Performance Measurement with Uncertain Risk Loadings

Francesco Franzoni and Martin C. Schmalz*

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Abstract

We study the implications of uncertainty about risk loadings for mutual fund investors' capital allocation decisions. We show that the signal-to-noise ratio is higher and rational investors give more weight to performance signals when market returns are moderate, compared to times of very high or low market returns. Consistent with the model predictions, the flow-performance relation is about twice as steep in moderate times, and the difference is larger for types of funds with more uncertainty about risk loadings. The model-implied degree of parameter uncertainty is consistent with direct estimates of parameter uncertainty from fund holdings and daily returns.

*Franzoni: University of Lugano and Swiss Finance Institute, francesco.franzoni@usi.ch; Schmalz: University of Michigan Stephen M. Ross School of Business, schmalz@umich.edu. This paper was previously circulated under the titles "Fund/Capital Flows in Rational Markets." For helpful comments and discussions, we would like to thank Yakov Amihud, Jonathan Berk (discussant), Jules van Binsbergen, John Campbell, Susan Christoffersen, Paolo Colla, Roger Edelen, Stefano Giglio, Vincent Glode, Itay Goldstein, Denis Gromb, Rick Green, Alexander Guembel, Burton Hollifield, Christian Julliard, Marcin Kacperczyk (discussant), Shimon Kogan, Robert Kosowski, Augustin Landier, Xuewen Liu, Massimo Massa, Lubos Pastor, Alberto Plazzi, Uday Rajan, Clemens Sialm, David Solomon (discussant), Robert Stambaugh, Luke Taylor, David Thesmar, Fabio Trojani, Dimitri Vayanos, Russ Wermers, Youchang Wu, Josef Zechner, Hong Zhang, Sergey Zhuk, as well as seminar and conference participants at IDC Herzliya, NBER Asset Pricing, SED Annual Meetings, Tel Aviv University, the UNC Junior Faculty Roundtable, University of Michigan, and the University of Toronto. Schmalz is grateful for generous financial support through an NTT Fellowship from the Mitsui Life Financial Center.

1 Introduction

How do investors allocate capital to risky investments when they are uncertain about both the projects' future cash flows and their risk exposure? For example, how do mutual fund investors evaluate a manager's performance if they do not precisely know how much systematic risk the manager took to generate the reported returns? The existing mutual fund literature posits that investors learn about the fund manager's skill from risk-adjusted performance, implicitly assuming that the fund's risk loading is known to investors (Berk and Green, 2004). However, in practice, even if investors make efficient use of all available information on fund returns and reported portfolio holdings, substantial uncertainty remains about mutual funds' exposure to systematic risk.[1] Such uncertainty makes the inference about managerial skill more complicated: at any given point in time, investors simply do not exactly know what risk loading they should use to compute risk-adjusted returns. This paper provides a theoretical model and empirical analysis to show that uncertainty about risk loadings has first-order implications for investors' reaction to fund performance – i.e., the flow-performance sensitivity (FPS).

The model's mechanics are simple. Investors are uncertain both about managers' ability to generate risk-adjusted performance (alpha) and the funds' risk loading (beta). Their goal is to update beliefs about alpha, using realized returns as a signal. The signal is polluted by two sources of noise: one is idiosyncratic risk, also considered in the existing literature. The other is the product of the market-wide risk factor realization and investors' beliefs about the fund's risk factor loading. Therefore, given uncertainty about risk loadings, the realization of the risk factor affects the signal-to-noise-ratio, which is the weight that investors put on a given observation, and thus the speed of learning. Specifically, when the factor realization is close to zero, the risk uncertainty is multiplied by a small number and, therefore, it is a less important obstacle to inference. As a result, investors

[1] One reason is that holdings are reported only quarterly and intra-quarter portfolio changes are hidden from investors (Kacperczyk, Sialm, and Zheng, 2008). Another is that the well-known Merton (1980) result derives its power from a quasi-continuous observation of returns, but mutual fund returns are available at most at a daily frequency.

put more weight on the observation, and more capital is reallocated. By contrast, during times of extreme market movements in either direction, the uncertainty about risk loadings is compounded by a large risk-factor realization, so that investors' inference about managerial skill is obstructed by more noise. As a result, for a given risk-adjusted performance signal, rational investors reallocate less capital when markets make large moves up or down and inefficient allocations persist longer.

We test both the qualitative and quantitative predictions of the model. First, we study whether mutual funds' FPS depends on risk-factor realizations, which we proxy with the return of the market portfolio in excess of the risk-free rate. We find that the FPS is 50% to 130% larger in "moderate" times (quarterly excess market returns between -5% and +5%) compared to "extreme" times with larger absolute market returns. These results confirm the main qualitative prediction of our model and reject the null hypothesis of a constant FPS across market states, which is implied by existing models that do not allow for uncertain risk exposure.

According to the theory, such FPS-variation across market states should be unique to funds with uncertain risk loadings. Index funds, which minimize the tracking error with respect to their benchmark, do not require learning about manager's skill and risk loading, and should therefore not exhibit FPS-variation across market states. Indeed, no such difference exists for index funds. Table 1 summarizes these key findings.

To strengthen the identification of our model beyond this simple difference across market states, we test more subtle model predictions as well. Specifically, the difference in FPS across market states should be more pronounced for types of active funds that display a higher relative uncertainty in betas (that is, a higher ratio of risk uncertainty to skill uncertainty). We draw inspiration from two papers in the literature to identify such funds. Cremers and Petajisto (2009) label funds as "Concentrated" if they deviate more than the median fund from their benchmark in terms of both stock selection (active share) and market timing (tracking error). Indeed, we find that Concentrated funds are characterized by higher beta uncertainty, indicating that investors in such funds have more difficulty inferring the fund's beta from its benchmark. Relatedly, Kacperczyk, Sialm, and Zheng

Table 1: The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund unexpected returns (flow-performance sensitivity, FPS) for Extreme and Moderate times. We compute quarterly flows as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the market return (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). We estimate daily betas by combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. The regressions include the following controls: total flows into funds with the same CRSP objective code; the total expense ratio of the fund; the logarithm of assets under management; the fund turnover ratio; return volatility over the prior 12 months; fund age computed as the number of quarters since the first appearance in CRSP; one-quarter lagged flows. Moderate times are defined as the quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -5% and below +5%. Extreme quarters are all other quarters. The sample ranges from 1998:Q3 to 2012:Q2. T-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Extreme	Moderate	Moder. minus Extr.
Panel A: Active Funds			
Flow-Performance Sensitivity	0.332***	0.518***	0.186***
t-stat	(8.462)	(10.968)	(3.026)
Panel B: Index Funds			
Flow-Performance Sensitivity	0.009	0.003	0.006
t-stat	(0.064)	(0.013)	(-0.025)

(2008) rank funds by their return gap, which is the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings. Our data confirm that high-return-gap funds display higher beta uncertainty than their complements, consistent with the idea that for these fund it is harder to infer beta from the reported portfolio. We contrast the FPS-difference across "moderate" and "extreme" times for Concentrated versus other funds, and for funds with high versus low return gaps. The difference in FPS across market states is significantly higher for the types of funds with higher beta uncertainty, and the difference-in-differences is highly statistically significant in both cases. Thus, the qualitative predictions of the model enjoy strong empirical support.

Yet, is the degree of uncertainty about risk loadings consistent with the magnitude of the variation of the FPS across market states? To approach this question, we use non-linear econometric techniques that not only provide additional support for the model's qualitative predictions, but also help gauge their quantitative plausibility. We first fit the predicted non-monotonic shape of the FPS-market-state relationship to the data and extract the ratio of beta uncertainty relative to skill uncertainty, as well as the ratio of idiosyncratic noise to skill uncertainty. These two ratios, implied by investor behavior, characterize the dependence of the FPS on the risk-factor realization in the model. Confirming the qualitative predictions and results above, we reject the null hypothesis that the FPS does not depend on the market state, which would be the case if uncertainty about risk loadings was negligible. Importantly, the hump-shaped function that this parametric test assumes also obtains when the FPS-market-state relation is estimated non-parametrically. We conclude that the non-monotonic shape of the relation between FPS and market returns is a robust feature of the data.

To test the quantitative predictions, we contrast the "implied estimates" of parameter uncertainty obtained from the non-linear parametric estimation to "direct estimates" of relative uncertainty about beta from holdings and returns data. The purpose is to assess whether even an investor that uses all available information faces a large enough level of uncertainty to explain the estimated variation in FPS across states. (A less-than perfectly informed investor will face even greater uncertainty.) Both sources of information need to be considered to establish a lower bound for parameter uncertainty, because an investor that forms beliefs about beta can make use of fund returns, but also of a fund's reported holdings, which is reported at a quarterly frequency.[2] We develop a technique to estimate mutual fund betas at the daily frequency that combines the information in reported holdings with daily fund returns. The resulting "direct estimates" of uncertainty about skill and risk exposure fall within the confidence intervals of the "implied estimates" from the non-linear estimation. We conclude that the model's quantitative predictions are consistent with realistic degrees of parameter uncertainty.

[2]Because a higher data frequency reduces the error in the estimation of second moments (Merton, 1980), rational investors should sample returns at the highest possible frequency.

It is difficult to reconcile the evidence with alternative theories without introducing ad-hoc parametrizations of the model or without generating counterfactual predictions. For example, differences in parameter distributions across good and bad market states can also lead to variations of the FPS. However, higher return volatility in bad market states would predict a lower FPS in such states compared to good states – a linear relation – but it would not yield the non-monotonic and mostly symmetric relationship that we find. Second, even if parameter distributions differed across extreme and moderate times in a way that reproduces the documented variation in FPS, it would not be obvious why that variation in parameters should be stronger for Concentrated and high return gap funds than for their complements. In fact, an alternative theory based on state-dependent volatility would require a parameter configuration that changes in each of the four terms of the double-differences that we compute. By contrast, the model proposed in this paper derives the variation across market states endogenously, without varying parameters across states. Third, we provide robustness tests that explicitly control for the effect of state-dependent volatility on the FPS, and find that the conclusions are unchanged. Of course, the difference in investor behavior across market states could also be ascribed to a "behavioral" theory. We do not attempt to make a claim as to the rationality of the observed investor behavior - we merely point out that the data can be conveniently described with a parsimonious rational theory.

Both the model and the empirical results 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). Specifically, the theoretical model can be combined with participation costs, which generate convexity (Lynch and Musto, 2003; Huang, Wei, and Yan, 2007), and our empirical results hold in both linear and convex specifications.

The problem of confounding variation in mutual fund risks and risk premia has been recognized at least since Jensen (1972); however, the literature has focused on the inference problem relating to time variation in risks and risk premiums (Ferson and Schadt, 1996). In contrast, we focus on the impact of cross-sectional variation in fund risks. Our model differs from Kacperczyk, Nieuwerburgh, and Veldkamp (2012) in that it contains no asymmetric information and we do not assume that parameter distributions or risk aversion vary exogenously as the state of the economy changes. All variation in the FPS across market states arises endogenously in our model. The model also abstracts away from how exactly managers generate excess returns, a question examined by Kacperczyk, Van Nieuwerburgh, and Veldkamp (2013) and how they allocate their attention Kacperczyk, Nieuwerburgh, and Veldkamp (2012), but focuses on the reduced-form analysis investors make if they care about risk-adjusted returns. Importantly, the level of skill of the manager, or variation across market states of that level of skill as documented by these authors, does not have an effect on the variation of the FPS across market states in our analysis. Our model also does not take a stand on whether the parameter distributions are the result of strategic choice by managers or the result of a matching process as modeled in Gervais and Strobl (2013) – we take the parameters as given. In computing our direct measures of skill uncertainty, we borrow from Pástor, Stambaugh, and Taylor (forthcoming)'s estimation of decreasing returns to scale and we draw inspiration from Berk and van Binsbergen (2012)'s approach for the estimation of managerial skill. Other authors have estimated daily risk loadings for managed portfolios (see Patton and Ramadorai (2013) for an application to hedge funds). However, to the best of our knowledge, this paper is the first to develop a methodology combining information from daily returns with quarterly holdings to estimate mutual fund risk loadings at the daily frequency.[3]

[3]Several other important papers are less closely related. Huang, Wei, and Yan (2012) derive cross-sectional predictions on the FPS in an economy in which Bayesian and performance-chasing investors coexist. Like these authors, we exploit heterogeneity in parameter uncertainty across funds to identify our model. By contrast, our theory relies on rational investors alone and focuses on the implications of parameter uncertainty on the dependence of the flow-performance relation on both fund types and market states. Li, Tiwari, and Tong (2013) develop a model with ambiguity-averse investors who receive multiple signals of unknown precision about fund performance. By contrast, our model only features uncertainty, but no ambiguity. Outside of the mutual fund literature, the present paper is related to Schmalz and Zhuk (2014), who study how equilibrium asset prices' reaction to low-frequency fundamental news depends on the market state when asset-specific cash-flow parameters are uncertain. An important distinction is that in their context, investors react more strongly in downturns than in upturns, as opposed to moderate versus extreme times. That is, they predict and find a strongly asymmetric relationship between reaction to news and market states, whereas the present paper predicts and finds a symmetric relationship. Adrian and Franzoni (2009) also postulate that investors learn about unobservable risk-factor loadings for stocks and show that this mechanism can explain part of the value premium under specific conditions on the learning process. Similarly, Gerakos, Linnainmaa, and Daniel (2013) split the SMB and HML factors into priced and unpriced factors, thus dissecting investors' inference problem. For an optimal contracting problem involving managerial risk choice see also Iovino (2011). The distinction

The paper proceeds as follows. Section 2 presents the model. Section 3 describes our methodology, including the new technique to estimate betas from reported holdings and daily returns. Section 4 describes the data. Section 5 gives the empirical results. Section 6 concludes.

2 Model

This section develops a model of learning about manager skill from observable fund-level returns and market-wide risk-factor realizations. The key distinction from Berk and Green (2004) is that we explicitly model the dependence of fund returns on the realization of an observable risk factor, while we let the risk-factor loading be unobservable. Technically, this assumption introduces a second parameter in investors' inference problem.

2.1 Setup

There are N funds to which investors can allocate their capital. The cash flow that fund i returns at time t from each dollar invested at time $t-1$ is denoted Y_t^i. Although the true return process may have different drivers, the returns can be decomposed in reduced form[4] as

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

where α^i is a fund-specific, time-fixed performance parameter indicating a manager's skill to generate excess returns over a benchmark net of fees; β^i is a fund-specific, time-fixed exposure to a

of our paper from Edelen and Warner (2001) is that we investigate the impact of market returns on fund-level flows, rather than the impact of aggregate flows on market returns.

[4]The investors' regression model should not be confused with the manager's investment strategy. Equation (1) is a *reduced-form* way of describing the cash flows that the fund generates for its investors. It does not make claims as to the source of skill or time-varying properties of its level. In particular, α^i can be generated by a manager who successfully times the market, i.e., employs time-varying risk loadings of high β^i when f_t is positive and low (or negative) β^i when f_t is negative. Alternatively, the manager can be good at picking underpriced stocks in all states of the market and thus generate α^i. While any combination of the two explanations can be the reason for fund manager skill in practice, and while the two are difficult to distinguish empirically (Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2013), an investor might only care about the magnitude and timing of the returns the fund delivers. The reduced-form way of characterizing the return-generating process is sufficient to model such an investor's problem.

time-varying systematic risk factor; f_t is the time-t realization of a traded risk factor, which in the empirical analysis we proxy using the market return in excess of the risk-free rate. While in principle, more factors could be considered in (1), we limit ourselves to one factor for two reasons. The first is that the equations of the model are notationally more simple with a one-dimensional factor. The other, more substantial, reason is that recent work by Berk and Van Binsbergen (2013) and Barber, Huang, and Odean (2014) indicates that mutual fund investors employ a single-factor model (the CAPM) when assessing fund performance, as opposed to a four-factor specification (Carhart, 1997). S^i_{t-1} is the size of the fund resulting from the investors' capital allocation in period $t-1$; $\eta > 0$ is an efficiency parameter, such that $-\frac{1}{\eta}S^i_{t-1}$ indicates decreasing returns to scale; and $\varepsilon^i_t \sim \mathcal{N}(0, \sigma^2_\varepsilon)$ is an idiosyncratic shock. Decreasing returns to scale do not play a role in the mechanism we describe. However, they make the model consistent with Berk and Green (2004) and subsequent literature. The existence of a risk-free asset, whose net return is normalized to zero without loss of generality, allows for flows into and out of the mutual fund sector.[5]

For simplicity, we assume overlapping generations of risk-averse investors who live for two periods. (An alternative modeling choice leading to the same conclusions is discussed below.) In the first period, they invest in mutual funds. In the second period, they consume the proceeds from their investments and pass down their fund holdings to the next generation. The young investors inherit their predecessors' beliefs. We are interested in how Bayesian investors reallocate capital across funds in response to learning enabled by the observation of a single cross section of fund returns $Y_t = (Y^1_t, Y^2_t, ...Y^N_t)$ at some time t, and a corresponding factor realization f_t, given a particular degree of parameter uncertainty at the time.

The key assumption of the model is that at any point in time t, investors are uncertain about the precise value of both α^i and β^i. However, they know that both parameters are sampled from a

[5] We use the risk-free rate as the outside investment opportunity in the model because the risk-free rate is the benchmark to which risk adjusted performance should be compared. Taking other asset classes as a benchmark requires only to re-define the systematic risk factor f_t as an excess return relative to this alternative benchmark. Our main result, a hump-shaped relationship that is expressed in equation (5), is unaffected by such re-definition.

jointly Normal distribution with known mean, variance, and covariance

$$\mathcal{N}\left(\left(\begin{array}{c}\hat{\alpha}^i_{t-1}\\ \hat{\beta}^i_{t-1}\end{array}\right),\left(\begin{array}{cc}\hat{\sigma^i}^2_{\alpha,t-1} & \hat{\sigma^i}_{\alpha\beta,t-1}\\ \hat{\sigma^i}_{\alpha\beta,t-1} & \hat{\sigma^i}^2_{\beta,t-1}\end{array}\right)\right). \tag{2}$$

This distribution corresponds to the prior beliefs about α^i and β^i that are a legacy of previous periods' learning. In the remainder of the paper, we omit time subscripts, fund superscripts, and the 'hats' in the beliefs about second moments to simplify the notation, because the empirical predictions are unrelated to the updating of the variance of the parameters, and would not change if dynamics were taken explicitly into account. In sum, at any point in time t, the model takes as given the degree of prior uncertainty about parameters characterized by equation (2). We discuss possible dynamic extensions in a separate section below. Although the model can be solved allowing for non-zero correlations between α and β, this generalization unnecessarily complicates the analytical solutions, without substantially affecting the intuition. We thus assume $\sigma_{\alpha\beta} = 0$.

2.2 Timing

At each point of time $t-1$, investors hold funds of equilibrium size S^i_{t-1} that is consistent with prior beliefs $\hat{\alpha}^i_{t-1}$ and $\hat{\beta}^i_{t-1}$ about the parameters α^i and β^i. Returns Y^i_t are realized and observed by investors. Also, investors observe the realization of the risk factor f_t. (We discuss below how this assumption can be relaxed.) Conditioning on f_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, as derived below. The change of fund sizes determines the reallocation of capital across funds. The relation of these flows to performance gives the FPS.

2.3 Equilibrium

Based on the above assumptions, the investors' posterior belief $\hat{\alpha}^i_t$ about α^i determines equilibrium fund sizes.

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

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

The formal proof is in the appendix. The intuition is straightforward. Investors determine allocations to funds so that the expected risk adjusted return from a marginal dollar in the fund equals the outside option of the risk-free rate.[6] In so doing, the expected value of fund returns based on current beliefs, $1 + \hat{\alpha}_t^i + \hat{\beta}_t^i \cdot f_t - \frac{1}{\eta} S_t^i$, is adjusted for the fund's estimated sensitivity to the risk factor, $\hat{\beta}_t^i$, multiplied by the factor realization f_t, thus canceling the $\hat{\beta}_t^i \cdot f_t$ term.[7] In other words, investors do not care about the risk exposure of funds, because they are appropriately compensated for the risk they are taking. The risk loading only matters in our model because uncertainty about β affects the speed of learning about α.

2.4 Fund Flows

2.4.1 Intuition

Equation (3) combined with (1) conveys the intuition of the model. The quantity of interest is α^i, whereas investors observe $Y_t^i = 1 + \alpha^i + \beta^i \cdot f_t - \frac{1}{\eta} S_{t-1}^i + \varepsilon_t^i$. That is, investors observe their quantity of interest (plus one, plus observable fund size) plus two types of noise that do not affect the investors' utility but complicate their inference about the quantity of interest. The two types of noise are the idiosyncratic realization of returns (ε_t^i) and the contribution of systematic risk to returns ($\beta^i \cdot f_t$). When $f_t = 0$, the only noise preventing investors from directly inferring α^i is ε_t^i. The β^i-related component of the noise is switched off, and uncertainty about risk loadings is inconsequential for learning. By contrast, when $|f_t| > 0$, an additional layer of noise obfuscates the inference. If β^i was known, investors would only need to subtract $\beta^i \cdot f_t$ from fund returns. With unknown β^i, however, investors do not know what exactly to subtract from any particular

[6]The (net) risk-free rate is normalized to zero, so the gross risk-free rate equals 1.

[7]Note that investors can condition on the realization of f_t because we are assuming that factor realizations are observed before investors allocate their capital.

fund i's return to calculate its risk-adjusted performance. Hence, they have to treat the additional term as noise. The more uncertain they are about β^i, the more noisy the observation seems to them – *in particular when* $|f_t|$ *is large*. As a result, the signal-to-noise ratio is highest when $f_t = 0$, and decreases symmetrically for both higher and lower factor realizations. The speed of capital reallocation is therefore highest for realizations of f_t close to zero.

2.4.2 Formal Result

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

Lemma 2.

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

where

$$\lambda(f_t) = \frac{1}{1 + \frac{\sigma_\beta^2}{\sigma_\alpha^2} f_t^2 + \frac{\sigma_\varepsilon^2}{\sigma_\alpha^2}}. \tag{5}$$

Recall that σ_α^2 and σ_β^2 denote the uncertainty about the parameters α^i and β^i, according to equation (2). The term $\eta \cdot \lambda(f_t)$ gives the FPS. In particular, $\lambda(f_t)$ corresponds to the signal-to-noise ratio.[8]

The intuition is straightforward. First, consider the case in which no uncertainty about risk exposure is present, $\sigma_\beta^2 = 0$, as in the existing literature. Then the FPS does not depend on the factor realization, f_t. In that case, the intuition developed in Berk and Green (2004) and other models obtains. Specifically, the more dispersed skill is believed to be, that is, the higher σ_α^2 is relative to σ_ε^2, the stronger the reaction to news, that is, the steeper the FPS. Intuitively, if very

[8]For the difference in fund sizes $S_t^i - S_{t-1}^i$ to correspond to the standard definition of net flows, it is implicitly assumed that each fund i distributes the net return $Y_t^i - 1$ at the end of period t. This assumption has the counterfactual implication of generating constant NAV pricing of mutual funds. However, similar theoretical results obtain for alternative definitions of flows, yet have more complicated functional forms. To show that our empirical results are not driven by any particular definition of flows, we offer several alternative specifications that make use of different specifications of flows.

high and low fund returns are deemed realistic and attributable to exceptionally high or low skill, rational investors are less prone to impute abnormal fund returns to random noise, and will therefore react more strongly to the news. In sum, the ratio of σ_ε^2 to σ_α^2 summarizes the signal-to-noise ratio in the case of $\sigma_\beta^2 = 0$.

Let us now introduce uncertainty about β^i, $\sigma_\beta^2 > 0$, thereby making the FPS depend on factor realizations, f_t. A positive σ_β^2 dampens the FPS. The strength of this effect depends positively on the absolute magnitude of the total factor realization f_t. For a given performance signal Y_t^i and uncertainty about skill, σ_α^2, the larger the uncertainty in beta and the larger the realization of the factor f_t, the more likely the observed performance is due to risk taking, and the less likely it is that the observed performance is due to skill. As a result, high σ_β^2 combined with high $|f_t|$ attenuates investors' reaction to unexpected performance. The dependence of λ on f_t, and the sensitivity of this dependence on the relative degrees of uncertainty about α^i and β^i, is the driver of all our empirical predictions.

2.5 Empirical Predictions

This section derives additional testable implications of the model. The first prediction, regarding the variation of the FPS between "moderate" and "extreme" realizations of the factor, does not require additional assumptions, but is directly implied by equation (5). For the difference-in-differences predictions, we conjecture that it is possible to identify two groups of funds that can be ranked in terms of $\frac{\sigma_\beta}{\sigma_\alpha}$, that is, the degree of investors' uncertainty about beta relative to the uncertainty about skill. (We confirm that conjecture in the empirical analysis.)

2.5.1 FPS in Extreme versus Moderate Market States

Our first prediction is that fund performance is less informative about skill when the realization of the factor is either very high or very low, compared to fund performance when the realization of the factor is closer to zero. As a result, fund flows are more sensitive to performance for factor realizations close to zero. To be able to formulate a prediction that can be tested in a linear fashion, let us denote as "moderate" those states that correspond to realizations of the factor that are in a neighborhood of zero which is defined by a positive constant c. Formally, λ in moderate times is $\lambda_{moderate} = \lambda(f_t)$ such that $|f_t| \leq c$. Conversely, let "extreme" states be those in which the realizations of the factor fall outside this neighborhood: $\lambda_{extreme} = \lambda(f_t)$, such that $|f_t| > c$.

Proposition 1. *The flow-performance sensitivity is larger in moderate than in extreme states,*

$$\lambda_{moderate} - \lambda_{extreme} > 0.$$

The proof is a direct consequence of the functional form of $\lambda(f_t)$ in equation (5) and is provided in the appendix. Notice that a difference in parameter distributions across booms and busts cannot generate that same prediction. For example, higher volatility in bad times than in good times would predict that the FPS is higher in good times than in bad times. It would not, however, predict, a non-monotonic pattern of low FPS in both good and bad times, and a high FPS in moderate times.

2.5.2 Difference-in-Differences Prediction for the FPS

We now predict that the difference in FPS differences across market states depends positively on the degree of relative uncertainty in beta, that is, the ratio $\frac{\sigma_\beta}{\sigma_\alpha}$. When differences exist in the precision of investors' beliefs about the degree of beta uncertainty across fund types compared to uncertainty about skill, the sensitivity of the FPS to the market state varies across fund types. Let us now assume that we can empirically identify two separate groups of funds that can be ranked in terms of their relative beta uncertainty. We denote by H the funds with high relative beta uncertainty and by L the funds with low relative beta uncertainty. Then we can state the following result.

Proposition 2. *The difference in flow-performance sensitivities between moderate and extreme* *times is larger for funds with high beta uncertainty than for funds with low beta uncertainty:*

$$(\lambda_{moderate} - \lambda_{extreme})_H - (\lambda_{moderate} - \lambda_{extreme})_L > 0.$$

The proof is in the appendix. To understand this result, recall that uncertainty about risk loadings relative to uncertainty about skill, drives the FPS's dependence on factor realizations (equation (5)). It is then intuitive that the dependence of the FPS on the state of the market is stronger for funds for which the relative beta uncertainty is larger.

Note that the prediction in proposition 2 helps distinguish the proposed mechanism from a number of alternative theories. For example, one might conjecture that the extreme-vs-moderate difference obtains because volatility is higher in extreme states. However, such a theory would not easily explain why the extreme-vs-moderate difference would vary across fund types.

2.6 Discussion

One apparent limitation of the model is that it is essentially static; that is, the dynamics of investors' beliefs are not explicitly developed within the model. One might suppose that after sufficiently many observations, investors learn parameter values well enough for the FPS not to depend on f_t (because β^i becomes known with certainty) and, eventually, for flows not to respond to performance anymore (because skill α^i becomes known with certainty). This logic would lead to the counterfactual prediction that the FPS is zero in the data. To explain why in practice uncertainty persists and the FPS is not zero, a dynamic model could be useful. In such an extension, funds could periodically disappear and be replaced with new ones, about whose parameters less is known (Pástor, Stambaugh, and Taylor, forthcoming). This replacement would introduce new uncertainty and investors would never fully learn the underlying parameters. Although this extension might make the model more realistic (and would certainly make it less tractable), it would not alter the prediction that, *for a given degree of parameter uncertainty*, the reaction to performance depends on the state of the economy.[9] This is the single key message of the present paper. For these reasons, we choose to present the simplest model that makes accurate empirical predictions for the question that we investigate.

Another simplifying assumption is the choice to shut down learning about the state of the economy, as featured, for example, in Veronesi (1999). The reason we abstract away from this mechanism is that by averaging performance across a large number of funds, investors can infer the realization of the factor in our setting. Relatedly, Jones and Shanken (2005) argue that performance of other funds is useful information for investors' inference about a specific fund's alpha (see also Pástor and Stambaugh, 2002). The present paper focuses on fund-specific performance measurement. To avoid the additional complexity that modelling learning from other funds' returns would entail, one can simply assume that the outcome of this learning process is subsumed in investors' priors, which are inherited from the previous period.

A third simplification is that the parameters α^i and β^i are exogenous in the model. The most important reason for this modeling choice is to keep the focus on uncertainty about beta as the single driver of our results. Including managers' choice of parameters would also come at the expense of having to make assumptions about their preferences and incentives, which would make it more difficult to understand which part of our results comes from assumptions about investor preferences, which from other assumptions. The model does not preclude, of course, 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, see also Gervais and Strobl (2013).

[9] Note also that the qualitative predictions of the model are entirely unaffected if a single agent with infinite horizon would make the capital allocation decisions, instead of overlapping generations of agents.

3 Empirical Methodology

In this section, we describe the empirical methodology for testing the model's predictions. All the testable implications concern the dependence of the flow-performance sensitivity (FPS) on the market state. The estimation of the FPS is therefore the core of our discussion.

In order to allow for the possibility that real-world investors make efficient use of all the available information when making inference about skill and risk loadings, we need to include past returns and disclosed holdings in our procedure to compute risk-adjusted performance. Thus, we develop a technique to estimate fund betas that approximates the learning process of rational investors with unlimited information capacity. This procedure, relying on reported holdings and daily fund returns, represents an original methodological contribution of the paper. Importantly, this methodology is not required to obtain our empirical results and by no means do our conclusions depend on the assumptions that investors perform a similar analysis, as shown in the robustness section. The purpose of the procedure is only to show that the FPS varies across market states, even when investors use the most granular information. Thus, our estimates of factor loadings and risk adjusted performance are likely to represent a lower bound to the uncertainty about parameter distributions that is faced by real-world investors.

3.1 Estimating the FPS

In defining the correct specification for the estimation of the FPS, we seek guidance from the model. Equation (4), which we report here for convenience (making more explicit the conditioning information),

$$F_t^i = \eta \cdot \lambda\left(f_t\right)\left(Y_t^i - E\left(Y_t^i | f_t, t-1\right)\right),$$

is our starting point. Based on this equation, the FPS is given by $\eta \cdot \lambda\left(f\right)$, where $\lambda\left(f\right) = \frac{1}{1+\frac{\sigma_\beta^2}{\sigma_\alpha^2}f_t^2+\frac{\sigma_\xi^2}{\sigma_\alpha^2}}$. Then, to estimate the FPS, the econometrician needs to regress flows, F_t^i, on unexpected returns,

$Y_t^i - E\left(Y_t^i | f_t, t-1\right)$.[10]

Unexpected returns, which we label X_t^i, can be written as

$$\begin{aligned} X_t^i &= Y_t^i - E\left(Y_t^i | f_t, t-1\right) \\ &= Y_t^i - \left(1 + \hat{\alpha}_{t-1}^i + \hat{\beta}_{t-1}^i f_t - \eta S_{t-1}^i\right) \\ &= Y_t^i - 1 - \hat{\beta}_{t-1}^i f_t, \end{aligned} \tag{6}$$

where the second step makes use of equation (1) and the last step follows from the equilibrium condition $\hat{\alpha}_{t-1}^i = \eta S_{t-1}^i$ presented in equation (3). To compute unexpected returns as in equation (6), one needs to use investors' beliefs of beta, $\hat{\beta}^i$, which are not observed. To this purpose, in the next subsection, we develop a methodology to estimate $\hat{\beta}^i$. We use these estimates of beta to compute unexpected returns.

Our regressions are run at the quarterly frequency and the explanatory variable (unexpected returns) is lagged by one quarter relative to the dependent variable (flows). This choice is dictated by the need to allow investors to infer the managers performance from various sources. Specifically, fund holdings, which are relevant for estimating betas, become known with a delay, as we explain below. Moreover, averaging daily unexpected returns over a given quarter provides a less noisy estimate of the performance signal that is relevant for investors. Thus, the main explanatory variable in the FPS regressions at the quarterly frequency is the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor,

$$exret_q^i = \sum_{d=1}^{D} \left(R_d^i - R_f - \hat{\beta}_{d-1}^i R_d^m\right),$$

where q denotes the quarter, d denotes days, and D is the number of days in a quarter. The daily excess return on the market, R_d^m, is used as the risk factor. Note that $exret_q^i$ is expressed as a

[10] Note that the theoretical model is based on fund returns, not ranks. We therefore compute FPS as a function of returns. However, we show robustness also to more traditional specifications based on performance ranks. A previous version of this paper's empirical analysis was entirely based on performance ranks.

quarterly return because the average daily unexpected return is multiplied by the number of days in a quarter.

With respect to the dependent variable in the estimation of the FPS, we provide results with different definitions of flows. For consistency with prior studies, in the main analysis, our empirical proxy for flows is the change in assets under management relative to the prior quarter minus the dollar return on prior quarter assets, divided by prior quarter assets,

$$Flows_{i,q} = \frac{TNA_q^i - TNA_{q-1}^i \left(1 + R_q^i\right)}{TNA_{q-1}^i}, \tag{7}$$

where TNA_q^i is total net assets in quarter q for fund i, and R_q^i is fund i's quarterly return, which is obtained from compounding monthly returns. So, flows are expressed as a fraction of assets under management. Yet in our model, flows are defined as the change in fund size, not scaled by assets (see equation (4)). To show robustness of our findings to definitions of flows that are closer to the model, we also provide results in which flows are just the change in fund size ("dollar flows"). Further, when testing the quantitative implications of the model, we estimate the FPS in dollars to adhere strictly to the model's predictions.

3.2 Estimating betas

Investors' richest information set for making their inferences about betas includes daily returns and reported holdings of each fund. To approximate the inference of investors that make efficient use of all data, we develop a technique that combines these two sources of information.

The first key input is reported holdings. Prior to May 2004, U.S. mutual funds were required to report holdings semi-annually, although funds could voluntarily disclose their portfolios more frequently. Since that date, the SEC has required mutual funds to disclose their holdings every quarter with a delay of at most 60 days. As a result of this 60-day delay, investors have access to reported holdings only toward the end the quarter.[11] We assume that investors make use of reported

[11] As described above, our estimation of the FPS is carried out at the quarterly frequency in a regression of next-

holdings in their inference, and let estimated betas at the beginning of the quarter correspond to the beta of the portfolio holdings at the end of the previous quarter, which we label β_0^i.

Next, we let fund betas evolve daily. On day d, the fund beta is

$$\begin{aligned} \beta_d^i &= \beta_0^i + \Delta\beta_1^i + \Delta\beta_2^i + \ldots + \Delta\beta_d^i \\ &= \beta_0^i + \sum_{j=1}^{d} \Delta\beta_j^i. \end{aligned} \tag{8}$$

Drawing inspiration from Ferson and Schadt (1996) and, in particular, from Patton and Ramadorai (2013), we further assume that fund managers modify daily betas as a linear function of changes in a set of k conditioning variables z_d:

$$\Delta\beta_d^i = \phi_i' \Delta z_d. \tag{9}$$

In our empirical implementation, we use the excess return on the market, R^m, to proxy for the systematic risk factor f. Thus, we start from the market model at the daily frequency to estimate the unobservable k-vector of parameters ϕ_i:

$$R_{d+1}^i = a_i + \beta_d^i R_{d+1}^m + \varepsilon_{d+1}^i. \tag{10}$$

Replacing equations (8) and (9) into (10), we obtain

$$R_{d+1}^i = a_i + \beta_0^i R_{d+1}^m + \phi_i' \left(\sum_{j=1}^{d} \Delta z_j \right) R_{d+1}^m + \varepsilon_{d+1}^i. \tag{11}$$

Let $\tilde{R}_{d+1}^i = R_{d+1}^i - \beta_0^i R_{d+1}^m$, and let $\tilde{R}_{d+1}^m = \left(\sum_{j=1}^{d} \Delta z_j \right) R_{d+1}^m$ (which is a k-vector), and then the

quarter flows on the current quarter's unexpected performance. Hence, the fact that investors can only compute daily betas and unexpected performance toward the end of the quarter does not constitute an obstacle for our approach.

vector ϕ_i can be estimated in the fund-level regression:

$$\tilde{R}^i_{d+1} = a_i + \phi_i' \tilde{R}^m_{d+1} + \varepsilon^i_{d+1}. \tag{12}$$

Given the estimates $\hat{\phi}_i$, we can finally estimate daily betas $\hat{\beta}^i_d$ using equations (8) and (9).

Other authors have estimated daily risk loadings for managed portfolios (see Patton and Ramadorai (2013) for an application to hedge funds). However, to the best of our knowledge, this paper is the first to develop a methodology combining information from daily returns with quarterly holdings to estimate mutual fund risk loadings at the daily frequency.

In the empirical implementation, we estimate the holdings betas β^i_0 using reported holdings at the end of the prior quarter along with stock-level betas. Stock betas are computed from daily returns using at least one month and at most one year of data, in a rolling window framework, where we let the window advance by one quarter (given that we only need end-of-quarter betas). To account for non-synchronous trading, we proceed as in Lewellen and Nagel (2006) and regress the daily excess return on the contemporaneous market return and four lags of this variable, imposing the constraint that lags 2–4 have the same slope to reduce the number of parameters. Then, the final estimate of beta is the sum of the estimates on all the lags and the comtemporaneous return. The fund beta on the first day of the quarter is the beta of the fund's portfolio as reported at the end of the previous quarter.

To proxy for the manager's conditional information, we use a set of conditioning variables that appear in prior literature (e.g., Ferson and Schadt, 1996; Ferson and Harvey, 1999; Patton and Ramadorai, 2013). We constrain ourselves to variables that are available at the daily frequency. As a result, for variables in the vector Δz_d, we use (1) the daily excess return on the CRSP value-weighted index, (2) the change in the Ted Spread, which is the difference between the three-month LIBOR and T-Bill rates, (3) the change in the VIX index from the CBOE, and (4) the change in the Credit Spread, which is the difference between Baa- and Aaa-rated corporate bonds (from the Federal Reserve Bank of Saint Louis).

Daily mutual fund data are available from September 1, 1998, which marks the beginning of our sample. Given that our availability of the linking tables to match S12 holdings to CRSP fund returns ends in 2012:Q1, we are able to compute daily betas up to the end of 2012:Q2. A thorough description of our sample selection procedure is given in section 4.

The output of the beta estimation procedure is reported in Table 2 at the fund-day level. The observations are winsorized at the 1st and 99th percentiles. Consistent with prior evidence (Fama and French, 2010), the mean and median betas are very close to one (Panel A). However, across fund-days, betas range from a minimum of 0.74 to a maximum of 1.25. A better gauge of the volatility of fund-level betas comes from Panel B. The total volatility of fund-level betas, which is on average 0.071 across 5,049 funds, is broken down into two components. One source of variation is the standard deviation of betas within a given quarter (on average 0.029). This variation originates from the volatility of the changes in the conditioning variables z_d and the volatility of $\tilde{R}^i_{d+1}$, which, in turn, depends on the extent to which daily betas deviate from holdings-betas.[12] The other source of variation in fund-level betas is the volatility of holdings-betas across quarters. This volatility, on average, amounts to 0.048, which clarifies that variation of holdings-betas across quarters is the more important source of variation in estimated betas.

Panel A of Table 2 also provides information on the dependence of daily betas on the conditioning variables. We learn that, on average, betas increase following positive market returns, suggesting that managers do not immediately rebalance toward cash when their portfolio increases in value. Betas also rise following an increase in the credit spread. Finally, betas decline when the VIX and the Ted Spread increase, which suggests that managers take more defensive positions in bad times.

To conclude, we note that this procedure is meant to approximate the type of inference made by investors who use all the available information at the highest possible frequency. Its purpose is to alleviate the concern that the results of this paper are driven by a failure to closely model the

[12] Recall that $\tilde{R}^i_{d+1} = R^i_{d+1} - \beta^i_0 R^m_{d+1}$, where β^i_0 is the beta computed from holdings.

dynamics of rational investors' expectations. It is still possible, however, that investors are much less sophisticated in making inference about risk loadings than this procedure assumes. For example, they could just use end-of-quarter holding betas and abstain from adjusting their expectations intra-quarter. In such a case, our procedure fails to introduce relevant constraints on the parameters (i.e. the slope on the conditioning variables should be zero) and it introduces unnecessary noise into the estimates of betas, so that the estimates of beta are not efficient. To address this concern, in the robustness section, we show that our main results remain intact when we estimate betas using end-of-quarter holding betas, or when investors do not adjust returns for risk altogether.

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. Following the literature standard, we further filter funds by matching this sample to the Thomson Financial S12 holdings database as in Kacperczyk, Sialm, and Zheng (2005).

To address the potential bias resulting from the fact that the fund incubation period is also reported, we exclude observations whose date is prior to the reported starting date of the fund, similar to Kacperczyk, Van Nieuwerburgh, and Veldkamp (2013). Because incubated funds tend to be smaller, we exclude funds before they pass the $5 million threshold for assets under management (but we do not exclude them if they fall below $5 million).

Mutual funds in CRSP include both retail and institutional share classes. Institutional funds are subject to a number of constraints in terms of minimum investment size, long-term investment agreements, and limited choice set whenever they are offered to individuals through a 401(k) plan, which impose restrictions on fund flows that our model does not capture. These considerations prompt us to focus our empirical analysis on mutual funds that are sold to retail investors. The retail-fund indicator is available in CRSP starting in December 1999. For the prior period, we backward-impute the retail indicator whenever available and we use the names of share classes to identify institutional funds. We exclude from the sample the funds for which no information can be gathered on whether they are retail or institutional. Nevertheless, we also show that our results are robust to including institutional funds in the sample.

Using the quarterly net asset values and returns from CRSP, for our main analysis, we compute net flows according to equation (7). Elton, Gruber, and Blake (2001) point out a number of errors in the CRSP mutual fund database that could lead to extreme values of flows. For this reason, we filter out the top and bottom 1% tails of the net flows distribution. The other variables we use in the analysis, and for which we require availability for sample inclusion, are the expense ratio, the portfolio turnover ratio, and return volatility, which is computed over the prior 12 months. These variables are winsorized at the 1^{st} and 99^{th} percentiles. We compute fund age as the time (in quarters) since the first appearance of the fund in the overall CRSP sample.

Our analysis uses daily returns that become available only in September 1, 1998. This availability defines the beginning of our sample. Further, we can match S12 holdings to CRSP fund returns only up to 2012:Q1. Then we are able to compute betas up to the next quarter. As a result, our extended sample at the quarterly frequency ranges between 1998:Q3 and 2012:Q2. Over this period, we have 135,832 mutual fund-quarter observations with valid information on returns and TNA in quarter q and quarter $q+1$, corresponding to 5,049 funds.[13] We also present robustness results relying only on monthly fund returns, in which case the sample starts in 1980:Q1.

Table 3 reports summary statistics for these variables. We notice that the average (median)

[13] Starting in the 1990s, some funds offer multiple share classes that represent claims to the same portfolio. We abstain from aggregating multiple share classes because our purpose is to study fund flows, which differ at the share-class level. This choice does not materially affect our results.

fund has a size of $686 million ($78 million). The maximum fund size is about $109 billion. Fund age ranges from five to 204 quarters. Our sample is comparable to other studies in terms of return volatility, asset turnover, and expense ratio (see Huang, Wei, and Yan, 2007).

Part of our analysis makes use of data on active share and tracking error, which are defined as in Cremers and Petajisto (2009) and Petajisto (2013).[14] 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 S12 database provided by Thomson Financial. The authors currently make their data available between 1980:Q1 and 2009:Q3. As a consequence, in the analysis using these data, our sample ranges between 1998:Q3 and 2009:Q3. In other parts of our study, we make use of data on the return gap from Kacperczyk, Sialm, and Zheng (2008). These authors construct the return gap as the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings. Using the code made available by the authors through WRDS, we update their sample through 2012:Q2.

5 Empirical Results

In this section, we carry out the empirical tests of the model's predictions. First, we test the qualitative prediction that the FPS varies across market states. Also, we show that this prediction holds more strongly for funds that a priori are expected to be characterized by more uncertainty in betas. (This is a test of the difference-in-differences prediction.) Next, we assess the validity of the model in terms of describing the quantitative properties of the data. In this context, we estimate the model-implied uncertainty about beta using non-linear techniques. We then compare this estimate to direct measures of beta uncertainty to gauge the plausibility of the model's quantitative predictions.

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

5.1 The FPS in Moderate and Extreme Market States

In section 3, we motivate our estimation of the FPS from a regression of quarterly flows on lagged unexpected returns,

$$Flows_{q+1}^{i} = a + b \cdot exret_{q}^{i} + \varepsilon_{q}^{i}, \tag{13}$$

where flows are measured as a fraction of lagged assets under management. As in a Fama and MacBeth (1973) approach, we estimate this regression every quarter and report the average of the quarterly b coefficients. The t-statistics are then computed using the standard error of the mean coefficients. In a later section, we show robustness along a few dimensions. We estimate equation (13) using pooled fund-quarter data and double-cluster standard errors by fund and quarter. Similar results obtain.[15] Also, we show that the results do not depend on risk-adjusted returns as explanatory variable, as they are robust to using performance ranking within a quarter for funds in the same style category. Finally, the conclusions remain intact if we use the change in market share instead of flows as dependent variable, as advocated by Spiegel and Zhang (2012).

Proposition 1 refers to a comparison between the FPS across periods with moderate and extreme realizations of the factor. Throughout our empirical application, we use the market return as the empirical counterpart of the systematic factor. Also, we define as extreme the quarters in which the excess return on the CRSP value-weighted index is below -5% or above 5%.[16] Table 4 provides the results. In the first column, we estimate the FPS for the 56 quarters of the sample and unsurprisingly find a positive and significant relation between flows and lagged performance. In columns (2) and (3), the FPS is estimated only in the extreme and moderate states, respectively. As Proposition 1 predicts, the FPS is larger in moderate than in extreme states. In fact, the FPS is more than

[15] A related concern is a potential time trend in the FPS. We verify that no significant time trend is present in the FPS in our sample, however.

[16] In our sample, the -5% cutoff represents the 25th percentile of the distribution of quarterly market returns. Then, because of the negative skewness in the distribution of the market return, choosing the symmetric 5% cutoff leaves leaves to its right more than 25% of the observations. In the end, about 59% of the quarters are defined as extreme and the remaining ones are moderate. The robustness analysis subsection provides results with other choices of the cutoff, which do not affect the conclusions.

twice as large in moderate times than in extreme times. At the bottom of the table, we report the results of a small-sample test that rejects the hypothesis that the two coefficients are equal. In the next three columns, we replicate the analysis introducing all the controls suggested by Spiegel and Zhang (2012). These variables are the aggregate flows in quarter $q + 1$ into the funds that have the same objective as fund i (flows_style), the total expense ratio (fee), the logarithm of TNA (logsize), the portfolio turnover ratio (turn_ratio), the return volatility computed as the standard deviation of fund returns over the prior 12 months (vol), and the logarithm of the fund's age (logage).[17] The difference between extreme and moderate states is only slightly muted and remains highly statistically significant. The sign and significance of the coefficients on the control variables conform to intuition and to the results in prior literature.

The economic magnitude of the effect is large. Based on the specifications including controls reported in columns (5) and (6), given the standard devision of flows of 0.106, a one-standard-deviation rise in unexpected returns in extreme times (0.047) increases flows by about 14.7% of a standard deviation (0.047*0.332/0.106= 0.147), whereas the same event during moderate times leads to a 23.0% increase in flows in standard deviation units (0.047*0.518/0.106=0.230). Simply taking the ratio of the coefficients (.518/.332) reveals that flows are 57% higher for the same change in returns in moderate than in extreme times. Overall, the analysis validates the main qualitative prediction of the model that the FPS is larger in states of the world in which the realizations of the factor are smaller in absolute value.

Table 5 shows that the effect is not driven by either up markets or down markets alone. In fact, the effect is quite symmetric with respect to zero market returns. The FPS in the left tail and the right tail of the market return distribution is approximately 0.31 to 0.35, respectively, whereas in moderate times, the FPS is 0.754 (without controls) and 0.518 (with controls).

[17] Recall that excess returns in the model are net of fees, as are the fund returns reported by CRSP. We conjecture that cross-sectional variation in fees does not have a first-order effect on FPS-variation across market states. Moreover, the "fee" control should soak up any FPS-variation across market states related to variation across states *and* funds in fees. Indeed, running the analysis using gross of fees returns leaves the point estimates and significance of the specifications without controls almost unchanged. The point estimates and significance of the specifications with controls are perfectly unchanged.

In equation (13), we are constraining flows to be a linear function of performance. Yet a large body of literature (starting with Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998)) identifies a convex flow-performance relation. More recently, other authors (Spiegel and Zhang, 2012) argue that convexity originates from a misspecified empirical model, and that the relation between flows and performance is truly linear. This paper does not intend to contribute to this debate, given that our predictions on the state dependency of the flow-performance relation can be derived for any monotonic shape of this relation. Still, to assess the robustness of our predictions to alternative empirical specifications of the flow-performance relation, we provide further analyses allowing for a piecewise linear relation:

$$Flows_{i,q+1} = a + b_1 \cdot bottom\_exret_q^i + b_2 \cdot mid\_exret_q^i + b_3 \cdot top\_exret_q^i + \varepsilon_q^i, \tag{14}$$

where $bottom\_exret_q^i$ is equal to $exret_q^i$ if $exret_q^i$ is in the first tercile of the distribution of unexpected returns in the quarter, and zero otherwise; $mid\_exret_q^i$ is equal to $exret_q^i$ if $exret_q^i$ is in the second tercile of the distribution of unexpected returns in the quarter, and zero otherwise; $top\_exret_q^i$ is equal to $exret_q^i$ if $exret_q^i$ is in the third tercile of the distribution of unexpected returns in the quarter, and zero otherwise.

Table 6 reports the Fama and MacBeth (1973) estimates of equation (14). In the first column, we find support for the convexity of the FPS as the slope at the bottom of the return distribution is significantly flatter than the slope in the rest of the distribution. More relevant for our purposes, the results in the second and third columns indicate that the prediction of Proposition 1 holds also for a convex specification of the FPS. In fact, in each of the three ranges of the distribution of returns, the slope is significantly larger in moderate than in extreme states. This result holds also when we include the controls (columns (5) and (6)). At the bottom of columns (2) and (3), as well as (5) and (6), we report p-values from a chi-squared test for the equality of the three slopes b_1, b_2, and b_3 between extreme versus moderate market states. The test rejects the null hypothesis that the slopes are jointly equal. (Unreported results reveal that this rejection occurs also when the test is carried out for each slope individually.) We conclude that the result that FPS is steeper in moderate than in extreme market states is robust to a piecewise linear empirical specification. Given the consistency of the conclusions between Tables 4 and 6, we feel legitimized to use the linear specification in the analysis that follows. Doing so allows us to more easily test the difference-in-differences predictions of the model in the following subsection.

To conclude this part of the analysis, we wish to further comment on the economic magnitude of the variation in the FPS between moderate and extreme states. The results in Table 4, columns (2) and (3), suggest that the FPS more than doubles between extreme and moderate quarters. Including controls (columns (5) and (6)), attenuates this variation, but leaves it at a sizable 57%. Because of its popularity in the existing literature, the convexity of the FPS may provide a relevant benchmark to understand whether this magnitude is economically important. The estimates in Table 6 suggest the slope increases by about 48% between the bottom and the top range in the return distribution (column (5)). We conclude that the variation in the FPS between extreme and moderate states is at least as large as the magnitude of the convexity, which has attracted much attention thus far.

5.2 Difference-in-Differences Results

The next step is to test the difference-in-differences prediction given in Proposition 2. The prediction arises from the heterogeneity in the degree of ex-ante uncertainty about a fund's parameters (captured by the model parameters σ_α and σ_β). In particular, we expect types of funds for which the relative uncertainty in beta is higher to exhibit larger variation in the FPS between moderate and extreme states. (As introduced in the model section, by relative uncertainty, we refer to the ratio of uncertainty in beta to the uncertainty in alpha: $\frac{\sigma_\beta}{\sigma_\alpha}$.)

We draw on the mutual fund literature to identify funds for which relative uncertainty in beta is a priori larger. Cremers and Petajisto (2009) and Petajisto (2013) study the degree of active management in mutual funds. They point out two dimensions of active management. The first is a fund's active share, which measures the deviation of a fund's portfolio from the holdings of its benchmark. The second is tracking error, which is the traditional measure of benchmark timing. In their study, "Concentrated" funds rank high (above the median) along both dimensions, whereas "Other" funds are the complement set. We conjecture that relative uncertainty in beliefs about beta is higher for these funds because investors have more difficulty inferring their beta from the beta of their benchmark.[18] Hence, our first test of the difference-in-differences prediction of Proposition 2 contrasts Concentrated funds with Other funds. (In section 5.4 and Table 10, where we compute direct estimates of uncertainty in beta and alpha, we provide evidence confirming the a priori conjecture that relative beta uncertainty is higher for Concentrated and high-return-gap funds than for their counterparts.)

Table 7 reports the results of estimating the FPS separately for the two groups of funds through an interaction between a dummy for Concentrated and unexpected returns. From column (1), we learn that Concentrated funds have slightly higher FPS unconditionally. The test of Proposition 2 emerges from the comparison of columns (2) and (3). Concentrated funds display a higher increment in FPS than Other funds in moderate times compared to extreme times. The difference-in-differences estimate for the FPS is 0.424 (= 0.372 - (-0.052)). The results of the statistical tests at the bottom of these two columns allow us to reject the hypothesis that this double-difference in the FPS is equal to zero. Adding the standard controls does not alter that conclusion (columns (4) through (6)). (The theory makes no claim as to whether differences across fund types during extreme or moderate times drive the difference-in-differences. The non-linear analysis below illustrates why.)

Another relevant dimension of cross-sectional heterogeneity in mutual funds that we can use to measure ex-ante uncertainty about parameters is the "return gap." Kacperczyk, Sialm, and Zheng (2008) define the return gap as the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings. The return gap matters in our

[18]Note that the level of skill or risk exposure does not affect learning in any way. Only the degree of uncertainty about the two parameters does.

context because reported holdings can be used as a source of information to learn about beta. If a fund's returns deviate substantially from the holding portfolio returns, investors have more difficulty reconstructing the fund's beta from the beta of its holdings. Consequently, we conjecture and verify that funds with high (above the median) return gaps in absolute value are characterized by higher relative beta uncertainty, see Table 10. We then test Proposition 2 for high- vs. low-return-gap funds.

In Table 8, we allow for a different FPS between the two groups by interacting unexpected returns with a dummy for high-return-gap funds. The relevant information comes from the comparison of the slopes on the interaction between moderate and extreme times. The p-value is 0.025 for the double difference. The statistical significance is retained with the additions of controls in columns (5) and (6) (p-value = 0.023).

Overall, the evidence is consistent with the predictions of Proposition 2. Funds with a priori higher relative uncertainty in betas display a higher increase in the FPS in moderate time, relative to extreme times.

5.3 Extracting Investors' Beliefs from the FPS

Given the parametric restrictions imposed by the model on the FPS, we can use the empirical estimates of the FPS to back out the uncertainty of investors' beliefs about relative uncertainty in beta, that is, the ratio of σ_β to σ_α. We then compare these model-based estimates to direct estimates of parameter uncertainty from realized returns and fund size to assess the plausibility of the model's quantitative predictions.

Recall that the model's expression for the FPS is

$$FPS_t = \eta \cdot \lambda\left(f_t\right),$$

where

$$\lambda(f_t) = \frac{1}{1 + \frac{\sigma_\beta^2}{\sigma_\alpha^2} f_t^2 + \frac{\sigma_\varepsilon^2}{\sigma_\alpha^2}}.$$

Combining these two equations yields the expression

$$\frac{FPS_t}{\eta} = \frac{1}{1 + \frac{\sigma_\beta^2}{\sigma_\alpha^2} f_t^2 + \frac{\sigma_\varepsilon^2}{\sigma_\alpha^2}}, \tag{15}$$

which provides restrictions on the parameters of interest.

Our goal is to estimate equation (15) using non-linear techniques. To construct the left-hand-side variable, we use estimates of the FPS from the quarterly regressions described in section 3.1. In the model, flows are computed as changes in the dollar size of the fund. Hence, to test the quantitative predictions of the model, we need to estimate parameters in units that are consistent with the model. We thus compute flows in dollars, as opposed to expressing them as a fraction of assets under management.

Next, we need an estimate for the coefficient η. To this purpose, we draw on recent research by Pástor, Stambaugh, and Taylor (forthcoming) who develop a methodology for unbiased estimates of decreasing returns to scale.[19] The parameter β in their equation (1) corresponds to $-\frac{1}{\eta}$ in our equation (1). We take their estimate of fund-level decreasing returns to scale, β, of -0.22×10^{-6} from their Table 3 and compute an estimate of η accordingly.[20] Thus, we have all the elements to construct the empirical counterpart of the left-hand side of equation (15) at the quarterly frequency as

$$L_q = \frac{\widehat{FPS}_q}{\hat{\eta}}.$$

[19]Previous estimates of returns to scale in the industry include Chen, Hong, Huang, and Kubik (2004) and Edelen, Evans, and Kadlec (2007).

[20]The authors' estimate of η is derived at the monthly frequency; hence, we multiply it by 3 to obtain a quarterly figure. The multiplication with 10^{-6} is necessary because they express mutual fund size in million of dollars (at the end of 2011).

Based on equation (15), we estimate the following non-linear regression:

$$L_q = \frac{1}{1 + \left(\frac{\sigma_\beta}{\sigma_\alpha}\right)^2 R_{M,q}^2 + \left(\frac{\sigma_\varepsilon}{\sigma_\alpha}\right)^2} + u_q. \tag{16}$$

Notice that the three parameters (σ_α, σ_β, and σ_ε) are not separately identified, so we express the estimated equation in terms of the ratios $\frac{\sigma_\beta}{\sigma_\alpha}$ and $\frac{\sigma_\varepsilon}{\sigma_\alpha}$. As in the previous analyses, we use the excess market return as the empirical counterpart of the factor f. The squared market return at the quarterly frequency is the right-hand-side variable in the non-linear regression.

We estimate equation (16) using non-linear least squares. The estimates of $\frac{\sigma_\beta}{\sigma_\alpha}$ and $\frac{\sigma_\varepsilon}{\sigma_\alpha}$ are reported in Table 9 (first two columns). They are both positive and significant, consistent with the model's prediction. In particular, the statistical significance of $\widehat{\frac{\sigma_\beta}{\sigma_\alpha}}$ confirms that the FPS depends on the factor realizations because of risk uncertainty, which is the main claim of the paper.

Figure 1 uses these estimates to plot the fitted values from equation (16).[21] Importantly, the hump shape is strongly consistent with the model's main prediction. Note that although the parametric estimation imposes the model-predicted functional form, the data can still reject the hypothesis of the dependence of the FPS on the state of the market. If the model's prediction had been rejected, the shape in Figure 1 would have looked closer to a straight line, reflecting an estimated $\left(\frac{\sigma_\beta}{\sigma_\alpha}\right)$ about equal to zero . Further, the fact that the FPS as a function of the market excess return first increases and then decreases rules out several alternative explanations of our results. For example, one could argue that the dispersion of skill in bad times is higher than the dispersion of skill in good times, or that σ_ε is greater in bad times than in good times. These alternative conjectures predict a monotonic behavior of FPS as a function of the market excess return, which is at odds with our finding of a non-monotonic shape. Moreover, such explanations cannot easily explain why any FPS-difference between extreme and moderate times should be greater for Concentrated than

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

for Other funds, or for funds with a large return gap relative to funds with a small return gap.

We can impose even less structure on the data by estimating the shape of the FPS non-parametrically. We fit a local polynomial smoother to L_t, using the Epanechnikov (1969) kernel with optimal bandwidth chosen with a rule-of-thumb estimator as described in Fan and Gijbels (1996).[22] The independent variable is again the excess market return. The resulting non-parametric function is plotted in Figure 2, along with its 95% confidence interval. The non-parametric plot mimics the hump-shaped plot of the fitted values from the parametric estimation (Figure 1). We conclude that the model's prediction fits the data even when we do not impose a functional form upon the estimation procedure.

We now repeat the non-linear estimation of the parameters in equation (16) separately for Concentrated and Other funds and report the results in Table 9 (columns (3) through (6)). The estimate of $\frac{\sigma_\beta}{\sigma_\alpha}$, which governs the dependence of the FPS on the aggregate factor, is statistically significant only for Concentrated funds. This finding provides further corroboration for the model's predictions. Investors' inference is exposed to the noise from the factor realization only in the case of funds for which relative uncertainty about beta is sufficiently large. As a result, only for these funds does the FPS depend on the market state. Figure 3 provides a graphical representation of these results. Note that the hump-shape is pronounced only for Concentrated funds (thick red line). By contrast, the thin black line corresponding to Other funds is not statistically distinguishable from a flat line.

Finally, Table 9 (columns (7) through (10)) and Figure 4 replicate the analysis for high- and low-return-gap funds. Analogously to the previous case, only the funds that are conjectured to have higher beta uncertainty (high-return-gap funds) display a significantly non-monotonic dependence of the FPS on the market realization. For low-return-gap funds, the FPS is markedly flatter across market states, as is apparent in Figure 4 (thin line).

[22]This procedure is implemented in Stata using the *lpoly* command.

5.4 Verifying the Model's Quantitative Predictions

Next, we assess the validity of the model's quantitative predictions. In particular, we obtain direct estimates of the parameters σ_α and σ_β from realized returns, fund size, and holdings and compare them to the model-implied estimates from section 5.3. The question we intend to address is whether the amount of model-implied parameter uncertainty is of the same order of magnitude as the uncertainty that real-world investors face. If it is, the plausibility of the channel that we propose as an explanation for our findings – uncertainty about risk loadings – will be strengthened.

The procedure described in section 3.2 makes use of the information that is available to investors in estimating fund betas. In particular, it exploits data on fund holdings, daily returns, and daily state variables. As a result, it likely approximates investors' filtering process. We use the betas resulting from this procedure as proxies for unobserved investors' beliefs. For each fund, we compute the standard deviation of the daily betas and use this value as an estimate of the fund-level uncertainty on beta (σ_β). To obtain a unique value across funds, we take the mean standard deviation of fund-level betas (0.071, see Panel B of Table 2. For convenience, we report this estimate in Table 10, Panel A, as well.)

We follow the spirit of Berk and van Binsbergen (2012) in using fund size multiplied by the efficiency parameter η as a measure of managerial skill. This choice is also motivated by equation (3) in our model. For each fund, at the quarterly frequency, we compute $\hat{\alpha}_t^i$ as $\eta \cdot S_t^i$, drawing the estimate of η from Pástor, Stambaugh, and Taylor (forthcoming). (Computing alpha before fees does not alter the conclusions because the focus is on the volatility of alpha at the fund level, while fees are mostly constant over time at the fund level.) Then, to estimate investors' uncertainty about skill (σ_α), we take the fund-level standard deviation of $\hat{\alpha}_t^i$. The average measure of uncertainty across funds is 1.29×10^{-4} (Table 10). Note that our regressions directly control for flows in and out of the sector; as a result, variation stemming from aggregate flows does not affect our empirical results.

Table 10 also reports the ratio between the estimates of σ_β and σ_α. This ratio amounts to

552.002. We are now in the position to compare the model's implied estimate of $\frac{\hat{\sigma_\beta}}{\sigma_\alpha}$ from Table 9 with the direct estimates of investors' uncertainty $\frac{\hat{\sigma_\beta}}{\hat{\sigma_\alpha}}$ reported in Table 10. We note that the direct estimate at 552.002 is remarkably similar to the parametric estimate in Table 9 (648.501) and is well within the 95% confidence interval of this coefficient, which is (399.614; 897.387). Formally, we cannot reject the hypothesis that the model-implied parametric estimates of relative uncertainty about beta coincide with a direct estimate of the same quantity from holdings and returns data. We conclude that the quantitative predictions of the model appear plausible.

Using the same methodology, we compute direct estimates of parameter uncertainty separately for Concentrated and Other funds and report them in Panel B of Table 10. First, we note that the estimate of $\frac{\hat{\sigma_\beta}}{\hat{\sigma_\alpha}}$ for Concentrated funds is more than twice as large as for Other funds. This evidence justifies our conjecture used in the OLS tests that the relative uncertainty in betas is higher for Concentrated funds. Then we validate the quantitative predictions of the model by observing that the direct estimates of relative beta uncertainty for both Concentrated (700.734) and Other funds (307.011) are very close to the parametric estimates in Table 9 (660.624 and 322.124, respectively) and fall within the 95% confidence intervals for these estimates, which are (61.168; 1260.079) and (-166.547; 810.795), respectively.

Finally, we repeat the same estimation for funds ranked by return gap, and report the results in Panel C of Table 10. Although to a smaller extent than the previous case, we find evidence supporting our conjecture that high-return-gap funds are characterized by larger relative uncertainty in betas than low-return-gap funds (the estimated relative uncertainty ratios are 346.174 and 315.724, respectively). The corresponding 95% confidence intervals for the parametric estimates reported in Table 9 are (363.482; 1065.724) and (-18.076; 890.399), respectively.

This exercise concludes the tests of the model's quantitative predictions. The data confirm the predicted shape of the relation between the FPS and the state of the market. Moreover, the amount of uncertainty in investors' beliefs that, within the model, generates this relation appears broadly consistent with direct estimates of parameter uncertainty from holdings and daily return data.

5.5 Robustness Analysis

In this last subsection, we provide robustness checks for several dimensions of the empirical modeling choices. The results are in Tables 11 through 13.

First, we investigate the extent to which changes in residual volatility (σ_ε^2) across market states affect the estimated variation of FPS across market states. This test addresses the concern that our main results could be driven by variation in the parameter distributions across states rather than by the noise introduced by extreme factor realizations. Because the FPS is the regression coefficient of flows on performance, to examine this question, we have to introduce as a control the interaction between performance and residual volatility. By doing that, we explicitly model the dependence of the FPS on residual volatility. We compute residual volatility in each quarter as the standard deviation of the difference between daily excess returns minus the alpha, which is estimated as in section 5.4. The question is whether the effect on the non-interacted performance variable (exret) continues to vary across market states after the introduction of this control. The results in Table 11 indicate that the answer is a clear "yes." Both before and after the introduction of the standard controls, the FPS is much higher in moderate than extreme states, and the differences are highly statistically significant in both cases. We conclude that state-dependent residual volatility is not a key driver of our results.

Next, as mentioned with regard to the estimation of the parameters of the FPS, flows in the model are expressed in dollars. In our main results on the estimation of the FPS, we follow the literature standard and measure flows as a fraction of prior-period assets under management. Here, we provide specifications that are more literally corresponding to their theoretical counterparts. In columns (1) and (2) of Table 12, flows are expressed in dollars (percentage flows multiplied by prior-period assets). The estimates confirm the main results in Table 4 (columns (1) and (2)), because the FPS in moderate times is still more than twice as large as that in extreme times, and the difference in slopes is statistically significant. To be even closer to the model's formulation, in columns (3) and (4), we express flows as the change in size between two quarters (measured in $

millions). Again, this modification of the dependent variable does not affect the main conclusions.

Our main estimation of the FPS relies on quarterly Fama and MacBeth (1973) regressions, which account for cross-sectional correlation of the residuals. At the fund level, the residuals can still be correlated over time. To account for this possibility, as in Huang, Wei, and Yan (2012), we pool the fund-quarter observations and estimate a unique regression with time fixed effects and standard errors that are clustered along both the time and fund dimensions. The difference in slopes between moderate and extreme times is tested via an interaction term between unexpected returns and a dummy for moderate periods. The estimates in columns (5) and (6) show that this change does not affect the main results: the FPS in moderate times is roughly twice as large as in extreme times, and the difference is statistically significant also in this specification.

In our sample selection procedure, we excluded institutional funds because of restrictions in their asset selection that our model does not capture. (Institutions establish long-term relations with mutual funds, which may limit the need for learning and to some extent constrain the fund manager's behavior.) In the specifications reported in columns (7) and (8) of Table 12, we extend the sample to include institutional funds. Again, the main results remain unchanged in terms of both magnitude and statistical significance.

The distribution of returns might change across moderate and extreme times in a way that affects the estimation of the FPS. This issue is a concern as long as returns are not rescaled to have equal distribution across quarters. Then, following the prior literature (e.g., Huang, Wei, and Yan (2007)), we redefine our main explanatory variable in terms of a fund's fractional rank within the quarter relative to funds with the same CRSP objective code. That is, mutual funds' unexpected returns are ranked within the group of funds with the same objective in the same quarter. Then we use as an explanatory variable in the FPS estimation a fund's ranking scaled to range between 0 and 1. Columns (9) and (10) of Table 12 show that this choice of performance variable does not impact the main inference. The FPS is still significantly larger in moderate than in extreme times.

We test the robustness of the results in Table 4 to the choice of the cutoff for the definition of moderate and extreme states, which is $\pm 5\%$ in the main results. In columns (11) and (12) of Table 12, the cutoff for the quarterly market return is 2.5%. That is, moderate times are those in which the quarterly market return in excess of the risk-free rate is above -2.5% and below 2.5%. According to this definition, 11 quarters are moderate and 45 quarters are extreme. In columns (13) and (14), the cutoff is 7.5%, so that 30 quarters are moderate and 26 are extreme. In both cases, the main conclusions are unchanged. In both specifications, the FPS is significantly larger in moderate times and about twice as high. The results are fully consistent with Proposition 1, which holds for any positive constant c.

Finally, we replicate the main analysis on a sample of index funds, which are identified using the CRSP flag variable. The theory that we propose hinges on uncertainty about skill and risk loadings. Index funds, because they track a benchmark, are not expected to generate abnormal returns. Also, their betas are known because they correspond to the benchmark's betas. Consequently, the model predicts no variation in the FPS between moderate and extreme times. The results in columns (15) and (16) provide full support for this prediction.

In Table 13, we show robustness with respect to three dimensions: the time range of the sample, the choice of the explanatory variable, and the choice of the dependent variable. The sample in the main analysis is constrained to start in 1998:Q3 by the availability of the daily returns, which we use to compute daily betas. Abstaining from the computation of daily betas allows us to let the sample start in 1980:Q1, which conforms with the literature standard. The estimation procedure follows Fama and MacBeth (1973).

In the top four rows of Table 13, the dependent variable is next quarter flows, the same as in our main analysis. In the first specification, we address the concern that our methodology for estimating betas is potentially inefficient and can lead to noise in risk adjusted performance. Thus, we estimate fund betas using only the end-of-quarter holdings, and keep the beta constant for the entire next quarter in adjusting returns for risk. The estimates suggest that this choice of explanatory variable does not affect our main conclusions. The second specification involves an even more radical simplification, as the explanatory variable is raw returns with no adjustment for the risk factor realization. It appears that our conclusions do not depend on the chosen methodology to compute betas. In the third specification, the explanatory variable is the fund's return ranking relative to funds in the same style category, where we use CRSP objective code to define styles. The ranking is normalized to range between 0 and 1. Also in this case, the conclusions are not impacted by the choice of the explanatory variable. In the fourth row, we follow Spiegel and Zhang (2012) and measure fund performance by the asset-under-management-weighted return of the funds in the same vigintile. Funds are ranked by quarterly returns and grouped so that in each vigintile there is about one-twentieth of the assets under management in a given quarter. Again, the main conclusions remain intact.

In the next four rows of Table 13, the dependent variable is the change in a fund's market share. This choice of the dependent variable is advocated by Spiegel and Zhang (2012) who argue that the standard controls are not sufficient to capture variation in FPS across funds that is due, for example, to fund age or aggregate flows. The four specifications mirror the top four rows in terms of explanatory variables.[23] Using this alternative dependent variable does not affect our main empirical conclusion: investors' sensitivity to fund performance is significantly larger in moderate than in extreme market states.

Finally, all the estimates in Table 13 are obtained using the long sample ranging between 1980:Q1 and 2012:Q3. The conclusion, therefore, is that our main result holds true also in this extended sample.

6 Conclusion

We provide a model of capital allocation by Bayesian investors to projects that are characterized by uncertainty about their exposure to a risk factor. We cast the interpretation of the model within the framework of flows to mutual funds and show that it explains first-order empirical regu-

[23] We winsorize the change in market share at the 5th and 95th percentiles to obtain a well-behaved distribution.

larities that existing models leave unexplained. In particular, we predict and find a non-monotonic relationship between the flow-performance sensitivity (FPS) and the state of the market, with the highest FPS when markets move sideways and lower FPS when market returns are either very high or very low. Indeed, the flow-performance relation is approximately twice as steep following moderate market realizations than following extreme market returns. Second, the FPS-difference between moderate and extreme times is larger for funds about whose risk loadings investors are more uncertain; no such difference exists for index funds. These findings, combined with the non-monotonicity of the relationship, are more difficult to reconcile with alternative explanations of the FPS-difference across market states.

The paper provides insights for both researchers of individual investor behavior and researchers with interests in macroeconomics. First, our results indicate that individual investors react much more strongly to news about their investments in some market states than in others. Interestingly, such differences in their reactivity are easily explained by a simple rational model. Second, uncertainty about project risks can be an important factor inhibiting capital reallocation decisions; given such uncertainty, reallocation is more effective at times when investors' inference is not obfuscated by large swings in aggregate factor realizations. The benefits of macroeconomic moderation may thus include a more efficient allocation of capital across investment projects.

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A Proofs

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*

$$p_t^i = 1 + \hat{\alpha}_t^i - \frac{1}{\eta} S_t^i. \tag{17}$$

Proof of Lemma 3 (Fund Value)

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

$$E_t \left[m_{t+1} f_{t+1} \right] = 0. \tag{18}$$

The cash flows from fund i are valued according to

$$\begin{aligned} p^i{}_t &= E_t \left[m_{t+1} Y_{t+1}^i \right] \\ &= E_t \left[m_{t+1} \left(1 + \alpha^i + \beta^i f_t - \frac{1}{\eta} S_t^i + \varepsilon_{t+1}^i \right) \right] \\ &= 1 + \hat{\alpha}_t^i - \frac{1}{\eta} S_t^i, \end{aligned}$$

where $\hat{\alpha}_t^i$ and $\hat{\beta}_t^i$ are the time-t beliefs for α^i and β^i. The last step follows from equation (18) and the fact that $E_t \left[m_{t+1} \right] = 1$ given that the net risk-free rate is normalized to 0. □

Proof of Lemma 1 (Fund Size)

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

Proof of Lemma 2 (Fund Flows)

Given our assumptions of normally distributed parameters, beliefs about fund returns conditional on the market shock ξ_t are normally distributed as well. As a result, the standard formulas for Bayesian updating of beliefs apply. Bayesian updating occurs according to

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

with

$$var[Y_t^i | f_t] = \sigma_\alpha^2 + \sigma_\beta^2 f_t^2 + \sigma_\varepsilon^2,$$

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

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

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

Flows, or changes in fund size, are then implied by how much is learned about skill, α^i:

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

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

Proof of Propositions 1 and 2

Let us start from equation (5), which states that $\lambda(f_t) = \frac{1}{1+\frac{\sigma_\beta^2}{\sigma_\alpha^2}f_t^2+\frac{\sigma_\varepsilon^2}{\sigma_\alpha^2}}$. Without loss of generality, let x denote a realization of f_t in extreme times and let 0 be a realization of f_t in moderate times. Further, to simplify notation, let $r = \frac{\sigma_\beta^2}{\sigma_\alpha^2}$ and $s = \frac{\sigma_\varepsilon^2}{\sigma_\alpha^2}$. We can then write

$$\begin{aligned}\lambda_{moderate} - \lambda_{extreme} &= \frac{1}{1+s^2} - \frac{1}{1+r^2x^2+s^2} \\ &= \frac{r^2x^2}{(1+s^2)\,(1+r^2x^2+s^2)} > 0.\end{aligned}$$

This completes the proof of proposition 1. Moreover, let us label funds with high relative uncertainty in beta; that is, higher $r = \frac{\sigma_\beta}{\sigma_a}$, with H and funds with low relative beta uncertainty with L. That is, $r_H > r_L$. Then we can compute the difference in differences as

$$\begin{gathered}(\lambda_{moderate} - \lambda_{extreme})_H - (\lambda_{moderate} - \lambda_{extreme})_L = \\ \frac{r_H^2x^2}{(1+s^2)\left(1+r_H^2x^2+s^2\right)} - \frac{r_L^2x^2}{(1+s^2)\left(1+r_L^2x^2+s^2\right)}.\end{gathered}$$

We want to prove that the double difference is positive:

$$\frac{r_H^2x^2}{(1+s^2)\left(1+r_H^2x^2+s^2\right)} - \frac{r_L^2x^2}{(1+s^2)\left(1+r_L^2x^2+s^2\right)} > 0.$$

The inequality is equivalent to

$$\begin{aligned}\frac{r_H^2x^2}{(1+s^2)\left(1+r_H^2x^2+s^2\right)} &> \frac{r_L^2x^2}{(1+s^2)\left(1+r_L^2x^2+s^2\right)}, \\ \frac{r_H^2}{\left(1+r_H^2x^2+s^2\right)} &> \frac{r_L^2}{\left(1+r_L^2x^2+s^2\right)}.\end{aligned}$$

Because the denominator on the left side of the inequality is larger than the denominator on the right side, the inequality can only hold if $r_H^2 > r_L^2$, which holds trivially because it is assumed that $r_H > r_L$.

$\square$

Figures and Tables

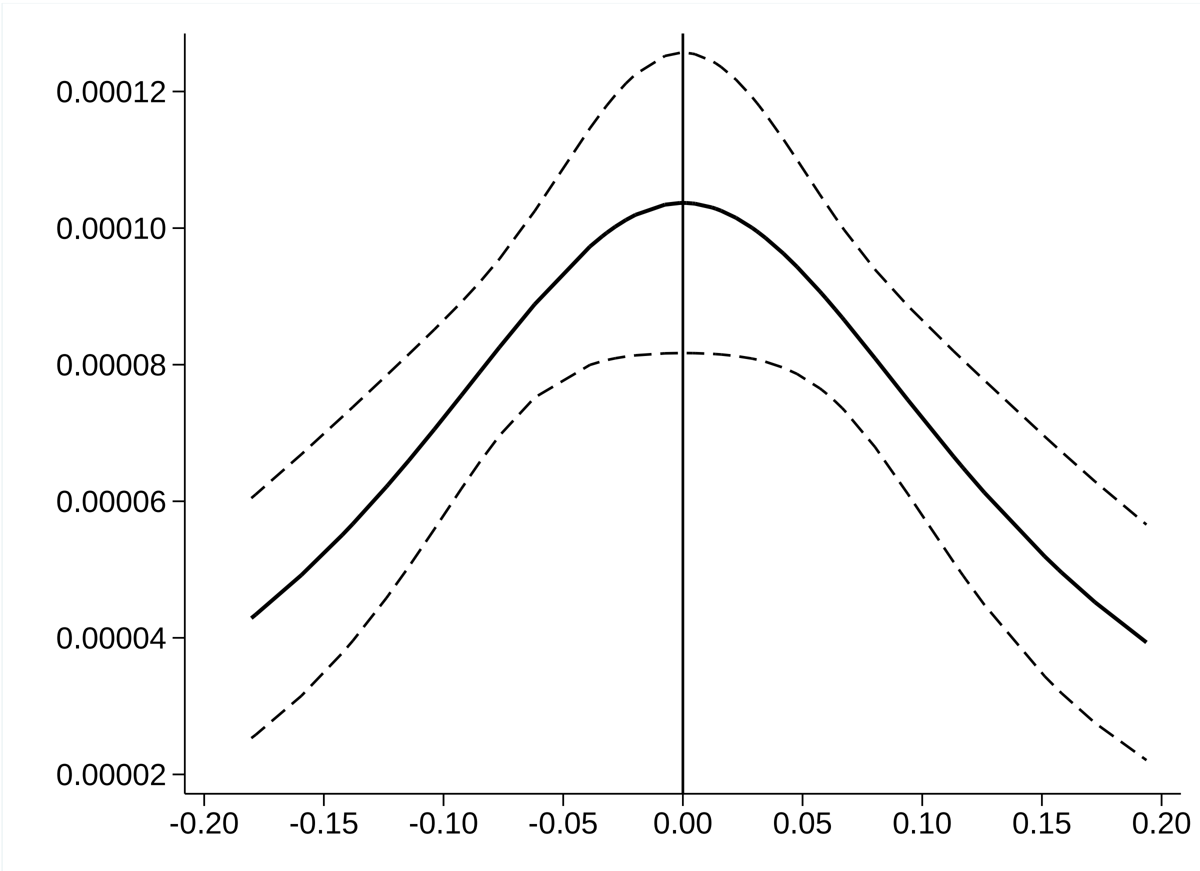

Figure 1: Parametric plot of the FPS.

The figure plots the fitted values from the non-linear estimation of the flow-performance sensitivity (FPS) along with 95% confidence intervals. The estimated functional form is $L_q = \frac{1}{1+\left(\frac{\sigma_\beta}{\sigma_\alpha}\right)^2 R_{M,q}^2 + \left(\frac{\sigma_\varepsilon}{\sigma_\alpha}\right)^2} + u_q$, where $L_q = \frac{\widehat{FPS_q}}{\hat{\eta}}$. FPS_q is the slope from quarterly cross-sectional regressions of quarterly flows on prior-quarter mutual fund unexpected returns and $R_{M,q}$ is the quarterly excess return on the CRSP value-weighed index. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. $\hat{\eta}$ is an estimate of the parameter capturing decreasing returns to scale and it is computed using results in Pástor, Stambaugh, and Taylor (forthcoming). Confidence intervals are computed using the delta method. The sample ranges from 1998:Q3 to 2012:Q2.

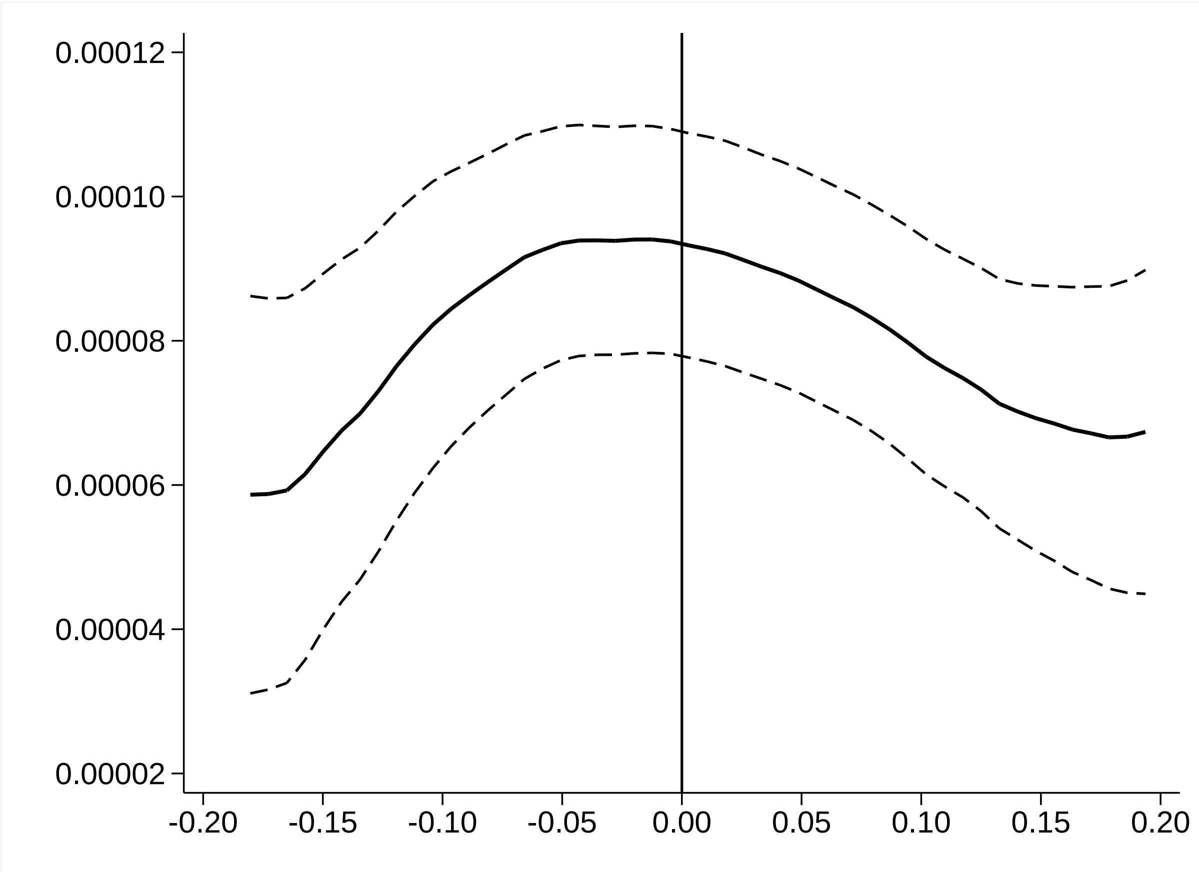

Figure 2: Non-parametric plot of the FPS.

The figure plots the fitted values from a local polynomial smoother applied to $L_q = \frac{\widehat{FPS_q}}{\hat{\eta}}$, along with 95% confidence intervals. The independent variable is the excess return on the CRSP value-weighted index. The smoother uses the Epanechnikov (1969) kernel with optimal bandwidth chosen with a rule-of-thumb estimator as described in Fan and Gijbels (1996). FPS_q is the slope from quarterly cross-sectional regressions of quarterly flows on prior-quarter mutual fund unexpected returns. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. $\hat{\eta}$ is an estimate of the parameter capturing decreasing returns to scale and it is computed using results in Pástor, Stambaugh, and Taylor (forthcoming). The sample ranges from 1998:Q3 to 2012:Q2.

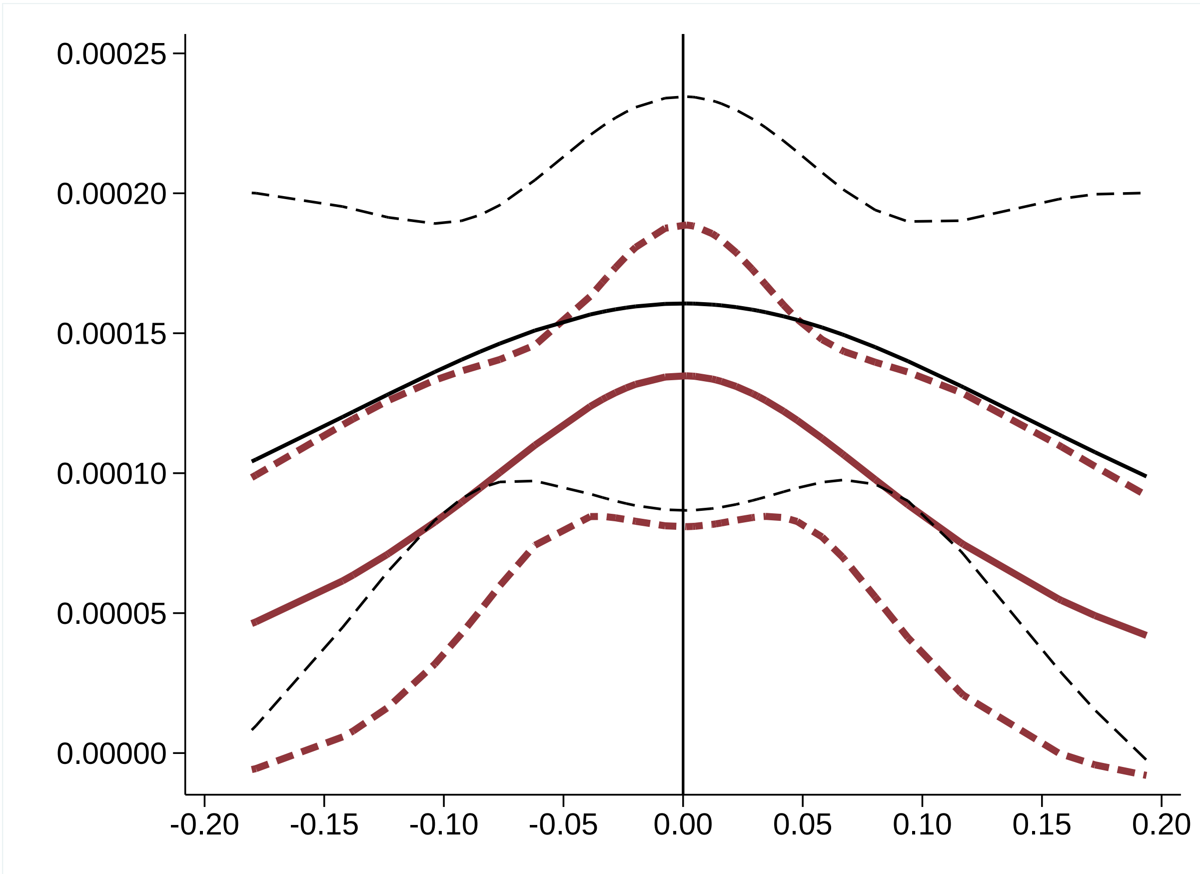

Figure 3: Parametric plot of the FPS for Concentrated and Other funds.

The figure plots the fitted values from the non-linear estimation of the flow-performance sensitivity (FPS) along with 95% confidence intervals for Concentrated (thick red lines) and Other funds (thin black lines). The estimated functional form is $L_q = \frac{1}{1+\left(\frac{\sigma_\beta}{\sigma_\alpha}\right)^2 R^2_{M,q}+\left(\frac{\sigma_\varepsilon}{\sigma_\alpha}\right)^2} + u_q$, where $L_q = \frac{\widehat{FPS}_q}{\hat{\eta}}$. FPS_q is the slope from quarterly cross-sectional regressions of quarterly flows on prior-quarter mutual fund unexpected returns and $R_{M,q}$ is the quarterly excess return on the CRSP value-weighed index. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. $\hat{\eta}$ is an estimate of the parameter capturing decreasing returns to scale and it is computed using results in Pástor, Stambaugh, and Taylor (forthcoming). Concentrated funds are those that in each quarter rank above the median both in terms of tracking error and active share, as defined by Cremers and Petajisto (2009). Other funds are defined as the complement. Confidence intervals are computed using the delta method. The sample ranges from 1998:Q3 to 2009:Q3.

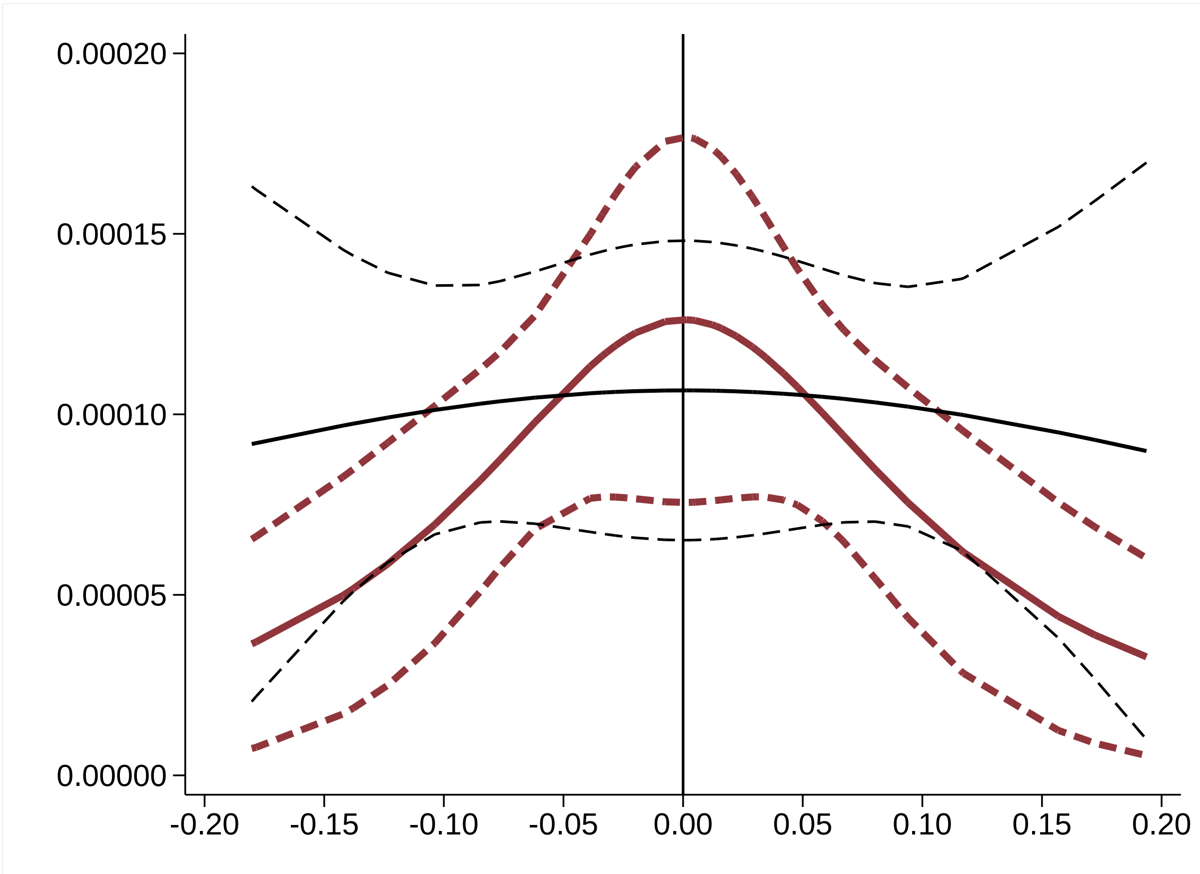

Figure 4: Parametric plot of the FPS for high- and low-return-gap funds.

The figure plots the fitted values from the non-linear estimation of the flow-performance sensitivity (FPS) along with 95% confidence intervals for high (thick red lines) and low-return-gap funds (thin black lines). The estimated functional form is $L_t = \frac{1}{1+\left(\frac{\sigma_\beta}{\sigma_\alpha}\right)^2 R^2_{M,t}+\left(\frac{\sigma_\varepsilon}{\sigma_\alpha}\right)^2} + u_t$, where $L_t = \frac{\widehat{FPS}_t}{\hat{\eta}}$. FPS_t is the slope from quarterly cross-sectional regressions of quarterly flows on prior-quarter mutual fund unexpected returns and $R_{M,t}$ is the quarterly excess return on the CRSP value-weighed index. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. $\hat{\eta}$ is an estimate of the parameter capturing decreasing return to scales and it is computed using results in Pástor, Stambaugh, and Taylor (forthcoming). High-return-gap funds are those that in each quarter rank above the median in terms of the quarterly return gap, as defined by Kacperczyk, Sialm, and Zheng (2008). Confidence intervals are computed using the delta method. The sample ranges from 1998:Q3 to 2012:Q2.

Table 2: Summary statistics (beta estimation).

Panel A reports summary statistics for daily betas and for the coefficients on the changes in conditioning variables in the estimation of beta. Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. The changes in conditioning variables are (1) the daily excess return on the CRSP value-weighted index, (2) the change in the Ted Spread, which is the difference between the three-month LIBOR and TBill rates, (3) the change in the VIX index from the CBOE, and (4) the change in the Credit Spread, which is the difference between Baa- and Aaa-rated corporate bonds (from the Federal Reserve Bank of St. Louis). Daily betas are estimated between September 1, 1998, and June 30, 2012. Panel B reports statistics on the fund-level standard deviation (volatility) in daily betas. The total standard deviation is broken down into fund-level intra-quarter volatility and across-quarter volatility. To compute across-quarter volatility at the fund level, only the first observation in each quarter is used. This observation corresponds to the beta of the reported holdings at the end of the previous quarter. Hence, across-quarter volatility corresponds to the volatility of the holding-betas.

Panel A: Summary Statistics of Betas and Coefficients on Conditioning Variables

	N	Mean	SD	Min	p25	Median	p75	Max
Beta	8,452,791	0.998	0.082	0.745	0.953	0.997	1.040	1.250
Coeff. on Market Return	8,452,791	0.039	1.070	-13.400	-0.381	0.100	0.563	12.200
Coeff. on Ted Spread	8,452,791	-1.080	18.300	-496.000	-3.760	-1.270	1.040	380.000
Coeff. on VIX	8,452,791	-0.097	0.840	-13.400	-0.390	-0.002	0.292	13.000
Coeff. on Cred. Spread	8,452,791	2.040	27.500	-408.000	-3.240	0.859	5.550	667.000

Panel B: Fund-Level Volatility of Beta Estimates

	N	Mean	SD	Min	p25	Median	p75	Max
Total volatility	5,049	0.071	0.033	0.006	0.047	0.064	0.087	0.233
Intra-quarter volatility	5,049	0.029	0.024	0.001	0.013	0.021	0.036	0.168
Across-quarter volatility	5,049	0.048	0.024	0.000	0.033	0.045	0.061	0.172

Table 3: Summary statistics (FPS estimation).

The table reports summary statistics for the variables that are used in the estimation of the flow-performance sensitivity (FPS) at the quarterly frequency: the fund's quarterly unexpected return, which is the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter; daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables.); assets under management in $ millions (TNA); the total expense ratio; the fund turnover ratio; return volatility over the prior 12 months; fund age computed as the number of quarters since the first appearance in CRSP; and quarterly flows computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. The sample ranges from 1998:Q3 to 2012:Q2.

	N	Mean	SD	Min	Median	Max
Ret	135,832	0.000	0.047	-0.733	-0.001	0.567
TNA	135,832	686	3202	5	78	109073
Expense ratio	135,832	0.016	0.005	0.000	0.015	0.089
Turnover	135,832	0.862	0.808	0.000	0.670	19.800
Volatility	135,832	0.051	0.024	0.004	0.047	0.287
Age (quarters)	135,832	41.600	35.100	5.000	32.000	204.000
Flows	135,832	-0.001	0.106	-0.261	-0.021	0.734

	Correlations					
	Ret	TNA	Expense	Turnover	Volatility	Age
Ret	1.00					
TNA	0.01	1.00				
Expense ratio	-0.01	-0.24	1.00			
Turnover	-0.01	-0.08	0.15	1.00		
Volatility	-0.04	-0.03	0.05	0.18	1.00	
Age (quarters)	-0.01	0.32	-0.30	-0.07	-0.03	1.00
Flows	0.14	0.00	-0.07	-0.02	0.00	-0.15

Table 4: Flow-performance sensitivity main results (extreme vs. moderate states).

The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund unexpected returns (flow-performance sensitivity, FPS). Columns (1) and (4) are for all quarters. Columns (2) and (5) are for Extreme quarters, and columns (3) and (6) are for Moderate quarters. Columns (4) through (6) include a set of control variables: total flows into funds with the same CRSP objective code; the total expense ratio of the fund; the logarithm of assets under management; the fund turnover ratio; return volatility over the prior 12 months; fund age computed as the number of quarters since the first appearance in CRSP; one-quarter lagged flows. At the bottom of the table, we report the z-statistic and p-value for the small-sample test of the null hypothesis that the FPSs in moderate and extreme times coincide. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. Moderate times are defined as the quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -5% and below +5%. Extreme quarters are all other quarters. The sample ranges from 1998:Q3 to 2012:Q2. T-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Flows (t+1)	All quarters	Extreme	Moderate	All quarters	Extreme	Moderate
exret	0.502***	0.326***	0.754***	0.409***	0.332***	0.518***
	(10.687)	(6.229)	(14.254)	(12.626)	(8.462)	(10.968)
flows_style				0.342***	0.404***	0.253**
				(5.841)	(6.015)	(2.429)
fee				-1.309***	-1.177***	-1.498***
				(-10.695)	(-7.275)	(-8.151)
logsize				-0.001***	-0.001**	-0.001***
				(-3.984)	(-2.302)	(-3.909)
turn_ratio				0.000	0.001	-0.000
				(0.425)	(0.736)	(-0.438)
vol				-0.152	-0.297**	0.055
				(-1.385)	(-2.071)	(0.335)
logage				-0.010***	-0.009***	-0.012***
				(-12.012)	(-8.842)	(-8.260)
flows				0.545***	0.563***	0.520***
				(35.280)	(27.686)	(22.341)
Constant	-0.003	-0.003	-0.004	0.071***	0.074***	0.066***
	(-1.250)	(-0.743)	(-1.089)	(12.587)	(8.831)	(9.974)
Observations	135,832	75,563	60,269	135,832	75,563	60,269
R-squared	0.048	0.036	0.065	0.416	0.403	0.433
Number of quarters	56	33	23	56	33	23
z-stat		5.748			3.026	
p-val		0.000			0.002	

Table 5: Flow-Performance Sensitivity Main Results (Comparison of the FPS in the Right and Left Tails of the Market Return Distribution).

The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund unexpected returns (flow-performance sensitivity, FPS). Columns (1) and (4) are for the "left tail" of the market return distribution ("extreme" times with negative market returns). Columns (2) and (5) are for the "right tail" of the market return distribution ("extreme" times with positive market returns). Columns (3) and (6) replicate "moderate" quarters from the previous table. Columns (4) through (6) include a set of control variables: total flows into funds with the same CRSP objective code; the total expense ratio of the fund; the logarithm of assets under management; the fund turnover ratio; return volatility over the prior 12 months; fund age computed as the number of quarters since the first appearance in CRSP; one-quarter lagged flows. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. Moderate times are defined as the quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -5% and below +5%. Extreme quarters are all other quarters. The sample ranges from 1998:Q3 to 2012:Q2. z-statistics and p-values for differences between tails and moderate times are reported at the bottom. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Flows (t+1)	Left Tail	Right Tail	Moderate	Left Tail	Right Tail	Moderate
exret	0.347***	0.311***	0.754***	0.307***	0.351***	0.518***
	(4.726)	(4.167)	(14.254)	(4.415)	(7.583)	(10.968)
flows_style				0.525***	0.316***	0.253**
				(4.262)	(4.530)	(2.429)
fee				-1.275***	-1.106***	-1.498***
				(-5.009)	(-5.170)	(-8.151)
logsize				-0.001	-0.001*	-0.001***
				(-1.164)	(-2.093)	(-3.909)
turn_ratio				0.001	0.001	-0.000
				(0.523)	(0.504)	(-0.438)
vol				0.175	-0.644***	0.055
				(0.727)	(-5.008)	(0.335)
logage				-0.008***	-0.010***	-0.012***
				(-4.263)	(-8.819)	(-8.260)
flows				0.592***	0.542***	0.520***
				(15.872)	(24.774)	(22.341)
Constant	-0.002	-0.003	-0.004	0.046***	0.095***	0.066***
	(-0.325)	(-0.750)	(-1.089)	(3.705)	(10.686)	(9.974)
Observations	31,586	43,977	60,269	31,586	43,977	60,269
R-squared	0.047	0.028	0.065	0.367	0.430	0.433
Number of quarters	14	19	23	14	19	23
z-stat	4.505	4.840		2.507	2.534	
p-val	0.000	0.000		0.012	0.011	

Table 6: Flow-performance sensitivity main results (extreme vs. moderate states): piecewise linear specification.

The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on three variables corresponding to three intervals in the support of prior-quarter mutual fund unexpected returns. The three intervals are determined according to the terciles of the distribution of unexpected returns in a given quarter. Each of the the three variables equals the fund's unexpected return if it falls in the corresponding interval of the distribution, and zero otherwise. Columns (1) and (4) are for all quarters. Columns (2) and (5) are for Extreme quarters, and columns (3) and (6) are for Moderate quarters. Columns (4) through (6) include a set of control variables: total flows into funds with the same CRSP objective code; the total expense ratio of the fund; the logarithm of assets under management; the fund turnover ratio; return volatility over the prior 12 months; fund age computed as the number of quarters since the first appearance in CRSP; one-quarter lagged flows. At the bottom of the table, we report p-values for the small-sample chi-square test of the null hypotheses of joint equality of the slopes between moderate and extreme quarters. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. Moderate times are defined as the quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -5% and below +5%. Extreme quarters are all other quarters. The sample ranges from 1998:Q3 to 2012:Q2. T-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Flows (t+1)	All quarters	Extreme	Moderate	All quarters	Extreme	Moderate
bottom_exret	0.431***	0.274***	0.655***	0.339***	0.283***	0.419***
	(7.994)	(3.966)	(10.622)	(10.790)	(6.609)	(10.220)
mid_exret	0.595***	0.430***	0.830***	0.530***	0.480***	0.601***
	(6.742)	(3.833)	(6.416)	(7.846)	(5.798)	(5.260)
top_exret	0.641***	0.441***	0.928***	0.501***	0.410***	0.630***
	(9.535)	(6.115)	(9.140)	(11.289)	(8.202)	(8.535)
flows_style				0.332***	0.404***	0.229**
				(5.623)	(6.059)	(2.168)
fee				-1.336***	-1.207***	-1.523***
				(-10.850)	(-7.300)	(-8.427)
logsize				-0.001***	-0.001**	-0.001***
				(-3.922)	(-2.268)	(-3.895)
turn_ratio				0.000	0.001	-0.000
				(0.340)	(0.604)	(-0.365)
vol				-0.175	-0.313**	0.022
				(-1.648)	(-2.306)	(0.136)
logage				-0.010***	-0.009***	-0.012***
				(-12.169)	(-9.024)	(-8.294)
flows				0.543***	0.560***	0.519***
				(35.463)	(27.851)	(22.366)
Constant	-0.005*	-0.004	-0.007	0.071***	0.075***	0.065***
	(-1.865)	(-1.099)	(-1.682)	(12.505)	(8.837)	(9.884)
Observations	135,832	75,563	60,269	135,832	75,563	60,269
R-squared	0.054	0.043	0.070	0.418	0.406	0.435
Number of quarters	56	33	23	56	33	23
p-val		0.000			0.029	

Table 7: Flow-performance sensitivity double-difference results: Concentrated vs. Other funds.

The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund unexpected returns and their interaction with an indicator for Concentrated funds. Columns (1) and (4) are for all quarters. Columns (2) and (5) are for Extreme quarters, and columns (3) and (6) are for Moderate quarters. Columns (4) through (6) include a set of control variables: total flows into funds with the same CRSP objective code; the total expense ratio of the fund; the logarithm of assets under management; the fund turnover ratio; return volatility over the prior 12 months; fund age computed as the number of quarters since the first appearance in CRSP; one-quarter lagged flows. At the bottom of the table, we report the z-statistic and p-value for the small-sample test of the null hypothesis that the slopes in moderate and extreme times on the interaction coincide. This test corresponds to a difference-in-differences test for a difference in the slope on concentrated funds in moderate times. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. Concentrated funds are those that in each quarter rank above the median both in terms of tracking error and active share, as defined by Cremers and Petajisto (2009). Moderate times are defined as the quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -5% and below +5%. Extreme quarters are all other quarters. The sample ranges from 1998:Q3 to 2009:Q3. T-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Flows (t+1)	All quarters	Extreme	Moderate	All quarters	Extreme	Moderate
exret × concentrated	0.150*	-0.052	0.372***	0.106	-0.050	0.276**
	(1.817)	(-0.541)	(3.061)	(1.497)	(-0.658)	(2.429)
exret	0.542***	0.416***	0.679***	0.425***	0.414***	0.437***
	(9.819)	(5.611)	(9.352)	(8.780)	(6.843)	(5.581)
concentrated	0.009**	0.008	0.011*	0.009***	0.008**	0.010***
	(2.357)	(1.345)	(2.019)	(3.894)	(2.547)	(2.906)
flows_style				0.387***	0.444***	0.326**
				(3.934)	(3.488)	(2.111)
fee				-0.711**	-0.272	-1.191***
				(-2.293)	(-0.537)	(-3.743)
logsize				-0.002***	-0.002**	-0.003***
				(-4.246)	(-2.462)	(-3.791)
turn_ratio				0.001	0.003	-0.002
				(0.416)	(0.999)	(-0.723)
vol				-0.295	-0.345	-0.240
				(-1.553)	(-1.197)	(-0.965)
logage				-0.009***	-0.007**	-0.011***
				(-5.082)	(-2.637)	(-4.948)
flows				0.543***	0.576***	0.507***
				(17.791)	(11.301)	(16.512)
Constant	0.004**	0.007*	0.002	0.073***	0.068***	0.079***
	(2.070)	(2.066)	(0.746)	(6.028)	(3.221)	(7.077)
Observations	15,666	7,811	7,855	15,666	7,811	7,855
R-squared	0.072	0.065	0.080	0.341	0.342	0.340
Number of quarters	44	23	21	44	23	21
z-stat		2.732			2.389	
p-val		0.006			0.017	

Table 8: Flow-performance sensitivity double-difference results by return gap.

The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund unexpected returns and their interaction with an indicator for high-return-gap funds. Columns (1) and (4) are for all quarters. Columns (2) and (5) are for extreme quarters, and columns (3) and (6) are for moderate quarters. Columns (4) through (6) include a set of control variables: total flows into funds with the same CRSP objective code; the total expense ratio of the fund; the logarithm of assets under management; the fund turnover ratio; return volatility over the prior 12 months; fund age computed as the number of quarters since the first appearance in CRSP; one-quarter lagged flows. At the bottom of the table, we report the z-statistic and p-value for the small-sample test of the null hypothesis that the slopes in moderate and extreme times on the interaction coincide. This test corresponds to a difference-in-differences test for a difference in the slope on high-return-gap funds in moderate times. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. High-return-gap funds are those that in each quarter rank above the median in terms of the quarterly return gap, as defined by Kacperczyk, Sialm, and Zheng (2008). Moderate times are defined as the quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -5% and below +5%. Extreme quarters are all other quarters. The sample ranges from 1998:Q3 to 2012:Q2. T-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Flows (t+1)	All quarters	Extreme	Moderate	All quarters	Extreme	Moderate
exret × high gap	0.127*	-0.003	0.312**	0.111	-0.022	0.301**
	(1.921)	(-0.044)	(2.477)	(1.599)	(-0.291)	(2.519)
exret	0.656***	0.486***	0.899***	0.532***	0.487***	0.597***
	(9.432)	(6.097)	(8.349)	(8.829)	(6.562)	(5.883)
high gap	0.008***	0.008**	0.007*	0.004*	0.004	0.003
	(2.882)	(2.275)	(1.730)	(1.761)	(1.434)	(1.002)
flows_style				0.306**	0.285	0.338*
				(2.212)	(1.455)	(1.757)
fee				-0.131	0.038	-0.374
				(-0.381)	(0.074)	(-0.909)
logsize				-0.001*	-0.002	-0.001
				(-1.757)	(-1.624)	(-0.778)
turn_ratio				-0.002	-0.003	-0.001
				(-0.931)	(-0.891)	(-0.320)
vol				-0.230	-0.316	-0.107
				(-1.264)	(-1.288)	(-0.391)
logage				-0.008***	-0.005**	-0.012***
				(-4.055)	(-2.133)	(-3.885)
flows				0.598***	0.626***	0.558***
				(15.726)	(11.253)	(11.828)
Constant	0.001	0.001	0.002	0.053***	0.050**	0.056***
	(0.502)	(0.223)	(0.534)	(3.563)	(2.292)	(3.123)
Observations	19,223	10,437	8,786	19,223	10,437	8,786
R-squared	0.056	0.040	0.078	0.270	0.264	0.279
Number of groups	56	33	23	56	33	23
z-stat		2.245			2.281	
p-val		0.025			0.023	

Table 9: Estimates of the parameters of the flow-performance sensitivity.

The table reports coefficients from the estimation of the parameters of the flow-performance sensitivity. The reported coefficients correspond to estimates of the ratios $\frac{\sigma_\beta}{\sigma_\alpha}$ and $\frac{\sigma_\varepsilon}{\sigma_\alpha}$. The estimation is carried out using non-linear least squares. The estimated functional form is $L_q = \frac{1}{1+\left(\frac{\sigma_\beta}{\sigma_\alpha}\right)^2 R^2_{M,q}+\left(\frac{\sigma_\varepsilon}{\sigma_\alpha}\right)^2} + u_q$, where $L_q = \frac{\widehat{FPS_t}}{\hat{\eta}}$. FPS_q is the slope from quarterly cross-sectional regressions of quarterly flows on prior-quarter mutual fund unexpected returns, and $R_{M,q}$ is the quarterly excess return on the CRSP value-weighed index. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. $\hat{\eta}$ is an estimate of the parameter capturing decreasing return to scales and it is computed using results in Pastor, Stambaugh, and Taylor (forthcoming). T-statistics are reported in parentheses. Columns (1) and (2) report results for the entire sample of funds, and the sample ranges from 1998:Q3 to 2012:Q2. Columns (3) through (6) report results separately for Concentrated and Other funds. Concentrated funds are those that in each quarter rank above the median both in terms of tracking error and active share, as defined by Cremers and Petajisto (2009). Other funds are defined as the complement. The sample ranges from 1998:Q3 to 2009:Q3. Columns (7) through (10) report results separately for high- and low-return-gap funds. High-return-gap funds are those that in each quarter rank above the median in terms of the quarterly return gap, as defined by Kacperczyk, Sialm, and Zheng (2008). Low-return-gap funds are defined as the complement. The sample ranges from 1998:Q3 to 2012:Q2. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	All funds		Active Share & Tracking Error				Return Gap			
			Concentrated		Other		High Gap		Low Gap	
	$\widehat{\sigma_\beta/\sigma_\alpha}$	$\widehat{\sigma_\varepsilon/\sigma_\alpha}$	$\widehat{\sigma_\beta/\sigma_\alpha}$	$\widehat{\sigma_\varepsilon/\sigma_\alpha}$	$\widehat{\sigma_\beta/\sigma_\alpha}$	$\widehat{\sigma_\varepsilon/\sigma_\alpha}$	$\widehat{\sigma_\beta/\sigma_\alpha}$	$\widehat{\sigma_\varepsilon/\sigma_\alpha}$	$\widehat{\sigma_\beta/\sigma_\alpha}$	$\widehat{\sigma_\varepsilon/\sigma_\alpha}$
Estimate	648.501***	98.200***	660.624**	86.122***	322.124	78.894***	714.603***	85.649***	436.161	92.866***
t-stata	(5.107)	(18.485)	(2.160)	(9.799)	(1.292)	(8.516)	(3.989)	(9.858)	(1.882)	(10.360)
Observations	56		44		44		56		56	
R-squared	0.762		0.487		0.448		0.512		0.463	

Table 10: Direct estimates of parameter uncertainty from fund holdings and daily returns.
The table reports summary statistics on fund-level measures of uncertainty in beta and skill. Uncertainty in beta is estimated as the fund-level standard deviation in daily betas. Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. Uncertainty in skill is estimated as the fund-level standard deviation in quarterly estimates of alpha. Alpha is estimated as fund size in (millions of dollars) at the end of the quarter divided by $\hat{\eta}$, which is an estimate of the parameter capturing decreasing returns to scale and is computed using results in Pastor, Stambaugh, and Taylor (forthcoming). The table also reports the ratio of the mean level of uncertainty in beta to the mean level in uncertainty in alpha. Panel A reports results for the entire sample of funds, and the sample ranges from 1998:Q3 to 2012:Q2. Panel B reports results separately for Concentrated and Other funds. Concentrated funds are those that in each quarter rank above the median both in terms of tracking error and active share, as defined by Cremers and Petajisto (2009). Other funds are defined as the complement. The sample ranges from 1998:Q3 to 2009:Q3. Panel C reports results separately for high- and low-return-gap funds. High-return-gap funds are those that in each quarter rank above the median in terms of the quarterly return gap, as defined by Kacperczyk, Sialm, and Zheng (2008). Low-return-gap funds are defined as the complement. The sample ranges from 1998:Q3 to 2012:Q2.

Panel A:	All funds					
	Mean	SD	Observations			
$\widehat{\sigma_\beta}$	0.071	0.033	5049			
$\widehat{\sigma_\alpha}$	0.000	0.001	5049			
$\widehat{\sigma_\beta}/\widehat{\sigma_\alpha}$		552.002				
Panel B:	Concentrated			Other		
	Mean	SD	Observations	Mean	SD	Observations
$\widehat{\sigma_\beta}$	0.079	0.038	743	0.054	0.031	1479
$\widehat{\sigma_\alpha}$	0.000	0.000	743	0.000	0.001	1479
$\widehat{\sigma_\beta}/\widehat{\sigma_\alpha}$		700.734			307.011	
Panel C:	High-return-gap			Low-return-gap		
	Mean	SD	Observations	Mean	SD	Observations
$\widehat{\sigma_\beta}$	0.071	0.035	937	0.067	0.033	930
$\widehat{\sigma_\alpha}$	0.000	0.001	937	0.000	0.001	930
$\widehat{\sigma_\beta}/\widehat{\sigma_\alpha}$		346.174			315.724	

Table 11: Flow-performance sensitivity controlling for residual volatility.

The table reports slopes from Fama and MacBeth (1973) regressions of quarterly flows on prior-quarter mutual fund unexpected returns (flow-performance sensitivity, FPS), the interaction of unexpected returns with residual volatility in the quarter, and the level of residual volatility. Residual volatility is computed as the standard deviation of daily residual returns within the quarter. Columns (1) and (4) are for all quarters. Columns (2) and (5) are for Extreme quarters, and columns (3) and (6) are for Moderate quarters. Columns (4) through (6) include a set of control variables: total flows into funds with the same CRSP objective code; the total expense ratio of the fund; the logarithm of assets under management; the fund turnover ratio; return volatility over the prior 12 months; fund age computed as the number of quarters since the first appearance in CRSP; one-quarter lagged flows. At the bottom of the table, we report the z-statistic and p-value for the small-sample test of the null hypothesis that the FPSs in moderate and extreme times coincide. Quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. Moderate times are defined as the quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -5% and below +5%. Extreme quarters are all other quarters. The sample ranges from 1998:Q3 to 2012:Q2. T-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Flows (t+1)	All quarters	Extreme	Moderate	All quarters	Extreme	Moderate
exret	0.656***	0.491***	0.893***	0.480***	0.409***	0.581***
	(10.082)	(5.743)	(11.345)	(12.274)	(7.456)	(12.321)
exret × resid. vol.	-14.041*	-15.836*	-11.465	-6.089	-7.096	-4.644
	(-1.798)	(-1.875)	(-0.770)	(-0.942)	(-1.085)	(-0.362)
residual volatility	-0.071	-0.534	0.593	1.183***	1.051**	1.373**
	(-0.109)	(-0.596)	(0.622)	(3.232)	(2.085)	(2.580)
flows_style				0.295***	0.340***	0.231**
				(5.192)	(5.369)	(2.202)
fee				-1.539***	-1.370***	-1.781***
				(-10.061)	(-6.602)	(-8.129)
logsize				-0.001***	-0.001**	-0.001***
				(-4.397)	(-2.570)	(-4.224)
turn_ratio				0.000	0.001	-0.001
				(0.096)	(0.512)	(-0.717)
vol				-0.279**	-0.429***	-0.063
				(-2.634)	(-3.071)	(-0.409)
logage				-0.010***	-0.009***	-0.012***
				(-11.999)	(-8.880)	(-8.205)
flows				0.541***	0.557***	0.517***
				(35.590)	(28.072)	(22.255)
Constant	-0.001	0.001	-0.005	0.077***	0.080***	0.072***
	(-0.321)	(0.229)	(-0.972)	(13.467)	(9.405)	(10.845)
Observations	135,832	75,563	60,269	135,832	75,563	60,269
R-squared	0.060	0.051	0.073	0.420	0.408	0.437
Number of quarters	56	33	23	56	33	23
z-stat		3.460			2.372	
p-val		0.001			0.018	

Table 12: Robustness analysis along several additional dimensions.

The table reports regressions of quarterly flows on prior-quarter mutual fund unexpected returns (flow-performance sensitivity, FPS) in Extreme and Moderate times. At the bottom of the table, we report the z-statistic and p-value for the small-sample test of the null hypothesis that the FPS's in moderate and extreme times coincide. Unless differently specified, quarterly flows are computed as the quarterly change in assets under management minus the dollar return on assets under management over the quarter and expressed as a fraction of prior-quarter assets. Unexpected returns are the average of daily returns (in excess of the risk-free rate) minus the daily beta times the daily realization of the risk factor (this variable is then expressed as a quarterly return, scaling it by the number of days in a quarter). Daily betas are estimated combining information on reported holdings at the end of the prior quarter and daily changes in a set of conditioning variables. Columns (1) and (2) report slopes from Fama and MacBeth (1973) regressions in which flows are measured in (millions of) dollars. Columns (3) and (4) report slopes from Fama and MacBeth (1973) regressions in which flows are measured as quarterly changes in fund size (in millions of dollars). Columns (5) and (6) report slopes from panel regressions with quarter fixed effects and standard errors clustered by quarter and fund. Columns (7) and (8) report slopes from Fama and MacBeth (1973) regressions in which flows are measured as a fraction of assets under management, but the sample is extended to include institutional mutual funds. Columns (9) and (10) report slopes from Fama and MacBeth (1973) regressions in which flows are measured as a fraction of assets under management and the dependent variables is expressed as the fractional rank of the unexpected returns (i.e., unexpected returns are ranked in each quarter and each fund is assigned its ranking, which is scaled to range between 0 and 1). In columns (11) and (12), moderate times are defined as those quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -2.5% and below +2.5%. In columns (13) and (14), moderate times are defined as those quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -7.5% and below +7.5%. In columns (15) and (16), the regressions are run on a sample of index funds. Unless differently specified, moderate times are defined as the quarters in which the realizations of the CRSP value-weighted index in excess of the risk-free rate are above -5% and below +5%. Extreme quarters are all other quarters. The sample ranges from 1998:Q3 to 2012:Q2. T-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dollar Flows		Change in Size		Double-clustering		With Institutional Funds	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Flow (t+1)	Extreme	Moderate	Extreme	Moderate	Extreme	Moderate	Extreme	Moderate
exret	142.619***	316.544***	146.077***	307.603***	0.320***	0.660***	0.349***	0.785***
	(4.642)	(10.531)	(3.802)	(6.310)	(5.540)	(9.511)	(6.579)	(14.367)
Observations	75,563	60,269	75,563	60,269	135,832		111,971	84,138
R-squared	0.007	0.011	0.017	0.016	0.393		0.029	0.052
z-stat	4.047		2.602		3.785		5.726	
p-val	0.000		0.009		0.000		0.000	

	Fractional Rank		Cutoff = 2.5%		Cutoff = 7.5%		Index Funds	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Flow (t+1)	Extreme	Moderate	Extreme	Moderate	Extreme	Moderate	Extreme	Moderate
exret	0.042***	0.065***	0.420***	0.837***	0.319***	0.661***	0.009	0.006
	(5.050)	(10.698)	(8.710)	(10.838)	(6.055)	(10.621)	(0.064)	(0.025)
Observations	75,563	60,269	105,893	29,939	59,846	75,986	12,493	8,898
R-squared	0.038	0.069	0.042	0.070	0.042	0.052	0.182	0.202
z-stat	2.274		4.573		4.192		0.0320	
p-val	0.023		0.000		0.000		0.974	

Table 13: Robustness analysis with respect to sample length, choice of main variables.

This table replicates the main flow-performance-sensitivity analysis extending the sample back to 1980:Q1 and using alternative measures of both the dependent variable and the main explanatory variable. In rows 1-4, the dependent variable is quarterly fund flows in the next quarter. In rows 5-8, the dependent variable is the change in a fund's market share in the next quarter. In row 1, the main explanatory variable is quarterly returns adjusted by end-of-quarter holding betas times the quarterly market return. In row 2, the explanatory variable is raw quarterly returns. In row 3, it is the fractional rank by quarterly returns for funds in the same style category, which ranges between 0 and 1. In row 4, the explanatory variable is the assets-under-management-weighted return for the vigintiles formed by ranking funds according to raw returns in the quarter so that the same amount of total assets under management is in each vigintile. Rows 5 through 8 have the same explanatory variables as the previous four rows. Control variables (where included) are: control variables: total flows into funds with the same CRSP objective code; the total expense ratio of the fund; the logarithm of assets under management; the fund turnover ratio; return volatility over the prior 12 months; fund age computed as the number of quarters since the first appearance in CRSP; one-quarter lagged flows. The sample ranges from 1980:Q1 to 2012:Q2. T-statistics are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Without Controls				With Controls			
	All Quarters	Extreme	Moderate	p-val Mod. - Ext.	All Quarters	Extreme	Moderate	p-val Mod. - Ext.
	Dep. Var.: Flows (t+1)							
Quarterly beta adj. return	0.562***	0.395***	0.746***	0.000	0.416***	0.275***	0.570***	0.000
	(13.112)	(6.750)	(13.772)		(10.060)	(6.717)	(8.239)	
Return	0.390***	0.248***	0.558***	0.000	0.330***	0.247***	0.427***	0.001
	(11.897)	(5.581)	(14.339)		(11.682)	(6.380)	(11.314)	
Frank	0.043***	0.029***	0.058***	0.000	0.034***	0.027***	0.043***	0.009
	(12.188)	(5.832)	(14.793)		(11.236)	(6.472)	(10.116)	
AUM weighted return	0.455***	0.270***	0.674***	0.000	0.322***	0.204***	0.462***	0.000
	(10.606)	(4.985)	(11.843)		(8.528)	(4.588)	(7.834)	
	Dep. Var.: Market Share Change (t+1)							
Quarterly beta adj. return	0.011***	0.006**	0.017***	0.004	0.013***	0.009***	0.017***	0.023
	(5.549)	(2.403)	(5.555)		(7.212)	(3.919)	(6.509)	
Return	0.011***	0.006**	0.018***	0.004	0.013***	0.010***	0.017***	0.036
	(5.497)	(2.309)	(5.658)		(6.883)	(3.597)	(6.531)	
Frank	0.001***	0.001**	0.002***	0.003	0.001***	0.001**	0.002***	0.029
	(5.222)	(2.080)	(5.443)		(5.281)	(2.471)	(5.223)	
AUM weighted return	0.028***	0.003	0.058***	0.000	0.030***	0.007	0.058***	0.000
	(3.813)	(0.364)	(4.919)		(4.130)	(0.805)	(5.213)	