Downside Risk and Mutual Fund Flows*

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Abstract

Despite its intuitive appeal and theoretical justification, the finance literature has yet to adopt downside risk as a standard factor for performance evaluation. We argue that Berk and van Binsbergen (2016)'s approach to testing asset pricing models using the relation between investor flows and risk-adjusted fund returns is well suited for testing the merits of downside risk because it circumvents problems inherent in estimating downside risk noted in Ang, Chen, and Xing (2006). We extend the recent findings of Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016) by showing that investors care more about downside market risk than unconditional market risk when choosing mutual funds. Additionally, consistent with time-varying risk aversion and investor clienteles, we find that investors' sensitivity to downside risk increased following the financial crisis and is more pronounced among funds with conservative investment objectives (e.g., income funds).

Keywords: Downside risk, Mutual Fund Flows, Asset Pricing, Investor behavior

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1 Introduction

The fact that investors chase past fund returns when allocating their money to mutual funds is well documented. A natural question concerns how investors process past fund returns when choosing funds. Do they compare absolute returns or do they adjust for risk? And if they adjust for risk, which asset pricing model best describes their allocations? Berk and van Binsbergen (2016) (BvB) and Barber, Huang, and Odean (2016) (BHO) address this question by comparing the predictability of mutual fund flows from past fund returns adjusted using different asset pricing models. Both studies find that returns adjusted with the Capital Asset Pricing Model (CAPM) [Sharpe (1964), Lintner (1965)] have the highest explanatory power, and conclude that investors care about market risk but tend to ignore exposure to additional factors such as size, value/growth, and momentum [Fama and French (1993), Carhart (1997)]. We extend this line of inquiry to consider whether investors distinguish between unconditional market risk (β) and downside market risk (β^{-}) when choosing mutual funds. We find that downside beta-adjusted returns explain investor flows better than unconditional beta-adjusted returns for a wide array of alternative test specifications.

Recognition that downside risk may be more relevant to investors' preferences than unconditional risk dates back to Roy (1952) and Markowitz (1959). Despite its intuitive appeal and theoretical justification, the finance literature has yet to adopt downside risk as a standard factor for performance evaluation. In their "horse-race" of competing asset pricing models for explaining mutual fund flows BvB and BHO examine the relative merits of fourteen different models, none of which include downside risk. More generally, the literature typically uses the CAPM, and various extensions such as the three-factor model [Fama and French (1993)], four-factor model [Carhart (1997)], and five-factor model [Fama and French (2015)] to adjust returns. The omission of downside risk from standard performance benchmarks is likely due to the fact that the empirical evidence from conventional asset pricing tests of downside risk is somewhat weak.

The most prominent empirical test regarding the pricing of downside risk is Ang, Chen, and Xing (2006), who examine a variation of Bawa and Lindenberg (1977)'s downside beta. They find that systematic downside risk commands a premium of approximately 6% per annum in U.S. stocks. However, their tests exclude 20% of the most volatile stocks. They note that downside covariation of very volatile stocks is difficult to predict– the average one-year autocorrelation of one-year downside betas for very volatile stocks is only 17.3% as compared to 43.5% for a typical stock. Standard asset pricing methodologies for testing downside risk are likely to be problematic for at least two reasons. First, estimates of downside beta use roughly half of the observations available for the estimation of unconditional beta – exacerbating the already substantial errors-in-variable problem inherent in these tests. Second, to the extent that downside beta reflects firm distress [Fama and French (1996), Artavanis and Kadlec (2012)], which is a somewhat temporary state of affairs, it may not be as persistent as unconditional beta.[1]

We argue that BvB's flow-performance approach to testing asset pricing models is particularly well suited for examining the relative merits of downside risk because it largely circumvents the aforementioned problems inherent in estimating downside risk. First, since the typical mutual fund portfolio includes a large number of stocks, the fact that downside beta is estimated with fewer time-series observations becomes less of a concern. Second, since mutual funds tend to manage their portfolios according to a given strategy, their factor exposures are likely to be more persistent than that of individual stocks. For example, the downside beta of a mutual fund that exploits distressed stocks will maintain its exposure through rebalancing, much like momentum funds maintain their factor loading on momentum as stocks fade into and out of momentum status. Finally, in contrast to conventional asset pricing tests which rely on moment conditions of returns to infer investors' risk-return choices, the BvB approach examines investors' preferences directly in the context of how well mutual funds' risk-adjusted returns explain mutual fund flows. Thus, the BvB approach further minimizes the errors-in-variable problem by replacing noisy realized stock returns with a more direct measure of investors' expectations.

We begin our empirical analysis with BvB's test that relates the signs of monthly fund flows to the signs of performance measures from competing models. We confirm the central result in BvB and BHO that CAPM-adjusted fund returns explain future investor flows better than the Fama-French (FF) three-factor or Fama-French-Carhart (FFC) four-factor models. We then show that downside risk-adjusted fund returns explain future investor flows significantly better than CAPM-adjusted fund returns. The BvB t-statistic for the pairwise comparison of these two models is 3.07. The superior performance of downside risk against the competing models persists, even when we

[1]We are not suggesting that unconditional beta is not time-varying [see e.g., Andersen, Bollerslev, Diebold, and Wu (2006)] but rather that it is more persistent than downside beta.

focus on extreme returns (as in BvB).

We continue our analysis using panel regressions, where we regress future monthly fund flows on performance measures from different models controlling for other variables that affect fund flows. We confirm that downside alpha explains future investor flows better than CAPM alpha, in terms of greater and more significant coefficient estimates and higher adjusted-R^2s. Including both downside alpha and CAPM alpha in the same regression, downside alpha completely subsumes CAPM alpha. As noted in BvB and BHO, the alphas from these competing models are highly correlated. Thus, we also focus on the orthogonal component of downside alpha ($\hat{\alpha}_D - \hat{\alpha}_C$). The orthogonal component is statistically significant in the presence of CAPM alpha, suggesting that downside risk has additional explanatory power not captured by unconditional beta, but it is insignificant in the presence of downside alpha.

Our inferences regarding the importance of downside risk in explaining investor flows are robust to a wide array of alternative test specifications. We obtain similar results when we use Spiegel and Zhang (2013)'s definition of fund flow, based on changes in market share rather than changes in total net assets, to address concerns over the disproportionate influence of small funds. Our results are also robust to alternative regression specifications including piecewise linear regressions to account for convexity (as in Sirri and Tufano (1998)), and Fama and Macbeth (1973) regressions, as well as alternative beta estimation methods and performance horizons.

Finally, we provide evidence of cross-sectional and time-series variation in investors' concern for downside risk by examining the flow-performance relation for different investor clienteles via different fund styles (e.g., small-cap and growth funds vs. income funds), and during different market environments (pre and post financial crisis). We find that investors of income funds are more sensitive to downside risk than those of small cap funds and growth funds. Moreover, investors' sensitivity to downside risk increased significantly following the collapse of Lehman Brothers in 2008. These findings are consistent with the clientele effect documented by Kumar and Lee (2006) and time-varying risk aversion that peaks following large, adverse shocks in the market as shown in Guiso et al. (2018).

Jegadeesh and Mangipudi (2017) raise concerns that small differences between competing models may yield misleading inferences regarding the "true" asset pricing model used by investors to allocate their money to funds. More specifically, they argue that if estimation error is sufficiently greater than specification error, these tests will tend to favor more parsimonious models (i.e. CAPM). Our results address this concern by showing that downside risk – a model with significantly higher estimation errors, due to the use of fewer observations to estimate systematic risk– performs better than the more precisely-estimated unconditional models.

Our paper contributes to two main strands of literature. First, our evidence of the relative merit of downside risk in explaining mutual fund flows is complementary to several recent studies that find support for downside risk using conventional asset pricing tests [Delikouras (2017), Farago and Tedongap (2018), Jiang, Wu, and Zhou (2018), Lu and Murray (2018)]. As such, our evidence pushes the literature closer to a consensus regarding the importance of downside risk in asset pricing– but using a very different approach to conventional asset pricing tests. While the flow-performance relation may not constitute a formal asset pricing test, this corroborating evidence is nevertheless encouraging. Second, our study contributes to the recent literature on the relative merits of alternative asset pricing models in explaining the flow-performance relation for mutual funds and extends it by showing that investors are more concerned with downside market risk than unconditional market risk.

Even though our evidence suggests that downside risk is of importance to investors and it has long been recognized by practitioners (e.g. Morningstar has reported a version of downside betas for more than 15 years[2]), it has received little attention in mutual fund literature with a few exceptions. De Andrade Jr (2009) examines whether investors respond differently to upside and downside systematic risk and finds that funds with relatively higher upside betas compared to their downside betas (with better timing ability as in Henriksson and Merton (1981)) attract more flows. However, the conditional alphas of his study are quite different from the alpha of downside CAPM examined here – the latter of which is more relevant to asset pricing. Bodnaruk, Chokaev, and Simonov (2015) also examine mutual fund managers' ability to time exposure to downside risk and find that those with the greatest timing ability earn higher returns and garner higher flows. Their study relates to time-series variation in downside portfolio beta and future market returns as in Henriksson and Merton (1981), and does not address whether investors account for cross-sectional

[2]Morningstar reports downside and upside capture ratios, which are similar to downside and upside betas in nature. It also reports Sortino ratio, which replaces standard deviation in Sharpe ratio with downside standard deviation. For a brief description see http://www.morningstar.com/InvGlossary/upside-downside-capture-ratio.aspx and http://www.morningstar.com/InvGlossary/sortino_ratio_definition_what_is.aspx

variation in downside risk when allocating money to funds. In this context, these studies highlight the importance of distinguishing between performance in up and down markets, whereas our work evaluates the relative merits of downside risk to standard benchmarks in the literature.

Finally, while our discussion focuses on the asset pricing implications/interpretation of the flow-performance relation similar to BvB, we recognize that our evidence is also consistent with behavioral interpretations as in BHO. The fact of the matter is, these two themes (asset pricing vs. behavior) are sufficiently overlapping that they are very difficult to differentiate empirically. As BHO note, the flow-performance based tests capture preferences but may not necessarily have implications for asset pricing. Nevertheless, we argue that evidence on preferences still provides support for the underlying tenets/assumptions of asset pricing models. Our study provides direct evidence regarding investors' attention to downside risk.

The rest of our paper is organized as follows: The second section provides a brief discussion of measures of downside risk. The third section describes the data and sample. The fourth section presents our empirical results and provides several robustness checks. The fifth section concludes our paper.

2 Downside Beta

Hogan and Warren (1974) and Bawa and Lindenberg (1977) develop equilibrium models in which the representative investor minimizes portfolio risk measured by semi-variance (instead of unconditional variance) while trying to achieve a target level of expected return. Their models retain the key features of CAPM – with downside beta replacing unconditional beta as the relevant measure of risk. Hence, we refer to this model as "downside CAPM". Fishburn (1977) shows that the downside CAPM is consistent with a representative investor with a kinked utility function. As such, downside CAPM derives its theoretical justification from the the notions of loss aversion [Kahneman and Tversky (1979)] and disappointment averse utility functions [Gul (1991)], as an extreme case where the representative investor is risk averse for returns below a threshold and risk neutral for returns above.

Nantell and Price (1979) show that if the joint distribution of the asset and market returns is bivariate normal, then downside beta (or upside beta) and CAPM beta are equivalent, since the asset comoves with the market symmetrically in rising and declining markets. However, as asset returns deviate from normality, downside betas tend to differ from their unconditional (CAPM) counterparts [see e.g., Price, Price, and Nantell (1982), Hong, Tu, and Zhou (2007), Jiang, Wu, and Zhou (2018)]. Thus, in theory, downside beta should help investors distinguish between assets with favorable and unfavorable asymmetries in their covariance with the market.

There is growing evidence in the literature that downside risk is priced in the cross-section of stock returns. Ang, Chen, and Xing (2006) show that downside risk commands a significant premium. More recently, studies have proposed more refined specifications of downside risk. Farago and Tedongap (2018) develop a model with generalized disappointment aversion and time-varying macroeconomic uncertainty, and find that three disappointment-related factors are priced. Delikouras (2017) develops a consumption-based asset pricing model with disappointment averse preferences and show that the performance of the disappointment model is comparable to that of the Fama-French three-factor specification. Jiang, Wu, and Zhou (2018) offer a model free entropy approach for quantifying the asymmetry in the joint distribution of individual stock and market returns. They find that their entropy-based measure of downside asymmetric comovement is priced. Lu and Murray (2018) construct bear market spreads from S&P500 index options and find that time-variation in the probability of a future bear market (bear beta) is priced.

Our specification of downside risk is drawn directly from Hogan and Warren (1974) and Bawa and Lindenberg (1977). Downside beta is defined as

$$\beta_i^- = \frac{E[(r_i - r_T)(r_M - r_T) \mid r_M \leq r_T]}{E[(r_M - r_T)^2 \mid r_M \leq r_T]} \tag{1}$$

where r_i denotes the excess return of asset i over the risk-free rate, r_M denotes the excess return of market portfolio and r_T denotes the threshold return that separates up and down markets.

It is important to note that our specification differs from that of Ang, Chen, and Xing (2006) which is also (loosely) based on Bawa and Lindenberg (1977):

$$\begin{aligned} \beta_i^{-ACX} &= \frac{Cov[r_i, r_M \mid r_M \leq r_T]}{Var[r_M \mid r_M \leq r_T]} \\ &= \frac{E[r_i r_M \mid r_M \leq r_T] - E[r_i \mid r_M \leq r_T]E[r_M \mid r_M \leq r_T]}{E[r_M^2 \mid r_M \leq r_T] - E[r_M \mid r_M \leq r_T]^2} \end{aligned} \tag{2}$$

The difference between the two specifications is material, and follows from the fact that the variance and covariance in equation (2) measures deviations with respect to the conditional means of the asset and the market, which relate to thresholds lower than r_T. This difference, which is apparent in the expectations formula of equation (2), leads to violations of state-preference theory. The issue is analyzed in detail in Artavanis (2012). Post, Van Vliet, and Lansdorp (2012) and Artavanis (2012) find much stronger support regarding the pricing of downside beta under the Hogan and Warren (1974) specification. While the focus of our paper is downside risk vs unconditional risk and not intended as a competition among downside risk measures, we note that the appropriate specification of downside beta is a prerequisite for the evaluation of the relative merits of downside CAPM to other asset pricing models.

3 Data and Sample

We obtain monthly fund returns and total net assets (TNA) from CRSP survivor-bias-free mutual fund database. Our sample period spans from January 1991 to December 2015, because TNA is available at a lower frequency prior to this period. Our sample includes only US domestic equity funds that are actively managed. We filter out foreign equity, sector equity, fixed income and mixed funds using CRSP objective codes in the database.[3] We also filter out index funds and ETFs based on index fund or ETF flag or on fund name containing a string associated with index funds or ETFs. We merge different share classes of a fund as commonly done in the literature. Finally, we exclude funds with TNA less than $15 million in a given month and monthly flows less than -90% or more than 1000% following the literature standard.

We define monthly fund flow F_{it} for fund i in month t as the change in its TNA after adjusting for its return as suggested by Sirri and Tufano (1998):

$$F_{it} = \frac{TNA_{it} - (1 + R_{it})TNA_{it-1}}{TNA_{it-1}} \tag{3}$$

where TNA_{it} is the total net assets under management for fund i at the end of month t, and R_{it} is the total return in month t. We also consider an alternative definition of fund flows, based on

[3]CRSP objective codes are constructed using objective codes from three different sources: Wiesenberger, Strategic Insight and Lipper. Detailed information on CRSP objective codes can be found on CRSP website: http://www.crsp.com/products/documentation/crsp-style-code

changes in market share following Spiegel and Zhang (2013):

$$F_{it}^{SZ} = \frac{TNA_{it}}{\overline{TotalTNA_t}} - \frac{TNA_{it-1}}{TotalTNA_{t-1}} \tag{4}$$

where $TotalTNA_{t-1}$ is the sum of TNAs of all funds in the sample as of month $t-1$ and $\overline{TotalTNA_t}$ is the sum of TNAs of the same funds that existed in $t-1$ as of t.

We estimate downside beta following Hogan and Warren (1974) and Bawa and Lindenberg (1977) using equation (1).[4] We set the threshold excess return for defining up and down market states as $r_T = 0$. In robustness tests, we use the average excess market return as an alternative threshold.

We estimate systematic risk measures (CAPM beta, downside beta, upside beta) and market, size, value, and momentum factor loadings using a rolling 60 months window. We obtain monthly returns for market, size, value, and momentum factors from Kenneth French's online data library.[5] To be included in the sample for a given month, a fund must have complete monthly returns for the past 60 months for the estimation of betas and next month's return and TNA for calculating next month's fund flows.[6]

Our final sample contains 2,890 distinct funds that meet the data requirements from 588 distinct fund families. Our test period includes 240 months (Dec1995 - Nov2015), since the first 60 months of the sample are used for the estimation of betas. Table 1 (Panel A) presents summary statistics for fund characteristics of our sample. The average monthly fund flow is slightly negative with -0.07%, with a median of -0.50%. The median fund has \$320.50 million in total net assets, while the average TNA is significantly higher (\$1,399.30 million), reflecting the positive skewness in fund size. The average fund age is 14.84 years (median 12.01 years), and the average expense and turnover ratios are 1.21% and 80.28%, respectively. Finally, 75% of the funds charge either front-end or back-end loads for at least one share class.

[4] Similarly, upside beta is defined as

$$\beta_i^+ = \frac{E[(r_i - r_T)(r_M - r_T) \mid r_M > r_T]}{E[(r_M - r_T)^2 \mid r_M > r_T]} \tag{5}$$

[5] Kenneth French's online data library can be accessed from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[6] In additional tests, we also estimate fund betas over a shorter time window (36 months) and our results remain robust.

Our main empirical tests relate mutual fund flows to alphas from different asset pricing models, similar to BvB and BHO. In addition to a simple market adjustment to returns, we consider four competing asset pricing models: CAPM, downside CAPM, FF three-factor model, and FFC four-factor model. We estimate all betas ($\hat{\beta}_{M,n,it}$) using past 60 months observations. We compute alphas over the most recent 12 months by subtracting factor related returns from the excess fund return as follows:

$$\hat{\alpha}_{M,it} = \frac{1}{12} \sum_{j=t-11}^{t} (r_{ij} - \sum_{n=1}^{N} \hat{\beta}_{M,n,it} \cdot f_{n,j}) \tag{6}$$

where M indicates the model, N the number of factors, r_{ij} the excess return of fund i in month j, f_{nj} the risk factor n in month j, and $\hat{\beta}_{M,n,it}$ the estimated beta for factor n in model M.

In Panel B, Table 1, we present summary statistics of fund betas estimated with a rolling 60-month window. The average unconditional and downside market betas are close to one; the average CAPM beta is 1.03, while the average downside beta is 1.04. In four-factor FFC model, the average betas for size, value and momentum factors are 0.24, 0.01, and 0.01, respectively, suggesting that funds tilt slightly toward small cap stocks and have almost no net tilt towards value or momentum stocks, consistent with the findings of Lewellen (2011).

In Panel C, we provide summary statistics for fund performance. The average monthly buy-and-hold excess return is positive (0.42%), while the average market-adjusted return is slightly negative (-0.03%). Consistent with the literature on actively-managed mutual funds [see e.g., Malkiel (1995), Fama and French (2010)], alphas from all asset pricing models are slightly negative. Average downside CAPM alpha is slightly lower than CAPM alpha as average downside beta is slightly higher than CAPM beta. Average alphas from models with additional factors are somewhat lower compared to alphas from single-factor models and have significantly lower sample variation.

The last two panels of Table 1 present correlations between betas and alphas from the different models. Unconditional beta is highly correlated with both downside (0.95) and upside (0.93) betas. The two one-side systematic risk measures are more modestly correlated (0.77), suggesting the existence of asymmetries in mutual fund returns that can justify the use of downside risk [see e.g. Price, Price, and Nantell (1982)]. In Panel E, we show that performance measures are also highly correlated, which posits an additional challenge on distinguishing between competing models, as argued by Jegadeesh and Mangipudi (2017).

4 Empirical Results

4.1 Sorts on Past Returns and Risk Measures

BvB and BHO find that CAPM-adjusted fund returns explain future investor flows better than simple market-adjusted returns or returns adjusted using other common factor models in the literature. In order to motivate how systematic risk effects investors' performance evaluations, Table 3 reports the average monthly flow for funds sorted by past returns and systematic risk measures. We first sort funds into three groups based on their past 12-month buy-and-hold return and form three groups; the lowest 30%, middle 40%, and highest 30%. We then sort funds within each return group into quintiles based on systematic risk measures; CAPM beta (Panel A), downside beta (Panel B), and upside beta (Panel C).

Our sorts confirm the fact that past returns have a significant impact on fund flows, as the relationship is monotonic, but also convex as first documented in Sirri and Tufano (1998); investors appear to reward top-performing mutual funds with increased flows, whereas they do not symmetrically penalize low-performing ones. Focusing within each return group, the variation in flows across systematic risk quintiles suggests that investors consider risk in addition to return when choosing funds. For example, in Panel A of Table 3, high return funds with low CAPM beta experience monthly inflows of 1.93% whereas high return funds with high CAPM beta experience monthly inflows of 1.06%. Comparing the variation in flows associated with CAPM beta (Panel A) to that of downside beta (Panel B), we find that investors appear to be more sensitive to differences in downside beta than CAPM beta. Sorting on downside beta yields significantly larger spreads in flows than sorting on CAPM beta for every return group. For example, among high-return mutual funds, those with low downside beta have average monthly inflows of 2.27%, while those with the high downside beta have average monthly inflows of 0.68%. By contrast, the variation in flows associated with upside beta (Panel C) is considerably smaller and marginally significant at best.

The results of Table 3 suggests that not only do investors consider market risk when making mutual fund allocations, but also that they put more weight on downside risk and less weight on upside risk. This is consistent with the notions of loss aversion [Kahneman and Tversky (1979)] and disappointment aversion [Gul (1991)], and justifies the use of the downside CAPM in a context where agents care about downside risk and exhibit risk neutrality for returns above the market threshold. Naturally, this simple exercise has limitations – it is only a rough approximation of the true risk-adjusted performance of funds. Nevertheless, it is suggestive that investors are sensitive to downside beta and relatively insensitive to upside beta, and motivates us to look closer on the relative effects of unconditional beta vs. downside beta.

4.2 Sign Test

BvB relate managerial skill to fund flows through the asset pricing model that investors use. In their framework, positive updates regarding managerial skill, signaled through positive risk-adjusted returns from the "true" asset pricing model, should generate positive capital flows and vice versa. They develop a sign test that relates the signs of fund flows and performance measures from different asset pricing models. This test provides a ranking of competing models on the basis of the frequency with which positive (negative) alphas from each model are followed by positive (negative) fund flows.

We follow their methodology with the exception that we use lagged, instead of contemporaneous, performance to avoid look-ahead bias, similar to BHO and Agarwal, Green, and Ren (2018). We estimate the coefficient B_M by regressing the sign of fund flows on the sign of alphas from different models, given by

$$B_M = \frac{cov(\phi(F_{it}), \phi(\hat{\alpha}_{M,it-1}))}{var(\phi(\hat{\alpha}_{M,it-1}))} \tag{7}$$

where M refers to the asset pricing model and $\phi()$ denotes the sign function.

The percent of signed flows explained by signed performance is given by $(1 + B_M)/2$. We also compare models M and K pairwise by checking the double-clustered t-statistic for γ_1 in regression (8). As in BvB, model M is a better asset pricing model than model K in predicting mutual fund flows if and only if $\gamma_1 > 0$.

$$\phi(Fit) = \gamma_0 + \gamma_1 \cdot \left(\frac{\phi(\hat{\alpha}_{M,it-1})}{var(\phi(\hat{\alpha}_{M,it-1}))} - \frac{\phi(\hat{\alpha}_{K,it-1})}{var(\phi(\hat{\alpha}_{K,it-1}))} \right) + \zeta_{it} \tag{8}$$

Similar to BvB and BHO, we examine market-adjusted returns, CAPM, FF three-factor and FFC four-factor alphas calculated over the past 12 months. We also include downside CAPM in the analysis. Table 4 reports the results of these sign tests. The first column presents the percent of signed fund flows explained by the signed performance measures from each of the models. The second column reports coefficient estimates B_M with double clustered t-statistics by fund and month in parentheses. Consistent with the central result of BvB and BHO, CAPM alpha outperforms market-adjusted returns and the two multi-factor model alphas; the sign of CAPM alpha explains 60.60% of the sign of fund flows, while the sign of market-adjusted return and multi-factor model alphas explains 59.98%-60.48% of the sign of fund flows. Turning to our central result, we find that downside CAPM performs better than all of the models including CAPM, explaining 60.89% of fund flow signs.[7]

In the last three columns of Panel A, we provide pairwise comparisons of asset pricing models. We report the coefficient estimates for γ_1 in equation (8) and its double clustered t-statistic in parentheses. Similar to the results in BvB, the t-statistics of coefficients comparing one-factor (CAPM or downside CAPM) to multi-factor models are below conventional 5% critical values, mainly due to the fact that multi-factor alphas have considerably lower variation than their one-factor counterparts (see Table 1, Panel C). By contrast, the coefficient γ_1 for comparing downside alpha to CAPM alpha is highly significant (t-stat: 3.07), which confirms that downside CAPM significantly outperforms its unconditional counterpart in explaining the sign of mutual fund flows.

A major limitation of the BvB flow-performance test is that it focuses only on the signs of flow and performance, and ignores the magnitudes. It is possible that investors react to small performance only weakly or not at all, especially in presence of frictions or nuisance costs. To address this concern, we repeat the sign test focusing on more extreme returns and gradually dropping observations where fund returns do not deviate from the market return by a certain threshold.[8] The results are presented in Panel B, which are similar to the findings of BvB; as we focus on more extreme returns the sign of performance measures explains a higher percent of the sign of investor flows. Importantly, downside alpha consistently outperforms CAPM alpha, and the two measures converge only at the very extreme, after excluding 82% of the observations in our

[7]Note that the order of the performance measures in this case is similar to BvB. When we include sector funds in the sample (which corresponds to roughly 10% of the initial sample) in unreported results, the order of the performance measures in the race becomes: Downside CAPM alpha $\succ$ CAPM alpha $\succ$ Market-adjusted return $\succ$ FF alpha $\succ$ FFC alpha, similar to the order in BHO. However, we prefer to exclude sector funds from the sample since their performance is usually measured against sector specific benchmarks, and market, size, value or momentum factors can not accurately capture the variation in their returns. We also do not include industry factors similar to BHO for brevity since our main focus is on comparing downside CAPM and unconditional CAPM, which is not affected by exclusion of sector funds.

[8]As in BvB robustness tests, we use thresholds based on standard deviations of market-adjusted returns.

sample.

4.3 Standardized Panel Regressions

The sign-tests of section 4.2 do not consider the magnitudes of flow and performance and do not control for other fund characteristics that may be related to fund flows. To overcome these limitations, we follow BHO and also examine the flow-performance relation using panel regressions of the form:[9]

$$F_{it} = a + b \cdot \hat{\alpha}_{M,it-1} + c \cdot X_{it-1} + FO_i + \mu_t + \epsilon_{it} \tag{9}$$

where monthly flow F_{it} is the percent change in TNA not attributable to investment returns, estimated from equation (3), and $\hat{\alpha}_{M,it-1}$ denotes the alpha from model M over the past 12 months ($t-12$ to $t-1$).[10] X_{it-1} is a vector of control variables, which includes the logarithms of fund size and age, turnover, expense ratio (value-weighted across share classes), a load dummy indicating if any share classes of a fund charges front-end or back-end loads, the logarithm of fund family size to control for fund family networks in attracting flows, aggregate flows to style (defined by CRSP objective code) to account for "hot" styles, and the number of distinct funds in a style to proxy level of competition within a style. We also include fund objective fixed effects (FO_i) and month fixed effects (μ_t). We present robust standard errors by double clustering by fund and month. To allow a direct comparison of the economic significance of different performance measures, we standardize all continuous independent variables by first demeaning and then scaling by their standard deviation.

Table 5 presents results from the estimation of equation (9). In columns (1)-(4) we consider market-adjusted returns, and alphas from the CAPM, FF three-factor, and FFC four-factor models. Consistent with the central result of both BvB and BHO, CAPM alpha outperforms market-adjusted returns and alphas from multi-factor models in predicting future fund flows. Specifically, a one standard deviation increase in CAPM alpha leads to 1.20% increase in fund flows. By comparison, a one standard deviation increase of FF three-factor alpha, FFC four-factor alpha, and market-adjusted return is associated with an 1.16%, 1.17% and 1.10% increase in flows, respectively.

[9] In our robustness tests (Table 9), we consider a piecewise linear regression to account for convexity in the flow-performance relation, and Fama-Macbeth regressions to focus on the cross-section of funds.

[10] There is no consensus in the literature over what time horizon investors evaluate performance, even though performance persistence studies typically assume a 12 months horizon. In our robustness tests, we also consider different performance horizons in Table 9 (6 ,18, and 24 months).

These results suggest that investors adjust for exposure to market risk, but not for exposures to size, book-to-market, or momentum, when choosing between funds.

In column (5) of Table 5 we introduce downside alpha in our regressions. The estimated coefficient is higher than any other model we consider, even the CAPM; a one standard deviation increase in downside CAPM alpha leads to a 1.23% increase in future fund flows. The inclusion of downside alpha yields the highest adjusted-R^2 among the models we examine. Note that the coefficient that corresponds to downside CAPM is higher and more statistically significant, even though the respective risk measure (β^-) is estimated with significantly higher estimation errors than the alternative models, due to the fact that it is estimated using roughly half the number of observations. This is important to note, in view of the critisism of Jegadeesh and Mangipudi (2017), who argue that the trade-off between estimation and misspecification errors may yield an erroneous ranking of models. In this context, we show that downside CAPM outperforms competing models, even if the respective risk measure is subject to higher estimation error.[11]

The remaining columns of Table 5 provide additional evidence regarding the relative merits of downside CAPM via joint tests of CAPM and downside CAPM. Column (6) shows that when we include downside alpha and CAPM alpha in the same regression, downside alpha completely subsumes CAPM alpha. However, given the high correlation between these two alphas (see Table 1), multicollinearity is a concern. Column (7) reports estimates from regression with CAPM alpha and the orthogonal component of downside alpha ($\hat{\alpha}_D - \hat{\alpha}_C$). The coefficient of $\hat{\alpha}_D - \hat{\alpha}_C$ is 0.21 and highly significant (t-stat: 5.21) indicating that downside alpha has additional predictive power regarding fund flows that CAPM alpha fails to capture. By contrast, when we include downside alpha and $\hat{\alpha}_D - \hat{\alpha}_C$ in the same regression (column (8)) the coefficient of $\hat{\alpha}_D - \hat{\alpha}_C$ is insignificant.

Table 6 presents estimates from regressions using an alternative measure of fund flow based on changes in market share (equation (9)) proposed by Spiegel and Zhang (2013). We examine this specification for two reasons. First, our regressions impose a linear relationship between fund flows and past performance, whereas the literature documents a convex relationship [see e.g., Sirri and Tufano (1998)]. Spiegel and Zhang (2013) show that convexity in the performance-flow relationship is a consequence of the measure of fund flow based on percent change in TNA, and that the

[11] When we estimate CAPM beta with reduced number of observations, equal to number of down months, in our robustness tests (Table 9), downside alpha wins over CAPM alpha with a much wider difference.

convexity disappears when fund flows are measured on the basis of changes in market share. Second, the alternative method alleviates concerns that small funds with economically insignificant flows drive our results. From Table 6, the results under the alternative specification of fund flows are qualitatively similar to our previous findings. CAPM alpha dominates market-adjusted returns and alphas from the three-factor and four-factor models in predicting future fund flows. Again, downside alpha outperforms all the other models with the highest estimated coefficient and adjusted-R^2; a one standard deviation increase in downside alpha leads to a 0.85% increase in market share (Adj.R^2=0.101). When we examine the CAPM and downside CAPM jointly, the CAPM alpha becomes insignificant (column (6)), whereas their difference is significant when included with the CAPM alpha (column (7)).

4.4 Sub-period and Fund Objectives Tests

This section provides evidence regarding cross-sectional and time-series variation in investors' concern for downside risk by examining the flow-performance relation for different investor clienteles via different fund styles (e.g., small-cap and growth funds vs. income funds), and during different market environments (pre and post financial crisis).

To this point, our tests treat mutual fund investors as a homogeneous group. Kumar and Lee (2006) provide evidence of different investor clienteles for growth and value stocks. Blackburn, Goetzmann, and Ukhov (2009) show that value investors tend to be more risk averse compared to growth investors. In Table 7, we investigate whether investors with different sensitivity to downside risk choose funds with different risk profiles by estimating the flow-performance relation separately among funds with different investment objectives. To test the implications of the clientele effect for the flow-performance relation, we divide our sample funds based on CRSP fund objective codes into four fund investment objectives: small capitalization (including micro and mid cap), growth, growth & income, and income funds. Table 7 repeats the analysis of Table 5 where regression (9) is estimated separately for each of the four fund objective groups. We also define a dummy variable INC that takes value 1 for income funds and 0 otherwise. Income funds garner more flows compared to small cap, growth & income or growth funds, and their investors react significantly more to performance, as shown by the significantly positive coefficients of INC and its interactions with performance measures. Consistent with the evidence in Blackburn, Goetzmann, and Ukhov

(2009), investors in income funds are more sensitive to variation in downside alpha than those in small cap, growth & income and growth funds. More importantly, the last column shows that the variation in downside alpha that is orthogonal to CAPM alpha ($\hat{\alpha}_D - \hat{\alpha}_C$) is more significant for income funds. Thus, our results suggest that investors of conservative fund types are especially more sensitive to downside risk compared to unconditional systematic risk.

Brandt and Wang (2003), Li (2007) and Berardi (2016) argue that time-varying risk aversion can explain stylized facts about asset returns. Using a repeated survey, Guiso, Sapienza, and Zingales (2018) show that investors' risk aversion increased significantly following the recent financial crisis and develop a fear-based model to explain their findings. In Table 8, we examine whether the sensitivity of investors to performance measures, as revealed by mutual fund flows, differs before and after the 2008 financial crisis. Specifically, we include the dummy variable $POST$ in regression (9) which takes value 1 in the period following Lehman Brothers collapse (Sep2008-Nov2015), and 0 otherwise (Dec1995-Aug2008). Fund flows decrease significantly in the Post-Lehman era (by -2.09%), and investor sensitivity to performance increases. In the last column of Table 8, we show that the difference of the two performance measures, when included in the same regression with CAPM alpha, not only remains significant, but its estimated coefficients also increases substantially in the post-crisis period. Our results suggest that investors exhibit increased sensitivity towards downside risk following the recent financial crisis and the ability of CAPM alpha, as a stand-alone performance measure to account for fund flows, deteriorates.

4.5 Robustness and Additional Tests

In this section, we test whether our findings on the relative merits of downside CAPM over unconditional CAPM in explaining investor flows is robust to different choices we make regarding our methodology. We first consider alternative regression specifications. As a further robustness check on the convexity of flow-performance relationship, we estimate piecewise linear regressions similar to Sirri and Tufano (1998). We divide performance ranks of funds in a given month using CAPM alpha or downside alpha into three groups: For any model M, we define low performance $\hat{\alpha}_M^{LOW}$ as $Min(Rank_M, 0.2)$, middle performance $\hat{\alpha}_M^{MID}$ as $Min(Rank_M - \hat{\alpha}_M^{LOW}, 0.6)$, and high performance $\hat{\alpha}_M^{HIGH}$ as $Rank_M - (\hat{\alpha}_M^{LOW} + \hat{\alpha}_M^{MID})$. Results from regressing fund flows on these performance groups appear in the first three columns of Panel A in Table 9. Our piecewise regressions confirm the convexity of the flow-performance relation as the coefficient on high performance group is highest, followed by the coefficient on middle performance group as second highest using both CAPM alpha and downside alpha. While it is stronger for the high performance group, investors respond more to downside alpha compared to CAPM alpha and the difference between these two performance measures is significant in every performance group. In the last three columns of Panel A in Table 9, we report estimates from Fama-Macbeth regressions which focus strictly on cross-sectional variation in the performance-flow relation. The results are consistent with our findings from panel regressions.

For our primary analyses of downside risk, we use a zero threshold return ($r_T = 0$) to classify upside and downside market states. An alternative threshold considered in the literature is the average excess return of the market portfolio over the estimation period [see e.g., Ang, Chen, and Xing (2006)]. Columns 1-3 of Panel B in Table 9 replicate our main regressions of Table 5 by calculating downside beta using the average market excess return as the threshold return, and yield very similar results. We then examine whether estimating fund betas over a shorter estimation window instead of a 60 months window effects our results. Having more observations yields more reliable beta estimates, yet we end up having fewer funds in the sample and the longer estimation period tilts our sample towards larger and older funds. In columns 4-6 of Panel B in Table 9, we estimate CAPM and downside betas using a 36 months window. As a result, we have now more observations in the sample (364,824 fund-month observations over 264 months versus 281,738 over 240 months), yet our results remain very similar.

As mentioned previously, another important point affecting the comparison of risk measures is the number of observations used for the estimation of betas. Due to the very definition of downside beta, capturing the co-movement of a portfolio with the market only in down states, we use roughly half the observations compared to CAPM beta, which leads to higher estimation errors. To investigate whether this affects our inferences regarding the relative merits of downside CAPM vs unconditional CAPM, we estimate CAPM beta with the same number of observations, by randomly sampling the same number of observations that were used to estimate downside beta (i.e., number of downside market states) from the original 60 observations. In columns 7-9 of Panel B in Table 9, we replicate the main regressions of Table 5, but we estimate CAPM beta with the same number of observations as downside beta. Not surprisingly, downside alpha now predicts fund flows better than CAPM alpha with an even greater difference, as the two performance measures have comparable estimation errors.

Finally, throughout the paper, we used performance over the past 12 months as an independent variable in our flow-performance regressions, yet it is not clear in the literature over which horizon investors evaluate performance. BHO, for example, consider performance over the past 18 months while they give exponentially more weights to more recent months' returns. To test if our choice of performance horizon affects our results, we calculate alphas over 6, 18 and 24 months in Panel C of Table 9. Coefficient estimates for alphas with 18 and 24 months (6 months) horizon are slightly higher (lower) compared to 12 months, suggesting that investors pay attention to the history of returns that is even older than a year. However, our main result regarding the superiority of downside alpha over CAPM alpha in predicting fund flows remains intact.

5 Conclusion

Our study brings new insights to the literature on the relative merits of alternative asset pricing models in explaining the flow-performance relation for mutual funds by showing that investors are more concerned with downside market risk than unconditional market risk. While downside risk has long been recognized as a relevant investment consideration by practitioners, it has yet to be considered a relevant factor in academic performance benchmarks. Our evidence of the relative power of downside risk in explaining mutual fund flows confirms its importance in characterizing investor preferences and is complementary to several recent studies that find support for downside risk using conventional asset pricing tests [Delikouras (2017), Farago and Tedongap (2018), Jiang, Wu, and Zhou (2018), Lu and Murray (2018)].

Also noteworthy is that our evidence addresses concerns regarding these flow-performance tests raised by Jegadeesh and Mangipudi (2017)– that small differences between competing models may yield misleading inferences regarding the "true" asset pricing model used by investors to allocate their money to funds. More specifically, they argue that if estimation error is sufficiently greater than specification error, these tests will tend to favor more parsimonious models (i.e. CAPM). Our results address this concern by showing that downside risk – a model with significantly higher estimation error than competing models, due to the use of roughly half the observations to estimate risk – performs better than the more precisely-estimated unconditional models.

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Tables

Table 1: Summary Statistics

Panel A: Fund characteristics

	Mean	Std Dev	Q1	Median	Q3
Monthly % Flow	-0.07%	11.58%	-1.56%	-0.50%	0.63%
Size ($mil)	1,399.30	5,033.77	101.60	320.50	1,034.10
Age (years)	14.84	9.97	8.25	12.01	17.68
Expense Ratio	1.21%	0.40%	0.96%	1.18%	1.44%
Turnover Ratio	80.28%	73.48%	34.00%	63.00%	104.00%
Load	0.75	0.43	1.00	1.00	1.00

Panel B: Fund betas

	Mean	Std Dev	Q1	Median	Q3
$\hat{\beta}$	1.0330	0.2248	0.9090	1.0212	1.1557
$\hat{\beta}^{-}$	1.0361	0.2484	0.9040	1.0285	1.1669
$\hat{\beta}^{+}$	1.0323	0.2285	0.8988	1.0131	1.1549
$\hat{\beta}^{-} - \hat{\beta}$	0.0031	0.0766	-0.0355	0.0004	0.0412
$\hat{\beta}^{MKT}$	1.0154	0.1535	0.9316	1.0113	1.0932
$\hat{\beta}^{SMB}$	0.2372	0.3535	-0.0585	0.1446	0.5244
$\hat{\beta}^{HML}$	0.0094	0.3148	-0.2040	-0.0005	0.2057
$\hat{\beta}^{MOM}$	0.0118	0.1375	-0.0658	0.0001	0.0734

Panel C: Fund performance measures

	Mean	Std Dev	Q1	Median	Q3
r_{BH}	0.42%	1.75%	-0.22%	0.71%	1.46%
r_{MKT}	-0.02%	0.83%	-0.40%	-0.07%	0.29%
$\hat{\alpha}_C$	-0.03%	0.77%	-0.40%	-0.07%	0.29%
$\hat{\alpha}_D$	-0.03%	0.79%	-0.42%	-0.08%	0.30%
$\hat{\alpha}_{3F}$	-0.10%	0.54%	-0.37%	-0.11%	0.14%
$\hat{\alpha}_{4F}$	-0.11%	0.51%	-0.36%	-0.11%	0.13%
$\hat{\alpha}_D - \hat{\alpha}_C$	-0.01%	0.11%	-0.05%	0.00%	0.04%

This table presents summary statistics of characteristics, betas and performance measures for the funds in the sample, which covers 281,738 fund-month observations for 2,890 distinct funds over Dec1995-Nov2015 (240 months). The data include only actively managed US domestic equity mutual funds and excludes sector funds. Monthly fund flow is the percentage change in Total Net Assets (TNA) after adjusting for fund's total return as in equation (3). Load is a dummy variable that takes value 1 if any share class of a fund charges front- or backend load. $\hat{\beta}$ is CAPM beta. Downside beta $\hat{\beta}^{-}$ and upside beta $\hat{\beta}^{+}$ are calculated as in equations (1) and (5). $\hat{\beta}^{MKT}$, $\hat{\beta}^{SMB}$, $\hat{\beta}^{HML}$, $\hat{\beta}^{MOM}$ are factor betas from four factor Fama-French-Carhart model. All fund betas are estimated using a rolling 60 months window. r_{BH} is the monthly buy and hold return over the last 12 months. r_{MKT} is the average market-adjusted monthly return over the last 12 months. $\hat{\alpha}_C$, $\hat{\alpha}_D$, $\hat{\alpha}_{3F}$, $\hat{\alpha}_{4F}$ are average risk-adjusted monthly returns over the last 12 months using CAPM, Downside CAPM, three factor Fama-French or four factor Fama-French-Carhart models, respectively, as in equation (6).

Table 2: Correlations of Risk and Performance Measures

Panel A: Correlations between fund betas

	$\hat{\beta}$	$\hat{\beta}^{-}$	$\hat{\beta}^{+}$	$\hat{\beta}^{-} - \hat{\beta}$
$\hat{\beta}$	1.00	0.95	0.93	0.15
$\hat{\beta}^{-}$	0.95	1.00	0.77	0.45
$\hat{\beta}^{+}$	0.93	0.77	1.00	-0.21
$\hat{\beta}^{-} - \hat{\beta}$	0.15	0.45	-0.21	1.00

Panel B: Correlations between fund performance measures

	r_{MKT}	$\hat{\alpha}_C$	$\hat{\alpha}_D$	$\hat{\alpha}_{3F}$	$\hat{\alpha}_{4F}$	$\hat{\alpha}_D - \hat{\alpha}_C$
r_{MKT}	1.00	0.90	0.89	0.66	0.63	0.13
$\hat{\alpha}_C$	0.90	1.00	0.98	0.71	0.66	0.17
$\hat{\alpha}_D$	0.89	0.98	1.00	0.70	0.65	0.30
$\hat{\alpha}_{3F}$	0.66	0.71	0.70	1.00	0.93	0.06
$\hat{\alpha}_{4F}$	0.63	0.66	0.65	0.93	1.00	0.07
$\hat{\alpha}_D - \hat{\alpha}_C$	0.13	0.17	0.30	0.06	0.07	1.00

This table presents correlations between fund betas and performance measures described in Table 1.

Table 3: Fund flows for Sorts on Returns and Risk Measures

Panel A: CAPM beta quintiles

Return	All	1	2	3	4	5	5-1
Low	-1.26%	-1.04%	-1.04%	-1.23%	-1.35%	-1.65%	-0.61%***
Medium	-0.04%	0.14%	0.01%	-0.08%	0.01%	-0.29%	-0.43%***
High	1.33%	1.93%	1.23%	1.21%	1.21%	1.06%	-0.86%***
All	0.00%	0.29%	0.12%	0.01%	-0.08%	-0.33%	-0.62%***

Panel B: Downside beta quintiles

Return	All	1	2	3	4	5	5-1
Low	-1.26%	-0.83%	-1.05%	-1.16%	-1.44%	-1.83%	-1.01%***
Medium	-0.04%	0.30%	0.07%	0.00%	-0.07%	-0.51%	-0.82%***
High	1.33%	2.27%	1.50%	1.16%	1.04%	0.68%	-1.59%***
All	0.00%	0.68%	0.17%	0.02%	-0.16%	-0.70%	-1.38%***

Panel C: Upside beta quintiles

Return	All	1	2	3	4	5	5-1
Low	-1.26%	-1.26%	-1.10%	-1.26%	-1.27%	-1.40%	-0.14%
Medium	-0.04%	-0.12%	-0.07%	-0.04%	-0.11%	0.13%	0.25%*
High	1.33%	1.34%	0.96%	1.26%	1.39%	1.70%	0.35%**
All	0.00%	-0.22%	-0.03%	-0.02%	0.06%	0.23%	0.44%***

This table presents average monthly fund flows for sorts based on CAPM, downside and upside betas after controlling for return. For each month, funds are first sorted into three return groups based on their buy-and-hold return over the past 12 months. Funds with buy-and-hold return less than or equal to 30th percentile of returns are considered as low return group, between 30th-70th percentile are considered as medium return group and greater than 70th percentile are considered as high return group. For each return group, funds are further sorted into 5 quintiles based on their CAPM, downside or upside beta. Average monthly flow is calculated for funds in every quintile for each month. Finally, average is calculated over all 240 months in the sample.***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 4: BvB Sign Test

Panel A: Sign test and pairwise comparisons

Model	% flow explained	B_M	CAPM	4F	3F	Market
Downside CAPM	60.89%	0.2178	0.0238	0.0125	0.0147	0.0305
		(27.9284)	(3.0651)	(1.6145)	(1.8238)	(4.2789)
CAPM	60.60%	0.2120		0.0091	0.0072	0.0251
		(27.2693)		(1.1006)	(1.2821)	(3.7844)
4F	60.48%	0.2095			0.0043	0.0090
		(28.0137)			(0.6954)	(1.9049)
3F	60.39%	0.2079				0.0099
		(27.9102)				(1.8562)
Market	59.98%	0.1996				
		(26.5096)				

Panel B: Sign test with extreme returns

		% flow explained				
Drop window in std	0	0.1	0.25	0.5	0.75	1
Data discarded	0%	13.17%	31.60%	56.23%	72.28%	81.83%
Downside CAPM	60.89%	61.94%	63.46%	66.07%	68.43%	70.40%
CAPM	60.60%	61.73%	63.39%	66.03%	68.42%	70.40%
4F	60.48%	61.33%	62.72%	65.03%	66.97%	68.33%
3F	60.39%	61.27%	62.72%	65.11%	67.17%	68.80%
Market	59.98%	61.33%	63.20%	66.03%	68.11%	69.68%

This table gives the results for sign tests as in Berk and van Binsbergen (2016). B_M is the coefficient estimate from regressing signed monthly flows on signed average monthly performance over the past 12 months with different asset pricing models as in equation (7). Percentage of signed flows explained by signed performance is obtained as $(1 + B_M)/2$. Models are ordered with the best model being on top. Tests for pairwise comparisons of models as in equation (8) are provided in the last four columns of Panel A. T-statistics given in parenthesis are calculated with double clustered standard errors by fund and month. Panel B repeats the sign tests with extreme returns. We drop observations where returns do not deviate from market return by more than a certain standard deviation of the market-adjusted returns. We gradually increase the window of dropped observations from 0.1 standard deviation to 1 standard deviation.

Table 5: Fund flow-Performance regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-1.76***	-1.96***	-1.47***	-1.65***	-1.92***	-1.93***	-1.90***	-1.92***
	(-6.92)	(-7.85)	(-5.96)	(-6.56)	(-7.69)	(-7.85)	(-7.65)	(-7.67)
r_{MKT}	1.10***							
	(14.85)							
$\hat{\alpha}_C$		1.20***				-0.30	1.18***	
		(19.52)				(-1.01)	(19.37)	
$\hat{\alpha}_{3F}$			1.16***					
			(20.68)					
$\hat{\alpha}_{4F}$				1.17***				
				(21.23)				
$\hat{\alpha}_D$					1.23***	1.53***		1.22***
					(20.33)	(5.21)		(19.37)
$\hat{\alpha}_D - \hat{\alpha}_C$							0.21***	0.04
							(5.21)	(1.01)
LogAge	-0.31***	-0.29***	-0.28***	-0.28***	-0.28***	-0.28***	-0.28***	-0.28***
	(-9.97)	(-9.58)	(-9.41)	(-9.25)	(-9.43)	(-9.42)	(-9.37)	(-9.39)
LogSize	-0.16***	-0.18***	-0.19***	-0.18***	-0.19***	-0.19***	-0.19***	-0.19***
	(-3.02)	(-3.40)	(-3.63)	(-3.41)	(-3.66)	(-3.52)	(-3.71)	(-3.61)
ExpenseRatio	0.02	0.05	0.04	0.05	0.05	0.05	0.05	0.05
	(0.44)	(1.08)	(0.99)	(1.21)	(1.17)	(1.19)	(1.19)	(1.20)
TurnoverRatio	-0.09**	-0.08**	-0.05	-0.01	-0.07**	-0.07**	-0.07**	-0.08**
	(-2.53)	(-2.32)	(-1.31)	(-0.21)	(-2.09)	(-2.04)	(-2.03)	(-2.07)
LogFamilySize	0.22***	0.24***	0.23***	0.23***	0.24***	0.24***	0.24***	0.23***
	(4.46)	(4.86)	(4.71)	(4.79)	(4.97)	(4.95)	(4.99)	(4.97)
StyleFlow	0.05	-0.01	0.09*	0.10**	-0.01	0.01	0.01	0.01
	(1.32)	(-0.03)	(1.80)	(2.00)	(-0.03)	(0.01)	(0.01)	(0.00)
StyleCount	-0.37**	-0.50***	-0.41**	-0.40**	-0.49***	-0.47***	-0.48***	-0.49***
	(-2.48)	(-3.34)	(-2.18)	(-2.09)	(-3.25)	(-3.21)	(-3.21)	(-3.22)
Load	0.15*	0.14	0.19**	0.18**	0.13	0.14	0.13	0.15
	(1.71)	(1.60)	(2.14)	(2.06)	(1.55)	(1.60)	(1.53)	(1.63)
Fund Obj FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.108	0.121	0.120	0.119	0.124	0.124	0.124	0.124
Observations	281,738	281,738	281,738	281,738	281,738	281,738	281,738	281,738

This table gives the results for the panel regressions as in equation (9). Dependent variable is monthly percentage fund flow. Performance measures are average monthly market-adjusted return or risk-adjusted returns with CAPM, downside CAPM, three factor Fama-French or four factor Fama-French-Carhart models calculated over the past 12 months as in equation (6). Control variables are log of fund size in million dollars, log of fund age in years, expense ratio, turnover ratio, log of fund's family size, percentage flow to fund's style as a whole, number of funds with the same style and load dummy. T-statistics given in parenthesis are calculated with double clustered standard errors by fund and month. All regressions include fund objective and month fixed effects. Fund objective is determined based on CRSP fund objective code. All continuous independent variables are standardized for ease of interpretation. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 6: Fund flow-Performance Regressions: Alternative Flow Definition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.09	0.12	0.10	0.08	0.12	0.12	0.13	0.12
	(1.01)	(1.26)	(1.08)	(0.93)	(1.33)	(1.25)	(1.39)	(1.25)
r_{MKT}	0.79***							
	(4.69)							
$\hat{\alpha}_C$		0.82***				-0.67	0.79***	
		(5.12)				(-1.53)	(4.94)	
$\hat{\alpha}_{3F}$			0.68***					
			(5.48)					
$\hat{\alpha}_{4F}$				0.73***				
				(5.57)				
$\hat{\alpha}_D$					0.85***	1.54***		0.85***
					(5.30)	(3.77)		(5.01)
$\hat{\alpha}_D - \hat{\alpha}_C$							0.20***	0.09
							(3.73)	(1.53)
LogAge	-0.17***	-0.16**	-0.17***	-0.16***	-0.15**	-0.16***	-0.15**	-0.17***
	(-2.82)	(-2.57)	(-2.76)	(-2.68)	(-2.5)	(-2.77)	(-2.47)	(-2.78)
LogSize	-0.02	-0.03	-0.04	-0.03	-0.04	-0.05	-0.05	-0.05
	(-0.18)	(-0.27)	(-0.34)	(-0.29)	(-0.37)	(-0.50)	(-0.43)	(-0.48)
ExpenseRatio	0.00	0.02	0.03	0.04	0.02	0.04	0.02	0.04
	(0.03)	(0.58)	(0.79)	(0.84)	(0.62)	(1.13)	(0.65)	(0.93)
TurnoverRatio	-0.09***	-0.09***	-0.07*	-0.04	-0.09**	-0.07**	-0.08**	-0.07**
	(-2.66)	(-2.65)	(-1.81)	(-1.03)	(-2.47)	(-2.04)	(-2.4)	(-2.07)
LogFamilySize	0.01	0.03	0.02	0.03	0.03	0.03	0.04	0.03
	(0.48)	(1.15)	(0.96)	(1.05)	(1.30)	(1.30)	(1.40)	(1.43)
StyleFlow	0.05	0.03	0.05	0.04	0.03	0.05	0.03	0.04
	(0.85)	(0.59)	(0.78)	(0.73)	(0.55)	(0.71)	(0.60)	(0.83)
StyleCount	-0.01	-0.01	-0.01	-0.01	-0.01	-0.36	-0.00	-0.06
	(-0.33)	(-0.24)	(-0.32)	(-0.14)	(-0.17)	(-1.2)	(-0.12)	(-1.12)
Load	-0.01	-0.03	0.00	0.00	-0.03	-0.03	-0.03	-0.03
	(-0.15)	(-0.34)	(0.03)	(0.00)	(-0.38)	(-0.36)	(-0.42)	(-0.39)
Fund Obj FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.092	0.097	0.071	0.078	0.101	0.102	0.102	0.102
Observations	281,738	281,738	281,738	281,738	281,738	281,738	281,738	281,738

This table replicates the regressions in Table 5 using an alternative definition of fund flows as the dependent variable: Following Spiegel and Zhang (2013), fund flow is defined as change in market share of a fund over a month as in equation (4), instead of growth in TNA. All the independent variables are same as in Table 5. T-statistics given in parenthesis are calculated with double clustered standard errors by fund and month. All regressions include control variables, fund objective and month fixed effects. All continuous independent variables are standardized for ease of interpretation. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 7: Fund flow regressions:
Different Fund Objectives

	Small Cap			Growth Style			Growth&Income Style			Income Style			All		
$\hat{\alpha}_C$	1.08***		1.05***	1.31***		1.28***	1.49***		1.47***	1.99***		1.94***	1.18***		1.15***
	(15.51)		(15.37)	(17.09)		(17.1)	(9.17)		(9.14)	(7.04)		(7.01)	(19.25)		(19.1)
$\hat{\alpha}_D$		1.11***			1.34***			1.54***			2.06***			1.21***	
		(15.95)			(17.52)			(9.28)			(7.53)			(20.06)	
$\hat{\alpha}_D - \hat{\alpha}_C$			0.15***			0.21***			0.25***			0.52***			0.20***
			(2.78)			(4.73)			(4.05)			(2.86)			(5.03)
INC													0.60***	0.62***	0.63***
													(3.44)	(3.57)	(3.63)
$\hat{\alpha}_C \cdot INC$													0.83***		0.84***
													(2.96)		(3.08)
$\hat{\alpha}_D \cdot INC$														0.91***	
														(3.37)	
$(\hat{\alpha}_D - \hat{\alpha}_C)$ $\cdot INC$															0.33** (2.28)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Obj FE	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.186	0.190	0.190	0.100	0.103	0.103	0.075	0.079	0.079	0.236	0.242	0.243	0.120	0.122	0.122
Observations		102,129			114,553			52,893			12,163			281,738	

This table gives the results of panel regressions as in equation (9) for small (including micro and mid) cap, growth, growth&income and income funds separately. Funds are assigned to an investment objective based on their CRSP objective code. The dependent and independent variables are as in Table 5. The last three columns use all observations in the sample and includes the dummy variable INC, that takes value 1 for income funds and 0 otherwise, as well as its interaction terms. T-statistics given in parenthesis are calculated with double clustered standard errors by fund and month. All regressions include control variables, month fixed effects but no fund objective fixed effects. All continuous independent variables are standardized for ease of interpretation. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 8: Fund-Flow Regressions:
Before and After Lehman Brothers Collapse

	Before			After			Entire Period		
$\hat{\alpha}_C$	1.12***		1.09***	1.67***		1.66***	1.11***		1.08***
	(16.84)		(16.54)	(16.61)		(17.51)	(16.82)		(16.41)
$\hat{\alpha}_D$		1.14***			1.72***			1.13***	
		(17.74)			(16.70)			(17.71)	
$\hat{\alpha}_D - \hat{\alpha}_C$			0.17***			0.29***			0.17***
			(3.27)			(3.83)			(3.20)
$POST$							-2.09***	-2.09***	-2.09***
							(-14.19)	(-14.22)	(-14.13)
$\hat{\alpha}_C \cdot POST$							0.53***		0.56***
							(4.47)		(4.94)
$\hat{\alpha}_D \cdot POST$								0.57***	
								(4.81)	
$(\hat{\alpha}_D - \hat{\alpha}_C) \cdot POST$									0.12**
									(2.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.173	0.176	0.176	0.084	0.086	0.086	0.124	0.127	0.127
Observations		156,918			124,820			281,738	

This table gives the results of panel regressions as in equation (9) for periods before (December 1995-August 2008) and after (September 2008-November 2015) Lehman Brothers collapse separately. The dependent and independent variables are as in Table 5. The last three columns use all the observations in the sample and include the dummy variable $POST$, that takes value 1 from September 2008 onward and 0 before, as well as its interaction terms. T-statistics given in parenthesis are calculated with double clustered standard errors by fund and month. All regressions include control variables, fund objective and month fixed effects. All continuous independent variables are standardized for ease of interpretation. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 9: Robustness Tests

Panel A: Alternative Regression Methods

Piecewise Linear Regressions			
$\hat{\alpha}_C^{LOW}$	0.37***		0.37***
	(12.28)		(12.36)
$\hat{\alpha}_D^{LOW}$		0.39***	
		(12.34)	
$\hat{\alpha}_D^{LOW} - \hat{\alpha}_C^{LOW}$			0.06***
			(2.74)
$\hat{\alpha}_C^{MID}$	0.50***		0.50***
	(14.01)		(13.95)
$\hat{\alpha}_D^{MID}$		0.53***	
		(14.44)	
$\hat{\alpha}_D^{MID} - \hat{\alpha}_C^{MID}$			0.11***
			(3.80)
$\hat{\alpha}_C^{HIGH}$	0.62***		0.63***
	(15.54)		(15.57)
$\hat{\alpha}_D^{HIGH}$		0.66***	
		(16.03)	
$\hat{\alpha}_D^{HIGH} - \hat{\alpha}_C^{HIGH}$			0.14***
			(5.05)
Controls	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj. R^2	0.133	0.136	0.136
Observations		281,738	

Fama-Macbeth Regressions			
$\hat{\alpha}_C$	1.36***		1.09***
	(20.03)		(15.36)
$\hat{\alpha}_D$		1.39***	
		(20.11)	
$\hat{\alpha}_D - \hat{\alpha}_C$			0.32***
			(3.48)
Controls	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes
Months	240	240	240
Avg Adj Rsq	0.058	0.062	0.065
Observations		281,738	

Panel B: Alternative Beta Estimations

	Down beta with avg threshold			Betas with 36m rolling window			CAPM beta with resampling		
$\hat{\alpha}_C$	1.20***		1.18***	1.31***		1.27***	1.16***		1.13***
	(19.52)		(19.07)	(19.67)		(18.95)	(19.39)		(19.13)
$\hat{\alpha}_D$		1.23***			1.34***			1.23***	
		(20.16)			(20.54)			(20.33)	
$\hat{\alpha}_D - \hat{\alpha}_C$			0.23***			0.22***			0.35***
			(4.98)			(5.17)			(13.75)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Obj. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.121	0.124	0.124	0.146	0.149	0.149	0.116	0.124	0.124
Observations		281,738			350,637			281,738	

Panel C: Alternative Performance Horizons

	Alphas with 6m horizon			Alphas with 18m horizon			Alphas with 24m horizon		
$\hat{\alpha}_C$	0.97***		0.96***	1.23***		1.21***	1.25***		1.22***
	(16.32)		(16.13)	(21.04)		(20.44)	(21.21)		(20.29)
$\hat{\alpha}_D$		1.01***			1.26***			1.27***	
		(16.94)			(22.03)			(22.30)	
$\hat{\alpha}_D - \hat{\alpha}_C$			0.24***			0.17***			0.12***
			(4.84)			(4.57)			(3.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Obj. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.092	0.095	0.095	0.125	0.127	0.127	0.126	0.127	0.127
Observations		281,738			281,738			281,738	

Panel A of this table replicates the main regressions of Table 5 using alternative regression methods: The first three columns give the results of piecewise linear regressions to account for convexity in the flow-performance relationship. Similar to Sirri and Tufano (1998), performance ranks of funds using CAPM alpha or downside CAPM alpha are divided into three groups. For any model M, low performance $\hat{\alpha}_M^{LOW}$ is defined as $Min(Rank_M, 0.2)$, middle performance $\hat{\alpha}_M^{MID}$ is defined as $Min(Rank_M - \hat{\alpha}_M^{LOW}, 0.6)$, and high performance $\hat{\alpha}_M^{HIGH}$ is defined as $Rank_M - (\hat{\alpha}_M^{LOW} + \hat{\alpha}_M^{MID})$. The last three columns use Fama-Macbeth regressions instead of panel regressions and report Newey-West t-statistics with 12 lags in parenthesis as well as average adjusted R-squares. Panel B uses alternative methods to estimate betas. In the first three columns threshold return used for estimating downside beta is average market excess return instead of 0. In the next three columns, CAPM beta and downside beta are estimated on a rolling 36 months instead of 60 months. In the last three columns, CAPM beta is estimated with a smaller sample where the new sample size is equal to number of down months over the past 60 months. Panel C uses alternative horizons (past 6 months, 18 months or 24 months instead of 12 months) to calculate alphas. Except for Fama-Macbeth regressions, all regressions include month fixed effects and T-statistics given in parenthesis are calculated with double clustered standard errors by fund and month. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.