# Capital Flows in Rational Markets

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**Abstract**

We provide a rational model of capital allocation to projects with uncertain exposure to a systematic risk factor. We show that signal-to-noise ratios are highest when the factor realization is close to zero. As a result, investors redirect more resources across projects during these times. This finding resonates with the Schumpeterian intuition that downturns have a cleansing effect on the economy by improving the efficiency of capital allocation. We measure the speed of capital reallocation with the sensitivity of mutual fund flows to performance and find supporting evidence for the model's nonlinear and linear predictions.

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# 1 Introduction

Schumpeter (1942) argues that recessions have a cleansing effect on the economy, in the sense of accelerating reallocation of capital to more productive uses. But what makes investors more willing to part with their less valuable projects in bad times than in good times? Is a behavioral friction necessary to generate such an asymmetry, or can it emerge even within a rational framework? More generally, under which assumptions does the speed of capital reallocation depend on the state of the economy?

In this paper, we show that a parsimonious rational model that assumes uncertainty about risk loadings can generate such a dependence, and in particular, a higher speed of cross-sectional capital reallocation in downturns.

In the model, rational agents allocate capital to investment projects. We assume no frictions besides uncertainty about the parameters of the cash-flow generating process. Investors learn about the NPV of the project (alpha) from its cash flows, but uncertainty about risk loadings (betas) complicates their inference. Whereas the realization of the risk factor is perfectly observable, the risk loading is estimated with some error, which introduces noise into the learning process. Under these assumptions, the informativeness of project returns about alpha is small when factor realizations are extreme – either very high or very low – because the large factor realization magnifies the uncertainty about beta. By contrast, for moderate factor realizations, the noise arising from uncertain betas is muted. As a result, the signal-to-noise ratio is highest for factor realizations around zero, and rational investors react more strongly to performance during these times. Identifying (moderate) downturns with periods of (moderately) low realizations of the systematic factor, the model generates the Schumpeterian intuition that in (moderately) bad times, investors reallocate more capital across projects.

The insights of the model apply equally to asset pricing, corporate finance, labor economics, and other fields.[1] In this paper, we test the model predictions with capital flows to mutual funds. Our choice has three motivations. First, about 30% of US corporate equity is held by US investment companies (ICI, 2012). Hence, mutual funds intermediate a significant fraction of capital allocation to firms. A high speed of capital reallocation across funds is therefore likely to be correlated with a high speed of capital reallocation across firms. Second, to the purpose of testing the predictions of our model, we can easily proxy the speed of capital reallocation across projects using the sensitivity of fund flows to fund performance. Third, given the sheer size of this sector and its importance for households' savings and retirement income, whether the allocation of capital to mutual funds follows rational patterns is an open and interesting question in itself.[2]

Most prominent in the mutual fund literature, Berk and Green (2004)'s (BG) model features Bayesian investors who allocate more capital to funds with high relative performance as a result of their learning about manager skill.[3] One dimension that the literature leaves unexplored is uncertainty about fund risk loadings. BG model fund returns in excess of a benchmark, implicitly assuming risk loadings are perfecly observable by investors. However, there seem to be reasons to relax this assumption. In contrast to stocks for which quasi-continuous observation of returns allows investors to infer second moments arbitrarily fast

[1]For example, Schmalz and Zhuk (2013) show that stock returns react more strongly to earnings news in downturns than in upturns. Jenter and Kanaan (2006) show that CEO turnover is higher in downturns than in upturns, challenging models of relative performance evaluation.

[2]US households invest 23% of their financial assets and more than 50% of their retirement savings through IRAs and 401(k)s in mutual funds (ICI, 2012). From a welfare perspective, the possibility that irrational forces drive savings decisions of that magnitude could be a major concern.

[3]The BG model explains lack of performance persistence by assuming rational investors combined with decreasing returns to scale of funds. Huang, Wei, and Yan (2007) add participation costs to generate a convex shape of the flow-performance relation (see also Lynch and Musto (2003)). Elaborating on the BG model, Huang, Wei, and Yan (2012) derive cross-sectional predictions on the flow-performance sensitivity (FPS) in an economy in which Bayesian and performance-chasing investors coexist.

(Merton, 1980), mutual fund returns are observed at most daily, which hinders similarly fast and accurate inferences about risk loadings. Fund betas cannot be perfectly inferred from portfolio holdings combined with stock returns either, because a large amount of portfolio rebalancing between reporting dates is concealed from investors (Kacperczyk, Sialm, and Zheng, 2008). Taken together, infrequent reporting of holdings combined with frequent portfolio rebalancing and the lack of continuously observed fund returns prevent investors from perfectly learning fund risk loadings. These considerations suggest that uncertainty about risk loadings is a realistic assumption regarding the allocation of capital to mutual funds.

In the empirical implementation, we measure the speed of capital reallocation by the sensitivity of mutual flows to performance, while we proxy for systematic risk using the market factor. Our main result is that the estimated flow-performance sensitivity (FPS) depends on the realization of market excess returns in a nonlinear and non-monotonic fashion, consistent with the model's predictions. Figure 1 displays a parametric estimate of the function linking the flow-performance sensitivity to the market excess return. We find that the FPS is more than twice as high for market realizations close to zero than for extreme market returns. We corroborate this result in linear regression tests comparing the FPS during extreme, positive or negative, market returns to the FPS during times with market returns around zero.

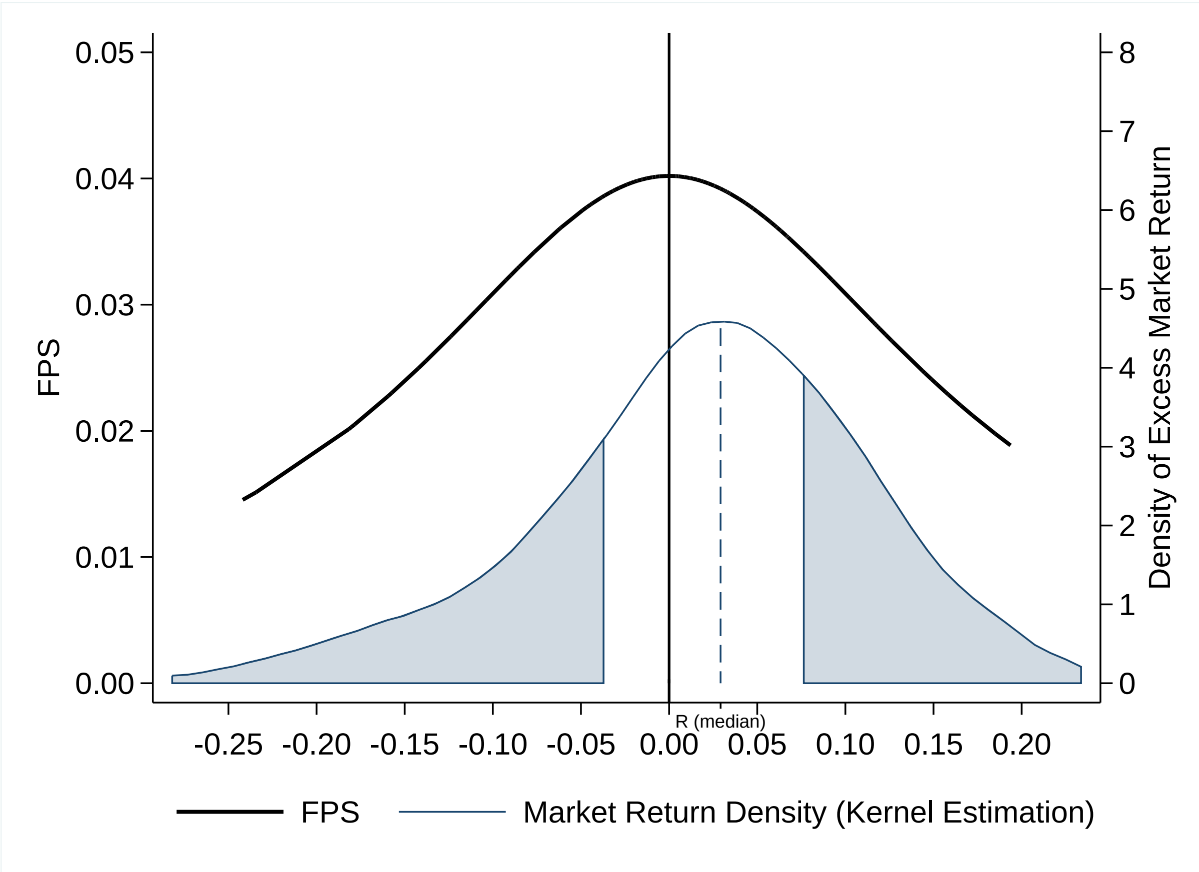


Figure 1: Parametric estimate of the flow-performance sensitivity as a function of the quarterly market return in excess of the risk-free rate, and density of excess market return (kernel estimation). The shaded areas are the lowest and highest quartiles of the excess market return distribution, a way the literature has measured "downturns" and "upturns," respectively (more details in sections 4 and 5).

Whereas the FPS is symmetric with respect to zero market returns in excess of the risk-free rate, an asymmetry between upturns and downturns arises because the empirical distribution of market excess returns peaks at positive values, that is, to the right of the peak of the FPS. As a result, relatively low realizations of the market return, compared to the median market return, are closer to the FPS's peak than relatively high relatizations of the market return. Figure 1 displays this asymmetry in the FPS relative to the empirical distribution of the excess market return. We follow the literature in labeling the realizations in the lowest quartile of historical market returns as "downturns" and the realizations in the highest quartile as "upturns" (Glode, Hollifield, Kacperczyk, and Kogan, 2012) and represent them as shaded areas under the empirical density function. Downturns, on average, are characterized by higher FPS than the upturns. Table 1 shows results from linear tests of the FPS upturn-downturn difference. Estimates of the FPS in downturns are twice as large as the estimates of the FPS in upturns, and the difference is statistically significant.

Table 1: Slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance ("flow-performance sensitivities") for upturns and downturns. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index since July 1926 as in Glode, Hollifield, Kacperczyk, and Kogan. The last column reports the difference in coefficients between Downturns and Upturns. T-statistics are reported in parentheses.

| | Upturns | Downturns | Down-Up |
|---|---|---|---|
| Flow-Performance Sensitivity | 0.020*** | 0.045*** | 0.025*** |
| t-stat | (3.489) | (5.551) | (2.564) |

We present additional tests of the model to help rule out alternative theories that could predict similar time-series patterns of the FPS. In particular, we wish to establish how differences in the FPS between upturns and downturns vary across fund types. This difference-in-differences approach helps eliminate endogeneity concerns that are present in the estimation of the time-series prediction alone. In particular, our inference about the upturn-downturn FPS difference might be driven by the new capital that flows into the sector in upturns and flows out of the sector in downturns, rather than by the reallocation of capital within the sector. Also possible, investors might be less scrupulous in their investment decisions in upturns than in downturns for behavioral reasons. The double-difference approach identifies our theory against these alternative explanations.

In particular, we first predict cross-sectional differences of the FPS. Similar to BG and other existing learning theories, when investors have less precise prior beliefs about funds' performance parameters (e.g., because the funds are young or follow a particularly active investment style), each observation leads to a more pronounced updating of prior beliefs, resulting in a higher FPS for these funds. Second, and unique to our model, we predict that these cross-sectional differences vary across states of the economy: we predict that funds that have a steeper unconditional FPS (i.e., funds associated with less precise prior beliefs) have a higher FPS difference between upturns and downturns. Inflows into the sector as a whole cannot easily generate such predictions for cross-sectional differences in the time variation of the FPS. Similarly, behavioral theories that might have the potential to explain the upturn-downturn difference do not easily predict a cross-sectional difference in the upturn-downturn difference at the same time.

The data bear out both the cross-sectional and difference-in-differences predictions for the FPS. We empirically proxy for investors' dispersion in beliefs using measures of active share and tracking error that are drawn from Cremers and Petajisto (2009), because these measures are correlated with higher dispersion of estimated alphas and betas. In particular, we take what these authors call "concentrated funds," that is, those ranking high in both active share and tracking error, as examples of funds for which investors have less precise prior beliefs. (Similar results obtain for young funds.) Figure 2 illustrates the empirical results comparing the FPS of *Concentrated* funds to all *Other* funds in different states of the economy. As the model predicts, the flow-performance relation of *Concentrated* funds is steeper on average, and the difference between slopes across downturns and upturns is larger

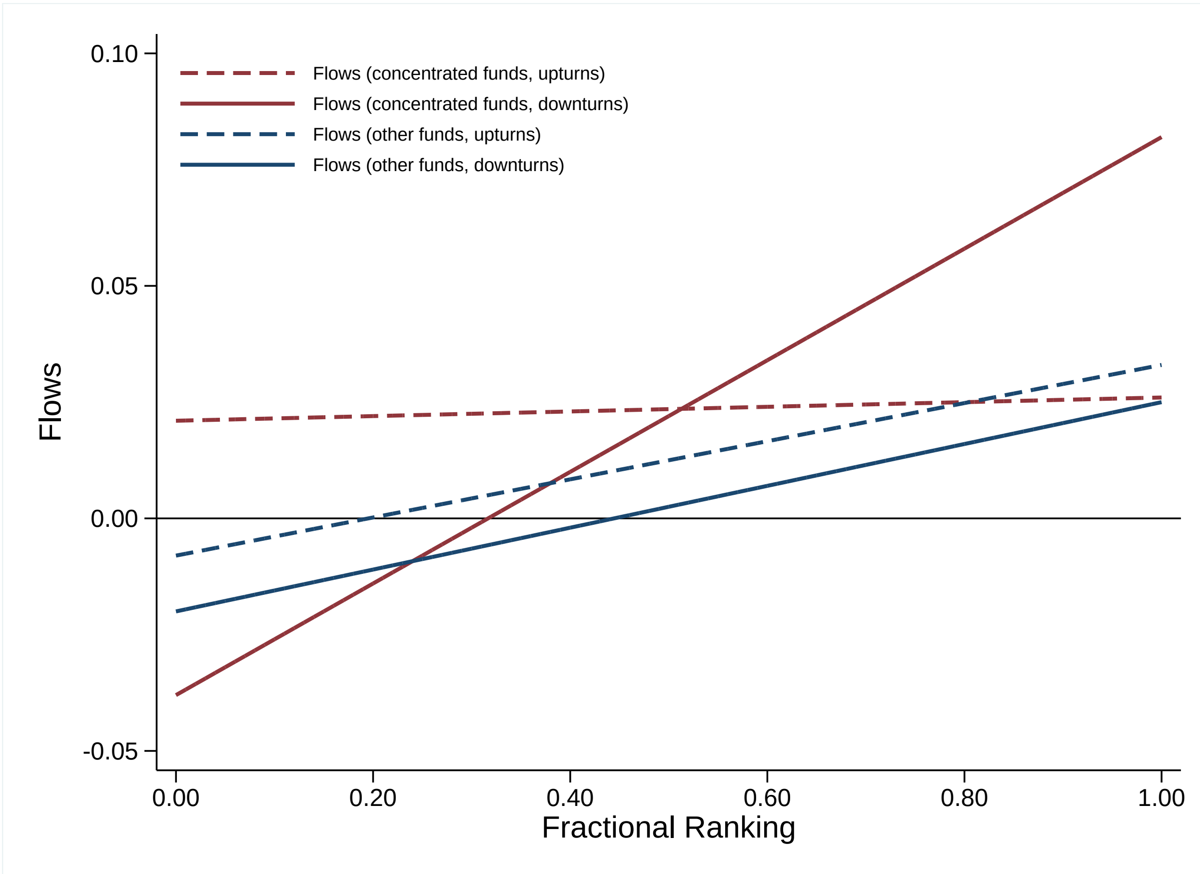


Figure 2: Flow-performance relation in upturns and downturns for "Concentrated" funds and all other funds (difference-in-differences results). The horizontal axis is the fractional rank of fund $i$ in period $t$ with respect to funds in the same style category. Percentage flows into fund $i$ at time $t+1$ are on the vertical axes.

compared to *Other* funds. This difference-in-differences is highly statistically significant.

Both the model and empirics are robust to whether the flow-performance relation is convex or linear – a long-dating question (Chevalier and Ellison, 1997; Sirri and Tufano, 1998) recently reinvestigated by Spiegel and Zhang (2012): our theoretical model can be combined with participation costs, which generate convexity (Huang, Wei, and Yan, 2007), and our empirical results hold in both linear and convex specifications.

The paper proceeds as follows. Section 2 describes the relation of our model and empirical results to the existing mutual fund literature. Section 3 presents the model. Section 4 describes the data, defines variables, and explains the empirical strategy. Section 5 gives the empirical results. Section 6 concludes.

## 2 Related Literature

Given the choice to use our model to explain the behavior of mutual fund investors, we restrict our review to papers within this literature.

Similar to (Berk and Green, 2004, BG), our model features the following: investors that provide capital to projects (here: mutual funds) in competitive ways, heterogeneity in the performance parameters of fund managers, decreasing returns to scale, and investors who rationally learn from past returns according to Bayes' law. The key difference from BG is that we allow for heterogeneous exposure of funds to time-varying benchmark returns and investors' uncertainty about that risk loading.

The assumption that investors do not have perfect knowledge about the extent to which fund returns load on systematic risk may seem counterintuitive at first. The fact that second moments can be learned arbitrarily fast when returns are continuously observed is well known (Merton, 1980). However, estimating performance parameters of mutual funds is necessarily less precise because fund returns are not continuously observed. Also, portfolio betas cannot be easily reconstructed, because the portfolio is often rebalanced in a way that is unobservable to outside investors (Kacperczyk, Sialm, and Zheng, 2008).

In an effort to focus on the model's new predictions about the dependence of the FPS on the market state, we do not speak to several questions BG's model is suited to address. In particular, we do not derive the optimal compensation contract for the fund managers

(Holmström, 1999), we do not endogenize the fee structure of the fund, and we do not explicitly discuss entry into and exit from the mutual fund sector (Berk and Green, 2004). Given little evidence of capital withdrawals from the sector in downturns (Pastor, Stambaugh, and Taylor, 2013) and our difference-in-differences design that mechanically controls for an effect from sector in- and outflows, we think withdrawals from and additions to the sector will have only a marginal impact on estimation results that speak to our research question.

Elaborating on the BG model, Huang, Wei, and Yan (2012) derive cross-sectional predictions on the FPS in an economy in which Bayesian and performance-chasing investors coexist. Like these authors, we exploit heterogeneity in parameter uncertainty across funds to identify our model. However, our theory relies on rational investors alone and focuses on the implications of parameter uncertainty on the dependence of the flow-performance relation on both fund types and market states.

Li, Tiwari, and Tong (2013) develop a model with ambiguity-averse investors who receive multiple signals of unknown precision about fund performance. Investors' flows react more strongly to the most negative signal. This prediction holds empirically when the authors use fund ranking over different horizons to proxy for the multiple signals. Our contribution differs from this model in that it is entirely cast within a Bayesian framework. Like us, these authors find stronger evidence among retails funds, for which the degree of uncertainty is likely higher.

Although we may be the first to jointly allow for uncertainty with respect to both alpha and funds' factor loadings, we are not the first to allow for uncertainty in more than one parameter. Pastor and Stambaugh (2012) allow for uncertainty with respect to the decreasing returns-to-scale parameter, which our model assumes is a known constant, and does not in fact drive any of the model's results. Their model explains the size of the actively managed fund industry, whereas ours focuses on cross-sectional and time-series differences in the sensitivity of investor flows to fund returns.[4]

The model does not specify the pricing kernel for the traded assets in which mutual funds invest. Also, it does not take a stand on whether managers are perfectly or only limitedly rational as in Kacperczyk, Nieuwerburgh, and Veldkamp (2012), whether they generate abnormal performance by market timing or stock picking (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2012), and whether the parameter distributions we assume are the result of strategic choice by managers or, instead, managers are endowed with them, as our model assumes.[5] Also, we do not model the fund-manager matching process (Gervais and Strobl, 2013), but we take the outcome as given.

Several authors have used the insight that risk-averse investors value mutual fund returns more in downturns than in upturns to study implications of the time variation in the value of active management as a whole (e.g., Moskowitz (2000); Kallberg, Liu, and Trzcinka (2000); Kosowski (2006); Sun, Wang, and Zheng (2009); Glode (2011)). Our contribution is to study the implications of the same insight for the cross-sectional reallocation of capital within the mutual fund sector, which is reflected in the flow-performance relation.

Empirically, we complement the literature on the flow-performance relation (see Spiegel and Zhang (2012)) by documenting that the FPS, which reflects within-sector flows across funds among retail mutual funds, depends in non-monotonic ways on the market state. It is higher in moderate than in extreme states of the market, and is twice as steep in downturns

[4]Outside of the mutual fund literature, Adrian and Franzoni (2009) also postulate that investors learn about unobservable risk factor loadings for stocks and show that this mechanism can explain part of the value premium under specific conditions on the learning process.

[5]Further distinctions from Kacperczyk, Nieuwerburgh, and Veldkamp (2012) are that our model contains no asymmetric information and we do not assume parameter distributions or risk aversion to vary exogenously as the state of the economy changes. The latter element clarifies that asymmetric fund flows obtain in our model even if no asymmetry is present in the model parameters.

than in upturns.

# 3 Model

We develop a model featuring uncertainty about factor loadings in which Bayesian agents learn the NPV of investment projects. When applied to mutual funds, the NPV refers to the fund's benchmark-adjusted returns, or alpha.[6] Aside from Bayesian learning, our model does not feature any other friction. Because we test the model using mutual fund data, we phrase its elements and predictions accordingly. Yet we believe that the predictions of the model extend to investment decisions that are taken under uncertainty on the relevant parameters of performance and risk.

## 3.1 Setup

There are $N$ funds to which investors can allocate their capital. The cash that fund $i$ returns at time $t$ from every dollar invested at time $t-1$ is denoted $Y_t^i$. Although the true return process may have different drivers, the returns can be decomposed in reduced form as

$$Y_t^i = 1 + \alpha^i + \beta^i \cdot f_t - \frac{1}{\eta} S_{t-1}^i + \varepsilon_t^i, \tag{1}$$

where $\alpha^i$ is a fund-specific, time-fixed performance parameter indicating a manager's skill to generate returns in excess of the benchmark, given fund size; $\beta^i$ is a fund-specific, time-fixed exposure to a time-varying systematic risk factor; $f_t$ is the time-$t$ realization in excess of the risk-free rate of a traded risk factor, which in the empirical analysis we proxy using the excess

[6] We draw inspiration from Schmalz and Zhuk (2013), who model learning about the value of assets from cash-flow news as a function of the market state when asset-specific cash-flow parameters are uncertain.

market return; $S_{t-1}^i$ is the size of the fund resulting from the investors' capital allocation in period $t-1$; $\eta > 0$ is an efficiency parameter, such that $-\frac{1}{\eta}S_{t-1}^i$ indicates decreasing returns to scale;[7] and $\varepsilon_t^i \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ are idiosyncratic shocks.

For convenience, we decompose the factor return as

$$f_t = \bar{f} + \xi_t, \tag{2}$$

where $\xi_t$ is a zero-mean transformation of the risk factor, which is normally distributed and *iid* over time, $\xi_t \sim \mathcal{N}(0, \sigma_\xi^2)$, and $\bar{f}$ is the expected return of the factor, which we assume is constant over time and known to the investors. We think of the risk premium on the benchmark as the stochastic discount factor applied to the factor $f_t$. We assume the benchmark $f_t$ covaries negatively with the stochastic discount factor. As a result, the expected return on the benchmark equals its risk premium and is positive in equilibrium, $\bar{f} > 0$.[8] The existence of a risk-free asset, whose return is normalized to zero without loss of generality, allows for flows into and out of the mutual fund sector base as overlapping generations of agents with identical risk-averse preferences who are uncertain about the precise values of both $\alpha^i$ and $\beta^i$.[9] Investors know that these parameters are sampled from a jointly Normal distribution with known mean, variance, and covariance that is identical for

[7]Decreasing returns to scale do not play a role in the mechanism we describe. They merely simplify the exposition and make the model consistent with BG.

[8]The only assumption needed to endogenize this assumption is risk-averse investors.

[9]Compared to the model of the allocation of capital to mutual funds by BG, the crucial difference is that we allow uncertainty about risk loadings $\beta^i$. Technically, this heterogeneity introduces a second parameter in investors' inference problem compared to BG.

all funds of a given category:

$$\mathcal{N}\left(\begin{pmatrix}\bar{\alpha}\\ \bar{\beta}\end{pmatrix}, \begin{pmatrix}\sigma_\alpha^2 & \sigma_{\alpha\beta}\\ \sigma_{\alpha\beta} & \sigma_\beta^2\end{pmatrix}\right). \tag{3}$$

We require investors' prior beliefs to be consistent with the true distribution of parameters in the cross section given by equation (3). A further discussion of the above assumptions follows.

## 3.2 Discussion

We assume that the benchmark investors use to value mutual funds, $f_t$, covaries positively with the stochastic discount factor, and, as a result, the risk premium on this benchmark, $\bar{f}$, is positive. Although plausible, a positive factor risk premium is not necessary to derive our key result – the function linking the FPS to the factor realizations (equation (6)) – , nor for the result deriving the ranking of the FPS between moderate and extreme factor realizations (proposition 1), and the cross-sectional predictions (proposition 3). However, a positive market risk premium is necessary to obtain the asymmetry between upturns and downturns (proposition 2) and the difference-in-differences prediction (proposition 4).

Although the model can be solved allowing for non-zero correlations between $\alpha$ and $\beta$, this generalization unnecessarily complicates the analytical solutions, without substantially affecting the intuition. We thus assume $\sigma_{\alpha\beta} = 0$. Also, whereas the parameters may be the outcome of a strategic interaction between managers and investors, here we assume fund investors take both $\alpha^i$ and $\beta^i$ as exogenous.

$\alpha^i$ can be interpreted as either stock-picking skill or market-timing skill. The stock-picking interpretation is straightforward. To gain intuition on market (or factor) timing, one can assume for a moment that the $\beta^i$ of manager $i$ is allowed to vary over time in a systematic fashion, whereas the manager has no stock-picking skill. In particular, suppose $\beta_t^i$ is always positive in upturns (when $\xi_t > 0$) and always negative in downturns (when $\xi_t < 0$) . Such a manager can generate high average returns $Y_t^i$ with low market correlation. To an investor running the regression (1) that constrains market exposure to be constant, $\beta_t^i = \beta^i$, this manager appears to have high static $\alpha^i$ and low static $\beta^i$. To the investor, this manager's performance is therefore observationally equivalent to and also equally valuable as the performance of a manager without timing ability but with stock-picking skill. Effectively, the investor is indifferent about how the manager generates returns. This example illustrates that we can assume the investor remains ignorant about the particular sources of the manager's skill. In sum, equation (1) is not necessarily the true cash-flow process of funds, nor do investors need to believe it is. It is merely one possible, and convenient, description of cash flows that is sufficient to describe the inference problem that is relevant to the investors' utility-maximization problem.

Although the model is generally compatible with any strategy managers may employ to generate returns, including stock picking and market timing, constructing cases in which the assumption of normality of the parameter distributions is violated is, of course, possible. For example, if managers systematically have skill only in particular states of the economy, investors could not reasonably believe the parameter distributions are normal. However, we deliberately assume symmetric parameter distributions to emphasize that asymmetric behavior across states of the economy obtains as an outcome of the model, even if parameters and their distributions do not change as a function of the state of the economy. For example, allowing for higher macro volatility in downturns than in upturns, that is, a negatively skewed $\xi_t$, or increased risk aversion in downturns, would presumably strengthen the prediction of a higher FPS in downturns. Of course, obtaining closed-form solutions would be difficult or impossible for such cases.

## 3.3 Timing

The investors hold funds of equibrium size $S^i_{t-1}$ consistent with prior beliefs $\hat{\alpha}^i_{t-1}$ and $\hat{\beta}^i_{t-1}$ about the true parameters $\alpha^i$ and $\beta^i$ according to equation (3). Returns $Y^i_t$ are realized and observed by investors, from which they can infer $f_t$, or equivalently $\xi_t$. Conditioning on $\xi_t$, investors then compute posterior beliefs $\hat{\alpha}^i_t$ and $\hat{\beta}^i_t$ and thus determine new equilibrium fund sizes $S^i_t$ (derived below). The change of fund sizes determines the reallocation of capital across funds. Relating these flows to performance $Y^i_t$ yields the flow-performance sensitivity.

## 3.4 Equilibrium

Based on the above assumptions, the market's current belief $\hat{\alpha}^i_t$ about $\alpha^i$ determine equilibrium fund sizes.

**Lemma 1.** *Fund i's equilibrium size $S^i_t$, based on the investors' belief $\hat{\alpha}^i_t$ at time t about skill $\alpha^i$ is given by*

$$S^i_t = \eta \cdot \hat{\alpha}^i_t. \tag{4}$$

The formal proof is in the appendix. The intuition is straightforward. Investors determine allocations to funds so that the expected utility of a marginal dollar in each fund equals the outside option of the risk-free rate, which is normalized to zero. In so doing, the expected value of fund returns based on current beliefs, $1 + \hat{\alpha}^i_t + \hat{\beta}^i_t \cdot \bar{f} - \frac{1}{\eta} S^i_t$, is adjusted for the fund's estimated sensitivity to the risk factor, $\hat{\beta}^i_t$, multiplied by the factor risk premium $\bar{f}$, which represents how much investors dislike risk exposure, thus canceling the $\hat{\beta}^i_t \cdot \bar{f}$ term. In words, investors do not care about the risk exposure of funds, because they are appropriately compensated for the risk they are taking. $\beta$ only matters in our model because uncertainty about $\beta$ affects the speed of learning about $\alpha$.

## 3.5 Fund Flows

### 3.5.1 Intuition

Equation (4) combined with (1) conveys the intuition of the model. The quantity of interest is $\alpha^i$, whereas investors observe $Y_t^i = ... + \alpha^i + \beta^i \cdot f_t + ... + \varepsilon_t^i$, that is, their quantity of interest plus different kinds of noise. When $f_t = 0$, the only noise preventing investors from directly inferring $\alpha^i$ is $\varepsilon_t^i$. The $\beta^i$-related component of the noise is "switched off" and uncertainty about risk loadings is inconsequential for learning. By contrast, when $|f_t| > 0$, an additional element of noise obscures the inference. If $\beta^i$ were known, investors would need only to subtract a constant from the fund's returns. With unknown $\beta^i$, however, investors do not know what exactly to subtract from any particular fund $i$'s return to calculate its risk-adjusted performance. Hence they have to treat the additional term as noise. The more uncertain they are about $\beta^i$, the more noisy the observation seems to them, particularly when $|f_t|$ is large. The signal-to-noise ratio is highest when $f_t = 0$, and decreases symmetrically both for higher and lower factor realizations.

To convey intuition about the relation between the speed of capital reallocation and the state of the market, let us interpret $f_t$ as the excess market return, $f_t = R_{M,t}$, and $\bar{f}$ as the average market excess return. This interpretation is legitimate in that any factor summarizing investors' pricing kernel is going to be positively correlated with the market return. Some empirical literature (Glode, Hollifield, Kacperczyk, and Kogan, 2012) defines upturns as realizations of the market return above a given percentile and downturns as realizations below the symmetric percentile. Then an asymmetry in the speed of capital reallocation between upturns and downturns arises because the mean and median market returns are above zero, whereas the speed of capital reallocation peaks at zero realizations of the factor, which are closer to downturns according to the above definition. Figure 1, discussed in the introduction, summarizes this intuition.

#### 3.5.2 Formal results

The main insight of the model is that the sensitivity $\lambda$ of flows, $F_t^i$, to unexpected performance, $Y_t^i - E_{t-1}[Y_t^i]$, depends on the factor realization, $\xi_t$, that is, $\lambda = \lambda(\xi_t)$.

**Lemma 2.**

$$F_t^i := S_t^i - S_{t-1}^i = \eta \cdot \lambda(\xi_t) \cdot (Y_t^i - E_{t-1}[Y_t^i]), \tag{5}$$

*where*

$$\lambda(\xi_t) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\beta^2 \left(\bar{f} + \xi_t\right)^2 + \sigma_\varepsilon^2}. \tag{6}$$

Recall that $\sigma_\alpha^2$ and $\sigma_\beta^2$ denote the dispersion of parameters $\alpha^i$ and $\beta^i$, according to (3), and thus the degree of uncertainty about these parameters. $\lambda(\xi_t)$ is the FPS and corresponds to the signal-to-noise ratio.[10] Note also that $Y_t^i$ are percentage returns (dollars returned for every dollar invested), and $S_t^i$ can also be scaled by dollars invested. Thus $\lambda(\xi_t)$ is closely linked to its empirical anologue.

The intuition is straightforward. First, consider the case in which no uncertainty about risk exposure is present, $\sigma_\beta^2 = 0$. Then the FPS $\lambda$ does not depend on the factor realization, $\xi_t$, and the intuition developed in BG and other models obtains. For example, the more dispersed alphas are believed to be, that is, the higher $\sigma_\alpha^2$ is relative to $\sigma_\varepsilon^2$, the stronger the

[10]For the difference in fund sizes $S_t^i - S_{t-1}^i$ to correspond to between-fund flows, it is implicitly assumed that each fund $i$ distributes the net return $Y_t^i - 1$ at the end of period $t$.

reaction to news, that is, the steeper the FPS. Intuitively, if very high and low fund returns are deemed realistic and attributable to exceptionally high or low skill, rational investors are less prone to impute abnormal fund returns to random noise, and will therefore react more strongly to the news. Young funds, or funds with a manager of low tenure, are candidates the literature has used for a high ratio of $\sigma_\alpha$ to $\sigma_\varepsilon$ (BG). In the main empirical analysis, we proxy this higher degree of parameter uncertainty using *Concentrated* funds, as defined below. Conversely, if signals are less informative, that is, lower $\sigma_\alpha^2$ for given $\sigma_\varepsilon^2$, then one-time abnormal performance of a given size triggers lower flows. In sum, the ratio of $\sigma_\alpha^2$ to $\sigma_\varepsilon^2$ summarizes the signal-to-noise ratio in the case of $\sigma_\beta^2 = 0$.

Let us now introduce uncertainty about $\beta^i$, $\sigma_\beta^2 > 0$, thereby making the FPS, $\lambda$, depend on the factor realization, $\xi_t$. A positive $\sigma_\beta^2$ dampens the FPS. This effect depends positively on the absolute magnitude of the total factor realization $f_t = \bar{f} + \xi_t$. The dependence of $\lambda$ on $\xi_t$, and the sensitivity of this dependence on uncertainty about $\alpha^i$ and $\beta^i$, is the driver of all our empirical predictions.

In the empirical analysis, we provide nonlinear estimation results that directly test for the functional form of the flow-performance relation in equation (6). In doing so, we can rule out alternative theories that could also drive the empirical predictions that follow. For example, a steeper FPS in downturns also arises when $\sigma_\beta^2 = 0$ (so the mechanism proposed in this paper is shut off), but $\sigma_\alpha^2$ is negatively correlated with the factor realization. In that case, $\lambda$ would be a monotonically decreasing function of $\xi_t$. By contrast, under our assumptions, $\lambda(\xi_t)$ is non-monotonic, thereby allowing us to distinguish between the two alternative theories empirically.

## 3.6 Empirical Predictions

This section derives empirical predictions that are testable with linear regression models. The first two predictions, regarding the variation of the FPS between "moderate" and "extreme" realizations of the factor as well as between upturns and downturns, do not require additional assumptions. For the cross-sectional and difference-in-difference predictions, we assume that identifying two groups of funds that can be ranked in terms of the dispersion of investors' beliefs about alpha and beta is possible.

### 3.6.1 Flow-Performance Sensitivity in Extreme Market States

Our first prediction is that fund performance is less informative when the realization of the factor is either very high or very low compared to the information contained in fund performance when the realization of the factor is closer to zero.

**Proposition 1.** *Flow-performance sensitivities are larger when the market excess return is close to zero than when it is either very high or very low. For any constant $c > 0$,*

$$\lambda(|f_t| < c) - \lambda(|f_t| > c) > 0.$$

We omit the proof because it follows directly from equation (6).

### 3.6.2 Upturn-Downturn Difference of Flow-Performance Sensitivity

Assuming that the factor $f_t$ correlates positively with market conditions, one can legitimately call positive (negative) realizations of the factor an upturn (downturn). Then the second testable prediction is that the FPS is larger in downturns (DT) than in upturns (UT).

**Proposition 2.** *Flow-performance sensitivities are larger in downturns than in upturns of equal magnitude. For any $x > 0$,*

$$\lambda\left(\xi_t = -x\right) - \lambda\left(\xi_t = x\right) > 0.$$

The proof is in the appendix.

#### 3.6.3 Difference-in-Differences Prediction for FPS

When differences exist in the precision of the investors' ex-ante beliefs across fund types, the FPS will vary across these fund types. Let us identify two groups of funds that can be ranked in terms of the dispersion of beliefs about alpha and beta. That is, for some constant $k > 1$, define

$$\sigma^2_{\alpha,Concentrated} = k \cdot \sigma^2_{\alpha,Other} \tag{7}$$

$$\sigma^2_{\beta,Concentrated} = k \cdot \sigma^2_{\beta,Other}, \tag{8}$$

where we use the label *Concentrated* for funds with higher dispersion of beliefs and *Other* for funds with low dispersion of beliefs. These labels reflect the empirical implementation in which we use results from Cremers and Petajisto (2009) to proxy for heterogeneity of beliefs regarding the parameters of interest.

It follows immediately from the $\lambda(\xi_t)$ expression in lemma 2 that investors react with higher flows to a given piece of news if it pertains to *Concentrated* funds. (A similar prediction obtains from established models of fund flows such as BG in comparing funds with higher parameter uncertainty to funds with lower uncertainty, such as young and old funds.)

**Proposition 3.** *Keeping everything else constant, the flow-performance sensitivity is higher for Concentrated funds than for Other funds on average:*

$$\lambda_{Concentrated} - \lambda_{Other} > 0.$$

The proof is in the appendix. Note the proposition relies on differences in the distributions of parameters introduced in equation (3), whereas it assumes both funds have investors with similar prior beliefs and restrictions. Thus it should hold across types of funds that are held by similar investors, but it need not hold across funds with investors with distinct sets of beliefs. For example, we would not think it appropriate to test the prediction comparing the FPS of mutual funds and hedge funds. Similarly, we would not necessarily expect the proposition to hold across funds that are predominantly held by retail investors versus funds that are predominantly held by institutions, which are likely to be more informed about underlying parameters, and have different restrictions to their investment policy. Because we do not model such constraints, we will test the proposition within funds that cater to retail investors.

Many things other than market returns themselves might change with market conditions, including flows into and out of the mutual funds sector. The cleanest way to control for such confounding factors is to difference them out. To that end, we predict and later show that the difference in FPS differences across market states depends positively on the dispersion of parameters of the fund type. (In other words, the cross-sectional differences of the FPS across funds depends on the market state.)

**Proposition 4.** *The difference in flow-performance sensitivities between downturns (DT)* *and upturns (UT) is larger for Concentrated funds than for Other funds:*

$$(\lambda_{DT} - \lambda_{UT})_{Concentrated} - (\lambda_{DT} - \lambda_{UT})_{Other} > 0.$$

The proof is in the appendix. The intuition is that the downturn-upturn difference comes from uncertainty about $\beta$ – and *Concentrated* funds feature more uncertainty about $\beta$.

The prediction in proposition 4, combined with the non-linear predictions, is unique to our model. If this difference-in-differences prediction finds support in the data, we will say the model is "identified" in the sense of ruling out several alternative explanations for the upturn-downturn difference predicted in proposition 2. For example, one might otherwise conjecture the upturn-downturn difference obtains because "everybody is happy in upturns" and investors do not check fund performance, whereas investors scrutinize fund performance in downturns. However, such a behavioral theory would not easily explain why the upturn-downturn difference would differ across different types of funds. In section 5, we describe alternative theories in more detail.

## 3.7 Model limitations

One limitation is that the model is essentially static. Taking the model as is seems to imply that after sufficiently many observations, investors learn parameter values well enough for the FPS first to fall, and then for all flows to disappear. A more realistic model would assume funds periodically disappear (for exogenous reasons or because they perform below a threshold) and get replaced with new ones, about which little is known. Similarly, in reality, turnover in fund managers occurs, which introduces new uncertainty about underlying parameters. When the model is modified in a way that parameters get periodically reassigned for a fraction of funds, the average precision of beliefs about fund value is highest following downturns (this result would be driven by the dynamics of $\sigma_{\alpha\beta}$, which is assumed to be zero in this presentation of the model). As a result, fund sizes most closely match a first-best allocation without parameter uncertainty following downturns, which strengthens the Schumpeterian intuition that recessions have a cleansing effect on the economy. We therefore think the static model captures a similar intuition a dynamic model would produce, but with a much simpler exposition.

A related limitation results from the assumption of no learning about the realization of the risk factor and, eventually, about the stochastic discount factor as featured, for example, in Veronesi (1999). Technically, investors need not learn about the realization of the factor, because the number of funds is large and the factor is assumed to be *iid*. To our knowledge, no existing model is able to track both the cross-sectional (fund types) and time-series (the risk factor) dimensions at the same time.

A third limitation is that the parameters $\alpha^i$ and $\beta^i$ are exogenous in the model. We have several reasons for this modeling choice. First, obtaining the key predictions may be prohibitively difficult if the parameters are endogenous and a result of fund managers' choice. Second, including the managers' choice would come at the expense of having to make assumptions about their preferences and incentives, which would make inferring which part of our results comes from assumptions about investor preferences, which from assumptions about managers' incentives, and which from investor behavior more difficult. We want to make clear that only Bayesian inference on behalf of investors drives the results in the present model. The model does not preclude, however, that the parameter distributions are already the outcome of an optimization on behalf of the fund managers. Studying the interaction of investor and manager behavior when skill $\alpha^i$ is exogenously distributed and known to the manager but uncertain to investors, and $\beta^i$ is a strategic choice of the manager and likewise uncertain to the investor, may be an interesting subject for future research.

A fourth observation warranting attention is that any cross-sectional predictions, and especially the difference-in-differences prediction on the FPS, rely on a homogenous set of investors across different types of funds that does not face constraints with respect to their capital reallocation other than the limitations imposed by parameter uncertainty. The model predictions should therefore only hold within a set of funds with a reasonably homogenous investor base that is unrestricted in its investment choices.

# 4 Description of the Data

The primary data source for this study is the CRSP Survivorship Bias Free Mutual Fund Database. These data contain fund returns, total net assets (TNA), investment objectives, and other fund characteristics. Following the prior literature, we select domestic equity open-end mutual funds and exclude sector funds using the CRSP objective code (which maps Strategic Insights, Wiesenberger, and Lipper objective codes). Because the reported objectives do not always indicate whether the fund is balanced, we exclude funds that on average hold less than 80% of their assets in stocks. Given that the focus of this study is on actively managed mutual funds, we also exclude index funds.

To address the potential bias resulting from the fact that the fund incubation period is also reported, we exclude observations whose date is prior to the reported starting date of the fund, similar to Kacperczyk, Van Nieuwerburgh, and Veldkamp (2012). Because incubated funds tend to be smaller, we exclude funds before they pass the $5 million threshold for assets under management.

Mutual funds in CRSP include both retail and institutional share classes. Our model's predictions are based on a homogenous set of investors. Therefore, pooling two classes of investors would blur the empirical tests of the model predictions. Besides, institutional funds are subject to a number of constraints in terms of minimum investment size, long-term investment agreements, and limited choice set whenever they are offered to individuals through a 401(k) plan, which impose restrictions on fund flows our model does not capture. These arguments prompt us to restrict our empirical analysis to mutual funds that are sold to retail investors and exclude institutional funds. The retail-fund indicator is available in CRSP starting in December 1999. For the prior years, we backward impute the retail indicator whenever available and we use the names of share classes to identify institutional funds. We exclude from the sample the funds for which no information can be gathered on whether they are retail or institutional. Although this choice has the potential to induce a selection bias, we show that our results also hold – and indeed are stronger and more significant – in the subsample in which the retail indicator is available, despite the much lower number of observations. Thus the imputation introduces noise that leads to attenuation bias but does not lead to a bias in favor of the hypotheses proposed here.

The sample spans the years from 1980 to 2012, in which complete information on investment objectives is available. Because CRSP does not report monthly TNA until 1990, we follow the existing literature and use quarterly data for the flow-performance sensitivity analysis (Huang, Wei, and Yan, 2007) for the main results. We replicate our results with monthly data as robustness tests.

Using the quarterly net asset values and returns from CRSP, we compute net flows according to the literature standard as

$$Flows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}\left(1 + R_{i,t}\right)}{TNA_{i,t-1}}, \tag{9}$$

where $TNA_{i,t}$ is total net assets in quarter $t$ for fund $i$, and $R_{i,t}$ is fund $i$'s quarterly return, which are obtained from cumulating monthly returns. Elton, Gruber, and Blake (2001) point out a number of errors in the CRSP mutual fund database that could lead to extreme values of returns and flows. For this reason, following Huang, Wei, and Yan (2007), we filter out the top and bottom 2.5% tails of the the returns and net flows distributions.

Between 1980:Q1 and 2012:Q4, we have 144,382 mutual fund-quarter observations with valid information on returns and TNA in quarter $t$ and quarter $t+1$, corresponding to 5,763 funds.[11] The other variables we use in the analysis, and for which we require availability for sample inclusion, are the expense ratio, the portfolio turnover ratio, and return volatility, which is computed over the prior 12 months. These variables are winsorized at the $1^{st}$ and $99^{th}$ percentiles. We compute fund age as the time (in quarters) since the first appearance of the fund in the overall CRSP sample. Table 2 reports summary statistics for these variables. From Panel A, we notice that the average (median) fund has a size of \$678 million (\$82 million). The maximum fund size is about \$109 billion. Fund age ranges from five to 151 quarters. Our sample is comparable to other studies in terms of return volatility, asset turnover, and expense ratio (see Huang, Wei, and Yan (2007)).

Part of our analysis makes use of data on active share and tracking error, which are defined

[11] Starting in the 1990s, some funds offer multiple share classes that represent claims to the same portfolio. Some authors aggregate different share classes at the portfolio level (see, e.g., Glode, Hollifield, Kacperczyk, and Kogan (2012)). Following Huang, Wei, and Yan (2007), we abstain from this aggregation because our purpose is to study fund flows, which differ at the share-class level. This choice does not materially affect our results.

as in Cremers and Petajisto (2009) and Petajisto (2013).[12] These variables are constructed using information on portfolio composition of mutual funds as well as their benchmark indexes. The stock holdings of mutual funds come from the CDA/Spectrum database provided by Thomson Financial. The authors currently make their data available between 1980:Q1 and 2009:Q3.

To define upturns and downturns, we procede as in Glode, Hollifield, Kacperczyk, and Kogan (2012) and use the distribution of the excess return on the market up to quarter $t$. We denote a quarter as an upturn if the excess return on the CRSP value-weighted index for that quarter lies in the top 25% of the distribution of the quarterly excess market returns up to quarter $t$. Symmetrically, a quarter is a downturn if the realization of the market in that quarter is in the bottom 25% of the distribution. In computing the distribution of the market excess return, we use the history going back to the third quarter of 1926. As a result, out of the 131 quarters in our sample, 32 are upturns and 30 are downturns. When using monthly data, we proceed similarly in defining upturns and downturns. Panels B and C of Table 2 have summary statistics on the relevant variables at the quarterly frequency in the subsamples of upturns and downturns. As expected, returns and flows are on average larger in upturns, whereas other variables are similar in magnitude across market states.

# 5 Empirical Methodology and Results

Next, we turn to the empirical analysis. We describe the variation of the flow-performance sensitivity across states of the market first with non-linear least squares and then with OLS within a Fama and MacBeth (1973) framework. Next, we again use OLS to describe the cross-sectional variation as well as the difference-in-differences of the FPS. Together with

[12]We are grateful to Antti Petajisto for making the data available on his website: www.petajisto.net

the non-linear estimates, the difference-in-differences identifies the model in the sense of ruling out a variety of alternative explanations.

Throughout the empirical application, we will assume the relevant factor can be proxied using the market excess return, $f_t = R_{M,t}$ and $\bar{R}_M = \bar{f}$. In doing so, we are motivated by the conjecture that whatever the underlying pricing kernel is, it is going to be positively correlatated with the market factor. Because we are not using the factor to compute risk-adjusted performance, but rather we use it to define upturns and downturns, this assumption seems warranted.

## 5.1 First Step: Estimating the Flow-performance Sensitivity

The predictions of the model are expressed in terms of the dependence of the slope of the relation tying flows to performance (flow-performance sensitivity, FPS). The first step is to estimate the FPS for a given market realization. To this purpose, we use the estimate of $\lambda_t$ in the regression:

$$Flows_{i,t+1} = a + \lambda_t \cdot frank\_style_{i,t} + \gamma \cdot X_{i,t} + \varepsilon_{i,t}, \tag{10}$$

where $frank\_style_{it}$ is the fractional rank of fund $i$ in period $t$ with respect to funds in the same style. Note that we allow the slope to depend on $t$; that is, we estiamte this regression every period, using the available cross section of funds. For mutual funds, the style is defined by the CRSP "objective" variable. $X_{i,t}$ are standard controls, described later. Focusing on relative performance within a group of funds with the same style, as opposed to fund risk-adjusted returns, simplifies the analysis in that one does not need to take a stand on the correct risk model. Also, it avoids introducing measurement error, which would result from the estimation error of the risk-adjusted performance. Finally, it complies with the literature standard for estimating the FPS (e.g., Sirri and Tufano (1998)).

In equation (10), we are constraining flows to be a linear function of performance. This assumption simplifies considerably the exposition of the results of tests of our predictions, because we do not need to make the estimated FPS dependent on a specific range in the support of performance. However, given that the literature also estimates non-linear specifications of the FPS (e.g., Huang, Wei, and Yan (2007)), in section 5.3, we show that our conclusions are robust to a convex specification for the FPS.

## 5.2 Empirical Results

### 5.2.1 Non-linear Least Squares (NLS) Estimation Results

One of the key features of the model is the predicted non-linear (and non-monotonic) shape for the FPS as a function of the state of the market, as per lemma 2. In this subsection, we formally test this prediction on the dependence of the FPS on the realization of the factor. In particular, we estimate the parameters of equation (6). Because $\sigma_\alpha$, $\sigma_\beta$, and $\sigma_\varepsilon$ are identified up to a common constant, we divide the numerator and denominator of equation (6) by $\sigma_\alpha^2$. Using non-linear least squares, we then estimate $\frac{\sigma_\beta}{\sigma_\alpha}$ and $\frac{\sigma_\varepsilon}{\sigma_\alpha}$ in the following specification:

$$\hat{\lambda}_t = \frac{1}{1 + \frac{\sigma_\beta^2}{\sigma_\alpha^2} R_{M,t}^2 + \frac{\sigma_\varepsilon^2}{\sigma_\alpha^2}} + u_t, \tag{11}$$

where $\hat{\lambda}_t$ is the estimate of the fFPS in quarter $t$ from regression (10), $R_{M,t}^2$ is the squared quarterly excess return of the market, and $u_t$ is an error term.

Figure 3 shows the results from the non-linear least squares estimation specified in equation (11), plotting the estimated FPS over market excess returns, including 95% confidence bands.[13] Table 4 presents the corresponding parameter estimates and t-statistics. Two observations are in order. First, the null hypothesis that the FPS does not depend on the state of the market is rejected with high significance: the estimate of $\frac{\sigma_\beta}{\sigma_\alpha}$ is 27.401 with a t-stat of 3.107. Note that an estimate for $\frac{\sigma_\beta}{\sigma_\alpha}$ that is statistically significant from zero is a test of the prediction of Lemma 2, which states that the FPS depends on the benchmark realization.[14]

Second, the FPS as a function of the market excess return first increases and then decreases. This fact rules out alternative explanations of the upturn-downturn difference, such as the one positing that the dispersion of skill in downturns is higher than the dispersion of skill in upturns. That conjecture would predict a monotonously decreasing FPS as a function of the market excess return.

In sum, the non-linear estimation results strongly confirm the predictions of Lemma 2, which is the main prediction of our model. The results furthermore clarify that the two key drivers of the linear estimation results that follow are (i) the fact that the FPS decreases symmetrically with the absolute value of deviations of the market excess returns from zero, and (ii) the fact that the average FPS is asymmetric with respect to the peak of the distribution of market returns (see Figure 1).

[13] The confidence intervals for the fitted values are computed conditioning on the realization of $R_{M,t}$. Also, we use the asymptotic normality of the estimators and the result that a non-linear function of $X$ tends to the same class of distributions as $X$ (Proposition 7.4 in Hamilton (1994)).

[14] Following more closely the model specification, that is, using absolute performance rather than fractional ranks as measures of performance, we obtain an estimate of 11.828 for $\sigma_\beta/\sigma_\alpha$. Comparing this figure with estimates of $\sigma_\alpha$ and $\sigma_\beta$ from realized monthly (!) returns (Table 3), we note that the estimated dispersion of betas relative to alphas based on realized returns is in the same order of magnitude, but at least as large as that implied by flows. As a result, the assumption of uncertainty about $\beta^i$ seems weak relative to the empirically observed measurement error in $\beta^i$.

### 5.2.2 OLS Estimation Results

Next, we test the empirical predictions in Propositions 1 through 4. Using the Fama and MacBeth (1973) methodology, we begin by estimating the regression model (10) separately for realizations of the market close to zero and for realization of the market further away from zero. This analysis tests Proposition 1, which states that the FPS is higher for realizations close to zero than for either large positive or large negative realizations. We use the cut-off $c = 5\%$ (other cut-offs give qualitatively similar results).

Table 5 provides the results. Column (1) reports a significant FPS of 0.043 without conditioning on the state of the market. Column (2) reports a highly significant FPS of 0.029 for "extreme" realizations of the market return that are either below -5% or above 5%. This finding compares to a highly significant FPS of 0.058 for "moderate" realizations of the market that are above -5% but below 5%. The difference in FPS between extreme and moderate market states is not only economically large, but also highly statistically significant (bottom of columns (2) and (3)).

In columns (4)-(6), the result is preserved after introducing all the controls suggested by Spiegel and Zhang (2012). These controls are the aggregate flows in quarter $t + 1$ into the funds that have the same objective as fund $i$ (flows_style), the total expense ratio (fee), the logarithm of TNA (logsize), the portfolio turnover ratio (turn_ratio), the return volatility over the prior 12 months (vol), and the logarithm of the fund's age (logage). Given that flows display some persistence, we also include the fund's flows in quarter $t$. Column (5) shows a highly significant FPS of 0.027 for extreme market states, and column (6) shows a highly significant FPS of 0.043 for moderate market states. Again, the difference is highly statistically significant.

Next, we estimate the regression model (10) separately in upturns and downturns. This analysis provides a test of proposition 2, which states that the flow-performance relation is steeper in downturns than in upturns.

Table 6 presents the results. The table describes the variation of FPS across binary upturn/downturn states of the economy. The first three columns give results that do not include additional controls. The FPS is more than twice as large in downturns (0.051) as in upturns (0.021) for the average fund (columns (2) and (1)), emphasizing the economic significance of the result. The difference is also highly statistically significant (bottom of columns (1/2)). After adding the standard controls in columns (3) and (4), we preserve the magnitudes as well as the statistical significance of the upturn/downturn difference (bottom of columns (3) and (4)). Overall, this evidence provides an empirical validation of Proposition 2.

The next step is to test the cross-sectional and difference-in-differences predictions across fund types and market states given in Propositions 3 and 4. The cross-sectional variation should arise from the heterogeneity in the degree of ex-ante uncertainty about a particular fund's parameters (captured by the model parameters $\sigma_a$ and $\sigma_b$). To this purpose, we use the variables constructed by Cremers and Petajisto (2009) and Petajisto (2013). We conjecture that for the funds these authors label *Concentrated*, investors have higher uncertainty about risk loadings and skill.

According to the authors, *Concentrated* funds are those that rank highest by both active share and tracking error. In our application, a *Concentrated* fund is one that appears in the top half of the distribution of these two variables. Our intuition is that the extent of active management that characterizes these funds, both in terms of stock picking and sector rotation, makes the inference on the underlying parameters of these funds' returns more difficult. To the extent that estimated (ex-post) volatility of risk loadings and alphas corresponds to ex-ante dispersion of prior beliefs, Table 3 confirms this intuition by comparing the standard deviation of alphas and factor-loading estimates between *Concentrated* and *Other* funds. Similar results obtain when other proxies for more disperse distributions are chosen, such as younger funds or smaller funds. We report results for younger funds in the robustness checks.

Importantly, for the interpretation of the cross-sectional difference results, both types of funds must have similar investor bases. We do not want differences in the inherent FPS of one investor group versus another to drive the results. To that end, we use the insight by Christoffersen and Musto (2002) that fees reflect the performance sensitivity of investors in a given fund. We compare the total expense ratio for *Concentrated* and *Other* funds and find they are both around 0.014, with a standard deviation of 0.004 and 0.005, respectively. We conclude that investor types do not significantly differ across these types of funds.

Table 7 summarizes the variation of the FPS across funds and differences of that variation across market states. The first column shows that the flow-performance relationship is almost 50% steeper for concentrated funds (coefficient on the interaction $frank\_style \times Concentrated$), irrespective of market states, as predicted by Proposition 3. The difference is statistically significant (t-stat=2.015). The significance is lost in column (4) when we introduce the controls, but the qualitative result remains. Further, statistical significance fully comes back in the comparison between young and old funds in Table 14.

Columns (2) and (3) of Table 7 show that the cross-sectional difference is entirely driven by downturns: the FPS for *Concentrated* funds in downturns is 0.12 compared to the FPS for *Other* funds of 0.045, whereas the FPS in upturns is not significantly different across fund types. The difference between the FPS of *Concentrated* and *Other* funds is therefore much higher in downturns than in upturns. In other words, the difference-in-differences (between downturns and upturns and between *Concentrated* and *Other* funds) is 0.111 and is highly significant (p-value$<$0.01, see the test at the bottom of columns (2) and (3)). This result confirms the prediction made in Proposition 4. Columns (4)-(6) report qualitatively and quantitatively similar results after the introduction of controls.

Econometrically, the double-difference result rules out a number of alternative theories that could drive the variation in the FPS across market states. For example, suppose new capital that flows into the mutual fund sector gets primarily allocated with medium performers, possibly attenuating our upturn-FPS estimate, whereas outflows from the sector primarily hit underperformers, which might steepen the FPS estimate in downturns. Taking the difference across fund types of the upturn-downturn difference would eliminate such an effect.

### 5.3 Robustness Checks

This section establishes that the linear estimation results are robust to (i) a piecewise linear specification, (ii) sample selection, (iii) the imputation of the retail/institutional indicator, (iv) the proxy for the precision of ex-ante beliefs about parameters, and (v) whether monthly rather than quarterly data are used, both in the linear and convex specifications.

A large body of literature (starting with Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998)) identifies a convex flow-performance relation. More recently, other authors (Spiegel and Zhang, 2012) argue that convexity originates from a misspecified empirical model, and that the relation between flows and performance is truly linear. This paper does not intend to contribute to this debate, given that our predictions on the state dependency of the flow-performance relation are insensitive to the shape of this relation. Still, to assess the robustness of our predictions to alternative empirical specifications of the shape of the flow-performance relation, we offer a robustness test that allows for a piecewise linear relation:

$$Flows_{i,t+1} = a + b_1 \cdot trank\_style1_{i,t} + b_2 \cdot trank\_style2_{i,t} + b_3 \cdot trank\_style3_{i,t} + \varepsilon_{i,t}, \quad (12)$$

where $trank\_style1_{i,t} = \min(\frac{1}{3}, frank\_style_{i,t})$, $trank\_style2_{i,t} = \min(\frac{1}{3}, frank\_style_{i,t} - trank\_style1_{i,t})$, and $trank\_style3_{i,t} = \min(\frac{1}{3}, frank\_style_{i,t} - trank\_style1_{i,t} - trank\_style2_{i,t})$.

Table 8 has the Fama and MacBeth (1973) estimates for the piecewise linear specification in equation (12) in the first column. The fourth column also includes the standard controls. Consistent with the prior literature, we find evidence of convexity of the flow-performance relation (columns (1) and (4)). More relevant for our purposes, the evidence strongly supports the predictions of the model. In each interval of the domain of the piecewise linear specification, the FPS is larger in moderate states than during extreme states of the market (columns (3) and (2)). This result holds also when we include the controls (columns (6) and (5)). At the bottom of columns (2), (3), (5), and (6), we report p-values from a chi-squared test for the equality of the three slopes $b_1$, $b_2$, and $b_3$ between extreme versus moderate market states. The test rejects the null hypothesis.

Table 9 provides the upturn-downturn test in a piecewise linear specification. The results are preserved. In each interval of the domain of the piecewise linear specification, the FPS is larger in downturns than in upturns (columns (2) and (1)). This result holds also when we include the controls (columns (4) and (3)). At the bottom of columns (1/2) and (3/4), we report p-values from a chi-squared test for the equality of the three slopes $b_1$, $b_2$, and $b_3$ between upturns and downturns. The test rejects the null hypothesis. Given the consistency of the conclusions between Tables 5 and 8, and between Tables 6 and 9, we feel legitimized to use the linear specification in the main analysis, which easily allows us to more easily test the difference-in-differences predictions of the model.

Table 10 replicates the main results on the upturn-downturn difference of the FPS using the subsample of the years 2000-2012, rather than the whole sample from 1980-2012. The flow-performance relation is steeper in downturns than in upturns also in the latter part of the sample. The importance of establishing robustness with respect to the sample is that the retail versus institutional ownership variable is available only following the fourth quarter of 1999, and imputed for the prior years in the regressions shown in the main paper. This imputation might introduce a selection bias in the regressions on the whole sample. The results in Table 10 show this imputation does not in any way drive our results. In fact, the upturn-downturn difference is larger and more significant using the shorter sample, consistent with the imputation introducing measurement error only but no bias. Table 12 shows the result also obtains using the shorter sample and using a piecewise-linear specification, which is the standard in the literature to capture the convexity of the flow-performance relation.

Table 11 replicates the FPS double-difference between upturns and downturns and *Concentrated* versus *Other* funds on the shorter sample. The results are stronger than with the longer sample, consistent with the imputation introducing measurement error only, but no bias.

Table 14 shows by the example of young versus old funds that the double-difference result is robust to using measures of dispersion of beliefs other than *Concentrated* and *Other*. The prior literature has used young funds as examples of funds with more widely dispersed beliefs. We show in Table 13 that this is indeed the case. Young funds should therefore have a higher FPS difference between upturns and downturns than old funds, as documented in Table 14.

The last two tables show that the FPS results are robust to the choice of sampling frequency. Although our main results are based on quarterly frequencies to be consistent with the existing literature, we show here that the results also obtain at the monthly frequency. Table 15 replicates the qualitative results from Table 10 at the monthly frequency, whereas Table 16 replicates the results from Table 12 at the monthly frequency.

# 6 Conclusion

We provide a model of capital allocation to projects by Bayesian investors who are uncertain about the projects' risk loadings. We cast the interpretation of the model within the framework of flows to mutual funds and show that it explains empirical key regularities that existing models leave unexplained. In particular, we predict and find a pronounced nonlinear and non-monotonic relationship between the flow-performance sensitivity and the state of the market. The model makes additional predictions that we verify empirically. First, investors reallocate less capital across funds following extreme market realizations compared to times following moderate market realizations. Second, the flow-performance relation is steeper following market downturns than following market upturns. Third, the difference between downturns and upturns is larger for funds about whose risk loadings investors are more uncertain.

We view our results as providing a rational formalization for the Schumpeterian intuition that downturns can have a cleansing effect on the economy in the sense of increasing the speed of cross-sectional capital reallocation. In particular, we show that no behavioral or other frictions are necessary, but that Bayesian learning about uncertain parameters is sufficient to generate an asymmetry between upturns and downturns with respect to investors' ability to identify better projects.

# Appendix

It is useful to derive an additional lemma before proving Lemma 1.

**Lemma 3.** *Based on current beliefs, investors value each dollar invested in the fund according to*

$$p_t^i = 1 + \hat{\alpha}_t^i - \frac{1}{\eta} S_t^i. \tag{13}$$

## Proof of Lemma 3 (Fund Value)

Recall that $f_t$ is the traded risk factor in mutual fund returns, and it is an excess return. Based on standard results in asset pricing (e.g., Cochrane (2001)), the factor $f$ can be priced using investors' stochastic discount factor $m_{t+1}$:

$$E_t \left[ m_{t+1} f_{t+1} \right] = 0.$$

It follows that the factor expected return $\bar{f}$ coincides with its risk premium:

$$\begin{aligned} \bar{f} &= -Cov \left[ m_{t+1}, \xi_{t+1} \right] \\ &= -E_t \left[ m_{t+1} \xi_{t+1} \right]. \end{aligned} \tag{14}$$

We assume this risk premium to be positive: $\bar{f} > 0$; that is, $\xi_{t+1}$ covaries positively with the stochastic discount factor. This assumption is discussed in section 3.2.

The cash flows from fund $i$ are valued according to

$$
\begin{aligned}
{p^i}_t &= E_t\left[m_{t+1}Y^i_{t+1}\right] \\
&= E_t\left[m_{t+1}\left(1+\alpha^i+\beta^i\left(\bar{f}+\xi_{t+1}\right)-\frac{1}{\eta}S^i_t+\varepsilon^i_{t+1}\right)\right] \\
&= 1+\hat{\alpha}^i_t+\hat{\beta}^i_t\bar{f}+\hat{\beta}^i_t E_t\left[m_{t+1}\xi_{t+1}\right]-\frac{1}{\eta}S^i_t \\
&= 1+\hat{\alpha}^i_t-\frac{1}{\eta}S^i_t,
\end{aligned}
$$

where $\hat{\alpha}^i_t$ and $\hat{\beta}^i_t$ are the time-$t$ beliefs for $\alpha^i$ and $\beta^i$. The last step follows from equation (14).

□

## Proof of Lemma 1 (Fund Size)

The equilibrium condition is that the value from the last dollar invested in each project must be equal to the value invested in the risk-free asset. Because the risk-free rate is normalized to zero, the value of a dollar invested in each fund $i$ must be one dollar. Combining this equilibrium condition with lemma 3, $p^i_t = 1+\hat{\alpha}^i_t-\frac{1}{\eta}S^i_t = 1$ immediately yields the result.

□

## Proof of Lemma 2 (Fund Flows)

Given our assumptions of normality, the beliefs about fund returns, conditional on the market shock $\xi_t$, are normally distributed. As a result, the standard formulas for Bayesian updating of beliefs apply. Bayesian updating occurs according to

$$
\hat{\alpha}^i_t = \hat{\alpha}^i_{t-1} + cov\left[\alpha, Y^i_t|\xi_t\right]\frac{(Y^i_t - E[Y^i_t])}{var[Y^i_t|\xi_t]}
$$

with

$$var[Y_t^i|\xi_t] = \sigma_\alpha^2 + \sigma_\beta^2(\bar{f} + \xi_t)^2 + \sigma_\varepsilon^2,$$

$$cov\left[\alpha, Y_t^i|\xi_t\right] = \sigma_\alpha^2.$$

The updating formula essentially replicates investors' learning from past performance, that is, regressing alpha on innovations in returns. Next, recall from the previous lemma that

$$S_t^i = \eta \cdot \hat{\alpha}_t^i.$$

Flows, or changes in fund size, are then implied by how much is learned about alpha:

$$\begin{aligned} S_t^i - S_{t-1}^i &= \eta \cdot (\hat{\alpha}_t^i - \hat{\alpha}_{t-1}^i) \\ &= \eta \cdot cov\left[\alpha, Y_t^i|\xi_t\right] \frac{(Y_t^i - E[Y_t^i])}{var[Y_t^i|\xi_t]} \\ &= \eta \cdot \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\beta^2\left(\bar{f} + \xi_t\right)^2 + \sigma_\varepsilon^2} \cdot \left(Y_t^i - E[Y_t^i]\right), \end{aligned}$$

which yields the desired expression for $\lambda(\xi_t)$. □

## Proof of Proposition 2

Note that $var[Y_t^i|\xi_t]$ from the previous lemma is larger in downturns than in upturns of equal magnitude. To be precise, we wish to prove

$$\lambda(\xi_t = -x) > \lambda(\xi_t = +x) \tag{15}$$

for any $x > 0$, where $\lambda(\xi_t) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\beta^2 \left(\bar{f} + \xi_t\right)^2 + \sigma_\varepsilon^2}$. By simply replacing $x$ for $\xi$ into the expression for $\lambda$, one needs to prove

$$\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\beta^2 \left(\bar{f} - x\right)^2 + \sigma_\varepsilon^2} > \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\beta^2 \left(\bar{f} + x\right)^2 + \sigma_\varepsilon^2},$$

which simplifies to

$$\left(\bar{f} + x\right)^2 > \left(\bar{f} - x\right)^2$$

or, computing the squares,

$$\bar{f}^2 + 2x\bar{f} + x^2 > \bar{f}^2 - 2x\bar{f} + x^2$$

and, after simplifications, one obtains

$$x > -x,$$

which is verified because $x > 0$ by assumption.

□

## Proof of Proposition 3

We wish to show $\lambda_{Concentrated} > \lambda_{Other}$ when

$$\bar{\sigma}^2_{a,Concentrated} = k \cdot \bar{\sigma}^2_{a,Other}$$

and

$$\bar{\sigma}^2_{a,Concentrated} = k \cdot \bar{\sigma}^2_{a,Other}$$

with $k > 1$. Plugging equations (7) and (8) into expression (6) yields

$$\begin{aligned}
\lambda_{Concentrated} &= \frac{\sigma^2_{\alpha,Concentrated}}{\sigma^2_{\alpha,Concentrated} + \sigma^2_{\beta,Concentrated}\left(\bar{f} + \xi_t\right)^2 + \sigma^2_{\varepsilon}} \\
&= \frac{k\sigma^2_{\alpha,Other}}{k\sigma^2_{\alpha,Other} + k\sigma^2_{\beta,Other}\left(\bar{f} + \xi_t\right)^2 + k\frac{\sigma^2_{\varepsilon}}{k}} \\
&= \frac{\sigma^2_{\alpha,Other}}{\sigma^2_{\alpha,Other} + \sigma^2_{\beta,Other}\left(\bar{f} + \xi_t\right)^2 + \frac{\sigma^2_{\varepsilon}}{k}} \\
&> \frac{\sigma^2_{\alpha,Other}}{\sigma^2_{\alpha,Other} + \sigma^2_{\beta,Other}\left(\bar{f} + \xi_t\right)^2 + \sigma^2_{\varepsilon}} \\
&= \lambda_{Other}.
\end{aligned}$$

□

## Proof of Proposition 4

Using the expression $\lambda(\xi_t) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2+\sigma_\beta^2\left(\bar{f}+\xi_t\right)^2+\sigma_\varepsilon^2}$ and assuming symmetric values for upturns and downturns of absolute magnitude $x > 0$, we can write

$$\begin{aligned}
\lambda_{DT} - \lambda_{UT} &= \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\beta^2\left(\bar{f}-x\right)^2 + \sigma_\varepsilon^2} - \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\beta^2\left(\bar{f}+x\right)^2 + \sigma_\varepsilon^2} \\
&= \frac{4\sigma_\alpha^2\sigma_\beta^2\bar{f}x}{\left(\sigma_\alpha^2 + \sigma_\beta^2\left(\bar{f}+x\right)^2 + \sigma_\varepsilon^2\right)\left(\sigma_\alpha^2 + \sigma_\beta^2\left(\bar{f}-x\right)^2 + \sigma_\varepsilon^2\right)} \\
&= \frac{4\sigma_\alpha^2\sigma_\beta^2\bar{f}x}{\left(\sigma_\alpha^2 + \sigma_\beta^2\bar{f}^2 + \sigma_\beta^2 x^2 + \sigma_\varepsilon^2\right)^2 - 4\sigma_\beta^4 x^2\bar{f}^2}.
\end{aligned}$$

Using (7) and (8), when $k > 1$, we have

$$\begin{aligned}
&(\lambda_{DT} - \lambda_{UT})_{Conc} = \\
&= \frac{4\sigma_{\alpha,Conc}^2\sigma_{\beta,Conc}^2 x}{\left(\sigma_{\alpha,Conc}^2 + \sigma_{\beta,Conc}^2\bar{f}^2 + \sigma_{\beta,Conc}^2 x^2 + \sigma_\varepsilon^2\right)^2 - 4\sigma_{\beta,Conc}^4 x^2\bar{f}^2} \\
&= \frac{4k^2\sigma_{\alpha,Other}^2\sigma_{\beta,Other}^2\bar{f}x}{k^2\left[\left(\sigma_{\alpha,Other}^2 + \sigma_{\beta,Other}^2\bar{f}^2 + \sigma_{\beta,Other}^2 x^2 + \frac{\sigma_\varepsilon^2}{k}\right)^2 - 4\sigma_{\beta,Other}^4 x^2\bar{f}^2\right]} \\
&= \frac{4\sigma_{\alpha,Other}^2\sigma_{\beta,Other}^2\bar{f}x}{\left(\sigma_{\alpha,Other}^2 + \sigma_{\beta,Other}^2\bar{f}^2 + \sigma_{\beta,Other}^2 x^2 + \frac{\sigma_\varepsilon^2}{k}\right)^2 - 4\sigma_{\beta,Other}^4 x^2\bar{f}^2} \\
&> \frac{4\sigma_{\alpha,Other}^2\sigma_{\beta,Other}^2\bar{f}x}{\left(\sigma_{\alpha,Other}^2 + \sigma_{\beta,Other}^2\bar{f}^2 + \sigma_{\beta,Other}^2 x^2 + \sigma_\varepsilon^2\right)^2 - 4\sigma_{\beta,Other}^4 x^2\bar{f}^2} \\
&= (\lambda_{DT} - \lambda_{UT})_{Other}.
\end{aligned}$$

□

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# Figures

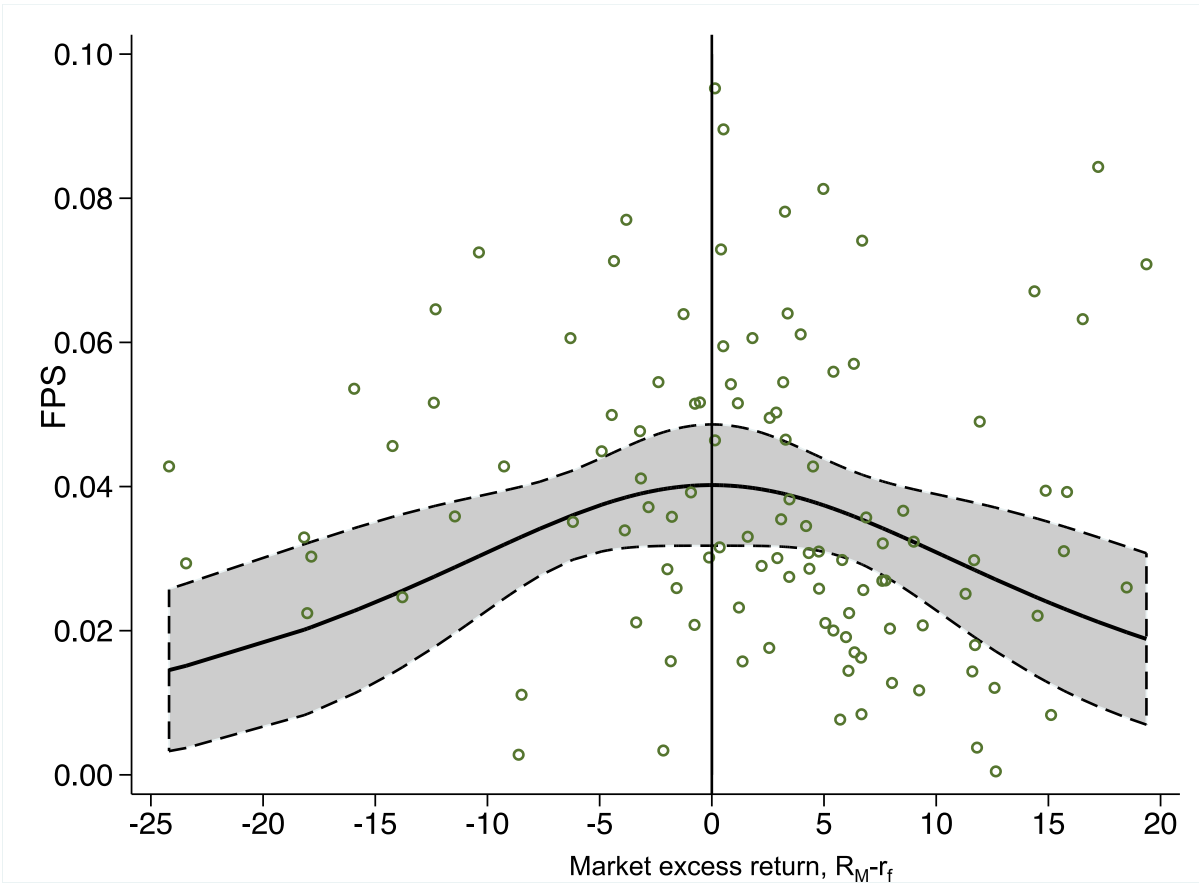


Figure 3: Parametric estimation results from a non-linear least squares regression of estimates of the flow-performance sensitivity on the market return in excess of the risk-free rate, in which the functional form is forced to conform to the specification in equation (6), with 95% confidence intervals.

# Tables

Table 2: Summary Statistics. The table reports summary statistics for the variables that are used in the analysis: the fund's monthly (net) return, assets under management (TNA), the total expense ratio, turnover, return volatility over the prior 12 months, fund age computed as the number of quarters since the first appearance in CRSP, and quarterly flows. The sample ranges from 1980:Q1 to 2012:Q4. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

**Panel A: WHOLE SAMPLE**

| | N | Mean | SD | Min | Median | Max | CORRELATIONS | Ret | TNA | Expense | Turnover | Volatility | Age |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ret | 144,382 | 0.015 | 0.092 | -0.230 | 0.025 | 0.205 | Ret | 1.00 | | | | | |
| TNA | 144,382 | 678 | 3134 | 5 | 82 | 109073 | TNA | 0.01 | 1.00 | | | | |
| Expense ratio | 144,382 | 0.015 | 0.005 | 0.000 | 0.015 | 0.090 | Expense ratio | -0.01 | -0.22 | 1.00 | | | |
| Turnover | 144,382 | 0.8 | 0.8 | 0.0 | 0.6 | 34.5 | Turnover | -0.02 | -0.07 | 0.17 | 1.00 | | |
| Volatility | 144,382 | 0.048 | 0.022 | 0.000 | 0.0457 | 0.338 | Volatility | 0.03 | -0.03 | 0.06 | 0.17 | 1.00 | |
| Age (quarters) | 144,382 | 25.600 | 21.600 | 1.000 | 20.000 | 171.000 | Age (quarters) | 0.05 | 0.12 | -0.17 | -0.04 | 0.01 | 1.00 |
| Flows | 144,382 | -0.002 | 0.085 | -0.171 | -0.018 | 0.415 | Flows | 0.07 | 0.00 | -0.10 | -0.05 | -0.02 | -0.19 |

**Panel B: UPTURNS**

| | N | Mean | SD | Min | Median | Max | CORRELATIONS | Ret | TNA | Expense | Turnover | Volatility | Age |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ret | 30,850 | 0.120 | 0.042 | -0.187 | 0.121 | 0.205 | Ret | 1.00 | | | | | |
| TNA | 30,850 | 642 | 2899 | 5 | 80 | 105939 | TNA | 0.00 | 1.00 | | | | |
| Expense ratio | 30,850 | 0.015 | 0.005 | 0.000 | 0.015 | 0.089 | Expense ratio | -0.02 | -0.22 | 1.00 | | | |
| Turnover | 30,850 | 0.824 | 0.790 | 0.000 | 0.630 | 24.000 | Turnover | -0.03 | -0.07 | 0.18 | 1.00 | | |
| Volatility | 30,850 | 0.1 | 0.0 | 0.0 | 0.1 | 0.3 | Volatility | 0.49 | -0.03 | 0.04 | 0.11 | 1.00 | |
| Age (quarters) | 30,850 | 27.400 | 22.500 | 1.000 | 21 | 169 | Age (quarters) | 0.11 | 0.12 | -0.17 | -0.05 | 0.11 | 1.00 |
| Flows | 30,850 | -0.003 | 0.086 | -0.171 | -0.020 | 0.415 | Flows | 0.04 | 0.00 | -0.09 | -0.08 | -0.11 | -0.18 |

**Panel C: DOWNTURNS**

| | N | Mean | SD | Min | Median | Max | CORRELATIONS | Ret | TNA | Expense | Turnover | Volatility | Age |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ret | 35,758 | -0.100 | 0.068 | -0.230 | -0.103 | 0.177 | Ret | 1.00 | | | | | |
| TNA | 35,758 | 654 | 3086 | 5 | 75 | 104718 | TNA | 0.03 | 1.00 | | | | |
| Expense ratio | 35,758 | 0.015 | 0.005 | 0.000 | 0.015 | 0.090 | Expense ratio | -0.02 | -0.22 | 1.00 | | | |
| Turnover | 35,758 | 0.849 | 0.810 | 0.000 | 0.660 | 34.500 | Turnover | -0.07 | -0.07 | 0.17 | 1.00 | | |
| Volatility | 35,758 | 0.1 | 0.0 | 0.0 | 0.0 | 0.3 | Volatility | -0.38 | -0.03 | 0.10 | 0.22 | 1.00 | |
| Age (quarters) | 35,758 | 24.200 | 21.300 | 1.000 | 18 | 167 | Age (quarters) | -0.03 | 0.11 | -0.16 | -0.05 | -0.10 | 1.00 |
| Flows | 35,758 | -0.006 | 0.079 | -0.171 | -0.020 | 0.414 | Flows | 0.12 | 0.00 | -0.08 | -0.02 | 0.02 | -0.21 |

Table 3: Summary statistics of estimated alphas and risk factor loadings by fund type. For each fund, a risk model (either a market model or a four-factor Carhart (1997) model) is estimated using the entire history of monthly returns. The table reports the F-test for the null hypothesis of equal standard deviations between subsamples of funds by fund type.

**Panel A: MARKET MODEL**

| | Concentrated | | Others | | F-test (St. Dev.) |
|---|---|---|---|---|---|
| | Mean | St. Dev. | Mean | St. Dev. | p-value |
| Alpha | 0.0009 | 0.0045 | -0.0003 | 0.0039 | 0.0000 |
| Beta | 1.0823 | 0.2479 | 1.0044 | 0.2037 | 0.0000 |

**Panel B: CARHART MODEL**

| | Concentrated | | Others | | F-test (St. Dev.) |
|---|---|---|---|---|---|
| | Mean | St. Dev. | Mean | St. Dev. | p-value |
| Alpha | -0.0005 | 0.0035 | -0.0009 | 0.0029 | 0.0000 |
| Mkt - Rf | 1.0376 | 0.1706 | 1.0012 | 0.1335 | 0.0000 |
| HML | 0.0440 | 0.3660 | 0.0518 | 0.3226 | 0.0000 |
| SMB | 0.4223 | 0.3245 | 0.1533 | 0.3253 | -0.9490 |
| UMD | 0.0401 | 0.1652 | 0.0151 | 0.1246 | 0.0000 |

Table 4: Non-linear estimation results. The table reports pararmeter estimates of the parameters in equation (6) from a non-linear least squares regression of the estimates of the flow-performance sensitivity on the market return in excess of the risk-free rate. T-statistics are reported in parentheses which are based on robust standard errors. The sample ranges from 1980:Q1 to 2012:Q4.

| | $\sigma_\beta/\sigma_\alpha$ | $\sigma_\varepsilon/\sigma_\alpha$ |
|---|---|---|
| Estimate | 27.401*** | 4.886*** |
| t-stat | (3.107) | (17.978) |
| Observations | 131 | |
| R-squared | 0.500 | |

Table 5: Flow-Performance Sensitivity Extreme versus Moderate Realizations Results. The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance (frank_style) and controls. T-statistics are reported in parentheses. At the bottom of the table, we report the test statistic and p-value (assuming normality) for the test of the null hypothesis that the difference between extremes and normal times in the slopes on frank_style is zero. The sample ranges from 1980:Q1 to 2012:Q4. Extremes are defined as periods with either below -5% or above 5% market excess returns (CRSP value-weighted index). Moderate states are periods with market excess returns above -5% but below 5%.

| Flows (t+1) | All quarters | Extreme | Moderate | All quarters | Extreme | Moderate |
|---|---|---|---|---|---|---|
| frank_style | 0.043*** | 0.029*** | 0.058*** | 0.034*** | 0.027*** | 0.043*** |
| | (12.188) | (5.832) | (14.793) | (11.236) | (6.472) | (10.116) |
| flows_style | | | | 0.207* | 0.060 | 0.382*** |
| | | | | (1.675) | (0.273) | (5.204) |
| fee | | | | -0.257 | -0.287 | -0.221 |
| | | | | (-1.037) | (-0.756) | (-0.726) |
| logsize | | | | -0.001 | -0.001 | -0.001 |
| | | | | (-1.298) | (-0.923) | (-0.910) |
| turn_ratio | | | | -0.003** | -0.003* | -0.002 |
| | | | | (-2.145) | (-1.679) | (-1.354) |
| vol | | | | 0.027 | -0.123 | 0.203 |
| | | | | (0.288) | (-1.014) | (1.457) |
| logage | | | | -0.008*** | -0.010*** | -0.006** |
| | | | | (-3.772) | (-2.912) | (-2.416) |
| flows | | | | 0.501*** | 0.497*** | 0.505*** |
| | | | | (25.612) | (16.817) | (20.418) |
| Constant | -0.016*** | -0.012*** | -0.020*** | 0.025** | 0.043*** | 0.005 |
| | (-6.385) | (-3.662) | (-5.509) | (2.407) | (2.777) | (0.342) |
| Observations | 144,382 | 77,856 | 66,526 | 144,382 | 77,856 | 66,526 |
| R-squared | 0.044 | 0.033 | 0.057 | 0.435 | 0.428 | 0.444 |
| Number of groups | 131 | 71 | 60 | 131 | 71 | 60 |
| z-stat | | 4.518 | | | 2.596 | |
| p-val | | 6.24e-06 | | | 0.00944 | |

Table 6: Flow-Performance Sensitivity Upturn-Downturn Results. The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance (frank_style) and controls. T-statistics are reported in parentheses. At the bottom of the table, we report the test statistic and p-value (assuming normality) for the test of the null hypothesis that the difference between downturns and upturns in the slopes on frank_style is zero. The sample ranges from 1980:Q1 to 2012:Q4. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

| Flows (t+1) | Upturns | Downturns | Upturns | Downturns |
|---|---|---|---|---|
| frank_style | 0.021*** | 0.051*** | 0.020*** | 0.045*** |
| | (2.771) | (6.178) | (3.489) | (5.551) |
| flows_style | | | -0.281 | 0.295*** |
| | | | (-0.596) | (3.116) |
| fee | | | 0.116 | -0.155 |
| | | | (0.191) | (-0.332) |
| logsize | | | -0.001 | 0.001 |
| | | | (-0.942) | (0.765) |
| turn_ratio | | | -0.009*** | -0.000 |
| | | | (-2.881) | (-0.087) |
| vol | | | -0.326* | 0.410* |
| | | | (-1.801) | (1.704) |
| logage | | | -0.015*** | -0.024*** |
| | | | (-2.819) | (-2.766) |
| flows | | | 0.530*** | 0.464*** |
| | | | (12.816) | (8.853) |
| Constant | -0.002 | -0.023*** | 0.079*** | 0.055* |
| | (-0.452) | (-4.742) | (3.447) | (1.778) |
| Observations | 30,850 | 35,758 | 30,850 | 35,758 |
| R-squared | 0.027 | 0.058 | 0.467 | 0.397 |
| Number of groups | 32 | 30 | 32 | 30 |
| z-stat | 2.623 | | 2.564 | |
| p-val | 0.00872 | | 0.0103 | |

Table 7: Flow-Performance Sensitivity Double-Difference Results. The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance (frank_style) and controls. The rank variable is interacted with a dummy variable denoting "Concentrated" funds, which are the funds with above-median levels of active share and tracking error. T-statistics are reported in parentheses. At the bottom of the table, we report the test statistic and p-value (assuming normality) for the test of the null hypothesis that the difference between downturns and upturns in the slope on frank_style×concentrated is zero. The sample ranges from 1980:Q1 to 2009:Q3. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

| | Panel A: No controls | | | Panel B: With controls | | |
|---|---|---|---|---|---|---|
| Flows (t+1) | All quarters | UT | DT | All quarters | UT | DT |
| frank_style × concentr. | 0.022** | -0.036 | 0.075*** | 0.015 | -0.023 | 0.063** |
| | (2.015) | (-1.449) | (2.833) | (1.334) | (-0.872) | (2.321) |
| frank_style | 0.050*** | 0.041*** | 0.045*** | 0.039*** | 0.032* | 0.034*** |
| | (9.173) | (2.974) | (3.632) | (7.330) | (2.028) | (3.249) |
| concentrated | 0.001 | 0.029 | -0.018* | -0.001 | 0.009 | -0.016 |
| | (0.098) | (1.308) | (-1.837) | (-0.160) | (0.308) | (-1.615) |
| flows_style | | | | 0.248*** | 0.209 | 0.250** |
| | | | | (3.933) | (1.703) | (2.716) |
| fee | | | | 0.602 | 2.449** | 0.092 |
| | | | | (1.351) | (2.260) | (0.087) |
| logsize | | | | -0.001 | -0.000 | -0.000 |
| | | | | (-1.185) | (-0.187) | (-0.026) |
| turn_ratio | | | | -0.003 | -0.017 | 0.006 |
| | | | | (-0.909) | (-1.488) | (1.306) |
| vol | | | | 0.087 | 0.183 | 0.268 |
| | | | | (0.304) | (0.157) | (0.848) |
| logage | | | | -0.023 | -0.071 | -0.009 |
| | | | | (-1.606) | (-1.214) | (-0.587) |
| flows | | | | 0.539*** | 0.523*** | 0.529*** |
| | | | | (16.734) | (9.058) | (5.912) |
| Constant | -0.018*** | -0.008 | -0.020*** | 0.076 | 0.272 | 0.006 |
| | (-6.065) | (-0.965) | (-3.303) | (1.453) | (1.301) | (0.076) |
| Observations | 19,577 | 3,540 | 4,881 | 19,577 | 3,540 | 4,881 |
| R-squared | 0.119 | 0.111 | 0.138 | 0.430 | 0.473 | 0.410 |
| Number of groups | 117 | 27 | 27 | 117 | 27 | 27 |
| p-val | | 0.00219 | | | 0.0232 | |
| z-stat | | 3.063 | | | 2.270 | |

Table 8: Flow-Performance Sensitivity Extreme versus Moderate Realizations Results (Piecewise Linear Specification). The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance and controls. The rank variable is defined to separately capture performance between 0 and 1/3 (trank_style1), between 1/3 and 2/3 (trank_style2), and between 2/3 and the top (trank_style3) of the distribution. T-statistics are reported in parentheses. At the bottom of the table, we report the p-value (assuming normality) for the test of the hypothesis that the differences between downturns and upturns in the slopes on trank_style1, trank_style2, and trank_style3 are jointly zero. The sample ranges from 1980:Q1 to 2012:Q4. Extremes are defined as periods with either below -5% or above 5% market excess returns (CRSP value-weighted index). Moderate states are periods with market excess returns above -5% but below 5%.

| | Panel A: No controls | | | Panel B: With controls | | |
|---|---|---|---|---|---|---|
| Flows (t+1) | All quarters | Extreme | Moderate | All quarters | Extreme | Moderate |
| trank_style1 | 0.042*** | 0.028* | 0.059*** | 0.025** | 0.023 | 0.029** |
| | (4.282) | (1.935) | (4.581) | (2.427) | (1.439) | (2.145) |
| trank_style2 | 0.032*** | 0.027** | 0.039*** | 0.031*** | 0.030* | 0.033** |
| | (3.699) | (2.084) | (3.387) | (3.155) | (1.986) | (2.631) |
| trank_style3 | 0.062*** | 0.037** | 0.092*** | 0.049*** | 0.031** | 0.069*** |
| | (5.929) | (2.566) | (6.352) | (5.046) | (2.221) | (5.550) |
| flows_style | | | | 0.210* | 0.066 | 0.381*** |
| | | | | (1.693) | (0.299) | (5.090) |
| fee | | | | -0.199 | -0.210 | -0.187 |
| | | | | (-0.762) | (-0.552) | (-0.527) |
| logsize | | | | -0.001 | -0.001 | -0.000 |
| | | | | (-1.132) | (-1.250) | (-0.317) |
| turn_ratio | | | | -0.003** | -0.003* | -0.002 |
| | | | | (-2.188) | (-1.698) | (-1.383) |
| vol | | | | 0.012 | -0.124 | 0.173 |
| | | | | (0.119) | (-0.913) | (1.257) |
| logage | | | | -0.009*** | -0.010** | -0.006* |
| | | | | (-2.946) | (-2.330) | (-1.806) |
| flows | | | | 0.501*** | 0.495*** | 0.508*** |
| | | | | (25.118) | (15.808) | (21.942) |
| Constant | -0.015*** | -0.012*** | -0.019*** | 0.029** | 0.046** | 0.007 |
| | (-4.768) | (-2.973) | (-3.754) | (2.242) | (2.484) | (0.450) |
| Observations | 144,382 | 77,856 | 66,526 | 144,382 | 77,856 | 66,526 |
| R-squared | 0.072 | 0.062 | 0.084 | 0.458 | 0.453 | 0.463 |
| Number of groups | 131 | 71 | 60 | 131 | 71 | 60 |
| p-val($\chi^2$) | | 6.31e-05 | | | 0.0255 | |

Table 9: Flow-Performance Sensitivity Upturn-Downturn Results (Piecewise Linear Specification). The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance and controls. The rank variable is defined to separately capture performance between 0 and 1/3 (trank_style1), between 1/3 and 2/3 (trank_style2), and between 2/3 and the top (trank_style3) of the distribution. T-statistics are reported in parentheses. At the bottom of the table, we report the p-value (assuming normality) for the test of the hypothesis that the differences between downturns and upturns in the slopes on trank_style1, trank_style2, and trank_style3 are jointly zero. The sample ranges from 1980:Q1 to 2012:Q4. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

| | Panel A: No controls | | Panel B: With controls | |
|---|---|---|---|---|
| Flows (t+1) | Upturns | Downturns | Upturns | Downturns |
| trank_style1 | 0.005 | 0.040** | 0.020 | 0.033 |
| | (0.189) | (2.486) | (0.748) | (1.219) |
| trank_style2 | 0.037 | 0.049** | 0.025 | 0.047** |
| | (1.481) | (2.591) | (0.876) | (2.315) |
| trank_style3 | 0.011 | 0.066*** | 0.015 | 0.053** |
| | (0.406) | (3.034) | (0.698) | (2.749) |
| flows_style | | | -0.268 | 0.297*** |
| | | | (-0.568) | (3.145) |
| fee | | | 0.242 | -0.132 |
| | | | (0.462) | (-0.201) |
| logsize | | | -0.001 | 0.001 |
| | | | (-1.348) | (1.103) |
| turn_ratio | | | -0.009*** | 0.000 |
| | | | (-3.037) | (0.049) |
| vol | | | -0.375* | 0.367 |
| | | | (-1.832) | (1.461) |
| logage | | | -0.021*** | -0.023** |
| | | | (-3.424) | (-2.711) |
| flows | | | 0.522*** | 0.468*** |
| | | | (11.869) | (8.753) |
| Constant | 0.000 | -0.021*** | 0.103*** | 0.052 |
| | (0.060) | (-3.629) | (4.963) | (1.663) |
| Observations | 30,850 | 35,758 | 30,850 | 35,758 |
| R-squared | 0.068 | 0.086 | 0.501 | 0.424 |
| Number of groups | 32 | 30 | 32 | 30 |
| p-val($\chi^2$) | 0.0348 | | 0.0456 | |

Table 10: Flow-Performance Sensitivity Upturn-Downturn Results: Robustness to Sample Selection. The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance (frank_style) and controls. T-statistics are reported in parentheses. At the bottom of the table, we report the test statistic and p-value (assuming normality) for the test of the null hypothesis that the difference between downturns and upturns in the slopes on frank_style is zero. The sample ranges from 2000:Q1 to 2012:Q4. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

| Flows (t+1) | All quarters | Upturns | Downturns | All quarters | Upturns | Downturns |
|---|---|---|---|---|---|---|
| frank_style | 0.042*** | 0.014** | 0.050*** | 0.031*** | 0.019*** | 0.038*** |
| | (-10.525) | (-2.795) | (-7.726) | (-14.129) | (-6.227) | (-8.875) |
| flows_style | | | | 0.510*** | 0.302** | 0.639*** |
| | | | | (8.018) | (3.111) | (4.206) |
| fee | | | | -1.190*** | -1.222*** | -1.258*** |
| | | | | (-10.258) | (-5.840) | (-3.921) |
| logsize | | | | -0.001*** | -0.000 | -0.001* |
| | | | | (-4.350) | (-0.587) | (-1.815) |
| turn_ratio | | | | -0.002*** | -0.003** | -0.000 |
| | | | | (-3.195) | (-3.049) | (-0.086) |
| vol | | | | -0.066 | -0.387*** | 0.097 |
| | | | | (-1.030) | (-5.720) | (0.677) |
| logage | | | | -0.007*** | -0.008*** | -0.005*** |
| | | | | (-12.026) | (-8.323) | (-7.100) |
| flows | | | | 0.592*** | 0.600*** | 0.588*** |
| | | | | (37.194) | (20.846) | (18.315) |
| Constant | -0.030*** | -0.015*** | -0.035*** | 0.036*** | 0.063*** | 0.021 |
| | (-10.377) | (-3.350) | (-5.309) | (8.258) | (11.588) | (1.759) |
| Observations | 129,482 | 25,941 | 33,832 | 129,482 | 25,941 | 33,832 |
| R-squared | 0.038 | 0.006 | 0.048 | 0.468 | 0.465 | 0.422 |
| Number of groups | 51 | 11 | 14 | 51 | 11 | 14 |
| p-val | | 1.07e-05 | | | 0.000324 | |
| z-stat | | 4.402 | | | 3.595 | |

Table 11: Flow-Performance Sensitivity Double-Difference Results: Robustness to Sample Selection. The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance (frank_style) and controls. The rank variable is interacted with a dummy variable denoting "Concentrated" funds, which are the funds with above-median levels of active share and tracking error. T-statistics are reported in parentheses. At the bottom of the table, we report the test statistic and p-value (assuming normality) for the test of the null hypothesis that the difference between downturns and upturns in the slope on frank_style×concentrated is zero. The sample ranges from 2000:Q1 to 2009:Q3. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

| | Panel A: No controls | | | Panel B: With controls | | |
|---|---|---|---|---|---|---|
| Flows (t+1) | All quarters | UT | DT | All quarters | UT | DT |
| frank_style × concentr. | 0.030*** | 0.006 | 0.041** | 0.017** | -0.012 | 0.028* |
| | (4.058) | (0.388) | (3.006) | (2.470) | (-1.911) | (1.931) |
| frank_style | 0.052*** | 0.031 | 0.050*** | 0.043*** | 0.045*** | 0.048*** |
| | (10.136) | (1.799) | (7.987) | (10.918) | (8.707) | (7.284) |
| concentrated | -0.005 | 0.004 | -0.004 | -0.000 | 0.007* | -0.002 |
| | (-1.181) | (0.370) | (-0.483) | (-0.137) | (2.128) | (-0.217) |
| flows_style | | | | 0.506*** | 0.003 | 0.658*** |
| | | | | (4.326) | (0.008) | (5.772) |
| fee | | | | -0.732** | -0.069 | -0.542 |
| | | | | (-2.200) | (-0.068) | (-0.710) |
| logsize | | | | -0.003*** | -0.003 | -0.002* |
| | | | | (-4.030) | (-1.142) | (-2.025) |
| turn_ratio | | | | -0.002 | -0.002 | 0.001 |
| | | | | (-1.258) | (-0.535) | (0.272) |
| vol | | | | -0.038 | -0.786 | 0.313 |
| | | | | (-0.240) | (-1.858) | (1.028) |
| logage | | | | -0.007*** | -0.010* | -0.003 |
| | | | | (-5.029) | (-2.483) | (-1.373) |
| flows | | | | 0.625*** | 0.633*** | 0.645*** |
| | | | | (21.562) | (11.236) | (11.202) |
| Constant | -0.022*** | 0.000 | -0.025*** | 0.035*** | 0.086** | -0.009 |
| | (-6.452) | (0.052) | (-5.367) | (3.285) | (3.151) | (-0.390) |
| Observations | 13,462 | 1,865 | 4,142 | 13,462 | 1,865 | 4,142 |
| R-squared | 0.054 | 0.021 | 0.054 | 0.318 | 0.334 | 0.276 |
| Number of groups | 38 | 6 | 12 | 38 | 6 | 12 |
| p-val | | 0.102 | | | 0.0114 | |
| z-stat | | 1.634 | | | 2.531 | |

Table 12: Flow-Performance Sensitivity Upturn-Downturn Results (Piecewise Linear Specification): Robustness to Sample Selection. The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance and controls. The rank variable is defined to separately capture performance between 0 and 1/3 (trank_style1), between 1/3 and 2/3 (trank_style2), and between 2/3 and the top (trank_style3) of the distribution. T-statistics are reported in parentheses. At the bottom of the table, we report the p-value (assuming normality) for the test of the hypothesis that the differences between downturns and upturns in the slopes on trank_style1, trank_style2, and trank_style3 are jointly zero. The sample ranges from 2000:Q1 to 2012:Q4. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

| | Panel A: No controls | | | Panel B: With controls | | |
|---|---|---|---|---|---|---|
| Flows (t+1) | All quarters | Upturns | Downturns | All quarters | Upturns | Downturns |
| trank_style1 | 0.046*** | -0.006 | 0.048*** | 0.032*** | 0.013 | 0.038*** |
| | (7.729) | (-0.533) | (6.656) | (8.971) | (1.734) | (5.824) |
| trank_style2 | 0.022*** | 0.016 | 0.022** | 0.014*** | 0.013** | 0.015** |
| | (4.128) | (1.659) | (2.421) | (5.258) | (2.623) | (2.729) |
| trank_style3 | 0.075*** | 0.030*** | 0.108*** | 0.063*** | 0.039*** | 0.082*** |
| | (11.435) | (3.502) | (9.088) | (13.225) | (4.760) | (10.064) |
| flows_style | | | | 0.491*** | 0.295*** | 0.583*** |
| | | | | (8.096) | (3.405) | (4.187) |
| fee | | | | -1.134*** | -1.188*** | -1.172*** |
| | | | | (-10.640) | (-6.385) | (-3.971) |
| logsize | | | | -0.001*** | -0.000 | -0.001 |
| | | | | (-3.772) | (-0.323) | (-1.592) |
| turn_ratio | | | | -0.001*** | -0.002*** | -0.001 |
| | | | | (-3.535) | (-3.260) | (-0.810) |
| vol | | | | -0.084 | -0.420*** | 0.083 |
| | | | | (-1.288) | (-5.922) | (0.563) |
| logage | | | | -0.007*** | -0.008*** | -0.005*** |
| | | | | (-12.176) | (-8.531) | (-6.753) |
| flows | | | | 0.579*** | 0.585*** | 0.576*** |
| | | | | (37.159) | (21.134) | (18.312) |
| Constant | -0.030*** | -0.011** | -0.032*** | 0.037*** | 0.066*** | 0.021* |
| | (-9.430) | (-2.498) | (-4.533) | (8.233) | (11.040) | (1.843) |
| Observations | 129,482 | 25,941 | 33,832 | 129,482 | 25,941 | 33,832 |
| R-squared | 0.041 | 0.008 | 0.053 | 0.466 | 0.462 | 0.421 |
| Number of groups | 51 | 11 | 14 | 51 | 11 | 14 |
| p-val($\chi^2$) | | 1.97e-08 | | | 0.00150 | |

Table 13: Summary statistics of alpha and risk factor loadings by fund type (Old vs. Young). For each fund, a risk model (either market model or four-factor Carhart (1997) model) is estimated using the entire history of monthly returns. The table reports the F-test for the null hypothesis of equal standard deviations between subsamples of funds by fund type.

**Panel A: MARKET MODEL**

| | Old | | Young | | F-test (St. Dev.) |
|---|---|---|---|---|---|
| | Mean | St. Dev. | Mean | St. Dev. | p-value |
| Alpha | -0.0012 | 0.0030 | -0.0008 | 0.0032 | 0.0480 |
| Beta | 1.0619 | 0.2009 | 1.0246 | 0.3187 | 0.0000 |

**Panel B: CARHART MODEL**

| | Old | | Young | | F-test (St. Dev.) |
|---|---|---|---|---|---|
| | Mean | St. Dev. | Mean | St. Dev. | p-value |
| Alpha | -0.0014 | 0.0029 | -0.0013 | 0.0027 | 0.0570 |
| Mkt - Rf | 1.0211 | 0.1233 | 0.9949 | 0.2826 | 0.0000 |
| HML | -0.0405 | 0.3050 | -0.0114 | 0.2998 | 0.6760 |
| SMB | 0.2068 | 0.3351 | 0.1932 | 0.3472 | 0.4420 |
| UMD | 0.0323 | 0.1311 | 0.0042 | 0.1226 | 0.1160 |

Table 14: Flow-Performance Sensitivity Double-Difference Results: Robustness to Sample Split Criteria. The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance (frank_style) and controls. The rank variable is interacted with a dummy variable denoting "young" funds, which are the funds with below-median levels of age. "Old" funds are defined symmetrically. T-statistics are reported in parentheses. At the bottom of the table, we report the test statistic and p-value (assuming normality) for the test of the null hypothesis that the difference between downturns and upturns in the slope on frank_style×young is zero. The sample ranges from 2000:Q1 to 2012:Q4. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

| | Panel A: No controls | | | Panel B: With controls | | |
|---|---|---|---|---|---|---|
| Flows (t+1) | All quarters | UT | DT | All quarters | UT | DT |
| frank_style × young | 0.010*** | -0.005 | 0.014*** | 0.006*** | -0.002 | 0.006* |
| | (3.913) | (-1.233) | (3.908) | (3.704) | (-0.609) | (1.909) |
| frank_style | 0.038*** | 0.017** | 0.044*** | 0.028*** | 0.020*** | 0.036*** |
| | (10.845) | (3.077) | (6.735) | (13.722) | (5.661) | (8.504) |
| Young | 0.023*** | 0.028*** | 0.018*** | -0.000 | 0.003 | -0.000 |
| | (15.257) | (8.323) | (6.502) | (-0.399) | (1.403) | (-0.003) |
| flows_style | | | | 0.510*** | 0.304** | 0.641*** |
| | | | | (8.053) | (3.126) | (4.262) |
| fee | | | | -1.178*** | -1.208*** | -1.244*** |
| | | | | (-10.168) | (-5.760) | (-3.920) |
| logsize | | | | -0.001*** | -0.000 | -0.001* |
| | | | | (-4.173) | (-0.416) | (-1.805) |
| turn_ratio | | | | -0.002*** | -0.003** | -0.000 |
| | | | | (-3.153) | (-3.068) | (-0.078) |
| vol | | | | -0.061 | -0.383*** | 0.101 |
| | | | | (-0.936) | (-5.545) | (0.699) |
| logage | | | | -0.005*** | -0.007*** | -0.004*** |
| | | | | (-8.157) | (-5.624) | (-3.587) |
| flows | | | | 0.591*** | 0.600*** | 0.587*** |
| | | | | (36.996) | (20.867) | (18.135) |
| Constant | -0.040*** | -0.027*** | -0.043*** | 0.031*** | 0.056*** | 0.014 |
| | (-15.279) | (-6.289) | (-7.370) | (6.676) | (9.480) | (1.230) |
| Observations | 129,482 | 25,941 | 33,832 | 129,482 | 25,941 | 33,832 |
| R-squared | 0.074 | 0.035 | 0.079 | 0.469 | 0.466 | 0.422 |
| Number of groups | 51 | 11 | 14 | 51 | 11 | 14 |
| p-val | | 0.000476 | | | 0.063 | |
| z-stat | | 3.494 | | | 1.859 | |

Table 15: Flow-Performance Sensitivity Upturn-Downturn Results: Robustness to Sampling Frequency. The table reports slopes from Fama and MacBeth (1973) regressions of monthly flows on prior-month mutual fund rank by style-adjusted performance (frank_style) and controls. T-statistics are reported in parentheses. At the bottom of the table, we report the test statistic and p-value (assuming normality) for the test of the null hypothesis that the difference between downturns and upturns in the slopes on frank_style is zero. The sample ranges from January 2000 to December 2012. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

| Flows (t+1) | All quarters | Upturns | Downturns | All quarters | Upturns | Downturns |
|---|---|---|---|---|---|---|
| frank_style | 0.009*** | 0.000 | 0.012*** | 0.006*** | 0.003*** | 0.006*** |
| | (8.991) | (0.141) | (5.619) | (18.236) | (4.586) | (9.199) |
| flows_style | | | | 0.323*** | 0.315*** | 0.301*** |
| | | | | (14.251) | (8.712) | (6.172) |
| fee | | | | -0.286*** | -0.184*** | -0.319*** |
| | | | | (-11.239) | (-4.127) | (-4.209) |
| logsize | | | | -0.000** | -0.000 | -0.000** |
| | | | | (-2.525) | (-0.564) | (-2.685) |
| turn_ratio | | | | -0.000*** | -0.001*** | -0.000 |
| | | | | (-3.332) | (-2.910) | (-0.141) |
| vol | | | | -0.034*** | -0.079*** | -0.013 |
| | | | | (-3.236) | (-4.193) | (-0.571) |
| logage | | | | -0.003*** | -0.003*** | -0.002*** |
| | | | | (-22.967) | (-12.643) | (-10.249) |
| flows | | | | 0.606*** | 0.597*** | 0.582*** |
| | | | | (72.923) | (40.362) | (32.706) |
| Constant | -0.005*** | 0.001 | -0.008*** | 0.015*** | 0.017*** | 0.012*** |
| | (-7.705) | (0.646) | (-4.777) | (18.279) | (11.549) | (5.535) |
| Observations | 431,437 | 79,593 | 108,911 | 369,549 | 65,362 | 92,088 |
| R-squared | 0.019 | 0.008 | 0.026 | 0.459 | 0.450 | 0.414 |
| Number of groups | 155 | 30 | 42 | 155 | 30 | 42 |
| p-val | | 3.80e-05 | | | 0.00410 | |
| z-stat | | 4.119 | | | 2.870 | |

Table 16: Flow-Performance Sensitivity Upturn-Downturn Results (Piecewise Linear Specification): Robustnes to Sampling Frequency. The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance and controls. The rank variable is defined to separately capture performance between 0 and 1/3 (trank_style1), between 1/3 and 2/3 (trank_style2), and between 2/3 and the top (trank_style3) of the distribution. T-statistics are reported in parentheses. At the bottom of the table, we report the p-value (assuming normality) for the test of the hypothesis that the differences between downturns and upturns in the slopes on trank_style1, trank_style2, and trank_style3 are jointly zero. The sample ranges from January 2000 to December 2012. Upturns and Downturns are defined, respectively, as the top and bottom 25% of periods according to the distribution of the CRSP value-weighted index in excess of the risk-free rate since July 1926.

| | Panel A: No controls | | | Panel B: With controls | | |
|---|---|---|---|---|---|---|
| Flows (t+1) | All quarters | Upturns | Downturns | All quarters | Upturns | Downturns |
| trank_style1 | 0.010*** | -0.002 | 0.011*** | 0.006*** | 0.001 | 0.007*** |
| | (7.124) | (-0.594) | (3.906) | (8.000) | (0.774) | (3.529) |
| trank_style2 | 0.003*** | -0.002 | 0.005** | 0.001* | 0.001 | 0.000 |
| | (2.656) | (-0.776) | (2.327) | (1.669) | (0.830) | (0.152) |
| trank_style3 | 0.019*** | 0.008*** | 0.025*** | 0.015*** | 0.010*** | 0.018*** |
| | (11.929) | (3.188) | (7.001) | (14.401) | (7.598) | (5.972) |
| flows_style | | | | 0.327*** | 0.320*** | 0.303*** |
| | | | | (14.158) | (8.746) | (6.187) |
| fee | | | | -0.293*** | -0.187*** | -0.332*** |
| | | | | (-11.091) | (-4.167) | (-4.165) |
| logsize | | | | -0.000*** | -0.000 | -0.000*** |
| | | | | (-2.644) | (-0.534) | (-3.137) |
| turn_ratio | | | | -0.000*** | -0.001*** | -0.000 |
| | | | | (-3.542) | (-2.933) | (-0.290) |
| vol | | | | -0.037*** | -0.083*** | -0.010 |
| | | | | (-3.477) | (-4.434) | (-0.434) |
| logage | | | | -0.003*** | -0.003*** | -0.002*** |
| | | | | (-21.741) | (-12.881) | (-7.891) |
| flows | | | | 0.603*** | 0.596*** | 0.575*** |
| | | | | (68.562) | (40.332) | (27.862) |
| Constant | -0.007*** | 0.000 | -0.008*** | 0.015*** | 0.018*** | 0.013*** |
| | (-8.927) | (0.005) | (-5.011) | (18.880) | (11.072) | (5.903) |
| Observations | 369,549 | 65,362 | 92,088 | 369,549 | 65,362 | 92,088 |
| R-squared | 0.024 | 0.011 | 0.036 | 0.461 | 0.451 | 0.418 |
| Number of groups | 155 | 30 | 42 | 155 | 30 | 42 |
| p-val($\chi^2$) | | 9.32e-05 | | | 0.0104 | |