Fund Flows in Rational Markets

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PRELIMINARY. COMMENTS WELCOME.

Abstract

We model the allocation of capital to mutual funds by rational risk-averse investors who are uncertain about both managers' skill and the funds' risk loadings. Uncertainty about risk loadings arises because fund portfolios are not continuously observed. Under these assumptions, investors learn more about alpha in downturns than in upturns. The reason is that, in downturns, the noise coming from the loading on aggregate risk is smaller, which increases the signal-to-noise ratio and thus simplifies the inference about skill. As a result, in downturns investors reallocate more wealth between funds and the flow-performance sensitivity is higher than in upturns. We test the model's cross-sectional and difference-in-difference predictions across fund types and market states, as well as its nonlinear predictions, and find supporting evidence.

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1 Introduction

Economists have long been concerned with the allocation of capital to mutual funds, and specifically with the question of whether mutual fund flows follow rational patterns, for at least three reasons. First, U.S. 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). It could be a major concern from a welfare perspective if irrational forces were driving savings decisions of that magnitude. Second, US mutual funds own a substantial share of financial assets in the economy: the $6 trillion invested in equity mutual funds (end of 2012) correspond to close to one half of US stock market capitalization (ICI, 2012). Given the large share of institutional asset ownership, an efficient allocation of capital to intermediaries seems crucial for efficient pricing of securities and, therefore, for the allocative efficiency in the economy (Shleifer and Vishny, 1997). Third, mutual fund flows directly affect funds' assets under management. Fund flows therefore are at the core of debates about manager compensation, incentives, and their effect on investment policy. For the above reasons, understanding the frictions leading to and possibly impeding fund flows are at the center of evaluating normative prescriptions for the organization of the money management industry.

A considerable body of theoretical literature has developed to explain the observed patterns of fund flows and returns. Famously, 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 process about manager skill. The model explains lack of performance persistence by assuming decreasing returns to scale and rent extraction by skilled managers. 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.

We add to this literature's efforts to build a general theory of rational fund flows. One dimension that has been left unexplored is uncertainty about fund risk loadings. Notably, BG model fund returns in excess of a benchmark, implicitly assuming that benchmark loadings are perfecly observable by investors, or homogeneous across funds, or stable over time. There seem to be good reasons to relax this assumption given that infrequent reporting of holdings combined with portfolio rebalancing and the lack of high frequency fund returns prevent investors from perfectly learning fund betas. Supporting this view, Kacperczyk, Sialm, and Zheng (2008) show that a large amount of portfolio rebalancing between reporting dates is concealed from investors. Also, in contrast to stocks for which quasi-continuous observation of returns allows investors to infer second moments arbitrarily fast (Merton, 1980), mutual fund returns are observed at most daily, which hinder perfect inference of risk loadings. Motivated by these considerations, we study the implications of uncertain risk factor loadings for fund flows.

We develop a rational model of mutual fund flows with no frictions other than parameter uncertainty that predicts variation of the flow-performance sensitivity across market states. In the model, investors rationally learn about manager skill (alpha), but their inference is complicated by uncertainty about risk loadings (betas). Based on these assumptions, we show that investors react more strongly to relative performance in downturns than in upturns. The intuition for this result is simple. In upturns, the informativeness of fund returns about manager skill is dimished because uncertainy about beta constitutes noise that is magnified by the positive realization of the market. In downturns, the noise arising from uncertain betas is dampened by the poor realization of the market. As a result, in bad markets, the signal-to-noise ratio is higher, and the rational investors react more strongly to performance.

This key model prediction about the variation of the sensitivity of flows to performance across states of the economy finds robust support in the data. The FPS is more than twice as high in downturns than in upturns. Table 1 gives a summary of that finding.

Table 1: Summary of the Main Empirical Result. 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 table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund rank by style-adjusted performance. 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 verify our predictions about the variation of the FPS across market states in more detail with a difference-in-differences approach. Specifically, our model correctly predicts the difference-in-differences for the FPS between upturns and downturns and across fund types, which helps eliminate endogeneity concerns that are present in estimations of the time-series prediction alone. In particular, our estimates of the upturn-downturn FPS-difference might be driven by the allocation of new capital that flows into the sector in upturn and flows out of the sector in downturns, rather than by the re-allocation of capital within the sector, or it might be that investors are less scrupulous in their investment decisions in upturns than in downturns for behavioral reasons. The double-difference approach distinguishes these alternative explanations from our theory of rational learning. 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 small, young, have a new manager, 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, is the prediction that these cross-sectional differences vary across states of the economy: funds that have a steeper unconditional FPS (funds associated with less precise prior beliefs) are predicted to have a higher FPS-difference between upturns and downturns. Such predictions for cross-sectional differences in the time variation of the FPS cannot be easily generated with inflows into the sector as a whole. Similarly, behavioral theories that might have the potential to explain the upturn-downturn difference do not easily explain the cross-sectional differences in the upturn-downturn difference at the same time.

Both the time-series and difference-in-differences predictions for the FPS are borne out in the data as well. We empirically proxy for investors' dispersion in beliefs using measures of active share and tracking error that are drawn from Cremers and Petajisto (2009). In particular, we take what these authors call "Concentrated funds," that is, those ranking high by both active share and tracking error, as examples of funds for which investors have less precise prior beliefs. (Similar results obtain for young funds, funds with managers with low tenure, etc. .) Figure 1 illustrates the empirical results comparing the FPS of Concentrated funds to all other funds in different states of the economy. As predicted by the model, the flow-performance relation of Concentrated funds is steeper on average, and the difference of slopes across downturns and upturns is larger, compared to other funds. This difference-in-differences is highly 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

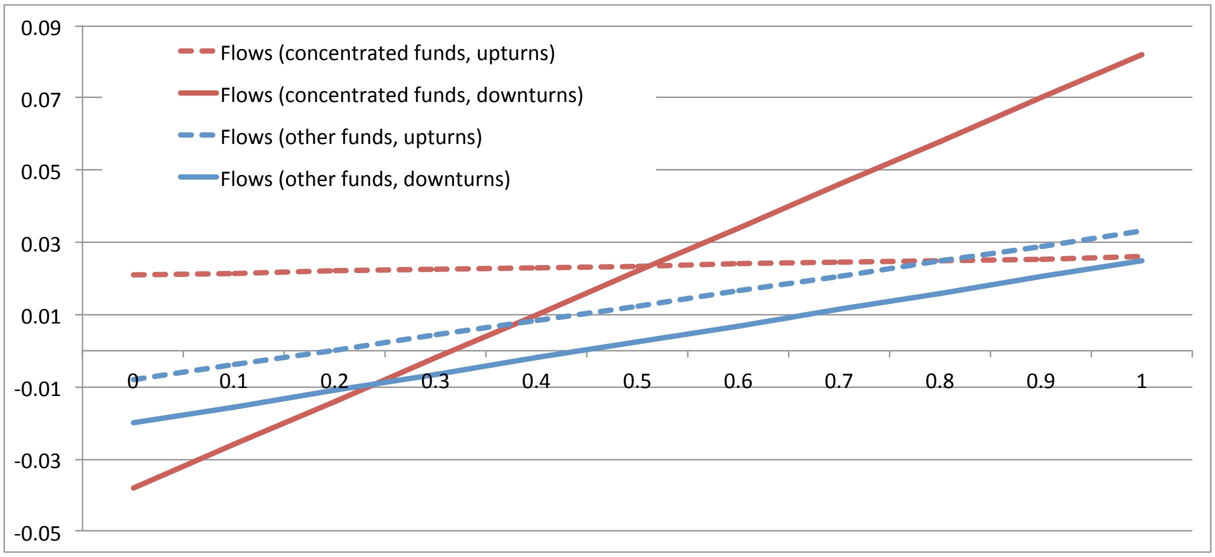

Figure 1: Flow-performance relation in upturns and downturns for "Concentrated funds" and all other funds (difference-in-differences results). The horizontal axis is the fractional rank of fund i in period t with respect to funds in the same style category. On the vertical axes are percentage flows into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

combined with participation costs, which generate convexity (Huang, Wei, and Yan, 2007), and our empirical results hold in both linear and convex specifications.

Finally, we provide parametric and non-parametric nonlinear estimation results that establish an even closer link between the model predictions and the data. Aside from providing a more direct validation of the theoretical predictions, these results also help rule out alternative theories that could potentially predict similar cross-sectional and time-series patterns of the flow-performance sensitivity as our model and that linear estimation approaches could potentially not reject.

The paper proceeds as follows. Section 2 describes the relation of our model and empirical results to the existing 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

We first describe the relation of our model to the existing theoretical literature and, in particular, to the benchmark model of BG. Then, we describe the differences from the prior literature that concern both our theory and empirical results. Finally, we focus on the unique aspects of our empirical methodology and results.

Similar to BG, our model features: investors that provide capital to 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. A key difference from BG is that we allow for heterogeneous exposure of funds to time-varying benchmark returns and uncertainty of investors' about that risk loading. Moreover, we model investors who explicitly maximize a risk averse utility function rather than expected returns over a risk-adjusted benchmark.

Aside from risk aversion, the key new assumption of our model is that investors do not have perfect knowledge about the extent to which funds' cash flows load on the market return, i.e. systematic risk. This assumption may seem counterintuitive at first, as it is well-known that second moments can be learned arbitrarily fast when returns are continuously observed (Merton, 1980). However, estimating performance parameters of mutual funds is necessarily less precise because fund returns are not continuously observed and cannot be easily constructed as the portfolio is often rebalanced (Kacperczyk, Sialm, and Zheng, 2008). Thus, while our model makes useful predictions about asymmetries in mutual fund flows, a similar asymmetry should not be expected to hold for learning about stock returns.

In an effort to focus on the model's new predictions, we draw tighter boundaries than BG along a few dimensions. 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 and exit from the mutual fund sector (Berk and Green, 2004). Given little evidence of capital withdrawals from the sector in downturns (Lubos Pastor and Taylor, 2013) and our identification efforts, we think that withdrawals and additions to the sector will have but 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 flow-performance sensitivity in an economy in which Bayesian and performance-chasing investors coexist. Like these authors, we exploit heterogeneity in prior uncertainty across funds to identify our model. However, our model relies on rational investors alone and focuses on the implications of risk aversion and parameter uncertainty on the dependence of the flow-performance relation on 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 multiple signals are proxied by fund ranking over different horizons. 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 uncertaintly is likely higher.

While 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 is assumed to be a known constant in our model. Their model explains the size of the actively managed fund industry, while ours focuses on cross-sectional and time-series differences in the sensitivity of investor flows to fund returns.[1]

[1]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

We model investor behavior in response to mutual fund performance in a given state of the economy, taking funds' performance parameters as given. In principle, the theoretical results obtain with any model of how assets are priced in the economy. Hence, the model does not take a stance on which asset pricing model fund managers use, 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 whether they are endowed with them, as our model assumes.[2] 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, is twice as steep in downturns than in upturns.

value premium under specific conditions on the learning process.

[2]A further distinction from Kacperczyk, Nieuwerburgh, and Veldkamp (2012) is that there is no asymmetric information in our model and that 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 there is no asymmetry in the model parameters.

3 Model

This section provides a rational model featuring Bayesian learning by mutual fund investors about managers' skill, which allows for uncertainty in factor loadings. We draw inspiration from Schmalz and Zhuk (2013) who model learning about the value of assets from cash flow news. Aside from Bayesian learning, the model does not feature any frictions such as liquidity constraints or limited rationality of investors. Compared to BG, the crucial difference is that we explicitly allow for time-varying benchmark returns, heterogeneous exposure of funds' returns to that benchmark, and risk-averse investors who dislike such exposure to systematic risk over and above what they get compensated for. Technically, this introduces a second parameter in investors' inference problem compared to BG.

3.1 Setup

There is a large number of funds, $i = 1, 2, ..., N$. The cash that fund i returns at time t from every dollar invested at time $t-1$ is denoted Y_t^i. While the true return process may have different drivers, the returns can be decomposed as

$$Y_t^i = 1 + \alpha^i + \beta^i (\phi + \xi_t) - \frac{1}{\eta} S_{t-1}^i + \varepsilon_t^i \tag{1}$$

where $\varepsilon_t^i \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ are idiosyncratic shocks; 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 $\frac{1}{\eta}$ indicates decreasing returns to scale; ξ_t is a market-wide shock or risk factor with zero expected value that is normally distributed and *iid* over time, $\xi_t \sim \mathcal{N}(0, \sigma_\xi^2)$; and β^i is a fund-specific, time-fixed correlation with the risk factor; ϕ is the compensation for systematic risk exposure[3]; α^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. The risk-free rate is assumed to be zero without loss of generality. Investors are uncertain about the precise value of both α^i and β^i, but they know both parameters are sampled from a jointly Normal distribution with known mean, variance, and covariance that is identical for all funds of a given category

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

While investors are not sure about the precise values of fund-level alphas and betas, we require that their prior beliefs have to be consistent with the true distribution of parameters in the cross section given by equation (2). (Time subscripts are ommitted.) A further discussion of the above assumptions follows.

3.2 Discussion

While not necessary for the model predictions, it can be assumed that $\bar{\beta} = 1$. What is necessary is that the market risk premium is positive, which obtains as long as risk-averse investors as a group are exposed to market risk. While it is necessary that there is a compensation ϕ for taking systematic risk ξ_t, it is not assumed that the CAPM is used or holds. Relatedly, we do not require that investors cannot short the market or undo their risk exposure. It is only required that they cannot do so at zero cost, which is satisfied as long as the risk premium is positive.

While the model can easily be solved allowing for non-zero correlations between α and β,

[3] We implictly assume that the risk premium in the asset market is the same as in the market for mutual funds capital. This assumption is not necessary but dramatically simplifies the exposition. The general case of the model with no assumptions about the risk premium in the asset market is available on request.

this generalization unnecessarily complicates the model. We will thus assume that $\sigma_{\alpha\beta} = 0$. Also, while the parameters may be the outcome of a game between managers and investors, here we assume that fund investors take both α^i and β^i as exogenous.

α^i can be interpreted as either stock picking skill or market timing skill. The stock picking interpretation is straightforward. To gain intuition on market timing, one can assume for a moment that the β^i of manager i, is allowed to vary over time in a systematic fashion, while the manager has no stock picking skill. In particular, suppose β_t^i is always positive in upturns (when $\xi_t > 0$) and always negative in downturns (when $\xi_t < 0$) . This manager generates high average returns Y_t^i with zero market correlation. To an investor running the regression (1) that constrains market exposure to be time-fixed β^i, this manager appears to have high static α^i and zero static β^i. To the investor, this manager's performance is therefore observationally equivalent, and equally valuable, to the performance of a manager without timing ability but with stock picking skill. In fact the investor is indifferent to how the manager generates returns. The investor merely evaluates cash flows which are appropriately weighted by her marginal utility in the state of the world in which the cash flow occurs. This example illustrates that the investor can be assumed to remain ignorant about the particular sources of skill of the manager. In sum, equation (1) is not necessarily the true cash flow process of funds, nor do investors need to believe that 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.

While the model is generally compatible with any strategy managers may employ to generate returns, including stock picking and market timing, it is of course possible to construct cases in which the assumption of normality of the parameter distributions is violated. For example, if managers systematically have skill only in particular states of the economy, investors could not reasonably believe that 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, i.e., a negatively skewed ξ_t, or increased risk aversion in downturns, would presumably strengthen the predictions. Of course, analytical solutions would be difficult or impossible to obtain for such cases.

3.3 Timing

The investor holds 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 α^i and β^i according to equation (2). Returns Y^i_t are realized and observed by investors, from which they can infer ξ_t. Conditioning on ξ_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 between-fund-flows. Relating these flows to performance Y^i_t yields the flow-performance sensitivity.

3.4 Equilibrium

We model mutual fund investors as overlapping generations of groups of investors with identical, risk-averse preferences.[4] Further, there is a risk-free asset that returns $R = 1 + r$. Without loss of generality, we set the risk-free rate to zero, $r = 0$. Equalizing the investors' marginal expected utility across funds yields the equilibrium fund size.

[4]Assuming an OLG economy is not necessary. Schmalz and Zhuk (2013) show that an equivalent result obtains when an infinite-horizon representative investor with CARA utility is assumed. Here we assume the OLG agent to stress that the results do not depend on a specific utility function, but only require risk aversion, and because the algebra is simpler.

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

$$S_t^i = \eta \cdot \hat{\alpha}_t^i. \tag{3}$$

All proofs are in the appendix. The intuition of the lemma is straightforward. Investors determine allocations to funds so that the expected utility of a marginal dollar in each fund equals the outside option of zero. In doing that, the value of expected fund returns, $1 + \alpha^i + \phi\beta^i - \frac{1}{\eta}S_t^i$, is adjusted for the fund's sensitivity to the risk factor, β^i, multiplied by the factor risk premium ϕ, which represents how much investors dislike risk exposure, thus canceling the $\phi\beta^i$ term. While with exponential utility, ϕ takes a simple tractable form (not shown here), no particular utility function is needed for the general result to obtain.

3.5 Fund Flows

3.5.1 Intuition

Equation (3) combined with (1) conveys the intuition of the model. The quantity of interest is α^i, while investors observe $Y_t^i = ... + \alpha^i + \beta^i(\phi + \xi_t) + ... + \varepsilon_t^i$, i.e., their quantity of interest plus diffent kinds of noise. In downturns, e.g. when $\xi_t = -\phi$, the only noise preventing investors to directly infer α^i is ε_t^i. In contrast, in upturns of symmetric magnitude, $\xi_t = +\phi$, there is an additional element of noise $\beta^i(\phi + \xi_t) = 2\beta^i\phi$ that obscures the inference. If β^i were known, investors would just need to subtract a constant from the fund's returns. With β^i unknown, 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. Thus, the signal-to-noise ratio is higher in downturns than in upturns – a component of the noise is "switched off" in downturns. The intuition carries over to any other magnitude x for upturns $\xi_t = +x$ and downturns $\xi_t = -x$.

3.5.2 Formal results

The main insight of the model is that the sensitivity of flows, F_t^i, to unexpected performance, $Y_t^i - E_{t-1}[Y_t^i]$, depends on the state of the market, ξ_t. In particular, the flow-performance sensitivity is larger for negative market shocks than for positive market shocks.

Lemma 2.

$$F_t^i := S_t^i - S_{t-1}^i = \eta \cdot \lambda(\xi_t) \cdot (Y_t^i - E_{t-1}[Y_t^i]) \tag{4}$$

where

$$\lambda(\xi_t) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\beta^2 (\phi + \xi_t)^2 + \sigma_\varepsilon^2} \tag{5}$$

Recall that σ_α^2 and σ_β^2 denote the dispersion of parameters α^i and β^i within a particular category of funds, according to (2), and thus the degree of uncertainty about these parameters. $\lambda(\xi_t)$ is the flow-performance sensitivity (FPS) and corresponds to the signal-to-noise ratio.[5] Note also that Y_t^i essentially are percentage returns (dollars returned for every dollar invested), and S_t^i is fund size normalized to that benchmark. Thus, $\lambda(\xi_t)$ is closely linked to its empirical anologue.

The intuition is straightforward. First, consider the case that there is no uncertainty about risk exposure, $\sigma_\beta^2 = 0$. Then, the flow-performance sensitivity λ does not depend on the state of the economy, ξ_t. In particular, there is no asymmetry in the flow-performance relationship between upturns and downturns, and the BG intuition obtains. One familiar result that also obtains in BG is that the more dispersed cash-flow alphas are believed to be, i.e. the higher σ_α^2, the stronger the reaction to news, i.e., the steeper the FPS. Intuitively, if

[5] 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 $Y_{i,t} - 1$ at the end of period t.

very high and low fund returns are deemed realistic and attributable to exceptionally high or low skill, rational investors are less prone to attribute abnormal returns to random noise. This may be the case for particularly young funds, or funds with a manager of low tenure. In the main empirical analysis, we proxy this higher degree of paramter uncertainty by using Concentrated funds, as defined below. Conversely, if signals are less informative, i.e., if σ_ε^2 is higher relative to σ_α^2, then one-time abnormal performance of a given size triggers lower flows. The ratio of σ_α^2 to σ_ε^2 is a sufficient description of the signal-to-noise ratio in that case.

Let us now introduce uncertainty about β^i, $\sigma_\beta^2 > 0$. This makes the FPS $\lambda(\xi_t)$ depend on the state of the economy, ξ_t. In particular, a positive σ_β^2 dampens the FPS, in particular in upturns. This is the driver of our empirical predictions.

While the following empirical predictions focus on implementation with linear estimation techniques, we also provide nonlinear estimation results that directly test for the functional form of the flow-performance relation predicted by equation (5). Doing so, we can rule out alternative theories that could also drive to 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 σ_α^2 is higher in downturns than in upturns. In that case, λ is a monotonically decreasing function of ξ_t. In contrast, in the case of time-invariant σ_α^2 and positive σ_β^2 discussed above, λ is not monotonous. That will allow us to distinguish the two alternative theories empirically.

3.6 Empirical Predictions

We make empirical predictions about variations of the FPS across market states and in the cross-section of funds, as well as for the difference-in-differences across market states and fund types. The upturn-downturn predictions do not require additional assumptions.

The only additional assumption needed for the cross-sectional and difference-in-difference predictions is that investors have less precise prior beliefs about returns of funds that display higher ex-post dispersion of fund returns and return correlations with the market, e.g. funds with higher tracking error, a particularly active investment style, or simply young funds, as discussed above.

3.6.1 Upturn-Downturn Difference of Flow Performance Sensitivity

The first testable prediction is that the flow-performance sensitivity (FPS) is larger in downturns (DT) than in upturns (UT).

Proposition 1. *Flow-performance sensitivities are larger in downturns than in upturns of equal magnitude. That is, let $x > 0$, then*

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

3.6.2 Difference-in-Differences Prediction for FPS

When there are differences in the precision of the investors' ex ante beliefs across fund types, cross-sectional variation of the FPS across these fund types arises. In particular, for some constant $k > 1$, define

$$\sigma^2_{\alpha,Concentrated} = k \cdot \sigma^2_{\alpha,Other} \tag{6}$$

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

where *Concentrated* indexes funds that have both high active share and high tracking error as in Cremers and Petajisto (2009) and *Other* stands for all other funds. Table 2 shows that this assumption is likely to be verified empirically to the extent that estimated (ex-post) volatility of risk loadings and alphas corresponds to ex-ante dispersion of prior beliefs. There is significantly more variation among both estimated alphas and betas for *Concentrated* funds compared to *Other* funds. This statement remains true also after controlling for the Carhart (1997) factors. It is important for the interpretation of the cross-sectional difference results that both types of funds have similar investor bases. We do not want the results to be driven by differences in the inherent flow-performance sensitivity of one investor group versus another. 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 that they are both 0.0137, with a standard deviation of 0.0040 and 0.0051, respectively. We conclude that investor types do not significantly differ across these types of funds.

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 funds flows such as BG in comparing funds with higher parameter uncertaint to funds with lower uncertainty, such as young and old funds.)

Proposition 2. *Keeping everything else constant, the flow-performance sensitivity is higher for Concentrated funds than for Other funds in the same state of the market.*

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

Note that the proposition relies on differences in the distributions of parameters introduced in equation (2), while it assumes that both funds have investors with similar prior beliefs. 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 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, or across mutual funds and hedge funds.

We can now state the second main empirical prediction, the difference in FPS-differences across market states and fund types.

Proposition 3. *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 intuition is that while learning about risk-adjusted performance is easy in downturns and more difficult in upturns for all types of funds, learning about alpha in upturns is particularly difficult for fund types with a high variance of prior beliefs about alpha and beta.

The difference-in-differences prediction in proposition 3 is unique to our model. If this 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 1. For example, one might otherwise conjecture that the upturn-downturn difference obtain because "everybody is happy in upturns" and investors do not check fund performance, while 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

The first 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 that 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, there is turnover in fund managers, which introduces new uncertainty about underlying parameters.

A related limitation results because our model of cross-sectional learning is tractable only because there is no learning about the stochastic discount factor at the same time. To our knowledge, no existing model is able to track both the cross-sectional and time-series dimension at the same time. One observation about dynamics is in place however. When the model is modified in a way that parameters get periodically re-assigned for a fraction of funds, the average precision of beliefs about fund value is highest following downturns, compared to following downturns. As a result, fund sizes most closely match a first-best allocation without parameter uncertainty following downturns. We view this as reminiscent of Schumpeter's assertion that recessions have a cleansing effect on the economy, as applied to the funds sector.

The second main limitation is that the parameters α^i and β^i are exogenous in the model. There are several reasons for this modeling choice. First is that the key predictions would be very difficult to obtain if the parameters were 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 obscure which part of our results comes from assumptions about investor preferences, which from assumptions about managers' incentives, and which from investor behavior. We want to make clear that the present model is about investor behavior alone. It is not precluded in the model, 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 α^i is exogenously distributed and known to the manager but uncertain to investors, and β^i is a strategic choice of the manager and likewise uncertain to the investor, may be an interesting subject for future research.

A third observation is that any cross-sectional predictions, and namely the difference-in-difference prediction on the FPS, rely on a homogenous set of investors across different types of funds – recall the key role of dispersions of prior beliefs in equation 5, which determines the extent of upturn-downturn differences of the FPS. The model predictions should therefore only hold true within a set of funds with a reasonably homogenous investor base.

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 for which the data is prior to the reported starting date of the fund, similar to Kacperczyk, Van Nieuwerburgh, and Veldkamp (2012). As incubated funds tend to be smaller, we exclude observations with reported assets under management smaller than $5 million in the prior quarter.

Mutual funds in CRSP include both retail and institutional share classes. The predictions of our model are based on a homogenous set of investors. So, 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. 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. The funds for which no information can be gathered on whether they are retail or institutional are excluded from the sample. While 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. Thus, the imputation introduces noise that leads to attenuation bias, but does not lead to a bias in favor of our hypothesis.

The sample spans the years from 1980 to 2012, when complete information on investment objectives is available. Since 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).

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

$$Flows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}\,(1 + R_{i,t})}{TNA_{i,t-1}} \tag{8}$$

where $TNA_{i,t}$ is total net assets in quarter t for fund i and $R_{i,t}$ is the 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.[6] The other variables that are used 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 twelve 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 3 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)). The performance persistence analysis is run on a monthly version of the above-described sample.

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

[6]Starting in the 1990's, 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 as our purpose is to study fund flows, which differ at the share class level. Nevertheless, our results are not materially impacted by this choice.

as in Cremers and Petajisto (2009) and Petajisto (2013).[7] 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. A quarter is denoted 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 3 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, while 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 economy and fund types, as well as the difference-in-differences of the FPS, which identifies the model in the sense of ruling out a variety of alternative explanations. Finally, we estimate the non-linear functional form of the FPS as a function

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

of the market state with parametric and non-parametric methods.

5.1 Empirical Methodology

5.1.1 Estimating the FPS

The predictions of the model are expressed in terms of the difference in slope of the relation between flows and performance (flow-performance sensitivity, FPS) between upturns and downturns. The most direct way to test these predictions is through a linear a specification. Then, our focus is on the slope b in the regression:

$$Flows_{i,t+1} = a + b \cdot frank\_style_{i,t} + \varepsilon_{i,t} \tag{9}$$

where $frank\_style_{it}$ is the fractional rank of fund i in period t with respect to funds in the same style. For mutual funds, the style is defined by the CRSP Objective variable. We estimate the regression in equation (9) using the Fama and MacBeth (1973) methodology.

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 mispecified 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 also estimate a piecewise linear relation

$$Flows_{i,t+1} = a + b_1 \cdot trank\_style1_{i,t} + b_2 \cdot trank\_style2_{i,t} + b_3 \cdot trank\_style3_{i,t} + \varepsilon_{i,t} \tag{10}$$

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

5.2 Empirical Results

5.2.1 Linear Estimation Results

Table 4 presents the main results for the linear FPS-regression specification. This analysis provides a test of proposition 1 which states that the flow-performance relation is steeper in downturns than in upturns. The table describes the variation of FPS across states of the economy. The first three columns give results that do not include additional controls, as in equation (9). Column (1) reports a significant FSP of 0.043, without conditioning on the state of the market. The FPS is more than twice as large in downturns (0.051) compared to upturns (0.021) for the average fund, emphasizing the economic significance of the result. The difference is also highly statistically significant (bottom of column (3)). Columns (4)-(6) include all controls suggested by Spiegel and Zhang (2012). These are the aggregate flows in quarter $t+1$ into the funds that have the same objective as fund i, the total expense ratio, the logarithm of TNA, the portfolio turnover ratio, the return volatility over the prior twelve months, and the logarithm of the fund's age. Given that flows display some persistence, we also include the fund's flows in quarter t. After adding these controls, the magnitudes as well as the statistical significance of the upturn/downturn difference (bottom of column (6)) are preserved. Overall, this evidence provides an empirical validation of proposition 1.

Table 5 has the estimates for the piecewise linear specification in equation (10). 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 downturns than in upturns (columns (2) and (3)). This result holds also when we include the controls (columns (5)-(6)). At the bottom of columns (3) 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 upturns and downturns. The test rejects the null hypothesis. Given the consistency of the conclusions between Tables 4 and 5, we feel legitimized to proceed with the linear specification, which more easily allows us to test the difference-in-difference predictions of the model.

The next step is to test the difference-in-difference prediction across fund types and market states given in Proposition 3. 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 that new capital that flows into the mutual fund sector gets primarily allocated with medium performers, possibly attenuating our upturn-FPS estimate, while outflows from the sector primarily hit underperformers, which might steepen the FPS-estimate. Taking the difference across fund types of the upturn-downturn difference would eliminate such an effect.

The first step to construct the difference-in-differences test is to define what constitutes the cross-sectional variation. To proxy for the heterogeneity in degree of ex ante uncertainty about a particular fund's parameters (captured by the model parameters σ_a and σ_b) we use the variables constructed by Cremers and Petajisto (2009) and Petajisto (2013). In detail, we conjecture that, for the funds that 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 intutition is that the extent of active management that characterizes these funds, both in terms of stock picking and sector rotation, makes it more difficult for investors to precisely know the underlying parameters of the distribution of these funds' returns. We confirm this intuition by comparing the standard deviation of alphas and factor loading estimates between *Concentrated* and *Other* funds in Table 2. Similar results obtain when other proxies for less certain distributions are chosen, such as younger funds or smaller funds. We report results for younger funds in the robustness checks. The second step is to calculate the upturn-downturn differences for each of these types of funds, and then taking the difference in differences.

Table 6 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 $frank\_style \times concentrated$), as predicted by proposition 2. The difference is statistically significant (t-stat=2.015). Columns 2 and 3 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-difference (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 3. Columns 4-6 report qualitatively and quantitatively similar results after the introduction of controls.

5.2.2 Non-linear Estimation Results

The previous section tested propositions 1 to 3 using linear tests. Yet, 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 by providing two non-linear estimation results. First, we assume that the shape specified in equation (5) is correct and estimate the parameters of the function $\lambda(\xi_t + \phi)$. Because σ_α, σ_β, and σ_ε are identified up to a common constant, with divide numerator and denominator of equation (5) by σ_α^2 and, using non-linear least squares, we estimate $\frac{\sigma_\beta}{\sigma_\alpha}$, $\frac{\sigma_\varepsilon}{\sigma_\alpha}$, and ϕ in the following specification

$$FPS_t = \frac{1}{1 + \frac{\sigma_\beta^2}{\sigma_\alpha^2}(\phi + \xi_t)^2 + \frac{\sigma_\varepsilon^2}{\sigma_\alpha^2}} + u_t \tag{11}$$

where FPS_t is the flow-performance sensitivity in quater t, ξ_t is the de-meaned excess return on the market, and u_t is the error term. Second, we estimate the shape itself using a non-parametric local polynomial regression to show that forcing the shape to the one predicted in lemma 2 is reasonable.

Figure 2 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 intervals. Table 7 presents the conditional parameter estimates and confidence intervals.[8]

Two observations are in order. First, the peak of the curve falls to the left of zero with confidence. Formally, the estimate of ϕ is estimated to be negative with high statistical significance. The fact that the peak is on the left of zero is the driver of the upturn-

[8]The confidence intervals for the fitted values are computed conditioning on the realization of ξ_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)).

downturn difference predicted and tested above with linear regressions models.[9] Second, the shape displays a pronounced non-monotonicity: 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 that the dispersion of skill conditional on downturns is higher than the dispersion of skill in upturns. That assumption would predict a monotonously decreasing FPS as a function of the market excess return. Note that this specific non-monotonicity is not mechanically implied by the regression specification either.

Figure 3 gives the non-parametric estimates of the FPS as a function of the market state as well as 95% confidence intervals. It shows that when no constraints are imposed on the functional form, a similar hump-shaped FPS as a function of the market excess return is obtained as the one imposed in the parametric specification above. Specifically, we run a local polynomial regression of degree zero (i.e. we estimate a constant) with an Epanechnikov kernel bandwidth of 5%.[10]

In sum, the non-linear estimation results strongly confirm the predictions of lemma 2, which is the basis for the empirical predictions. The results clarify that the two key predictions and drivers of the linear estimation results are: (i) the asymmetry of the peak of the FPS with respect to zero market excess returns, and (ii) the FPS decreases with the absolute value of deviations of the market excess returns from the reference point given by negative the market risk premium.

[9]Note that an entirely different shape of the curve would obtain for different parameter values. The hump-shape is not forced by equation (11).

[10]In Stata, we use the command *lpoly* for kernel-weighted local polynomial smoothing. For a complete treatment, see Fan and Gijbels (1996).

5.3 Robustness Checks

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

Table 8 replicates the main results on upturn-downturn difference of the flow-performance sensitivity (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 vs. 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 8 show that our results are not in any way driven by this imputation. 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 10 shows that the result also obtains using the shorter sampler and using a piecewise-linear specification, which is the standard in the literature to capture the convexity of the flow-performance relation.

Table 9 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 12 shows by the example of young vs. 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 11 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 12.

The last two tables show that the FPS results are robust to the choice of sampling frequency. While 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 13 replicates the qualitative results from Table 8 at the monthly frequency, while Table 14 replicates the results from Table 10 at the monthly frequency.

6 Conclusion

We provide a rational model with parameter uncertainty as the only friction that explains key regularities left unexplained by existing models of the allocation of capital to mutual funds. In particular, our model predicts that rational investors re-allocate less capital between funds following upturns than following downturns, leading to lower flow-performance sensitivity in upturns, compared to downturns. We show that the model predictions about the flow-performance sensitivity in different states of the economy, across types of funds, and about the difference-in-differences are strongly confirmed empirically: the flow-performance relation is more than twice as steep following market downturns than following market upturns. Furthermore, we show parametric and non-parametric results that confirm the predicted shape of the flow-performance sensitivity as a function of the market state.

We view our results as providing a formalization of why downturns can have a cleansing effect on the economy in the sense of improving the cross-sectional efficiency of capital allocation. In particular, we show that no behavioral or other frictions are necessary but that Bayesian learning about uncertain parameters is sufficient to generate the asymmtry between upturns and downturns with respect to risk-averse investors' ability to distinguish good from bad 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*

$$p_t^i = 1 + \hat{\alpha}_t^i - \frac{1}{\eta} S_t^i. \tag{12}$$

Proof of Lemma 3 (Fund Value)

First, we derive the stochastic discount factor in the economy. Then we use this result to derive the value of a fund, conditional on beliefs and its equilibrium size. Assuming a set of overlapping generations mutual fund investors with homogeneous preferences allows us to obtain analytic solutions for cross-sectional learning, because we do not need to keep track of learning about the aggregate economy. (See Schmalz and Zhuk (2013) for a more detailed explanation.)

We derive first order conditions by considering marginal deviations from equilibrium for a representative agent. The representative agent framework is homogenous to a framework with a group of investors with identical preferences. Assume the agent consumes the aggregate payoff of the economy Y_{t+1} at $t+1$. Consider the case in which this agent borrows at the risk free rate to buy x additional units of $t+1$ fund flows Z_{t+1}, which cost p_z per unit at time$t$. Then, the expected utility of the agent is

$$U(x) = E_t[u(Y_{t+1} + x(Z_{t+1} - Rp_z))].$$

For the agent to decide not to deviate from equilibrium, the agents' utility must be maximized when $x = 0$

$$0 = U'(x)|_{x=0} = E_t[u'(Y_{t+1})(Z_{t+1} - Rp_z)].$$

This can be rewritten as

$$0 = E_t[u'(Y_{t+1})Z_{t+1}] - E_t[u'(Y_{t+1})]Rp_z$$

$$p_z = \frac{1}{R}\frac{E_t[u'(Y_{t+1})Z_{t+1}]}{E_t[u'(Y_{t+1})]}.$$

Define the stochastic discount factor (SDF) to be

$$m_{t+1} = \frac{1}{R}\frac{u^{'}(Y_{t+1})}{E_t[u^{'}(Y_{t+1})]}.$$

Then, the standard pricing equation obtains

$$p_z = E_t\left[m_{t+1}Z_{t+1}\right]. \tag{13}$$

Notice that given our assumption of zero net risk free rate, i.e. $R = 1$, we have

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

The aggregate source of risk in this economy is ξ, which is defined in equation (1) to have zero mean. Also from equation (1), the compensation for this source of risk is ϕ. Which can be interpreted as a risk premium on systematic risk, as the net risk free rate is zero. Then, applying standard results in asset pricing (see Cochrane (2001)), it has to be the case that

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

where the last step follows because ξ has zero mean.

Finally, apply equation (13) to the cash flows from fund i

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

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

□

Proof of Lemma 1 (Fund Size)

The equilibrium condition is that the marginal utility from the last dollar invested in each fund must be equal to the marginal utilty invested in the risk-free asset. As the risk-free rate is normalized to zero, it must be that the value of a dollar invested in each fund i is 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 ξ_t, are normally distributed. As a result, the standard formulas for Bayesian updating of beliefs apply. Bayesian updating occurs according to

$$\hat{\alpha}_t^i = \hat{\alpha}_{t-1}^i + cov\left[\alpha, Y_t^i|\xi_t\right] \frac{(Y_t^i - E[Y_t^i])}{var[Y_t^i|\xi_t]}$$

with

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

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

The updating formula essentially replicate investors' learning from past performance, i.e. 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.

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

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

Proof of Proposition 1

Notice 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 $\lambda(\xi_t) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\beta^2(\phi+\xi_t)^2 + \sigma_\varepsilon^2}$. By simply replacing x for ξ into the expression for λ, one needs to prove

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

which simplifies to

$$\left(\phi + x\right)^2 > \left(\phi - x\right)^2$$

or, computing the squares,

$$\phi^2 + 2x\phi + x^2 > \phi^2 - 2x\phi + x^2$$

and, after simplifications, one obtains

$$x > -x$$

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

$\square$

Proof of Proposition 2

We wish to show that $\lambda_{Concentrated} > \lambda_{Other}$ 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 in equations (6) and (7) into expression (5) yields:

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

$\square$

Proof of Proposition 3

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

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

Using (6) and (7), when $k > 1$, we have

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

□

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Figures

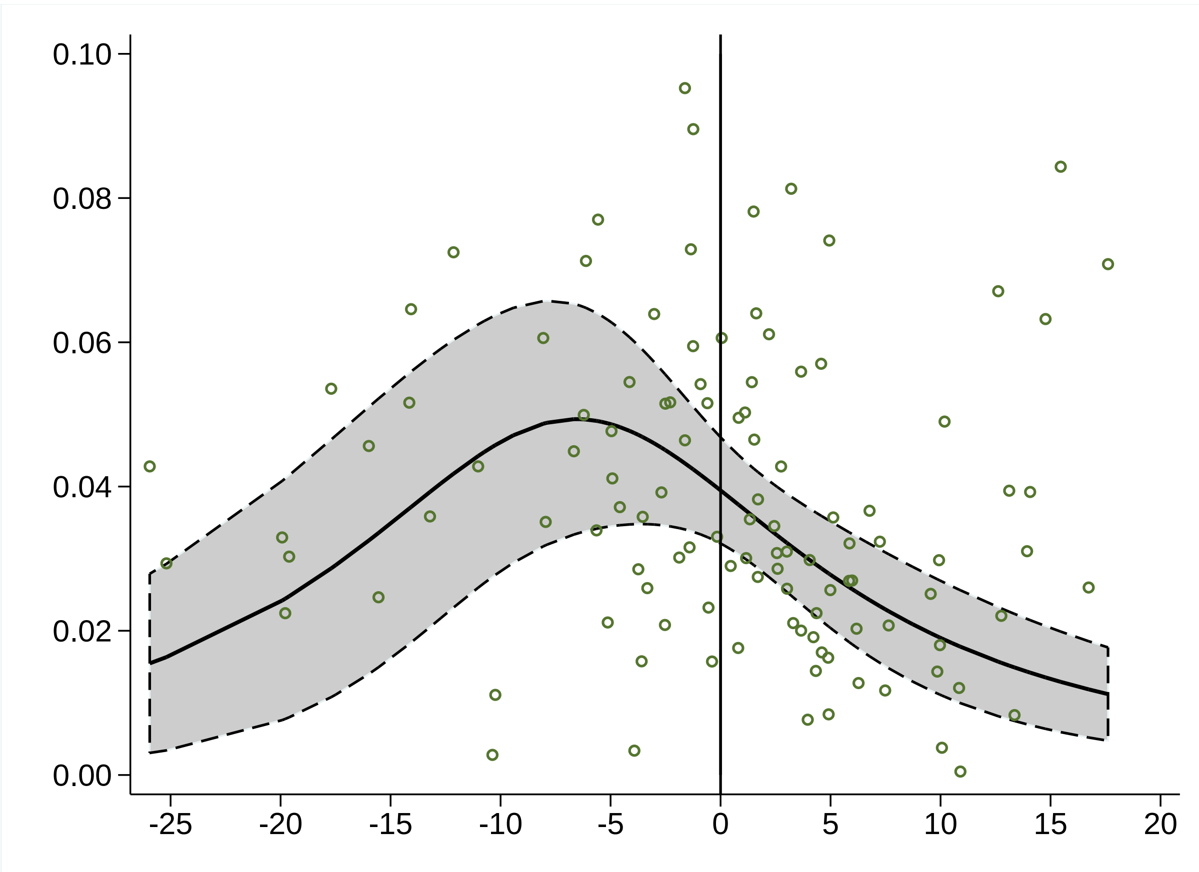

Figure 2: Parametric estimation results from a non-linear least squares regression of estimates of the flow-performance sensitivity on the market return in excess of the risk-free rate, in which the functional form is forced to conform to the specification in equation (5), with 95% confidence intervals.

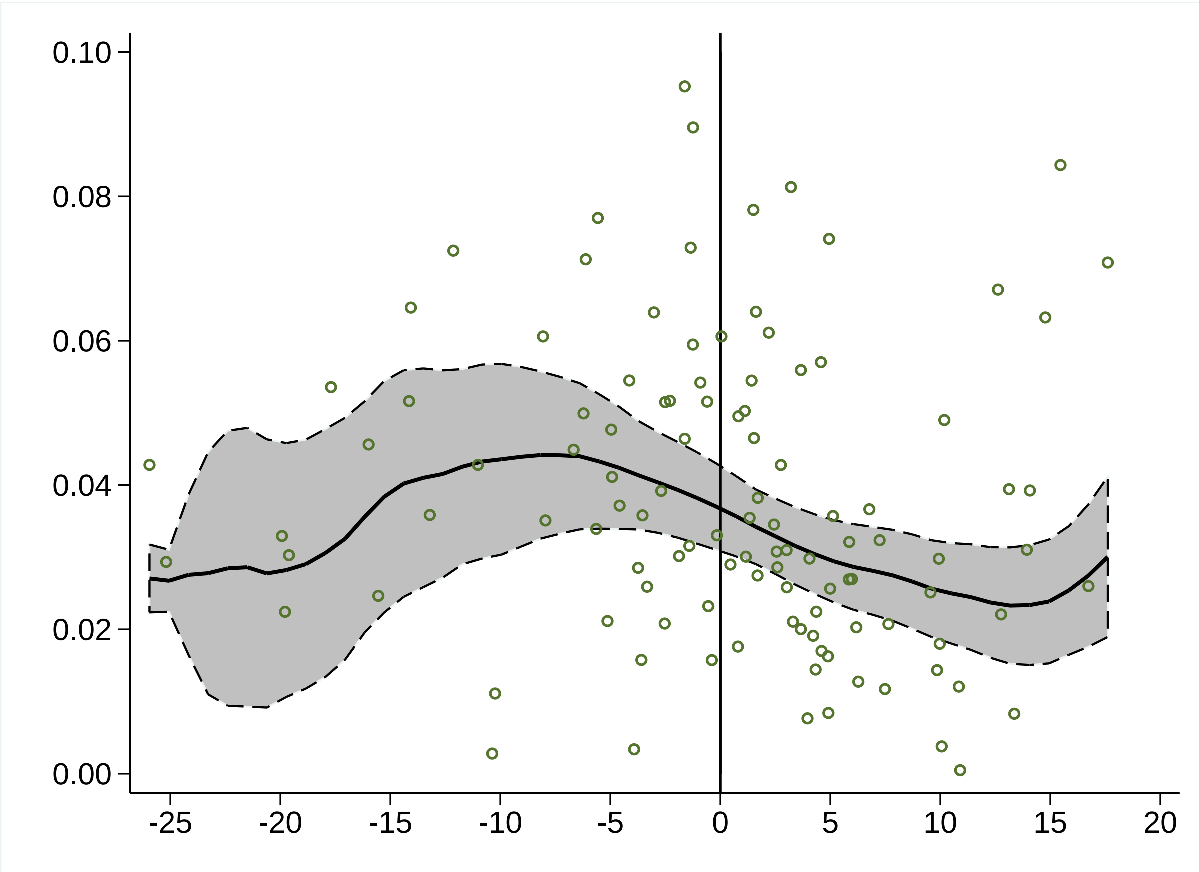

Figure 3: Non-parametric estimation results from a local polynomial regression of estimates of the flow-performance sensitivity on the market return in excess of the risk-free rate, without imposing a functional form, with 95% confidence intervals.

Tables

Table 2: Summary statistics of alpha and risk factor loadings by fund type. For each fund, a risk 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: CAPM

	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 3: 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 twelve months, fund age computed as the number of quarters since the first appearance in CRSP, 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 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 4: Flow-Performance Sensitivity Main 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 dowturns 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 since July 1926.

Flows (t+1)	All quarters	Upturns	Downturns	All quarters	Upturns	Downturns
frank_style	0.043***	0.021***	0.051***	0.034***	0.020***	0.045***
	(12.188)	(2.771)	(6.178)	(11.498)	(3.489)	(5.551)
flows_style				0.222*	-0.281	0.295***
				(1.780)	(-0.596)	(3.116)
fee				-0.248	0.116	-0.155
				(-1.070)	(0.191)	(-0.332)
logsize				-0.001*	-0.001	0.001
				(-1.917)	(-0.942)	(0.765)
turn_ratio				-0.003**	-0.009***	-0.000
				(-1.992)	(-2.881)	(-0.087)
vol				0.028	-0.326*	0.410*
				(0.310)	(-1.801)	(1.704)
logage				-0.011***	-0.015***	-0.024***
				(-3.717)	(-2.819)	(-2.766)
flows				0.500***	0.530***	0.464***
				(24.744)	(12.816)	(8.853)
Constant	-0.016***	-0.002	-0.023***	0.032***	0.079***	0.055*
	(-6.385)	(-0.452)	(-4.742)	(2.893)	(3.447)	(1.778)
Observations	144,382	30,850	35,758	144,382	30,850	35,758
R-squared	0.044	0.027	0.058	0.439	0.467	0.397
Number of groups	131	32	30	131	32	30
z-stat		2.623			2.564	
p-val		0.00872			0.0103	

Table 5: Flow-Performance Sensitivity Main 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 dowturns 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 since July 1926.

	Panel A: No controls			Panel B: With controls		
Flows (t+1)	All quarters	Upturns	Downturns	All quarters	Upturns	Downturns
trank_style1	0.042***	0.005	0.040**	0.030***	0.020	0.033
	(4.282)	(0.189)	(2.486)	(2.972)	(0.748)	(1.219)
trank_style2	0.032***	0.037	0.049**	0.029***	0.025	0.047**
	(3.699)	(1.481)	(2.591)	(3.167)	(0.876)	(2.315)
trank_style3	0.062***	0.011	0.066***	0.047***	0.015	0.053**
	(5.929)	(0.406)	(3.034)	(5.215)	(0.698)	(2.749)
flows_style				0.225*	-0.268	0.297***
				(1.805)	(-0.568)	(3.145)
fee				-0.208	0.242	-0.132
				(-0.839)	(0.462)	(-0.201)
logsize				-0.001*	-0.001	0.001
				(-1.829)	(-1.348)	(1.103)
turn_ratio				-0.002*	-0.009***	0.000
				(-1.947)	(-3.037)	(0.049)
vol				-0.005	-0.375*	0.367
				(-0.050)	(-1.832)	(1.461)
logage				-0.012***	-0.021***	-0.023**
				(-4.009)	(-3.424)	(-2.711)
flows				0.499***	0.522***	0.468***
				(24.039)	(11.869)	(8.753)
Constant	-0.015***	0.000	-0.021***	0.039***	0.103***	0.052
	(-4.768)	(0.060)	(-3.629)	(3.477)	(4.963)	(1.663)
Observations	144,382	30,850	35,758	144,382	30,850	35,758
R-squared	0.072	0.068	0.086	0.460	0.501	0.424
Number of groups	131	32	30	131	32	30
p-val(χ^2)		0.0348			0.0456	

Table 6: 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 dowturns 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 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 7: Non-linear estimation results. The table reports pararmeter estimates of the parameters in equation (5) 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. The sample ranges from 1980:Q1 to 2009:Q3.

	σ_β	ϕ	σ_ε
Estimate	0.343***	6.558***	4.389***
t-stat	(4.315)	(2.992)	(11.565)
Observations	131		
R-squared	0.522		

Table 8: Flow-Performance Sensitivity Main 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 dowturns 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 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 9: 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 dowturns 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 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 10: Flow-Performance Sensitivity Main 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 dowturns 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 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(χ^2)		1.97e-08			0.00150	

Table 11: Summary statistics of alpha and risk factor loadings by fund type (Old vs. Young). For each fund, a risk 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: CAPM

	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 12: 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 dowturns and upturns in the slope on frank_style×concentrated 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 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 13: Flow-Performance Sensitivity Main 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 dowturns 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 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 14: Flow-Performance Sensitivity Main 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 dowturns 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 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(χ^2)		9.32e-05			0.0104	