditionally and address the flow-performance relationship.

We begin by reporting the cross-sectional and time-series properties of the monthly flow and return distributions for each of these fund subsets. Cross-sectional results document fund-level variation within each fund subset for a particular month. Normalized flows to long-short (LS) funds and market-neutral (MN) funds have similar flow volatilities and flows to bear (BR) funds are the most volatile. Flow variation in the cross-section hints at investor sensitivity to fund performance. Time-series flows to LS funds are weakly negatively correlated with those for MN and BR funds. In contrast, the latter two are strongly positively correlated (0.83) reflecting investor perceptions of some commonality in the investment objectives of these two subsets. In addition, monthly flows to each subset are generally significantly auto-correlated, perhaps suggesting that some portion of them constitute mechanical, periodic remittances. Return distributions also display differences in volatility and similar correlation characteristics. In particular, the strong negative correlation between LS fund returns and BR fund returns of -0.81 underscores the importance of studying the fund subsets separately.

We then examine the performance of our individual style subsets (LS, MN and BR) as well as the full sample using the unconditional CAPM, the Fama and French (1993) three-factor model (hereafter three-factor model) and its momentum augmented version, the Carhart (1997) four-factor model (hereafter four-factor model). We find important differences between LS, MN and BR funds. Returns to LS funds vary with the market, returns to MN funds are uncorrelated with the market and returns to BR funds are negatively correlated with large significant negative betas. LS funds are the only ones independent from variation in the HML and SMB mimicking portfolios, while the loading on the UMD factor is significant only for BR funds. These individual differences wash out when we treat LS, MN and BR as one comprehensive portfolio.

Next, we conduct an evaluation of portfolio performance using a conditional CAPM (Petkova and Zhang, 2005), estimated via the generalized method of moments (GMM). While concerns about this model’s role in asset pricing have been raised (Lewellen and Nagel, 2006; Hansen and Richard, 1987), we find that it fits our purpose for several reasons. First, the stated investment objectives of MN and BR funds require relatively frequent adjustments to market-risk exposure to achieve those goals. For us, the appeal of the conditional CAPM is its ability to model this time-variation in risk in addition to explaining returns. Second, GMM estimation allows us to relax the assumption of normality in return distributions – an assumption that is unlikely for some of our fund subsets with derivatives exposure. Third, by their very nature, the funds we study are likely to attract more investor attention near turning points in the economic climate. At these points, the price of risk is likely to be different and our analytical framework permits these changes to be explicitly modeled. In our application, we find that the conditional CAPM has an explanatory power that is somewhat better than the static multi-factor models that we also employ. We then build extreme economic climates (BOOM/BUST) into this analysis based upon extreme values of the expected market return distribution in keeping with recent asset pricing literature. We find that the average conditional beta for LS funds is positive and relatively unchanged in both climates. For MN funds the average conditional beta is close to zero in both climates. BR funds exhibit the most time-variation in risk. We also implement a version of the conditional CAPM that permits time-varying alphas and find that of our three subsets, only BR funds exhibit significantly different performance in BOOM and BUST states with the largest underperformance in extreme recessions. Furthermore, the conditional CAPM allows us to predict BR fund returns with remarkable accuracy.

Finally, we assess the flow-performance relationship subsequent to UP and DOWN-market states by implementing an event-study methodology used to study momentum by Cooper et al. (2004). This event-study framework offers a different perspective from our earlier conditional CAPM analysis since it enables us to study both flows and returns and additionally how they behave at multiple horizons subsequent to a market state event. Specifically, we study both normalized and adjusted flows to these funds as well as the raw and four-factor-adjusted returns for a period of up to 60 months following that event. Long-short fund flows do not show much difference between UP and DOWN markets. The flow analysis indicates that investors direct their money towards MN and BR funds for several months subsequent to a DOWN market, in the hope that this will provide them with an adequate hedge. Our return analysis documents that MN funds show superior realized and risk-adjusted performance following DOWN vs. UP-market states. BR funds do show some superior performance following DOWN markets for the first 2 post-event years, but model-adjusted returns are barely positive. It appears that while MN funds offer hedging benefits for investors, the BR funds, perhaps constrained by persistently high flows, do not appear to.

The rest of this paper is organized as follows. Section 2 describes our sample of funds. Section 3 describes the cross-sectional and time-series patterns of fund flows and returns. Section 4 reports performance evaluation results based on the CAPM and multi-factor models. Section 5 describes our findings using the conditional CAPM. Section 6 reports results from our event-study investigation of the behavior of flows and returns following UP and DOWN-market states and Section 7 concludes.

2 Mutual funds that mimic other hedge fund strategies such as merger arbitrage, distressed securities, precious metals, emerging markets and other sectors also exist.


4 Lipper categories applicable to the funds in our sample are EMN, SESE, and DSP. Our name-search algorithm augments this sample. Additionally, we also search through the objective codes for each fund from Weisenberger and Strategic Insight that are provided by CRSP. This enables us to capture all applicable funds across objective codes from different providers.
Our sample comprises 110 mutual funds. When compared to the number of hedge funds following similar strategies, our sample appears small, but we have taken care to obtain as much of the universe of mutual funds operating in this space as feasible. At the end of our sample period in 2007, the total dollar value in all three subsets is about $16 billion. LS funds constitute 36%, MN funds are 38% and BR funds make up the remainder. The dollar value of assets under management for our sample is also a small fraction of the total market value of assets managed by mutual funds. We offer three possible explanations. First, the investment objectives that our sample funds follow are specific in relation to the broad-based equity funds. Second, the dollars under management in other mutual fund subsets of similar vintage with similarly narrow investment objectives is small as well.

Third, most retail mutual fund investors tend to be long-biased and therefore investment objectives that include short selling are likely to appeal to only a small portion of that investor cohort. Roughly one-quarter of the funds in our sample are not survivors with their time-series terminating before the ending date of December 2007 for our sample period. An examination of fund portfolio holdings and selected fund prospectuses sheds some light on how fund managers attempt to achieve their stated investment objectives. Portfolio composition is fairly eclectic with exposure to equities, bonds, and international markets. Some funds are fairly focused while others report positions in over 1000 securities. Expense ratios and portfolio turnover are typically much higher for BR funds than for long-only funds with the latter being anywhere from 2 to 4 times. This higher turnover for bear funds may in part be a consequence of frequent portfolio rebalancing required for some of the leveraged inverse funds in that subset. Multiple strategies are employed. In addition to the usual “paired” trades, outright short positions in bonds and equities are common. These are occasionally leveraged with index options, futures and swap arrangements. Taken together it appears that the funds in our sample resemble hedge funds more than typical long-only mutual funds.

It is for these reasons that we divide our sample of funds into three subsets. To reiterate, these are: (a) long-short (LS) funds that use a mix of long and short positions, often within the same sector and at other times with a broad market-wide hedge; (b) market-neutral (MN) funds that strive to maintain a low correlation with traditional asset classes and; (c) bear (BR) funds that either exclusively short-sell and/or use derivative arrangements. Funds from families such as Rydex and Direxion appear in this third subset.

Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>Long-short (LS) funds</th>
<th>Market-neutral (MN) funds</th>
<th>Bear (BR) funds</th>
<th>LS + MN + BR funds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of mutual funds</td>
<td>43</td>
<td>27</td>
<td>40</td>
<td>110</td>
</tr>
<tr>
<td>Average TNA ($ millions)</td>
<td>105.5</td>
<td>152.5</td>
<td>90.7</td>
<td>111.6</td>
</tr>
<tr>
<td>Standard deviation (TNA)</td>
<td>199.9</td>
<td>314.4</td>
<td>134.5</td>
<td>214.6</td>
</tr>
<tr>
<td>Total TNA as of December 2007 ($ billions)</td>
<td>5.7</td>
<td>6.1</td>
<td>4.1</td>
<td>15.9</td>
</tr>
<tr>
<td>Proportion of grand total TNA in subset</td>
<td>35.8%</td>
<td>38.3%</td>
<td>25.9%</td>
<td>100%</td>
</tr>
</tbody>
</table>

We test this assumption with other cases where data is available and find it to be reasonable.

3. Flows and returns of sample funds

We generate flow estimates for each fund in each subset in the usual way by recognizing that assets under management can either grow internally or by the flow of new cash to these funds. We define the normalized flows, NFLOW(t), as:

\[
\text{NFLOW}(t) = \frac{\text{MTNA}(t) - \text{TNA}(t - 1) \times \{1 + R(t)\}}{\text{MTNA}(t)/\text{TNA}(t - 1)}
\]
where TNA represents the total net asset value of the mutual fund at times \( t - 1 \) and \( t \), \( R(t) \) represents the return earned by the fund over the period \( t - 1, t \), and \( \text{MGTNA}(t) \) represents the increase in assets due to mergers.

There is a vast literature on fund flows. Gruber (1996) argues that flows constitute smart money, while Frazzini and Lamont (2008) contend that they are sentiment driven. Flows are negatively related to market volatility (Cao et al., 2008) and are time-varying in nature (Glide et al., 2009). Aggregate flows to mutual funds mask several, often competing considerations. At the fund level, a portion of the flows may be regular if they reflect a long-term asset allocation strategy consistent with the fund’s stated objectives as well as investor responses to fund performance. Flow variation due to individual fund performance should largely cancel out at the fund-subset level and any regularity in flows can be attributed to investor preferences for subset investment objectives. This component of flows is likely to be longer term in nature and may result in auto-correlated flows. Flows may also be directed to sample funds as a hedge against long-side portfolios in response to (or anticipation of) adverse market conditions and may be short-term.

Accordingly, Table 2 provides statistics on NFLOW, the normalized flow variable defined in Eq. (1). In Panel A, we choose the end of our sample period (December 2007) for a cross-sectional snapshot. Focusing on a particular point in time enables us to examine differences in flows within mutual funds in a subset. Flow variance, and range are different for each of our three subsets. At the cross-section, BR funds exhibit the largest flows with the most in-sample variation. We also report the proportion of funds receiving positive (negative) flows. In the cross-section, extreme values for this variable would indicate that investors view the funds in the group homogenously and direct their flows towards or away from the group without discriminating among the performance of the individual funds. About 48% of LS funds receive positive flows in December 2007. This decreases to about 40% for MN and BR funds, suggesting that investors do pay attention to fund performance.

Panel B of Table 2 reports time-series statistics on the flows over the sample period. To provide a feel for the distribution, we also report the range and the inter-quartile range in addition to the usual measures of central tendency. Range values suggest that larger flows are concentrated at both extremes of the distribution with distinct patterns for our fund subsets. LS funds exhibit the smallest range, lowest means and standard deviations in flows while BR funds exhibit the largest, and MN funds are somewhere in between. This is consistent with the interpretation that LS funds attract longer term flows, and BR funds attract short-term flows. Flows are positive for MN funds in 72% of the months in our sample period, perhaps due to a more passive asset-allocation pattern. The large value of 0.222 for the flow volatility of BR funds merits further investigation. Although we weight the individual BR mutual funds by TNA in obtaining this estimate, it is still possible that the volatility may arise from individual BR funds being smaller than their LS and MN cohorts. From Table 1, we note that mean TNA values for LS, MN and BR funds are comparable. We also estimate correlations between average TNA and flow volatility for funds in each subset and find it to be negative and significant (-0.443) for BR funds but small and insignificant for LS and MN funds. Together with the fact that subset TNA are similar, we believe that the bearish investment objective for the BR subset is at least partly driving the flow volatility that we observe.

Finally, in this panel we report statistics from a simple AR(1) model for flows. We adjust for prior period flows to capture the tendency of investors to automate the allocation of their investment dollars as a response to asset allocation or performance considerations. Flows to all three subsets are significantly related to prior month flows – a result that disappears when flows are aggregated into a single all-sample portfolio. Consequently, in later subset analysis we also report results based on this AR(1) adjustment.

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15 In results not reported, we also examine the relationship between normalized flow, flow volatility and TNA for fund subsets other than those we study in the paper. We find that some fund subsets with TNA larger than ours (such as some equity sector funds) have similar flow and flow volatility characteristics to our sample. Other fund subsets with TNA similar to ours (such as growth and income funds and balanced funds) have smaller flow and flow volatility characteristics. Thus, in addition to TNA, other factors such as the narrowness of the investment objective and the riskiness of the asset classes chosen in pursuit of those objectives can also affect normalized flows and their volatility.

16 We recognize that an AR(1) specification is an extremely simple one. Jaiprakash and Kumar (2009) find that lags 1 and 4 in an AR specification do matter for monthly flows, but systematic factors other than mechanical remittances can complicate inferences from longer lags.

### Table 2

**Distribution of normalized flows. Normalized flows are estimated according to Eq. (1) in the text. For each subset, statistics in Panel A are aggregated across mutual funds with available normalized flows in the snapshot month of December 2007. Time-series statistics in Panel B are at the fund-subset level, are weighted by fund TNA and exclude the extreme 2.5% of observations. The time-series begins in July 1982 for long-short funds (LS), October 1990 for market-neutral funds (MN) and February 1994 for bear funds (BR). All time-series end in December 2007.**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Long-short (LS) funds</th>
<th>Market-neutral (MN) funds</th>
<th>Bear (BR) funds</th>
<th>LS + MN + BR funds</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Properties of fund-level normalized flows (December 2007)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean normalized flow</td>
<td>0.025</td>
<td>0.015</td>
<td>-0.059</td>
<td>-0.002</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.152</td>
<td>0.142</td>
<td>0.245</td>
<td>0.183</td>
</tr>
<tr>
<td>Range</td>
<td>0.847</td>
<td>0.668</td>
<td>0.914</td>
<td>0.980</td>
</tr>
<tr>
<td>Inter-quartile range</td>
<td>0.087</td>
<td>0.062</td>
<td>0.289</td>
<td>0.090</td>
</tr>
<tr>
<td>Proportion funds w/≥0 flows</td>
<td>0.484</td>
<td>0.389</td>
<td>0.400</td>
<td>0.420</td>
</tr>
<tr>
<td>Avg. normalized flow (≥0 flow funds)</td>
<td>0.091</td>
<td>0.104</td>
<td>0.175</td>
<td>0.134</td>
</tr>
<tr>
<td>Proportion funds w/0 flows</td>
<td>0.516</td>
<td>0.606</td>
<td>0.600</td>
<td>0.580</td>
</tr>
<tr>
<td>Avg. normalized flow (&lt;0 flow funds)</td>
<td>-0.053</td>
<td>-0.034</td>
<td>-0.216</td>
<td>-0.100</td>
</tr>
<tr>
<td><strong>Panel B: Time-series properties of subset-level normalized flows</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean normalized flow</td>
<td>0.010</td>
<td>0.028</td>
<td>0.058</td>
<td>0.024</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.038</td>
<td>0.061</td>
<td>0.222</td>
<td>0.110</td>
</tr>
<tr>
<td>Range</td>
<td>0.274</td>
<td>0.377</td>
<td>1.268</td>
<td>0.834</td>
</tr>
<tr>
<td>Inter-quartile range</td>
<td>0.027</td>
<td>0.055</td>
<td>0.155</td>
<td>0.067</td>
</tr>
<tr>
<td>Proportion months w/0 flows</td>
<td>0.502</td>
<td>0.722</td>
<td>0.558</td>
<td>0.561</td>
</tr>
<tr>
<td>Avg. normalized flow (≥0 flow months)</td>
<td>0.034</td>
<td>0.053</td>
<td>0.179</td>
<td>0.105</td>
</tr>
<tr>
<td>Proportion months w/0 flows</td>
<td>0.498</td>
<td>0.278</td>
<td>0.442</td>
<td>0.439</td>
</tr>
<tr>
<td>Avg. normalized flow (&lt;0 flow months)</td>
<td>-0.014</td>
<td>-0.038</td>
<td>-0.096</td>
<td>-0.039</td>
</tr>
<tr>
<td>Intercept of AR(1) regression</td>
<td>0.021</td>
<td>0.058</td>
<td>0.027</td>
<td>0.027</td>
</tr>
<tr>
<td>Slope of AR(1) regression</td>
<td>0.315</td>
<td>0.435</td>
<td>0.325</td>
<td>0.095</td>
</tr>
<tr>
<td>Adjusted-(R^2) for AR(1) regression</td>
<td>0.095</td>
<td>0.185</td>
<td>0.13</td>
<td>0.010</td>
</tr>
</tbody>
</table>

* Indicates statistical significance at the 5% level.
Additionally, we estimate time-series flow correlations between our fund subsets over their common period February 1994 to December 2007. Normalized flows to LS funds are negatively correlated with those for MN and BR funds with values of −0.11 and −0.13 respectively. We interpret this to mean that investors view LS funds as serving a different purpose than the other two subsets in our sample. In contrast, the normalized flow correlation between MN and BR funds of 0.63 suggests that investor appear to view MN and BR funds as having similar objectives.

To further understand the patterns of flows to sample funds, we also examined their responsiveness to macro-economic information contained in the commonly used Chen et al. (1986) (hereafter CRR) economic factors. These variables are the monthly growth in industrial production (MP), changes in expected inflation (DEI), unanticipated inflation (UI), unanticipated changes in risk premia (UPR) and term spread (UTS).17 Sample flows are not extremely sensitive to these innovations. We also investigated the responsiveness of flows to variables that investors directly observe such as the Conference Board’s leading composite index, the personal savings rate, the ratio of durable goods expenditures to personal income and the unemployment rate. In a kitchen-sink regression with AR(1), CRR, and the above macro-variables, the latter set offers a considerable increase in explanatory power.18

### 3.1. Returns

Table 3 provides similar cross-sectional and time-series properties for monthly returns. From Panel A, for our snapshot month of December 2007 both LS and MN fund subsets exhibit relative uniformity in returns, with 83–89% of their component funds exhibiting positive return performance. BR funds are more evenly divided. In general, the BR fund cross-sectional return distribution appears different in character from the other two subsets. Time-series properties of fund subsets in Panel B are also revealing. MN funds exhibit a mean monthly return of 0.3% with 75.8% of the months being positive. Other characteristics of the time-series return distribution for MN funds are aligned more closely with those for BR funds. Time-series return correlation between the three subsets are also informative with LS funds negatively correlated with MN funds (−0.10) and BR funds (−0.81). MN and BR fund returns have a weak positive correlation of 0.19. In general, the direction of the time-series return correlations between our fund subsets is similar to those for the flow correlations we reported earlier. The last column for all sample funds shows how these potentially important differences get masked in aggregation.

Friesen and Sapp (2007) make an important distinction about how fund returns should be calculated and inferences about performance made. Specifically, they argue that the usual geometric returns that are estimated reflect manager performance while dollar-weighted return better captures the timing ability of fund investors. They label this difference as a “performance gap”.19 They find that in the aggregate, geometric returns are greater than the corresponding dollar-weighted return implying that investors are not particularly good at market timing. We first replicate the Friesen and Sapp (2007) procedure for the entire universe of mutual funds and find similar results. We then recalculate these returns for each of our subsets of mutual funds and find that BR fund investors have especially poor timing ability. We also investigate correlations between returns and flows at leads and lags of 1, 3 and 6 months respectively. Flows turning positive after returns would imply performance chasing while flows turning positive before returns would imply that investors have some anticipatory timing ability. For LS and MN fund subsets, we observe some performance chasing but not for bear funds.

Finally, in Table 4, we motivate an examination of fund performance in different economic climates. This table provides cumulative portfolio rates of return over different horizons for our three fund subsets and at three different points in time, 2000, 2005 and 2007. These calendar points are chosen because of easily recognizable variation in economic climates. Panel A reports this performance over different horizons culminating in the year 2000. Leading up to the peak of that bull market, LS funds earn consistently larger returns as the horizon increases. BR funds on the other hand report consistently worse returns as the holding period increases. Panel C reports similar patterns for the period.

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17 As our sample is more recent than the one in the original work of Chen et al. (1986), minor variations of their exact definition of the factors are necessary. For MP we use the index of Industrial Production (Federal Reserve of Saint Louis), for UPR we substitute the Long-Term Government Bonds with the Aaa corporate bond series to eliminate collinearity with UTS. The Long-Term Government Bond series is from Liborson and the 1-month T-bill rate used to define UTS is from CRSP. The inflation variable is derived using the CPI from the Bureau of Labor Statistics. The construction of the expected inflation variable (used in UI and DEI) follows closely Fama and Gibbons (1984).

18 We believe that this analysis holds enough promise, but is better pursued with the universe of mutual funds in our database. Results for our sample are available on request.

19 We thank an anonymous referee for this valuable suggestion.
ending in 2007. Generally, MN funds post returns somewhat in between. Note that, in both these panels, the terminal year and the preceding 5-years exclusively span bull market periods and the return characteristics of our subset funds are consistent with what one would expect for those times. On the other hand, Panel B reports holding period returns culminating in 2005 and the 5-years preceding that date include the bear market of 2000–02. The same monotonic return behavior that we observed in Panels A and C above are visible here as well, except for the 4 and 5 year horizon returns. When these longer horizon returns encompassing bear market periods are examined, the return performance reverses, tapering off for LS funds and becoming mildly positive for BR funds. Returns to MN funds continue to increase with the horizon. We recognize that, without stronger empirical validation, these comments may have limited value. We offer these to motivate the notion that there are distinct differences in the behavior of our mutual fund subsets in different economic states, potentially arising from their different investment objectives. A more formal examination of fund performance and their behavior in different market states appears in the next two sections of the paper.

4. Performance evaluation with static models

In Table 5, we provide results on mutual fund performance using the single-factor CAPM, the Fama and French (1993) three-factor and the Carhart (1997) four-factor models. Monthly data for the factors are obtained from Professor French’s website. Regressions are estimated using monthly returns for the three different subsets of our sample. The time-series begins in July 1982 for long-short funds (LS), October 1990 for market-neutral funds (MN) and February 1994 for bear funds (BR). All time-series end in December 2007. Panel D reports results for all three subsets together. Significant statistics at the 5% percent level (denoted by an asterisk) are computed using Newey–West (1987) corrections for heteroskedasticity and autocorrelation for up to 6 lags.

Table 5

Performance evaluation. The table reports portfolio performance using the single-factor CAPM, the Fama and French (1993) three-factor and the Carhart (1997) four-factor models. Monthly data for the factors are obtained from Professor French’s website. Regressions are estimated using monthly returns for the three different subsets of our sample. The time-series begins in July 1982 for long-short funds (LS), October 1990 for market-neutral funds (MN) and February 1994 for bear funds (BR). All time-series end in December 2007. Panel D reports results for all three subsets together. Significant statistics at the 5% percent level (denoted by an asterisk) are computed using Newey–West (1987) corrections for heteroskedasticity and autocorrelation for up to 6 lags.

Table 5

<table>
<thead>
<tr>
<th>Variable</th>
<th>CAPM</th>
<th>Three-factor model</th>
<th>Four-factor model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Long-short (LS) funds</td>
<td>x</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td>Rm</td>
<td>0.768*</td>
<td>0.765*</td>
<td>0.762*</td>
</tr>
<tr>
<td>HML</td>
<td>-0.025</td>
<td>-0.028</td>
<td></td>
</tr>
<tr>
<td>SMB</td>
<td>0.038</td>
<td>0.036</td>
<td></td>
</tr>
<tr>
<td>UMD</td>
<td>0.018</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted-R²</td>
<td>0.842</td>
<td>0.842</td>
<td>0.840</td>
</tr>
<tr>
<td>Panel B: Market-neutral (MN) funds</td>
<td>x</td>
<td>0.000</td>
<td>-0.001</td>
</tr>
<tr>
<td>Rm</td>
<td>-0.040</td>
<td>-0.012</td>
<td>-0.001</td>
</tr>
<tr>
<td>HML</td>
<td>0.132*</td>
<td>0.137*</td>
<td></td>
</tr>
<tr>
<td>SMB</td>
<td>0.145*</td>
<td>0.138*</td>
<td></td>
</tr>
<tr>
<td>UMD</td>
<td>0.037</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted-R²</td>
<td>0.001</td>
<td>0.033</td>
<td>0.030</td>
</tr>
<tr>
<td>Panel C: Bear (BR) funds</td>
<td>x</td>
<td>0.002</td>
<td>0.000</td>
</tr>
<tr>
<td>Rm</td>
<td>-1.372*</td>
<td>-1.244*</td>
<td>-1.154*</td>
</tr>
<tr>
<td>HML</td>
<td>0.384*</td>
<td>0.433*</td>
<td></td>
</tr>
<tr>
<td>SMB</td>
<td>0.192*</td>
<td>0.139*</td>
<td></td>
</tr>
<tr>
<td>UMD</td>
<td>0.244*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted-R²</td>
<td>0.832</td>
<td>0.858</td>
<td>0.890</td>
</tr>
<tr>
<td>Panel D: All sample (LS + MN + BR) funds</td>
<td>x</td>
<td>0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td>Rm</td>
<td>0.097</td>
<td>0.170</td>
<td></td>
</tr>
<tr>
<td>HML</td>
<td>0.221*</td>
<td>0.249*</td>
<td></td>
</tr>
<tr>
<td>SMB</td>
<td>0.025</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>UMD</td>
<td>0.161*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted-R²</td>
<td>0.021</td>
<td>0.059</td>
<td>0.120</td>
</tr>
</tbody>
</table>

The adjusted-R² also reinforces this conclusion with MN funds barely responding to the market excess return factor.

This pattern in adjusted-R² extends to the multifactor pricing models and is visible in all three mutual fund subsets. For them, alphas from the three-factor and four-factor models confirm CAPM predictions for LS and MN funds. BR funds have a significant negative four-factor alpha. When we treat all the subsets as one aggregate portfolio (Panel D), the adjusted-R² is generally low and stems from two influences. First, MN fund returns are insensitive to economy-wide factors. Second, the overall LS and BR fund contribution to return volatility washes out due to the negative correlation in their returns that we documented earlier. This panel argues for evaluating the fund subsets individually rather than collectively.

We next discuss the loading on the various factors. While LS funds do not load on the value-premium factor, HML, MN and BR funds appear more tilted towards value with BR funds exhibiting a coefficient that is almost three times in magnitude. Similar results obtain for the loadings on the size related factor. LS funds are unaffected by SMB while MN and BR funds exhibit significant and similar sensitivities. Since SMB and HML represent average returns to small/large and value/growth stocks, they are somewhat similar to long-short portfolios. As an illustration, consider a mutual fund that follows the strategy of being long small-cap stocks and short large-cap stocks. The loading of this fund on SMB will be different from unity since its exposure is obviously different from that represented by the mechanical SMB portfolio. The difference in loading represents the location of that mutual fund on the bearish continuum we describe earlier. Viewed on this continuum,

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20 We thank Ken French for making data on CRSP value-weighted market portfolio, HML, SMB and UMD factors available at http://www.mba.tuck.dartmouth.edu/pages/faculty/ken.french/datalibrary.html.
LS funds provide a hedge against HML and SMB, MN, funds provide an effective hedge against the market factor and BR funds do not provide a hedge against any of the four mimicking factors. One reason why MN mutual funds are not effectively neutral to HML and SMB is that they may interpret neutrality differently from their hedge fund cohorts. Recall that Patten (2008) identifies other forms of neutrality which MN mutual funds may not employ.

The coefficient on the momentum related factor UMD is positive and significant only for BR funds. To some extent, this coefficient captures a part of the time-variation arising from the aggressive risk management strategy inherent in BR fund investment objectives. Alternatively, this coefficient may be reflecting the common auto-correlation structure of BR fund and momentum returns.

We also estimate four-factor regressions at the individual fund level rather than the subset level and find that half the individual funds in the BR fund subset display significant negative alphas.\(^{21}\) Finally we investigate the nature of the entry and exit of funds during our sample period and find that this does not drive the portfolio negative alpha of 30 basis points.

The above analysis, of alphas, overall explanatory power, and coefficient magnitudes across the different pricing models, leads us to suspect that a parsimonious single-factor conditional CAPM model that allows for time-variation in risk and risk premiums may represent a more suitable tool for exploring the performance of funds in our sample.

5. Performance with the conditional CAPM

The mutual funds literature has long recognized the merits of the conditional CAPM approach (Ferson and Schadt, 1996; Christoforson et al., 1998). The investment objective of MN and BR funds requires close monitoring and a rapid response to market conditions and makes the conditional CAPM a natural tool to study the ensuing time-variation in both performance and risk. Critiques of the conditional CAPM include Lewellen and Nagel (2006) who use a short-horizon rolling window analysis to show its limitations. We do not follow such a procedure. The other main criticism of the conditional CAPM (Hansen and Richard, 1987) is that the true set of conditioning variables, as common instruments for estimating the coefficient vector \(\hat{\beta}_t\), is unknown. Our choice of conditioning variables, as shown in Table 3, is consistent with the literature on conditional performance evaluation. The monthly expected market risk premium, \(\gamma\), is estimated as the fitted value, including the constant, of the following regression:

\[
r_{mt-1} = \beta_0 + \beta_1 r_{mt-1} + \beta_2 DEF + \beta_3 TERM + \beta_4 TB + \epsilon_{mt-1}
\]

where \(r_{mt-1}\) is the excess return, with respect to the 1-month Treasury bill rate, on the value-weighted market return referring to the CRSP universe of all NYSE, AMEX, and NASDAQ stocks. The lagged predictors are the monthly dividend yield (DIV), the default premium (DEF), the term premium (TERM), and the nominal 1-month T-bill yield (TB).\(^{22}\) The monthly conditional beta is estimated in a two-step procedure, using the same set of lagged predictors. First, a full sample estimation of the coefficient vector \([b_{00}, b_{11}, b_{22}, b_{33}]\) is obtained from the following equation:

\[
r_{t-1} = \beta_0 + (b_{00} + b_{11})DIV_t + b_{22}DEF_t + b_{33}TERM_t + b_{44}TB + \epsilon_{t-1}
\]

where \(r_t\) is the excess return, with respect to the 1-month Treasury bill rate, on each fund subset \(i\), and \(z_i\) represents the related conditional CAPM alpha. Next, a linear combination of a constant and lagged predictors times-series (DIV\(_t\), DEF\(_t\), TERM\(_t\), TB\(_t\)) according to the coefficient vector \([b_{00}, b_{11}, b_{22}, b_{33}]\) delivers the estimated conditional beta, \(\beta_i\), for each fund category \(i\). To dissipate the econometric problems stemming from the generated regressor \(\hat{\gamma}\) in Eq. (5), and from the use of a common set of lagged predictors to estimate the conditional betas and the expected risk premium, we rely on HAC robust standard errors with 6 lags (Newey and West, 1987) and jointly estimate \(\beta_i, \gamma\) and \(\phi_i\) via GMM.\(^{23}\) We also define the different economic climates building on the counter-cyclical nature of the expected risk premium: “Boom”/”Bust” is identified by the lowest/highest 20% of the ex-ante market premium distribution.

\(^{21}\) About a quarter of the individual funds in the LS and MN subsets have significant negative alphas.

\(^{22}\) The dividend yield is the sum of dividends, over the previous 12 months, accruing to the Center for Research in Securities Prices (CRSP) value-weighted portfolio, divided by the contemporaneous level of the index. The default premium is the yield spread between Moody’s Baa and Aaa corporate bonds. The term premium is the yield spread between the 10-year and the 1-year Treasury bond. The default yield is from the monthly database of the Federal Reserve Bank of St. Louis, and the government bond yield is from the Ibbotson database. Finally, the short-term interest rate is the 1-month Treasury bill rate from CRSP.

\(^{23}\) The GMM system of orthogonality conditions follows Petkova and Zhang (2005, p. 191).
“Minus”/“Plus” is identified by the lowest/top 30% of the premium distribution centered on its average.24

5.1. Conditional CAPM

We start with a simple version of the model where the alphas do not vary with time in order to permit a direct comparison with results from the static models in Section 4. The results of this estimation are reported in Table 6. Panel A reports unconditional and conditional mean monthly realized returns for the period February 1994–December 2007 for all three mutual fund subsets. These subsets show return patterns consistent with the counter-cyclical nature of our expected market risk premium measure. LS (BR) funds exhibit negative (positive) returns in the BOOM state and this pattern reverses in the BUST state. MN funds show the smallest return spread in the two economic climates. Adjusted-\( R^2 \) in Panel B for the conditional CAPM regressions are similar to those obtained in the four-factor model suggesting that this parsimonious model has similar explanatory power.

Moreover, none of the alphas are statistically significant at conventional levels. The transition from the BUST to the BOOM state produces substantial variation in average betas for BR funds and considerably less variation for LS and MN funds. Fig. 1A plots the conditional betas of our three mutual fund subsets and the expected market risk premium. This figure also clearly shows that during this transition, BR fund average conditional betas decrease from \(-0.703\) to \(-1.749\).25 Being dedicated short funds, their reaction during BOOM conditions is to increase the strength of their short exposure. When we examine the beta-premium sensitivities, we find that BR funds are the only fund subset that exhibits a large and statistically significant value of 54.154.26 The implication of this large beta-premium sensitivity is clearly visible in Fig. 1A which shows that the BR conditional beta closely tracks the expected market risk premium.27 To reiterate, a high beta-premium sensitivity implies that the managers respond rapidly to expected changes in economic conditions. In the aggregate the all-sample group as a whole shows a large but insignificant beta-premium sensitivity (\( \phi = 27.669, t(\phi) = 1.519 \)).

5.2. Conditional CAPM with time-varying alphas

Ferson et al. (2008) show that the omission of time-varying alphas may lead to biased conditional betas estimates. Accordingly, we allow for time-variation in alphas using the same set of lagged predictors used for our conditional betas. As reported in Table 7 (Panel A), average time-varying conditional CAPM alphas exhibit different patterns in BOOM and BUST climates for our mutual fund subsets. MN funds have insignificant alphas in both BOOM and BUST climates, LS funds have negative and significant alphas in BUST climates and BR funds have significant alphas in both. For BR funds, the alpha spread (BUST–BOOM) of 46 basis points is negative and significant. Most of this spread is generated by the negative average alpha in BUST. In our assessment this is the one

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24 We repeat the analysis using a 10% threshold to define the extreme economic states. The results are similar and available on request.

25 A comparison of the magnitude of our estimates with those obtained in other applications of the conditional CAPM in the asset pricing literature attests to the power of the conditional CAPM in our context. Petkova and Zhang (2005) use the conditional CAPM to show that value portfolios are riskier than growth portfolios. Their result hinges Boom vs. Bust spread of 0.73 for the average conditional beta for HML portfolios. The associated beta-premium sensitivity is 33.34 and is their strongest result [Petkova and Zhang, 2005, Table 2, Panel A (January 1927–December 2001), p. 195]. Our results for BR funds are well above these levels.

26 For comparability, the results in Table 5 are for the period February 1994–December 2007, when all three mutual fund subsets have data, although individual subsets have data for longer time periods. In unreported results we repeat the conditional CAPM analyses on these longer samples, and find that MN funds also exhibit a significant beta-premium sensitivity of 13.931 \( t(\phi) = 2.506 \).

27 It is curious that despite a value for \( \phi = 54.154, BR \) funds show alphas that are similar to the LS fund subset (\( \phi = 7.625, from Table 6, Panel B \). This perhaps arises from the interaction between the specificity of the BR funds and the features of the expected risk premium. We look at the relative contribution of the two additive terms in Eq. (3) for BR and LS funds which have, across the overall sample, an average conditional beta of \(-1.202 \) and \(0.901\), respectively. The expected risk premium on the same sample exhibits an average of 0.006 and a variance of 0.00005. Simple calculations show that the larger contribution of the beta-premium sensitivity of BR vs. LS funds is first minimized by the small expected risk premium volatility, then counterbalanced by opposite but similar in magnitude average betas for BR and LS funds. The ability of the conditional CAPM to describe the two antithetic risk profiles is then reinforced by large and similar indexes of linear determination.
subset where spread changes are most likely to be economically important.

The transition from BUST to BOOM for BR funds and its impact on time-varying alpha is instructive. In Fig. 1B, the BUST period (on the left of the graph) results in a negative alpha which then steadily increases as the economy moves towards BOOM. This BOOM occurs during 1999–2002 when BR funds generally earn positive alphas. This pattern of reversal is also revealed in the conditional
beta spread in the BUST and BOOM state that, despite being about and BOOM climates, respectively, leading to a significant spread of \( \beta \). They exhibit average betas of under unity. BR funds have the highest volatility in conditional be-
senstivities. Our conditional CAPM with time-varying alphas iden-
tifies MN funds as exhibiting a near-zero exposure to market risk.

Finally, we place our results in the context of the dynamics be-
tween managers and investors. Under the restrictive assumption that the conditional CAPM has a uniform accuracy in measuring beta time-variation across economic climates, the negative (positive) values of the conditional alphas may arise from the differential speeds at which managers position their portfolios in BUST (BOOM) climates. Our results suggest that managers of BR funds generate positive alphas by being aggressively short in the BOOM periods (beta of \(-1.744\)), and negative alphas by not being as aggressively long in the BUST periods (beta of \(-0.690\)). In other words, BR fund managers appear more successful at identifying and exploiting BOOM conditions and are perhaps a little more hes-
tant in capitalizing on BUST climates. On the other hand, if managers
do discharge their fiduciary obligations evenly across economic climates, then the patterns in alphas could stem from differences in the flows that investors direct to BR managers in different economic states, rather than in the manager's deployment of BR. We explore this dynamic more formally in the next section.

6. Flow-performance relationships

In a world where expected returns are generally positive, the value of short-oriented funds as a component of an investor's port-
folio will depend on how they perform during up and down-market states. Analysis of this flow-performance relationship is
typically conducted in a regression setting which attempts to ex-
plain flows as a function of market-states, lagged return variables
and fund characteristics. We offer an event-time approach to investigate this behavior, following a procedure outlined in Cooper et al. (2004) in their study of momentum. This procedure essen-
tially treats market states as an event, categorizing markets as
UP or DOWN depending on the level of the aggregate past market
return at each particular point in time. While we recognize that a
realized market signal is a noisy one, it is one that we believe naive
investors are more likely to follow. A second advantage of this ap-
proach is that it permits us to investigate the speed at which inves-
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tors are more likely to follow. A second advantage of this ap-
proach is that it permits us to investigate the speed at which inves-

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28 This small volatility is visible in Fig. 1A.
**Fig. 2.** Number of 1-year DOWN-market states. The graph documents the number of DOWN-market states, as measured by the number of months in a given year where the cumulative return, over the months $t = 12$ to $t = 1$, on the VW CRSP universe is negative over the period 1982–2007.

**Fig. 3.** Plots of cumulative flows following UP and DOWN-market states. Figures in the first column plot the cumulative normalized flows in% (NFLOWS) over the months $t + 1$ to $t + 60$ for each of our three fund subsets following UP and DOWN-market states. UP (DOWN) market states are identified by non-negative (negative) returns on the VW CRSP universe over months $t = 12$ to $t = 1$. Figures in the second column plot the unexpected normalized flows from an AR(1) model (unexp. NFLOWS). The last pair has all three fund subsets together. Graphs for each pair appear on the same scale for visual clarity.
We report our findings for each mutual fund subset over multiple holding periods. For a market state event at time \( t \), we use three holding periods from \( t + 1 \) to \( t + 6 \), \( t + 1 \) to \( t + 12 \), and \( t + 1 \) to \( t + 24 \) months to investigate the nature of lags in post-event investor flow patterns. Formally, for \( i = 6, 12, \) and 24:

\[
\text{CUMFLOW}(t + 1, t + i) = \sum_{t+1}^{t+i} F(t)
\]

(8)

where \( F(t) \) is either the monthly normalized flow or the AR(1) adjusted normalized flow and the \((t + 1, t + i)\) pairs represent subsequent months \((1, 6), (1, 12), \) and \((1, 24)\). For example, for the month of June 1990, the CUMFLOW over holding-period months 1–6 is the sum of the monthly normalized or AR(1) adjusted normalized flows from the preceding 6 month.\(^{30}\) These successively longer horizons enable us to discern the extent (if any) by which investor flows represent lagged responses to changing market states. For completeness we also examine a \( t + 25 \) to \( t + 60 \) holding period.

The first column of graphs in Fig. 3 presents results for cumulative normalized flow (NFLows) subsequent to UP or DOWN markets. The second column of graphs reports cumulative normalized “unexpected” flow using a simple AR(1) model. On these graphs, the (thick/thin) lines denote (UP/DOWN) market behavior. Graphs are presented separately for LS funds, MN funds and BR funds. The behavior of these flows is substantially different for our three subsets of funds. For relatively short horizons (up to 2 years), the difference in flows between UP- and DOWN-market states is positive for LS funds and negative for MN and BR fund subsets. This is not surprising given that a cohort of bearish investors are the most likely to direct flows to these classes of funds, but what is surprising is that over longer horizons (over 2 post-event years), flows to LS reverse while flows to MN and BR funds remain consistently higher. To us, it appears that these investors continue to remain anchored to bear market sentiments long after a related event has taken place.

\(^{30}\) Adjusted flows represent the sum of the constant and error terms in the AR(1) regression.

Table 8 reports Wald tests of significance between UP- and DOWN-market flows for four different post-event holding periods for each of our subsets. These tests confirm the observations from our graphical exposition above. Flows to LS funds are significantly larger in UP-market states for holding periods up to 24 months, while flows to MN funds are significantly smaller. Curiously, for the BR fund subset, significant differences between UP- and DOWN-market flows are evident only for the \((1–24)\) month holding period - a result that we suspect obtains due to that subset’s especially high flow volatility that we documented earlier. MN funds also receive significantly larger flows for the \((25–60)\) month holding period. A similar pattern is evident in AR(1) flows as well.

To further examine how the investor need for bear market hedges is reflected in fund performance, we next replicate our event-study framework using returns for each of our mutual fund subsets. In Fig. 4, we present corresponding graphs for cumulative returns (CARs) calculated in a manner analogous to Eq. (8) for flows. Formally, for \( i = 6, 12, \) and 24:

\[
\text{CAR}(t + 1, t + i) = \sum_{t+1}^{t+i} C(t)
\]

(9)

where \( C(t) \) is either the monthly raw return or the four-factor model-adjusted return and the \((t + 1, t + i)\) pairs represent subsequent months \((1, 6), (1, 12), \) and \((1, 24)\).\(^{31}\) The first column of graphs reports raw returns and the second presents graphs for CARs adjusted by the four-factor model. Once again, differences between our fund subsets are evident. MN funds exhibit superior performance return performance for up to 60 months after a DOWN-market and BR funds outperform for up to about 2 years. While these patterns obtain with the four-factor model as well, the performance is not quite so stellar. For MN funds, these CARs reach about 5% within 2 years following a down market but remain at that level for the subsequent 3 years. BR funds do perform better in the 2-years subsequent to down mar-

\(^{31}\) The four-factor adjustment is the sum of the constant and the error terms in a regression of excess returns over the risk-free rate on the set of relevant factors.

---

**Table 8**

Significance tests for flows following UP and DOWN-markets states. The table reports mean monthly normalized (NFLows) and unexpected normalized flows from an AR(1) model following UP and DOWN-market states. Unexpected normalized flows represent the sum of the constant and error terms in the AR(1) regression. The flows are cumulated across four holding periods: months \( t + 1 \) to \( t + 6 \), months \( t + 1 \) to \( t + 12 \), months \( t + 1 \) to \( t + 24 \), and months \( t + 25 \) to \( t + 60 \). UP (DOWN) market states are identified by non-negative (negative) returns on the VW CRSP universe over months \( t + 12 \) to \( t + 1 \). A Wald statistic and the associated probability for the test of the equality of flows following UP and DOWN-market states are reported. The standard errors are computed using the Newey–West (1987) correction for heteroskedasticity and autocorrelation. Lag lengths are 5, 11, 23 and 35 depending on the respective holding periods.

<table>
<thead>
<tr>
<th>Holding period</th>
<th>UP</th>
<th>DOWN</th>
<th>Wald</th>
<th>P-value</th>
<th>UP</th>
<th>DOWN</th>
<th>Wald</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Long-short (LS) funds</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1–6 months</td>
<td>0.0142</td>
<td>0.0034</td>
<td>12.05</td>
<td>0.0005</td>
<td>0.0117</td>
<td>–0.0006</td>
<td>25.35</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>1–12 months</td>
<td>0.0135</td>
<td>0.0033</td>
<td>11.08</td>
<td>0.0009</td>
<td>0.0111</td>
<td>–0.0003</td>
<td>15.96</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>1–24 months</td>
<td>0.0123</td>
<td>0.0043</td>
<td>3.63</td>
<td>0.0566</td>
<td>0.0106</td>
<td>0.0013</td>
<td>3.28</td>
<td>0.0702</td>
</tr>
<tr>
<td>25–60 months</td>
<td>0.0071</td>
<td>0.0023</td>
<td>1.53</td>
<td>0.2158</td>
<td>0.0070</td>
<td>0.0233</td>
<td>1.53</td>
<td>0.2124</td>
</tr>
<tr>
<td>Panel B: Market-neutral (MN) funds</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1–6 months</td>
<td>0.0268</td>
<td>0.0478</td>
<td>3.57</td>
<td>0.0587</td>
<td>0.0229</td>
<td>0.0403</td>
<td>2.42</td>
<td>0.1201</td>
</tr>
<tr>
<td>1–12 months</td>
<td>0.0265</td>
<td>0.0409</td>
<td>4.49</td>
<td>0.0342</td>
<td>0.0267</td>
<td>0.0404</td>
<td>3.57</td>
<td>0.0587</td>
</tr>
<tr>
<td>1–24 months</td>
<td>0.0254</td>
<td>0.0368</td>
<td>7.05</td>
<td>0.0070</td>
<td>0.0254</td>
<td>0.0359</td>
<td>6.59</td>
<td>0.0103</td>
</tr>
<tr>
<td>25–60 months</td>
<td>0.0214</td>
<td>0.0244</td>
<td>6.99</td>
<td>0.0082</td>
<td>0.0217</td>
<td>0.0244</td>
<td>3.15</td>
<td>0.0759</td>
</tr>
<tr>
<td>Panel C: Bear (BR) funds</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1–6 months</td>
<td>0.0949</td>
<td>0.0597</td>
<td>0.14</td>
<td>0.7130</td>
<td>0.0597</td>
<td>0.0584</td>
<td>0.01</td>
<td>0.9276</td>
</tr>
<tr>
<td>1–12 months</td>
<td>0.0565</td>
<td>0.0657</td>
<td>0.84</td>
<td>0.3583</td>
<td>0.0508</td>
<td>0.0642</td>
<td>1.96</td>
<td>0.1615</td>
</tr>
<tr>
<td>1–24 months</td>
<td>0.0473</td>
<td>0.0723</td>
<td>120.50</td>
<td>&lt;0.0001</td>
<td>0.0437</td>
<td>0.0711</td>
<td>116.22</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>25–60 months</td>
<td>0.0375</td>
<td>0.0212</td>
<td>1.89</td>
<td>0.1695</td>
<td>0.0352</td>
<td>0.0206</td>
<td>1.49</td>
<td>0.2219</td>
</tr>
<tr>
<td>Panel D: All sample (LS + MN + BR) funds</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1–6 months</td>
<td>0.0178</td>
<td>0.0242</td>
<td>0.65</td>
<td>0.4219</td>
<td>0.0177</td>
<td>0.0234</td>
<td>0.50</td>
<td>0.4776</td>
</tr>
<tr>
<td>1–12 months</td>
<td>0.0167</td>
<td>0.0262</td>
<td>0.99</td>
<td>0.3198</td>
<td>0.0164</td>
<td>0.0252</td>
<td>0.84</td>
<td>0.3587</td>
</tr>
<tr>
<td>1–24 months</td>
<td>0.0158</td>
<td>0.0252</td>
<td>0.62</td>
<td>0.4299</td>
<td>0.0155</td>
<td>0.0246</td>
<td>0.56</td>
<td>0.4552</td>
</tr>
<tr>
<td>25–60 months</td>
<td>0.0172</td>
<td>0.0176</td>
<td>0.00</td>
<td>0.9589</td>
<td>0.0171</td>
<td>0.0178</td>
<td>0.01</td>
<td>0.9140</td>
</tr>
</tbody>
</table>

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\[^{31}\] The four-factor adjustment is the sum of the constant and the error terms in a regression of excess returns over the risk-free rate on the set of relevant factors.
kets but barely achieve positive status. After this 2 year period however, the performance of BR funds in down markets is actually worse than during up-markets! Table 9 reports the corresponding Wald tests for significant differences between UP- and DOWN-market states for returns and we again observe significance in the directions implied in the graphical analysis above. The higher DOWN-market flows result in slightly better cumulative returns for MN funds for up to 24 months post-event. For BR funds, corresponding cumulative returns are not significant. For the 25–60 month holding period, BR funds generate better returns in UP-than in DOWN-markets.

In sum, while MN funds appear to offer some hedging potential, BR funds do not appear to be serving that purpose. Despite the significance of the AR(1) component of flows, we cannot ignore the possibility that flows to these funds are at least partly driven by different investors becoming bearish at different times subsequent to a DOWN-market event. To the extent that fund managers typically have a charter of full investment, performance may be hampered by their fiduciary obligation to invest received flows. Some of the BR funds in our sample have explicitly stated short-term objectives of obtaining returns that are inverse multiples of narrow and broad indexes and maintaining a large cash component would be detrimental to the execution of that strategy. Manager response to anchored, persistent flows may also result in more dynamic short-term adjustments to portfolio risk exposure instead. Nevertheless, investors committing a portion of their assets to BR funds should be cognizant of these implications.

7. Conclusions

We examine the characteristics and portfolio performance of mutual funds that employ long-short, market-neutral and bear strategies as part of their investment objective. While these strategies are common among hedge funds and have been widely studied, the mutual fund literature is relatively silent on this front. We view these fund styles as representing different locations on a bearish continuum and find clear implications for the performance of these mutual funds. Returns to long-short funds vary with the market, returns to market-neutral funds are uncorrelated with broad indexes and maintaining a large cash component would be detrimental to the execution of that strategy. Manager response to anchored, persistent flows may also result in more dynamic short-term adjustments to portfolio risk exposure instead. Nevertheless, investors committing a portion of their assets to BR funds should be cognizant of these implications.

**Fig. 4.** Plots of cumulative returns following UP and DOWN-markets states. Figures in the first column plot the cumulative raw returns over the months $t + 1$ to $t + 60$ for each of our three fund subsets (LS, MN and BR) following UP and DOWN-market states. UP (DOWN) market states are identified by non-negative (negative) returns on the VW CRSP universe over months $t - 12$ to $t - 1$. Figures in the second column plot the pattern for Carhart (1997) four-factor model-adjusted returns. The last pair plots all three fund subsets together. Graphs for each pair appear on the same scale for visual clarity.

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32 The IRR derived returns for bear funds were much smaller than the geometric return providing some support for this conjecture.
Significance tests for returns following UP and DOWN-markets states. The table reports mean monthly raw and Carhart (1997) four-factor model-adjusted returns following UP and DOWN-market states. The returns are cumulated across four holding periods: months $t+1$ to $t+6$, months $t+1$ to $t+12$, months $t+1$ to $t+24$, and months $t+25$ to $t+60$. UP (DOWN) market states are identified by non-negative (negative) returns on the Fama-Carhart CRSP universe over months $t+1$ to $t+12$ (the Ba correctly). A Wald statistic and the associated probability for the test of the equality of returns following UP and DOWN-market states are reported. The standard errors are computed using the Newey–West (1987) correction for heteroskedasticity and autocorrelation. Lag lengths are 5, 11, 23 and 35 depending on the respective holding periods.

Since the investment objectives of these funds often require dynamic changes to market-risk exposure, we then conduct an evaluation of portfolio performance using the conditional CAPM. We consider both time-varying alphas and changing economic climates in our specification. Long-short funds appear little different from long-only funds although their investment objectives might lead investors to expect otherwise. Market-neutral funds appear to adhere closely to their investment objectives. They have very low $R^2$ for both the conditional CAPM and the four-factor model along with small loadings on HML and SMB. In BOOM/BUST periods, they exhibit no raw return differential, insignificant conditional alphas, and a small significant beta spread. Time variation in risk is the most pronounced for bear funds and perhaps the most economically meaningful. Bear fund alphas are negative, significant and vary with the economic climate with most of the underperformance arising in the BUST period when the portfolios appear to have a larger short exposure than economic conditions might warrant. Our conditional CAPM specification is able to predict returns of bear funds with remarkable accuracy.

We then examine the behavior of both flows and returns subsequent to UP and DOWN-market states by carrying out an event-study. We find substantial differences in both variables across our three subsets of mutual funds. These differences have important implications for investors allocating their assets to these mutual funds. Although they have the potential to opportunistically generate performance from the short side, long-short funds do not seem very different from long-only funds and mildly bearish investors who direct flows to such funds are likely to be disappointed. Market-neutral funds adhere to their stated objectives, have little market exposure and are able to provide their investors with superior performance for long horizons following down markets. Bear funds adjust their risk exposure significantly in BOOM/BUST climates and also receive flows for long periods after a down market. However bear fund managers are not able to generate commensurate performance.

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References