Salience and Mutual Fund Investor Demand for Idiosyncratic Volatility*

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Abstract

We find that mutual fund investors are more likely to both purchase and redeem funds with high idiosyncratic volatility (IV). Investors' tendency to purchase high IV funds is largely driven by high IV funds having more extreme returns, which increases the salience of the fund. Including flexible controls for extreme past returns over multiple horizons decreases the effect of IV on new investment, and experimental evidence corroborates that increasing the salience of extreme returns increases investor demand for IV. Demand for IV is higher among retail investors and funds with otherwise lower salience. Collectively, the evidence suggests that extreme returns attract investor attention and contribute to investors' risk seeking behavior when purchasing mutual funds.

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Idiosyncratic Volatility, Limited Attention, Mutual Funds, Salience

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1. Introduction

A central tenet in finance is that investors are risk averse, yet how investors assess risk is not well understood. Recent literature argues that studying mutual fund flows can provide new insight into how investors evaluate risk. For example, Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016) find that CAPM alphas are the best predictor of flows across various performance models, which is consistent with investors viewing market beta as a risk factor.[1]

In this paper, we explore how mutual funds investors respond to another potentially important measure of risk: idiosyncratic volatility (hereafter IV). Under the classical CAPM assumptions investors could diversify away all IV suggesting that investors should be indifferent between funds with high and low IV. Alternatively, if investors are risk averse and have incomplete information (e.g., Merton, 1987; Malkiel and Xu, 2002), or simply use total volatility as a rough approximation for risk, then investors may shy away from funds with high IV. Finally, it is possible that investors may exhibit greater demand for funds with high IV. For example, funds with greater IV are more likely to have salient features (e.g., extreme returns) that could attract investor attention and lead to greater demand for the asset (Barber and Odean, 2008).

We estimate mutual fund investors' demand for IV by examining the relationship between mutual funds' gross flows and IV. We document a strong asymmetric pattern: Investors gravitate towards IV when making purchasing decisions but shun IV when making redemption decisions. Specifically, after including a host of fund controls including prior year performance and fund fixed effects, we find that a one standard deviation increase in IV is associated with a 0.21 percentage point increase in inflows and a 0.11 percentage point increase in outflows. While the positive association between outflows and IV is consistent with

[1] We note, however, that the finding is also consistent with other plausible interpretations. For example, investors could simply discount returns attributable to market beta because such returns could be earned more cheaply through low-cost passive investments.

rational models with risk-averse investors and incomplete markets, the positive association between inflows and IV is more puzzling.

We consider several explanations for the positive association between IV and inflows. First, investors may be willing to take on extra IV because they are compensated with higher returns. However, we find no evidence that IV predicts fund performance. Second, investors may view IV as a hedge against some missing risk factor (e.g., Chen and Petkova, 2012). To test this possibility, we follow Barber, Huang, and Odean (2016) and decompose the annual return earned by each fund into alpha and returns related to factor exposures, and examine how flows respond to each of the return components. We augment the Carhart (1997) four-factor model with an IV factor, $LIVH$ (low IV minus high IV), which represents the returns on a portfolio that goes long stocks in the bottom decile of IV and short stocks in the top decile of IV. Given recent evidence that the IV anomaly can be partially explained by the investment (CMA) and profitability (RWA) factors (Fama and French, 2016), we also consider the Fama and French (2015) five-factor model. Using either model, we find that fund returns traced to IV-related risk factors attract significant flows, with sensitivities ranging from 55%-75% of that observed for alpha. This finding suggests that the majority of capital treats returns attributable to IV as alpha rather than risk.

We next consider a behavioral explanation based on fund salience. In particular, since evaluating thousands of different mutual funds is often a difficult proposition, investors may first limit their purchase decisions to funds that catch their attention (Barber and Odean, 2008). Consistent with this view, a large literature finds that mutual fund flows are associated with other salient fund attributes including rankings by Morningstar and the Wall Street Journal (Del Guercio and Tkac, 2008; Hartzmark and Sussman, 2018; Kaniel and Parham, 2017), advertising expenditures (Jain and Wu, 2000), and media coverage (Solomon, Soltes, and Sosyura, 2014). Funds with higher levels of IV are also more likely to be salient to some investors since such funds tend to have more extreme returns over various horizons. An implication of this hypothesis is that controlling for salient fund attributes correlated with IV, such as extreme returns, should attenuate the relation between IV and inflows. Consistent with this view, in fund fixed effect regressions, adding flexible measures of past returns for holding periods ranging from one month to five years reduces the relation between inflows and IV by 50%, and the estimated effect is no longer statistically significant.

Experimental evidence corroborates the relation between IV, salience, and inflows. Specifically, users on Amazon Mechanical Turk allocate significantly more capital to the high IV fund when 1) there is more information about the fund's returns over various holding periods and 2) the salience of past returns increases. Further, controlling for past returns and the salience of past returns eliminates investors' preferences for IV.

In addition, several auxiliary predictions of the salience hypothesis are borne out in the data. First, consistent with the experimental evidence, we find that in settings where fund salience is unlikely to matter, investors do not exhibit a preference for IV. For example, the relation between IV and inflows among funds that are closed to new investors or among institutional funds is statistically insignificant and economically small. Similarly, the relation between IV and fund flows is insignificant among funds that are already highly visible, such as funds in the top quintile of fund size, funds that engage heavily in marketing, and funds with a 5-star rating by Morningstar. Lastly, funds with greater IV have significantly higher Google search frequency (Search), and funds with greater Search experience significantly larger inflows. This result provides further support for the joint hypothesis that 1) IV generates increased investor attention and 2) increased investor attention results in greater inflows.

While much of our focus is on understanding the puzzling positive relation between IV and inflows, we also document novel patterns between IV and outflows. For example, we find that the relation between IV and outflows is not driven by extreme past returns, but is significantly stronger among less-visible funds. We conjecture that the positive relation between IV and outflows is at least partially attributable to a clientele effect, where high IV funds attract attention-based traders who tend to have shorter holding periods. Consistent with this view, using discount brokerage data, we document that households prone to buying attention-grabbing funds (i.e., funds with recent extreme returns) have significantly shorter holding periods.

Our final set of tests examine whether our findings have broader implications for fund behavior. Since high IV funds tend to attract investors with shorter holding periods, such funds would particularly benefit from more liquidity management tools. Consistent with this view, we find that high IV funds are more likely to have short-term redemption fees (Greene, Hodges, and Rakowski, 2007) and access to the internal markets of a large mutual fund family (Goncalves-Pinto and Schmidt, 2013). These findings highlight an important equilibrium relation between IV and the liquidity management tools of a fund.

Our paper makes several contributions. First, we paint a more comprehensive picture of investors' preferences for IV. Prior work on equities suggest that stocks with high IV earn lower expected returns (e.g., Ang, Hodrick, Xing and Zhang, 2006), pointing to the puzzling possibility that equity investors prefer IV. However, investors' demand for IV across other investment options remains largely unexplored. Our study fills this gap by studying investor demand for IV among mutual funds, which represents an increasingly large fraction of retail investors' total investments (French, 2008). Our finding that investors also seek out IV when purchasing mutual funds is perhaps especially surprising, since mutual fund investors, who have revealed their preference for a diversified portfolio, are presumably more interested in reducing IV.[2] We explain this puzzling behavior by highlighting the importance of fund salience as a driver of investors' apparent preference for high IV mutual funds.

Our results also contribute to the literature that explores the determinants of mutual fund flows (see, e.g., Sirri and Tufano, 1998; Barber, Odean, and Zheng 2005; and Huang, Wei, and Yan, 2007). This literature has generally not focused on IV, presumably because the impact of IV on net flows is relatively small. In contrast, we show that IV is an

[2]For example, a common explanation for investors' preference for IV among equities is lottery-like preferences (e.g., Bali, Cakici, and Whitelaw, 2011; and Boyer Mitton, and Vorkink, 2010). However, an investor with lottery-like preferences would likely avoid mutual funds which tend to have just a fraction of stock IV.

economically important determinant of both inflows and outflows. Further, we show the relation between IV and gross flows can help explain the equilibrium relation between IV and liquidity management tools. These findings highlight the importance of separately examining purchase and redemption decisions when assessing the behavior of mutual fund investors or inferring the incentives of fund managers.

Finally, our results have implications for the growing literature that relies on fund flows to assess investors' risk-preferences. Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) both find that flows are more strongly correlated with CAPM alphas than alphas from other asset pricing models. Berk and van Binsbergen (2016) interpret this result to mean that the CAPM is closest to the asset pricing model investors actually use. However, this conclusion relies heavily on the assumptions of Berk and Green (2004) that investors allocate capital across funds in a rational manner. Our findings are inconsistent with this assumption and instead suggest that fund salience can significantly contribute to investors' apparent risk-preferences. Consistent with this view, contemporaneous papers by Ben-David, Li, Rossi, and Song (2019) and Evans and Sun (2019) find that Morningstar rankings, a salient fund attribute, is a far more important driver of flows than CAPM alphas. Further, Evans and Sun (2019) show that changes in Morningstar rating methodology correspond to changes in how investors respond to risk. A unifying theme from this recent literature is that it is critical to carefully control for salient fund attributes, be it extreme returns or Morningstar ratings, when relying on fund flows to assess investors' preferences.

2. Data and Summary Statistics

2.1. Data and Variable Construction

Our mutual fund sample comes from Morningstar Direct and CRSP. Using both sources allows us to check data accuracy by comparing the two databases. In addition, each source has advantages and limitations. A critical advantage of Morningstar is that it provides information on gross flows (i.e., both inflows and outflows), while CRSP only allows one to infer net flows. Morningstar also reports fund objectives based on the fund's holdings, while CRSP relies on self-reported objectives that are often chosen for more strategic reasons (Sensoy, 2009). Advantages of the CRSP data include more regularly updated data on assets under management (AUM) (Berk and van Binsbergen, 2015), greater clarity on the timing of expense ratios (Pastor, Stambaugh, and Taylor, 2015), and greater comparability to the existing literature, which largely relies on CRSP data.

We limit our sample to actively managed domestic equity mutual funds from December 1999 to December 2012. We begin in December 1999 because this is the first month in which the retail, institutional, and closed fund data are well populated in CRSP. We include a fund in our sample if, based on CRSP, the fund holds at least 80% of its assets in equity and has at least $20 million in total net assets (TNA).[3] We screen out foreign funds, sector funds, index funds, variable annuities, ETFs, tax-managed products, REITs, and lifecycle funds.

We merge the Morningstar and the CRSP mutual fund database using share class tickers, CUSIPs, and names broadly following the process described in the Data Appendix of Pastor, Stambaugh, and Taylor (2015). Specifically, we examine data accuracy by comparing the returns reported in Morningstar and CRSP. As in Berk and van Binsbergen (2015), if reported monthly returns differ by more than 0.10%, we use dividend and net asset value (NAV) information reported in CRSP to compute the return. In cases in which the reported return from one database is inconsistent with the computed return, but in which the other database is consistent, we use the consistent database. If neither is consistent, the observation is dropped from the sample.[4]

[3] To avoid selection/survivorship bias for funds that attempt to market time or whose assets fall below $20 million due to poor performance, we include a fund once it crosses the 80% equity and $20 million TNA threshold for the first time. Once a fund enters our sample, it remains in the sample even if it drops below either cut-off. In unreported analyses, we also considered alternative size and equity thresholds and find similar results.

[4] We also repeat the analysis after including these fund-months and use the CRSP-reported returns. All of our main conclusions remain unchanged.

We also check consistency for the reported TNA. Similar to Pastor, Stambaugh, and Taylor (2015), we set assets to missing if CRSP and Morningstar disagree by at least $100,000 and the relative disagreement is at least 5%. If TNA data is missing from one database, we use the data from the other database. In all other cases, we use TNA as reported in CRSP.

Using the merged sample, we combine share classes of a single fund using the Morningstar *Fund ID* variable. The assets of the combined fund are the sum of the assets held across all share classes. We weight all other fund attributes by the assets held in each share class. We collect *net flows, inflows, outflows, investment objective*, and star rankings from Morningstar. We drop monthly flows of more than 200% of assets or less than -50% as in Coval and Stafford (2007). Fund age *(age)* is calculated as the number of months from the oldest first offer date for any share class in Morningstar. We collect *turnover ratio, expense ratio, 12b-1 fees*, and dummy variables for whether the fund has a load *(load fund)*, is offering a new share class *(new share class)*, is closed to new investors *(closed)*, and is an institutional fund *(institutional)* from CRSP. Additional details on variable construction are provided in the Appendix. We measure *total volatility* as the standard deviation of the fund's returns over the past 12 months *(t-1 to t-12)*. We define the fund's idiosyncratic volatility (IV) as the standard deviation of the fund's residuals from the Carhart (1997) four-factor model over the previous 12 months and define systematic volatility (SV) as the difference between *total volatility* and IV. We also require lagged values for each independent variable. Our final sample contains 2,481 unique actively managed equity funds, and 204,072 fund-month observations.

2.2. Descriptive Statistics

Panel A of Table 1 reports summary statistics on fund characteristics. The average fund manages $1,540 million in assets and earns an annualized four-factor alpha of -0.48%. There is substantial dispersion in IV among funds. Funds at the 10th percentile of IV have an IV of 0.43% per month, while the corresponding measure for funds in the 90th percentile of IV

is 2.18%. Panel B of Table 1 provides summary statistics on gross flow data. The average net flows is 0.41%, but there is considerable variation. At the 10th and 90th percentiles, net flows are -1.63% and 2.62% per month. The fact that the average fund has a monthly net flow close to zero masks the fact that inflows and outflows, while often similar in size, can be quite large. The average fund experiences monthly inflows (outflows) of 4.19% (3.78%) of beginning-of-month TNA.[5]

Interestingly, inflows and outflows are positively correlated ($\rho = 0.78$). The positive correlation is likely partially attributable to investors shifting across different share classes within the same fund, which is recorded as a simultaneous inflow and outflow. Consistent with this view, we find that among *Offsetting Funds*, defined as funds that have share classes with net flows in the opposite direction, (e.g., share class A received net inflows, while share class B received net outflows) the correlation increase to 0.78. However, even among *Non-Offsetting Funds*, the correlation between inflows and outflows remains economically large ($\rho = 0.58$), suggesting that other factors contribute to the positive correlation between inflows and outflows.[6] A second potential contributing factor is clientele effects. For example, if a subset of investors trade frequently and are attracted to funds with certain characteristics, funds with these characteristics will likely experience both greater inflows and outflows. We evaluate the importance of clientele effects in greater detail in Section 5.

Table 2 reports summary statistics for funds partitioned based on past 12 month IV. In particular, each month we split funds into low IV (the bottom 20%), mid IV (the middle 60%) and high IV (the top 20%). The results indicate that high IV funds and low IV funds differ along a number of important dimensions. High IV funds tend to be smaller and charge higher fees. There does not appear to be an economically large difference in net flows for the average or median fund. However, when we decompose net flows into inflows and outflows,

[5]Our inflow data exclude reinvestment of distributions and thus focuses only on new flows into the funds. In unreported analyses, we study the behavior of reinvested flows, and we find little sensitivity to returns, IV, or any other variables in our regressions.

[6]In later tests, we also confirm that our central findings are robust to limiting the sample to *Non-Offsetting Funds*.

we find that high IV funds attract substantially more inflows and experience substantially more outflows. The results suggest that investors are attracted to high IV funds when making purchase decisions, but have an aversion to IV when making redemption decisions. We explore this possibility more formally in the next section.

3. Idiosyncratic Volatility (IV) and Fund Flows

We begin by examining the flow-IV relationship at a monthly frequency using a panel regression over the 2000 to 2012 sample period. We use a piecewise linear specification for performance to capture the previously documented nonlinear flow-performance relation (Ippolito, 1992; Chevalier and Ellison, 1997; and Sirri and Tufano, 1998). Following Sirri and Tufano (1998), each month we calculate a fractional rank ($RANK_{t-1}$) ranging from 0 to 1 for each fund based on the fund's return over the prior 12 months. The variable *Ret Low* is defined as Min(0.2, $RANK_{t-1}$), while *Ret Mid* is defined as Min(0.6, $RANK_{t-1}$ - *Ret Low*). Finally, *Ret High* is defined as ($RANK_{i,t-1}$ - .8) for funds in the top quintile of performance and zero otherwise. Our model takes on the following general form:

$$\begin{aligned} Flow_{i,t} = \alpha + \beta_1 RetLow_{i,t-1} + \beta_2 RetMid_{i,t-1} + \beta_3 RetHigh_{i,t-1} \\ + \beta_4 SV_{i,t-1} + \beta_5 IV_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + FE + \epsilon_{i,t}. \quad (1) \end{aligned}$$

The dependent variable, $Flow_{i,t}$, is either the inflow, outflow, or net flow, expressed as a percentage of beginning-of-month TNA for each fund i and month t. Our variable of primary interest is $IV_{i,t-1}$, which measures the standard deviation of the fund's residuals from the Carhart (1997) four-factor model over the previous 12 months. We also include systematic volatility ($SV_{i,t-1}$), as defined in the Appendix.

$\mathbf{X}_{i,t-1}$ is a vector of controls that consist of variables widely used in previous research. In particular, we include Log *age*, Log *size* (fund *TNA* from the previous month), Log *family* *size* (family *TNA* from the previous month), *turnover ratio*, *expense ratio*, and dummy variables that indicate whether the fund charges loads (*load fund*), is closed to new investors during the month (*closed*), or introduces a new share class in the period (*new share class*). In addition, following Huang, Wei, and Yan (2007), we include the aggregate flow as a percentage of aggregate assets for each Morningstar investment category in month t, to help control for other unobserved factors, such as sentiment shifts towards certain styles. All specifications include time fixed effects, and where noted include fund fixed effects. To ease interpretation of the results, we convert all continuous independent variables (but not the dependent variable or the performance rank variables) to z-scores (the values are de-meaned and then divided by their standard deviations). We cluster standard errors by fund.[7]

Table 3 presents the results. Specifications 1, 2, and 3 report the results for net flows, inflows, and outflows, respectively, prior to including fund fixed effects. Consistent with existing studies, in Specification 1 we find a strong relationship between net flows and past performance. More relevant for our study, we find that a one standard deviation increase in IV is associated with a modest 0.08 percentage point increase in net flows.

Specifications 2 and 3, however, reveal that the patterns in net flows conceal a strong relationship between IV and gross flows. Specifically, a one standard deviation increase in IV is associated with a 0.84 percentage point increase in inflows (roughly a 20% increase for the average fund) and a 0.84 percentage increase in outflows.[8] Our results suggest that current shareholders flee from IV when making redemption decisions (a seemingly rational response), but new shareholders are attracted to funds with high IV (a seemingly irrational response) when making purchase decisions. Specifications 4 through 6 repeat the results after including fund fixed effects. IV is highly persistent at the fund-level, indicating that most of the variation in IV occurs across funds rather than within funds. Despite the potentially lower power of this test, we continue to find that investors are significantly more likely to

[7] Clustering standard errors by both fund and time yields very similar results.

[8] We note that the coefficient on net flows does not equal the coefficient on inflows minus the coefficient on outflows because the controls for style-level flows differ across the three specifications.

both buy and sell a given fund when it experiences an increase in IV. In Table IA.1 of the Internet Appendix we also confirm that the positive relation between IV and both inflows and outflows is robust to a number of different methodological choices.

4. What explains the positive relation between inflows and IV?

In this section, we explore three potential explanations for the puzzling positive association between inflows and IV. Sections 4.1 and 4.2 examine whether inflows to high IV funds are attributable to higher expected returns (*Return Hypothesis*) or lower systematic risk (*Risk Hypothesis*), and Section 4.3 examines whether IV increases the salience of the fund, resulting in attention-based buying (*Salience Hypothesis*).

4.1. The Return Hypothesis

The positive relation between inflows and IV may simply be a consequence of investors purchasing funds with higher expected returns. The above explanation would be particularly compelling if 1) IV is a predictor of fund performance and 2) investor flows can forecast future performance.[9] To explore these possibilities, we estimate the following panel regression:

$$Performance_{i,t} = \alpha_{i,t} + \beta_1 IV_{i,t-1} + \beta_2 Inflow_{i,t-1} + \beta_3 Outflow_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + FE + \epsilon_{i,t}. \tag{2}$$

[9] The existing evidence for both points is somewhat mixed. With respect to the first point, fund characteristics that tend to be correlated with IV such as 1-R^2 (Amihud and Goyenko, 2013) or industry concentration (Kacperczyck, Sialm, and Zheng, 2005) are associated with superior performance. On the other hand, Kacperczyck, Sialm, and Zheng, 2011 find that funds that experience an increase in IV significantly underperform. With respect to the second point, early work finds some evidence that mutual fund flows are associated with better subsequent performance (e.g., Gruber, 1996), however other studies suggest this relation is driven by return chasing coupled with momentum (Sapp and Tiwari, 2004) or persistent price pressure (Lou, 2012).

$Performance_{i,t}$ is either the return of fund i in month t in excess of the risk-free rate (*Excess Return*) or the return of the fund in excess of the return predicted by the Carhart (1997) four-factor model, computed from factor loadings estimated over the prior 12 months (*Carhart Alpha*). Our main variables of interest include $IV_{i,t-1}$, $Inflow_{i,t-1}$, and $Outflow_{i,t-1}$. $\mathbf{X}_{i,t-1}$ is a vector of controls that may also predict performance including past performance, Log *age*, Log *size*, Log *family size*, *turnover ratio*, and *expense ratio*. All independent variables are converted to z-scores. All regressions also include time and style fixed effects, and standard errors are clustered by time.

Specifications 1 and 2 of Table 5 offer little evidence that IV is associated with superior performance. A one standard deviation increase in IV is associated with a 0.06% increase in excess returns and a 0.04% increase in Carhart (1997) alphas, both of which are statistically insignificant.[10] We also find that a one standard deviation increase in inflows is associated with a 0.02% increase in excess returns, while a one-standard deviation increase in outflows is associated with a 0.04% decrease in excess returns. While the point estimates are directionally consistent with flows forecasting fund performance, the estimates are statistically insignificant and economically small. Collectively, the evidence is inconsistent with the view that flows induced by IV are a consequence of smart investors gravitating towards funds with superior future performance.

4.2. The Risk Hypothesis

Although high IV funds do not earn higher expected returns, it is possible that investors gravitate towards high IV funds because such funds are less risky. Consistent with this

[10] This finding appears inconsistent with Amihud and Goyenko (2013) who find that R^2 is a significant predictor of fund performance. We also find that R^2 is significantly negatively associated with fund performance in our sample. However, as discussed in Li, Rajgopal, and Venkatachalam (2014), idiosyncratic volatility, measured as the variance of the residual from a regression of a firm's stock return on a factor model, and selectivity, measured as 1 - R^2, are not necessarily interchangeable. We find that funds often have significant differences in exposure to systematic risk, which results in a more modest negative correlation between R^2 and IV (ρ = -0.65). The patterns we document are also consistent with Jordan and Riley (2015) who find that systematic volatility is negatively related to future fund performance, while IV is unrelated to total performance.

view, Chen and Petkova (2012) show that portfolios with high IV have significantly greater exposure to innovations in average stock variance. In their study, the difference in loadings, combined with the negative premium for average stock variance, completely explains the average return spread between high and low IV stocks. Relatedly, Fama and French (2016) show that the high returns associated with low IV stocks are largely explained by their positive exposures to the profitability (RMW) and investment (CMA) risk factors.

To test the *Risk Hypothesis*, we follow Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016), and assume that investor flows chase perceived past alpha, but do not chase returns that stem purely from taking on extra risk.[11] We begin by constructing an IV factor, $LIVH$ (low IV minus high IV). The construction of the $LIVH$ factor is similar to the approach in Jordan and Riley (2015), except we sort stocks on IV rather than total volatility. Specifically, we sort all common stocks into deciles based on the standard deviation of a stock's residuals from a Carhart (1997) four-factor model using daily returns over the prior 12 months. The $LIVH$ factor is equal to the return on a value-weighted portfolio of stocks in the lowest decile of IV less the return on a value-weighted portfolio of stocks in the highest decile of IV. We find that the $LIVH$ factor earns a significant three-factor alpha of 0.50% per month over our sample period.

Using the framework of Barber, Huang, and Odean (2016), we decompose a fund's returns into a five-factor alpha and the returns that stem from factors related to market, size, value, momentum, and IV tilts. Specifically, for each fund i in month t we estimate the following

[11] We acknowledge that investors may discount returns to a factor even if they do not view the factor as risk. For example, investors may not reward managers for returns attributable to a (non-priced) industry factor since they may be able to obtain exposure to this factor through a low-cost ETF. At a minimum, however, investors should clearly not ignore factors that they do associate with risk. Thus, if investors treat the returns attributable to the IV factor as alpha, this suggests that investors do not view IV as a risk factor.

time-series regression using return data from months $\tau = t$-1 to t-60:[12]

$$R_{i,\tau} - R_{f,\tau} = \alpha_{i,t} + \gamma_{i,t} YDUM_\tau + \beta_{1i,t}(R_{m,\tau} - R_{f,\tau}) + \beta_{2i,t} SMB_\tau + \beta_{3i,t} HML_\tau + \beta_{4i,t} UMD_\tau + \beta_{5i,t} LIVH_\tau + \epsilon_{i,\tau}, \quad (3)$$

where $R_{i,\tau}$ is the return of fund i in month τ, $R_{f,\tau}$ is the risk-free rate of return, $R_{m,\tau}$ is the return on the value-weighted market index, SMB_τ is the return on the size factor, HML_τ is the return on the value factor, UMD_τ is the return on the momentum factor, and $LIVH_\tau$ is the return on the IV factor. The parameters $\beta_1 - \beta_5$ represent the betas of the funds with respect to the market, size, value, momentum, and IV factors; $\alpha_{i,t}$ is the mean return unrelated to the factor exposures; and $\epsilon_{i,\tau}$ is a mean zero error term. $YDUM_\tau$ is a dummy variable equal to 1 for fund returns in the most recent 12-month period ($\tau = t$-1 to t-12) and 0 otherwise. Thus, the estimated annual five-factor alpha for the most recent 12-month period is $\alpha_{i,t} + \gamma_{i,t}$.

We next decompose a fund's annual excess return into its alpha plus the return that is attributed to tilts towards each of the five factors as follows:

$$\overline{R_{i,t} - R_{f,t}} = (\widehat{\alpha_{i,t}} + \widehat{\gamma_{i,t}}) + \widehat{\beta_{1i,t}}(\overline{R_{m,t} - R_{f,t}}) + \widehat{\beta_{2i,t}}(\overline{SMB_t}) + \widehat{\beta_{3i,t}}(\overline{HML_t}) + \widehat{\beta_{4i,t}}(\overline{UMD_t}) + \widehat{\beta_{5i,t}}(\overline{LIVH_t}) \quad (4)$$

$\overline{R_{i,t} - R_{f,t}}$ is the average excess return of fund i over the prior 12 months (t-1 to t-12). Similarly, $\overline{(R_{m,t} - R_{f,t})}$ is the average market risk premium over the prior 12 months and $\widehat{\beta_{1i,t}}$ is the fund's estimated sensitivity to the market factor. Thus, $\widehat{\beta_{1i,t}}\overline{(R_{m,t} - R_{f,t})}$ captures the return due to the fund's exposure to the market factor. The remaining four terms capture the returns due to the fund's exposure to size, value, momentum, and IV factors, respectively.

[12]If 60 months of historical data are not available we estimate the regression over all available data. We exclude funds with less than 24 months of historical data.

To examine how investors respond to returns that stem from exposure to the IV factor, we estimate the following panel regression:

$$Flow_{i,t} = \psi_0 + \psi_1(\widehat{\alpha_{i,t}} + \widehat{\gamma_{i,t}}) + \psi_2 \left[\widehat{\beta_{1i,t}}(\overline{R_{m,t} - R_{f,t}})\right] + \psi_3 \left[\widehat{\beta_{2i,t}}\overline{SMB_t})\right] + \psi_4 \left[\widehat{\beta_{3i,t}}\overline{HML_t})\right]$$
$$+ \psi_5 \left[\widehat{\beta_{4i,t}}\overline{UMD_t})\right] + \psi_6 \left[\widehat{\beta_{5i,t}}\overline{LIVH_t})\right] + \psi_7 SV_{i,t-1} + \psi_8 IV_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + FE + \epsilon_{i,t}. \quad (5)$$

$Flow_{i,t}$, $SV_{i,t-1}$, $IV_{i,t-1}$, $\mathbf{X}_{i,t-1}$, and FE are defined as in equation (1). The parameter of greatest interest is ψ_6, which measures how investors respond to returns due to exposure to the IV factor.

Panel A of Table 5 reports the results. We find that net flows are strongly related to returns traced to the IV factor. Specifically, a one percentage point increase in returns due to IV exposure is associated with a 0.86 percentage point increase in net flows. Alternatively, the estimated coefficient on returns traced to IV risk is 59% (0.86/1.45) of the estimated coefficient on the five-factor alpha. Similarly, using fund fixed effects (Specification 4) the estimated coefficient on returns traced to IV risk is 65% (0.82/1.26) of the estimated coefficient on the five-factor alpha. Thus, while investors discount returns that stem from exposure to the IV factor, the magnitude of the discount is relatively small.

It is also worth noting that controlling for a fund's return due to its IV exposure has very little impact on the conclusion that inflows are strongly associated with the fund's IV (i.e., ψ_8). In other words, investors' tendency to buy funds with high IV is not driven by simply chasing funds that earned extreme returns due to their exposure to the IV factor.

Panel B conducts analogous tests after replacing the *UMD* and *LIVH* factors with the *RMW* and *CMA* factors from Ken French's online data library. The results of this analysis are consistent with the findings from Panel A. In particular, Specification 1 indicates that the estimated coefficient on returns traced to the *RMW* and *CMA* risk factors are 56% (0.77/1.38) and 76% (1.05/1.38) of the estimated coefficient on the five-factor alpha. Similarly, Specification 4 confirms the results are similar after including fund fixed effects.

Collectively, the evidence suggests that flows into high IV funds are unlikely to be entirely driven by investors who simply want to reduce the risk-level of their portfolio.

4.3. The Salience Hypothesis

We next consider the possibility that investors do not actually view IV as an important return characteristic. Instead, investors gravitate towards high IV funds because IV is correlated with attention-grabbing (i.e., salient) fund attributes, which result in increased inflows. In other words, the salience hypothesis argues that 1) investors are more likely to buy salient funds and 2) funds with greater IV are more likely to be salient.

The first premise is consistent with recent evidence that investors are more likely to buy assets that catch their attention (e.g., Barber and Odean, 2008). The second premise is also intuitively appealing. Funds with higher levels of IV are more likely to have extreme returns. Even among funds with average returns over the prior year, high IV funds are more likely to have extreme returns over other horizons (e.g., 1 day, 1 month, 5 years, etc.) that may be more attention grabbing to particular investors. Further, newspapers, webpages, and TV business channels frequently rank top performing funds (measured over various holding periods) and being listed as a top performing fund has a sizeable impact on fund flows independent of the information conveyed in the rankings (Kaniel and Parham, 2017).

To get a better sense for the relationship between IV and extreme returns, we sort funds into deciles based on past 12 month IV. For each decile, we examine the fraction of funds that are in the top 10% of returns over the past one month or past five years (extreme winners). The results reported in Figure 1 indicate that funds in the top decile of IV are extreme winners 34% of the time at the five-year horizon (a 240% increase relative to the unconditional probability of 10%) and 29% of the time at the one-month horizon.[13] In Table

[13]Figure 1 also highlights that the relationship between IV and the likelihood of being a winner is highly convex, which points to the possibility that the relation between IV and inflows is also convex. Consistent with this view, piecewise linear regressions of IV on inflows indicate that the relation between IV and inflows is concentrated among funds in the top 20% of IV. These results are tabulated in Table IA.3 of the Internet Appendix.

IA.4 of the Internet Appendix we provide a more rigorous analysis by considering to what degree extreme returns are related to observed IV controlling for various fund characteristics. We estimate regressions of IV and past extreme returns measured over one month, three months, three years and five years, in addition to all the fund characteristics included in equation (1). We continue to find a strong positive relation between extreme returns across all horizons and IV.

In the following subsections, we explore the salience hypothesis in four parts. First, we consider the impact of controlling for returns over multiple horizons on the demand for IV. Second, we design an experiment that explicitly changes the salience of extreme returns to investors and observe the resulting demand for IV. Third, we consider situations where fund salience would be more or less important, and explore how this correlates with investor demand for IV. Fourth, we more directly examine the link between IV and investor attention, as proxied by Google search volume.

4.3.1. Fund Flows, IV, and Salient Returns

Figure 1 suggests that the positive relation between IV and inflows may be driven by the fact that high IV funds have more salient returns over a wide range of holding periods. This implies that regressions that include flexible measures of past returns should attenuate the relation between IV and inflows. To examine this possibility, we estimate the following panel regression:

$$
\begin{aligned}
Flow_{i,t} = \alpha &+ \beta_1 RetLow_{i,1m} + \beta_2 RetMid_{i,1m} + \beta_3 RetHigh_{i,1m} \\
&+ \beta_4 RetLow_{i,3m} + \beta_5 RetMid_{i,3m} + \beta_6 RetHigh_{i,3m} \\
&+ \beta_7 RetLow_{i,1Y} + \beta_8 RetMid_{i,1Y} + \beta_9 RetHigh_{i,1Y} \\
&+ \beta_{10} RetLow_{i,3Y} + \beta_{11} RetMid_{i,3Y} + \beta_{12} RetHigh_{i,3Y} \\
&+ \beta_{13} RetLow_{i,5Y} + \beta_{14} RetMid_{i,5Y} + \beta_{15} RetHigh_{i,5Y} \\
&+ \beta_{16} SV_{i,t-1} + \beta_{17} IV_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + FE + \epsilon_{i,t}, \quad (6)
\end{aligned}
$$

where *Flow, SV, IV, X,* and *FE* are all defined as in equation (1). *Ret Low, Ret Mid, and Ret High* are also defined as in equation 1, but now in addition to controlling for prior year returns ($Ret_{i,1Y}$), we also control for returns over the prior month ($Ret_{i,1m}$), prior three months ($Ret_{i,3m}$), prior three years ($Ret_{i,3Y}$) and prior five years ($Ret_{i,5Y}$). We focus on one-month, three-month, three-year, and five-year returns because these returns are commonly listed on financial resources used by investors, including financial websites and fund prospectuses.

As this analysis requires at least five years of return data, we drop funds with a return history of less than five years (roughly 20% of our sample). To ensure that differences in sample composition are not driving our results, Specifications 1 through 4 of Table 6 report the baseline results (i.e., equation 1) for inflows and outflows for the abridged sample. While the coefficients on IV are slightly reduced relative to the magnitudes reported in Table 3, IV remains significantly related to both inflows and outflows. For example, a one-standard deviation increase in IV is associated with a 0.79% increase in inflows in specifications that exclude fund fixed effects, and a 0.14% increase in specifications that include fund fixed effects.

Specifications 5 through 8 repeat the analysis after including piecewise linear controls for returns over the prior month, three months, three years, and five years. The coefficient on

RetHigh is statistically significant for all periods and is much larger than the coefficient on *RetLow*. In other words, across all holding periods, the performance-inflow relationship is highly convex. As a result, the inclusion of the flexible measures of past returns attenuates the relation between IV and inflows. For example, prior to including fund fixed effects, the coefficient on IV falls by 32% (from 0.78% to 0.54%), while after including fund fixed effects the coefficient on IV falls by 50% (from 0.14% to 0.07%) and the point estimate is no longer statistically significant. These results suggest that a significant portion of investors' demand for IV can be explained by more salient past returns over a wide range of different holding periods. We also note that the inclusion of past returns has very little impact on the relation between IV and outflows, which is consistent with salience influencing purchasing decisions to much a greater extent than redemption decisions (Barber and Odean, 2008).

A natural question is whether the inclusion of additional controls and even more flexible functional forms for past returns can further attenuate the relation between IV and inflows. In Table IA.5 of the Internet Appendix we add controls for the maximum and minimum daily returns over the prior month and the absolute daily returns over the past 10 days, and we replace the piecewise linear specifications with indicators for whether the fund was in the top (or bottom) 1%, 5%, 10%, and 20% of past returns measured over the past 1 month, 3 months, 1 year, 3 years, and 5 years. We find this specification further reduces the coefficient on IV by an additional 30% relative to Specification 5 (from 0.54% to 0.38%). In Table IA.6 we also include three non-return based measures that are likely to be strongly correlated with IV: *Industry Concentration*, defined as in Kacperczyk, Sialm, and Zheng, 2005; *Stocks Held*, the total number of stocks held by the mutual fund at the end of the prior quarter; and *HHI*, the portfolio concentration of the fund. We find that the inclusion of these non-return based measures does not significantly alter the relation between IV and inflows, which is consistent with these fund attributes being less salient than extreme returns.

4.3.2. *Fund Flows, IV, and Salient Returns - Experimental Evidence*

We next conduct online experiments using Amazon Mechanical Turk (MTurk).[14] The experimental setting allows us to more cleanly examine how investors' demand for IV varies as we 1) include more information on past returns across various holdings periods and 2) vary the salience of the past returns. We develop an experiment with three settings. In our baseline setting, *Setting 1*, MTurk workers (hereafter: investors) are asked to allocate $100 across three mutual funds (Funds A, B, and C). They are given information about six fund characteristics: fund size, fund age, expense ratio, fund turnover, past one-year return, and IV. The funds differ significantly with respect to IV: the low, mid, and high IV funds are assigned an IV equal to the 5th, 50th, and 95th percentile of the sample distribution (which equals 0.32%, 0.92%, and 2.93%, respectively). The funds are similar along the other five characteristics, which are randomly assigned to each fund.[15]

Setting 2 augments *Setting 1* by reporting the fund's one-month, three-month, three-year, and five-year returns, which mirrors the augmented return analysis in Section 4.3.1. The reported returns are simulated based on a market model (i.e., $R_{i,t} = \alpha_i + \beta_i R_m + \epsilon_{i,t}$) where the mean and standard deviation of the excess market return are set equal to 0.66% and 5.34% (their corresponding values estimated from July 1926 to December 2017), the alphas and betas for all funds are set equal to 0 and 1, respectively, and the idiosyncratic volatility of each fund is given by the values from *Setting 1*. Thus, by construction, the expected returns are identical for all three funds, but the high IV fund has a higher probability of having the best (or worst) performance across any horizon.[16] Finally, *Setting 3* augments

[14] Other studies that use Amazon Mechanical Turk to examine mutual fund investment decisions include Kumar, Niessen-Ruenzi, and Spalt (2015) and Hartzmark and Sussman (2019). Choi, Laibson, and Madrian (2010) and Anufriev, Bao, Sutan, and Tuinstra (2019) also use a laboratory setting to examine mutual fund investor behavior.

[15] Specifically, we set the values for fund size and past one-year return equal to the 49th, 50th, and 51st percentile of the distribution, and we set the values for all other fund characteristics equal to the 45th, 50th, and 55th percentile of the distribution. We use a narrower band for fund size and fund returns due to their significantly higher standard deviation.

[16] Simulations indicate that the probability that the high IV fund has the highest (or lowest) return over any horizon is roughly 45%, compared to 30% for the mid IV fund, and 25% for the low IV fund.

Setting 2 by including an additional line in bold print that reports whether a given fund has the highest three-year and five-year return. While *Setting 3* does not offer any new information relative to *Setting 2*, it should increase the salience of the more extreme returns. We view this manipulation as analogous to any event that increases the salience of funds' past returns, such as being given a five-star rating by Morningstar (Del Guercio and Tkac, 2008) or being listed as a "Category King" in the Wall Street Journal (Kaniel and Parham, 2017).

For each setting, we conduct 250 surveys. Each survey is associated with a different simulation and thus different one-month, three-month, three-year, and five-year returns, but the six baseline characteristics included in *Setting 1* remain constant. We provide examples of these surveys in the Internet Appendix (Figures IA.1 through IA.6).

Using the fund information above, in each survey we ask four questions: a baseline question, the same question where the first four fund characteristics of the high and low IV funds are switched, a question where IV (and the corresponding simulated returns) of the high and low IV funds are switched, and a final question where all the characteristics of the high and low IV funds are switched. Figures IA.2 IA.4, IA.5, and IA.6 of the Internet Appendix provide an example of each of the four questions for a single simulation. Our initial sample includes 3,000 responses (3 settings $\times$ 250 surveys $\times$ 4 questions per survey). We drop 69 responses where the answer appeared to be inconsistent, resulting in a final sample of 2,931 responses.[17]

Figure 2 plots the average allocation to the high IV fund across the three settings. In *Setting 1*, investors allocate \$24.36 to the high IV fund, which is roughly 27% less than the average allocation of \$33.33. The allocation to the high IV fund increases to \$31.20 in *Setting 2*, and \$35.39 in *Setting 3*, a 45% increase relative to *Setting 1*. These findings suggest that in the absence of IV being associated with other salient fund characteristics

[17] For example, an allocation of \$100 to Fund A for all four questions suggests the user was not paying attention to fund characteristics when making the allocation decision, particularly since Questions 1 and 4 reverse the characteristics of Funds A and C. Our results are robust to using the full set of responses.

(*Setting 1*), investors have an aversion to IV. This is inconsistent with investors viewing high IV as a signal of fund skill or as a tool to hedge against risk. Instead, the negative estimate is consistent with rational theories of risk aversion and costly diversification. However, when investors are provided information on past returns across a range of holding periods, investors allocate relatively more to the high IV fund (*Setting 2*), particularly when extreme returns are made more salient (*Setting 3*). Consistent with this view, Figure 3 confirms that the increased allocation to the high IV fund across *Setting 2* and *Setting 3* is very large when the high IV fund has either the highest three-year or five-year return, but non-existent when the high IV fund has neither the highest three-year nor highest five-year return.

We next examine whether the univariate evidence is robust to controlling for other fund characteristics by estimating the following regression:

$$Inflow_i = \alpha + \beta_1 HighIV_i + \beta_2 HighRet1YR_i + \beta_3 HighFees_i + \epsilon_i, \tag{7}$$

where *Inflow* is the total capital allocation to the fund, and *High IV*, *High Ret1Yr*, and *HighFees* are dummies equal to one if the fund has the highest IV, highest one-year return, or highest expense ratio, respectively, and zero otherwise.[18] To account for correlation across the same user, standard errors are clustered at the survey level.

Specifications 1, 2, and 3 of Table 7 report the results for *Settings 1, 2,* and *3*, respectively. The patterns are consistent with the univariate evidence. In particular, in Specification 1, investors allocate \$6.63 less to the high IV fund. However, in *Setting 2* investors allocate \$0.54 more to the high IV fund, and this increases to a statistically significant \$5.94 increase in *Setting 3*. We also confirm that the estimates on High IV from Specifications 2 and 3 are significantly greater than the estimates from Specification 1.[19]

[18] Due to collinearity, we can estimate the effects for IV and at most two of the five remaining characteristics (size, age, expense ratio, turnover, and past one-year return). We report the results for past return and expense ratio because of our priors that flows will be positively related to past returns and negatively related to expenses. This choice has no impact on the coefficients on IV.

[19] To compare the coefficients from Specifications 2 (3) to Specification 1, we augment equation (7) by including dummies for each setting (S2 and S3), and interacting each dummy with *HighIV*, *HighRet1Y*, and

To investigate whether the allocation to the high *IV* fund from *Setting 1* to *Setting 3* stems from investors chasing more extreme returns over other horizons, we re-estimate the results for *Setting 3* after augmenting equation (1) with dummies for whether the fund had the highest return over the past one month, three months, three years, and five years, and a dummy variable for whether the fund had both the highest three-year and five-year returns. The results are presented in Specification 4. We find that investors allocate significantly more to funds with the highest three-month return ($4.82), the highest three-year return ($7.47), and the highest five-year return ($15.04), and even more if a fund has both the highest three-year and five-year return ($9.71). Further, the coefficient on *High IV* reverses from significantly positive ($5.41) to marginally significantly negative (-$3.35), and the coefficient on *High IV* in Specification 4 is not significantly different from the estimate in Specification 1. Alternatively, of the $12.57 increase from Specifications 1 to Specification 3, $9.22 (or 73%) is explained by controlling for returns over alternative holding periods.[20]

Overall, the experimental results in this section, and the evidence using the actual inflow data (Section 4.3.1) are broadly consistent. In particular, the evidence from both sections suggests that more salient returns across various holdings periods significantly contributes to investors demand for *IV*. One noteworthy difference, however, is that after controlling for fund salience (e.g., extreme fund returns), the experimental evidence suggests that investors have an aversion to high *IV* (Specification 4 of Table 7), while the main analysis documents a positive, albeit statistically insignificant coefficient on *IV* (Specification 7 of Table 6). We believe that at least two factors contribute to this discrepancy. First, in the experimental setting we know exactly how *IV* increases fund salience, and as a result, we can perfectly control for fund salience. In contrast, in our main analysis it is not possible to directly control

HighFees. In Specification 2 (3), the difference is given by the value of *HighIV* * S2 (*HighIV* * S3) and statistical significance is computed from standard errors clustered by survey.

[20] In the Internet Appendix, we confirm that the findings are qualitatively similar when: 1) the high IV fund is labeled as Fund A (i.e., Questions 1 and 2) or Fund C (i.e., Questions 3 and 4), 2) investors have wealth greater than (or less than) the median breakpoint ($50,000), or 3) investors have an education level greater than (or less than) the median breakpoint (a bachelor's degree). See Tables IA.7, IA.8, and IA.9 respectively.

for all possible channels through which IV is associated with salient fund characteristics. To the extent that IV is associated with unobservable salient features that attract investors, our estimates on IV in our main analysis will be biased upwards.

Second, in our experimental setting, we effectively made IV itself quite salient. For example, in Specification 1 of Table 7, where IV has the most negative effect on inflows, IV is one of only six variables that investors can consider. Further, the variance in IV across funds was far larger than the variance in the other five variables. As a result, our experimental setting was nudging investors towards considering IV in their investment decisions. In practice, investors can obtain information on hundreds, or even thousands, of fund characteristics. Further, of all the potential characteristics to consider, IV itself is likely not a very salient fund attribute. For example, it is not reported anywhere on Yahoo! Finance. Thus, it seems plausible that investors who have to evaluate funds along a number of different dimensions, likely do not pay much attention to IV. This would imply that after properly controlling for fund features that are correlated with IV, we would expect no significant relation between fund flows and IV. This prediction is broadly consistent with the insignificant relation between IV and inflows in Specification 7 of Table 6.[21]

4.3.3. Fund Flows and IV: Cross-Sectional Predictions

In this section, we explore whether the impact of IV on inflows varies systematically with certain fund characteristics. The salience hypothesis suggests that the relation between IV and inflows should be stronger among less visible funds, such as smaller funds, younger funds, funds that engage is less marketing (Sirri and Tufano, 1998; Huang, Wei, and Yan, 2007), and funds without a five-star rating by Morningstar (Del Guercio and Tkac, 2008). Intuitively, a smaller fraction of potential investors are aware of less visible funds, and thus extreme

[21] There are, of course, many other potential explanations. For example, our results are also consistent with a rational response from risk-averse investors. In our experimental setting, investors can only diversify across three mutual funds. Thus, investing in a fund with high IV would lead to a large increase in the volatility of an investor's total investments. In contrast, in a real-world setting investors could choose to hold enough mutual funds that the impact of IV could be completely diversified away.

returns or other attention-grabbing events are likely to have a more significant impact on these funds relative to more well-known funds. Relatedly, we expect that fund salience is more relevant for funds that are open to new investors, since inflows in closed funds reflect the decisions of investors who already own the fund and thus are already aware of the fund's existence.

Finally, we expect salience to be more important for retail funds relative to institutional funds, which largely reflect defined contribution (DC) plans. In DC plans, a menu of funds is selected by plan sponsors. Plan sponsors, due to their greater sophistication and fiduciary responsibilities, are less likely to have extreme returns or other salient features that influence their decision to add a fund. Within the menu of investment options, IV is likely to be less relevant, since plan participants have far fewer investment options to evaluate and rarely adjust their allocations (see, e.g., Madrian and Shea, 2001; Choi et al., 2002; and Sialm, Starks, and Zhang, 2015.)

To examine the above predictions, we estimate equation (1) after including a conditioning variable (CV), and also interacting the conditioning variable with every other independent variable in the model. More specifically, we examine the following panel regression:

$$Flow_{i,t} = \alpha + \beta_1 RetLow_{i,t-1} + \beta_2 RetLow_{i,t-1} \times CV_{i,t-1} + \beta_3 RetMid_{i,t-1} + \beta_4 RetMid_{i,t-1} \times CV_{i,t-1} + \beta_5 RetHigh_{i,t-1} + \beta_6 RetHigh_{i,t-1} \times CV_{i,t-1} + \beta_7 CV_{i,t-1} + \beta_8 IV_{i,t-1} + \beta_9 IV_{i,t-1} \times CV_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + \delta(\mathbf{X}_{i,t-1} \times CV_{i,t-1}) + Time_t + \epsilon_{i,t}. \quad (8)$$

CV is one of 6 conditioning variables: *Small*, a dummy variable equal to one if the fund is not in the top quintile of fund size based on the fund's prior month TNA; *Young*, a dummy variable equal to one if the fund is not in the top quintile of fund age; *Low Marketing*, a dummy variable equal to one if the fund is not in the top quintile of marketing expenditures, defined as the 12b-1 fees + 1/7th of the front-end load; *Non-Star Fund*, a dummy variable equal to one if the fund is not rated 5-stars by Morningstar; *Open*, a dummy variable equal to one if the fund is open to new investors and zero if it closed to new investors; and *Retail*, a dummy variable equal to one if all the share classes of the fund are classified as retail and zero if all the share classes are classified as institutional.[22] Thus, the coefficient on IV captures the impact of IV on flows among funds where salience is likely to be less relevant (i.e., very large funds, very old funds, 5-star funds, funds with heavy marketing, funds closed to new investors, and funds catering to institutional investors). All other variables are defined in equation (1). We exclude fund fixed effects since the conditioning variables often exhibit minimal within-fund variation.[23]

Panels A through F of Table 8 report the results for each of the conditioning variables. In the interest of parsimony, we only report the coefficients on IV and $IV \times CV$. Two consistent patterns emerge across all six conditioning variables. First, the coefficient on $IV \times CV$ is always significantly positive and economically large. This is consistent with the relation between IV and inflows being stronger among less visible funds (i.e., smaller funds, younger funds, funds that engage in less marketing, non-star funds) and funds that are open to new investors and retail investors.[24] Second, the coefficient on IV is typically insignificant and economically small. In particular, the coefficients on IV itself range from 0.06% to 0.21% with a median value of 0.11%, which is less than one seventh of the estimated effect of IV for the full sample (see Specification 2 of Table 3). This finding suggests that in settings where fund salience is less relevant, investors exhibit no preference for IV. Interestingly, we also document very similar patterns for outflows. This is perhaps surprising since salience should have a less pronounced effect on redemption decisions. However, this finding would

[22] Roughly 13% of the funds are classified as institutional and 42% are classified as retail. The remaining funds either have a mix of retail and institutional share classes or provide no indication of the intended investor and are excluded from the analysis that conditions on *Institutional*.

[23] Of the conditioning variables, fund size and fund age exhibit the most within-fund variation. We find that our conclusions for these variables are qualitatively similar when including fund fixed effects.

[24] In Table IA.10 of the Internet Appendix, we also examine the relationship between IV and inflows among investors who have previously owned the funds (existing investors) versus investors who have not previously held the fund (new investors) as reported in a discount brokerage dataset. Consistent with the results in Table 8, we find that demand for high IV mutual funds is significantly greater among new investors.

be consistent with a clientele effect, where investors who purchase funds that catch their attention are also more likely to subsequently sell such funds. We explore this possibility more formally in Section 5.

4.3.4. Fund Flows, IV, and Google Search

Our evidence is consistent with the views that 1) IV results in increased investor attention, and 2) increased investor attention results in greater inflows. In this section, we offer more direct evidence for each of the above conjectures using Google search volume as a proxy for investor attention (as in Da, Engelberg, and Gao, 2011).

We collect the monthly normalized search volume index ($NSVI$), as reported by Google Trends, for each fund ticker from January 2004 (the begin date for Google Trends data) through December 2012. Google defines the $NSVI$ for fund i in month t as: $NSVI_{i,t} = \frac{SearchVolume_{i,t}}{Max(SearchVolume_i)} \times 100$, where $Max(SearchVolume_i)$ is the maximum search volume for fund i over the time period of the search. By scaling by $Max(SearchVolume_i)$, $NSVI$ abstracts from cross-sectional differences in search volume. To circumvent this limitation, we estimate a scaling factor that accurately portrays the relative popularity of each fund (which we describe in greater detail in Section IA.8 of the Internet Appendix). We compute a fund-level measure of *Search* by summing the *Search* of each ticker (i.e., share class) of the fund. Our sample includes 164,378 fund-month observations over the 2004-2012 period. We find that *Search* exhibits significant cross-sectional variation; the mean (median) value of *Search* is 3,466 (0) and the standard deviation is 13,209. To the extent that *Search* is a good measure of investor attention, our findings suggest that while a few funds garner massive amounts of attention, the typical fund attracts very little investor attention.

We begin by examining whether funds with greater IV also experience greater *Search*. We expect that many of the same factors that drive purchase and redemption decisions will also drive search volume. Accordingly, we re-estimate the baseline flow regression (i.e., equation (1)) after replacing the dependent variable $Flow_{i,t}$, with $\text{Log}(1+Search_{i,t})$. In the interest of brevity, we only report the coefficient on IV, past returns, and fund size.

The results are reported in Specification 1 of Table 9. Intuitively, large funds have greater *Search*. In addition, the positive coefficient on *RetHigh* and the negative coefficient on *RetLow* indicate that *Search* tends to increase with either extremely good or extremely bad past one-year performance. However, even after controlling for extreme past one-year returns, we find a strong positive relation between IV and *Search*. In particular, a one-standard deviation increase in IV is associated with a 66% increase in *Search*.

We next examine whether *Search* forecasts greater inflows and outflows. We re-estimate equation (1) after replacing $IV_{i,t-1}$ with $\text{Log}(1 + Search_{i,t-1})$. Specifications 2 through 4 report the results for *net flows*, *inflows*, and *outflows*, respectively. We find that a one standard deviation increase in average monthly *Search* over the prior 12 months is associated with a 0.41 percentage point increase in monthly inflows and a 0.21 percentage point increase in *outflows*, both of which are highly significant. This finding supports the view that increased investor attention leads to greater capital inflows and outflows.[25] We also find that *Search* is positively associated with net flows, consistent with investor attention having a larger effect on buying decisions than selling decisions.

We next include both $IV_{i,t-1}$ and $\text{Log}(1+Search_{i,t-1})$. We find that both IV and *Search* are incrementally useful in forecasting inflows (Specification 6). The incremental predictive ability of IV, after controlling for *Search*, could be consistent with IV measuring something above and beyond active attention. However, the findings are also consistent with *Search* simply being a noisy proxy for active attention. For example, *Search* omits searches through other sites such as Yahoo! Finance, Morningstar, a brokerage firm's website, the mutual fund's website, etc. Further, shocks to active attention can lead to increased buying behavior without leading to increases in search. For example, an attention-grabbing event may make a financial advisor more likely to recommend a fund to his clients, many of whom may simply

[25]In unreported results, we also estimate a model with fund fixed effects. We continue to find positive coefficients, but the magnitudes decline, and the estimate for outflows loses statistical significance.

follow their advisors' recommendation without conducting any additional research. Finally, *Search* is only available when search volume surpasses an unknown, time-varying threshold determined by Google, and is set to zero otherwise. Indeed, in our sample *Search* is set equal to 0 for roughly 65% of all observations. Missing values are most prevalent among smaller funds, where the impact of IV on inflows is particularly pronounced (see Table 8).

Examining outflows (Specification 7), we find that IV remains significantly positive, while *Search* is no longer significantly different from zero. The insignificant coefficient on *Search* is consistent with the view that existing investors, who are already very familiar with the fund, generally do not need to conduct additional research before selling the fund. As noted earlier, the positive coefficient on IV is consistent with a clientele effect, where attention-constrained investors tend to be more likely to both buy and subsequently sell funds with high IV. We explore this possibility next.

5. IV and Investor Holding Period

The results from the prior section suggest that IV not only has a stronger impact on inflows for less visible funds, but also a stronger effect on outflows for such funds. The outflow results are perhaps surprising, since the effect of attention should be more pronounced for purchase decisions, where investors can select from thousands of different funds, than for redemption decisions, where investors can only sell the few funds they already own. One potential explanation is that attention-based traders also tend to have much shorter holding periods (perhaps because they are more likely to re-allocate their investments when a new fund catches their attention). Thus funds that tend to attract a higher fraction of attention-based traders (e.g., high IV funds) may have more outflows as a consequence of investors more rapidly exiting their positions.

Unfortunately, we cannot identify the actions of individual investors in the CRSP and Morningstar datasets. Instead, we examine the trading behavior of 78,000 households from

January 1991 to November 1996 at a large discount brokerage firm.[26] We merge the discount brokerage trading data with the CRSP mutual fund universe by fund CUSIP. We limit our analysis to households that trade at least five equity-oriented mutual funds, resulting in a final sample of 16,456 households and 798 unique mutual funds. The average (median) household in this sample executes 26 (15) mutual fund trades over the sample period, and the average (median) value of each trade is roughly \$10,000 (\$3,900).

We begin by identifying a proxy for each household's tendency to engage in attention-based buying behavior. One example of attention-based trading is simply buying funds with very high returns over various holding periods (as shown in Table 6). Thus, we classify a mutual fund purchase as attention-based if the purchased fund was in the top 5% of returns in the current month, past month, or past year.[27] In the average month in our sample, 12% of funds meet these criteria.

For each household, we also compute the average percentile rank of the IV across all purchased funds, and the fraction of purchased funds that are at least partially sold within the subsequent three months or one year. In addition, we compute a turnover measure for each household (*Household Turnover*), defined as the annual dollar volume of mutual fund trades during the year scaled by the value of the household's mutual fund holdings at the end of the prior year. We winsorize *Household Turnover* at 12, which corresponds to turning over the entire portfolio every month.

Table 10 sorts households into quintiles based on the total fraction of purchases that are classified as attention based. For households in the top quintile, more than 62% of all purchases are classified as attention based, while households in the bottom quintile never engage in attention-based trading. The next column confirms that attention-based traders gravitate towards high IV funds. Specifically, the percentile IV rank increases monotonically from

[26]This dataset is described in detail in Barber and Odean (2000 and 2001) and has also been used in several papers to study the trading behavior of mutual fund investors (e.g., Ivkovic and Weisbenner, 2009; Bail, Kumar, and Ng, 2011; and Gerken, Starks, and Yates, 2018).

[27]Our results are similar if we consider alternative breakpoints (e.g., top 10%), alternative performance horizons, or if we sort directly on investors' tendency to purchase high IV funds.

40.5% for households in the bottom quintile to 65.2% for households in the top quintile. The last three columns show that households that engage in attention-based trading have significantly shorter holding periods. For example, the turnover of households in the top quintile of attention-based trading is more than double the turnover of households in the bottom quintile. Similarly, households in the top quintile of attention-based trading sell nearly 20% of their purchased funds within three months, compared to roughly 5% for households in the bottom quintile. These results suggest that the positive association between IV and outflows is at least partially attributable to high IV funds attracting attention-based traders with shorter holding periods.

6. IV and Liquidity Management

In this section, we explore whether our findings also have implications for fund manager behavior. In particular, we previously document that pursuing high IV strategies attracts investors with relatively short holding periods, and increases both inflows, outflows, and the volatility of net flows.[28] Higher volatility of net flows is costly to mutual fund operations, and imposes significant externalities on longer-term investors (see, e.g., Edelen, 1999; Rakowski, 2010; and Fulkerson and Riley, 2017). Thus, we expect that funds pursuing high IV strategies will place greater emphasis on liquidity management to offset the increased costs associated with higher flow volatility.[29]

One potential liquidity management tool for high IV funds are redemption fees. Funds charge redemption fees to investors for selling the fund shortly after buying the fund. These fees are specifically intended to compensate long-term investors for any costs the fund must

[28] We confirm that high IV funds (as defined in Table 2) have more than 75% higher volatility in monthly net flows than low IV funds.

[29] We note that our objective is to simply describe equilibrium relationships, rather than determine causality. We remain agnostic on whether the presence of a liquidity management tool results in funds taking on more IV or whether funds with greater IV choose to implement liquidity management tools.

incur to rebalance the portfolio and have been shown to be effective in decreasing the volatility of a fund's net flows (Greene, Hodges, and Rakowski, 2007).[30]

Another liquidity management tool is access to the internal markets of a large mutual fund family. Goncalves-Pinto and Schmidt (2013) show that trading costs can be minimized by coordinating trades with other funds within the same family, and they document that the strongest predictor of coordinating trades is the number of funds within the family. Accordingly, we expect that funds that belong to families with a larger number of funds will be more likely to pursue high IV strategies.[31] To test these predictions, we gather data on redemption fees from SEC Form N-SAR. The data are matched by CIK and ticker, and verified by hand to our sample. We are able to match 79% of the data in our original sample.

We use this sub-sample to estimate the following panel regression for each fund:

$$IV_{i,t} = \alpha + \beta_1 RedemptionFee_{i,t-12} + \beta_2 CountofFundsinFamily_{i,t-12} + \gamma \mathbf{X}_{i,t-12} + \epsilon_{i,t}, \tag{9}$$

where the dependent variable, $IV_{i,t}$, is the standard deviation of the fund's residuals from the Carhart (1997) four-factor model estimated over the previous 12 months. $RedemptionFee_{i,t-12}$ is a dummy variable equal to one if the fund has a redemption fee in place and $CountofFundsinFamily_{i,t-12}$ is the number of US equity funds in the fund family. $\mathbf{X}_{i,t-12}$ is a vector of controls that includes *Ret High, Ret Mid, Ret Low, Log age, Log size, turnover, expense ratio, load fund, closed,* and *new share class*. All variables are calculated in the month prior to the 12 month estimation period for IV. All specifications include time fixed effects and Specification 2 also includes fund fixed effects.

Specification 1 of Table 11 shows that both redemption fees and the number of funds in the fund family are strongly correlated with IV. Specifically, funds with redemption fees have

[30]Load fees can also discourage short-term trading. However, load fee revenue does not accrue to the fund adviser and therefore cannot offset the additional costs that the fund incurs.

[31]Funds have several other tools that could help mitigate trading costs, including holding more cash or holding more liquid assets. However, these investment-related variables can have a direct impact on IV. For example, holding more cash will mechanically reduce IV and more liquid firms typically have lower IV.

IV that is 0.32% larger than funds without redemption fees, and a one standard deviation increase in the number of funds in a family is associated with a 0.12% increase in IV. Both estimates are economically large relative to the mean (1.19%) and standard deviation (0.98%) of IV. Specification 2 repeats the analysis with fund fixed effects. IV, *RedemptionFee*, and *CountofFundsinFamily* exhibit relatively little variation within a given fund, which limits the power of this specification. Nevertheless, we continue to find positive coefficients on *RedemptionFee* and *CountofFundsinFamily*, although the magnitudes are reduced, and the latter estimate is no longer statistically significant. Nevertheless, the collective evidence is consistent with managers being more likely to pursue high IV strategies when they have the liquidity management tools in place to help mitigate the higher trading costs associated with such strategies.

7. Conclusion

We examine mutual fund investors' demand for IV by studying their capital flows into and out of mutual funds. We find that both inflows and outflows are strongly related to IV, indicating that mutual fund investors gravitate toward IV when making purchase decisions, but flee from IV when making redemption decisions. While the outflow results are consistent with rational models of risk aversion and costly diversification, the inflow results are more puzzling since they suggest that mutual fund investors prefer IV. Further, we find little support for rational explanations for investors' tendency to buy high IV funds. For example, we find no evidence that high IV funds earn superior returns; nor do we find strong evidence that investors view high IV funds as a way to hedge against a missing risk factor.

We propose that salience can help explain investors' tendency to purchase high IV funds. Intuitively, assets with greater IV are more likely to have extreme returns over various holding periods, and funds with extreme returns are more likely to be purchased by attention-based traders (Barber and Odean, 2008). Several pieces of evidence support this conjecture. First, including flexible controls for past returns over various holding periods attenuates the positive relation between IV and inflows. Second, in an experimental setting, we find that explicitly increasing the salience of past returns leads to large increases in investor demand for IV. Third, the relation between IV and inflows is stronger among less visible funds and less-sophisticated investors, where the benefits of salience are likely to be stronger. Lastly, funds with greater IV have significantly higher Google Search Volume, and funds with greater Google Search Volume experience greater inflows.

These findings complement recent work that suggests investors attentiveness to market-based risk is attributable to the fact that CAPM alphas tend to be highly correlated with other salient fund features, such as Morningstar ratings (Evans and Sun, 2020). These results highlight that researchers should take great care in controlling for fund salience when interpreting fund flows as a measure of investors' true preferences. Our findings also have implications for mutual fund investor welfare. In particular, the results suggest that attention-based buying results in investors inadvertently gravitating towards high IV funds. Given the increasingly large weight of mutual funds in investors' portfolios, coupled with the fact that many investors hold very few assets, attention-based buying can result in many investors holding overall portfolios that are riskier than they otherwise would. Our experimental evidence suggests that making IV itself more salient could help attenuate investors' tendency to gravitate towards high IV funds and ultimately increase the Sharpe ratios of their investment portfolios.

Appendix: Variable Definitions

Note: Unless otherwise stated, we aggregate multiple share classes of a fund into one observation by computing a TNA-weighted average across all share classes.

- Inflow: the monthly new inflow of a fund scaled by the fund's TNA at the beginning of the month (Source: Morningstar). This measure excludes the reinvestment of distributions.
- Outflow: the monthly new outflow of a fund scaled by the fund's TNA at the beginning of the month (Source: Morningstar).
- Net Flow: Inflow - Outflow.
- Standard Deviation Net Flow: The time-series standard deviation in monthly Net Flow for a fund over a specified time period.
- Style Flow: the average monthly flow (i.e., Inflow, Outflow, or Net Flow) across all funds in a given style. Style classifications are based on Morningstar investment categories (Source Morningstar).
- Total Volatility (TV): the standard deviation of a fund's returns of the prior 12 months (Source: CRSP/Morningstar).
- Idiosyncratic Volatility (IV): the standard deviation of the fund's residual from the Carhart (1997) four-factor model over the previous 12 months (Source: CRSP/Morningstar).
- Systematic Volatility (SV): $\sqrt{(TV^2 - IV^2)}$.
- Return: the average monthly returns over the prior 12 months (Source: CRSP/Morningstar).
- RANK: the percentile ranking of a fund based on its Return.
- Ret Low: Min (.2, RANK).

- Ret Mid: Min(.6, RANK - Ret Low).
- Ret High: Max (RANK - .8, 0).
- Carhart Alpha: the alpha from a regression of the fund's return on the Carhart (1997) four-factor model, estimated using monthly returns over the prior 12 months (Source: CRSP/Morningstar).
- Total Net Assets (TNA): the total amount of money managed by the fund ($ millions) (Source: CRSP/Morningstar).
- Family TNA: the total amount of money managed by the family across all funds that appear in CRSP ($ millions) (Source: CRSP/Morningstar).
- Age: The number of months since the first offer date for the oldest share class of the fund (Source: Morningstar).
- Expense Ratio: the annual expense ratio (Source: CRSP).
- Turnover Ratio: the annual turnover ratio (Source: CRSP).
- New Share Class: a dummy variable equal to one if the fund introduced a new share class within the past year (Source: CRSP).
- Load Fund: a dummy variable equal to one if the fund charges either a front-end or back-end load. (Source: CRSP).
- Marketing Expenditures: the sum of a fund's 12b-1 fees and 1/7 of front-end loads (Source: CRSP).
- Star Fund: a dummy variable equal to one if the fund is assigned a five-star rating based on the past three-year performance (Source: Morningstar).
- Closed: a dummy variable equal to one if the fund is closed to new investors (Source: CRSP).

- Institutional Fund: a dummy variable equal to one if the fund serves institutional investors, and zero otherwise (Source: CRSP).

- Search: a ticker's normalized search volume (NSVI) from Google Trends multiplied by a scaling factor that estimates the relative popularity of a fund relative to the smallest fund. Section 5.3.1 and IA.7 provide additional details on the NSVI data and the construction of the scaling factor. (Source: Google Trends).

- LIVH: the return on a zero-cost portfolio that is long stocks with low IV and short stocks with high IV (Source: CRSP).

- HHI: the Herfindahl-Hirschman index for portfolio weights (Source: Thomson-Reuters).

- # of positions: count of the number of unique stocks in a portfolio (Source: Thomson-Reuters).

- ICI: the industry concentration index, constructed as the sum of squared deviations of the mutual fund's industry weight from the overall market industry weight (Source: Thomson-Reuters).

- Holdings exist: a dummy variable equal to one if a fund-month observation was matched to holdings from a quarter in the prior six months that had at least ten holdings with sufficient stock data for constructing the ICI index (Source: Thomson-Reuters).

- Setting 1: testing environment where MTurk works were given basic mutual fund information.

- Setting 2: testing environment where MTurk works were give the information from Setting 1, plus additional information on how a fund performed relative to its peers.

- Setting 3: testing environment where MTurk works were give the information from Setting 2, but that data explicitly highlights those funds that outperformed relative to its peers.

- High Fees: dummy variable equal to one if a fund had the highest expense ratio in an MTurk setting.

- High Return (X years): a dummy variable equal to one if a fund had a high return over the prior X years in an MTurk setting.

- Highest Return Indicator (3 5 years): a dummy variable equal to one if a fund had the highest expense return in an MTurk setting.

- High IV: a dummy variable equal to one if a fund had high IV in an MTurk setting.

- Redemption fee: a dummy variable equal to one if a fund had a redemption fee (Source: SEC Form N-SAR).

- Count of funds in family: the number of US equity funds in a fund family (Source: CRSP).

References

Amihud, Yakov, Ruslan Goyenko. 2013. Mutual fund's R^2 as predictor of performance. *The Review of Financial Studies*, **26** 667–694.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, Xiaoyan Zhang. 2006. The cross-section of volatility and expected returns. *Journal of Finance*, **61** 259–299.

Anufriev, Mikhail, Te Bao, Angela Sutan, Jan Tuinstra. 2019. Fee structure and mutual fund choice: An experiment. *Journal of Economic Behavior & Organization*, **158** 449–474.

Bailey, Warren, Alok Kumar, David Ng. 2011. Behavioral biases of mutual fund investors. *Journal of Financial Economics*, **102** 1–27.

Bali, Turan G., Nurset Cakici, Robert F. Whitelaw. 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, **99** 427–446.

Barber, Brad, Terrance Odean. 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, **21** 785–818.

Barber, Brad, Terrance Odean, Lu Zheng. 2005. Out of sight, out of mind: The effects of expenses on mutual fund flows. *Journal of Business*, **78** 2095–2119.

Barber, Brad M, Xing Huang, Terrance Odean. 2016. Which factors matter to investors? evidence from mutual fund flows. *The Review of Financial Studies*, **29** 2600–2642.

Barber, Brad M, Terrance Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, **55** 773–806.

Barber, Brad M, Terrance Odean. 2001. Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, **116** 261–292.

Ben-David, Itzhak, Jiacui Li, Andrea Rossi, Yang Song. 2019. What do mutual fund investors really care about? *Working Paper*.

Berk, Jonathan, Jules van Binsbergen. 2015. Measuring skill in the mutual fund industry. *Journal of Financial Economics*, **118** 1–20.

Berk, Jonathan, Jules van Binsbergen. 2016. Assessing asset pricing models using revealed preferences. *Journal of Financial Economics*, **119** 1–23.

Berk, Jonathan B, Richard C Green. 2004. Mutual fund flows and performance in rational markets. *Journal of Political Economy*, **112** 1269–1295.

Boyer, Brian, Todd Mitton, Keith Vorkink. 2010. Expected idiosyncratic skewness. *Review of Financial Studies*, **23** 169–202.

Carhart, Mark. 1997. On persistence in mutual fund performance. *Journal of Finance*, **52** 57–82.

Chen, Zhanhui, Ralitsa Petkova. 2012. Does idiosyncratic volatility proxy for risk exposure? *Review of Financial Studies*, **25** 2745–2787.

Chevalier, Judith, Glenn Ellison. 1997. Risk taking by mutual funds as a response to incentives. *Journal of Political Economy*, **105** 1167–1200.

Choi, James, David Laibson, Brigitte Madrian, Andrew Mettrick. 2002. *Defined contribution pensions: Plan rules, participant decisions, and the path of least resistance*. Cambridge, MA: MIT Press.

Choi, James J., David Laibson, Brigitte C. Madrian. 2010. Why does the law of one price fail? An experiment on index mutual funds. *The Review of Financial Studies*, **23** 1405–1432.

Coval, Joshua, Eric Stafford. 2007. Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, **86** 479–512.

Da, Zhi, Joseph Engelberg, Pengjie Gao. 2011. In search of attention. *The Journal of Finance*, **66** 1461–1499.

Del Guercio, Diane, Paula Tkac. 2008. Star power: The effect of morningstar ratings on mutual fund flow. *Journal of Financial and Quantitative Analysis*, **43** 907–936.

Edelen, Roger. 1999. Investor flows and the assessed performance of open-end mutual funds. *Journal of Financial Economics*, **53** 439–436.

Evans, Richard B, Yang Sun. 2020. Models or stars: The role of asset pricing models and heuristics in investor risk adjustment. *The Review of Financial Studies (Forthcoming)*.

Fama, Eugene, Kenneth French. 2015. A five-factor asset pricing model. *Journal of Financial Economics*, **116** 1–22.

Fama, Eugene F, Kenneth R French. 2016. Dissecting anomalies with a five-factor model. *The Review of Financial Studies*, **29** 69–103.

French, Kenneth R. 2008. Presidential address: The cost of active investing. *The Journal of Finance*, **63** 1537–1573.

Fulkerson, Jon A, Timothy B Riley. 2017. Mutual fund liquidity costs. *Financial Management*, **46** 359–375.

Gerken, William Christopher, Laura T Starks, Michael Yates. 2018. The importance of family: The role of mutual fund family reputation in investment decisions. *Working Paper*.

Goncalves-Pinto, Luis, Breno Schmidt. 2013. Co-insurance in mutual fund families. *Working Paper*.

Greene, Jason T, Charles W Hodges, David A Rakowski. 2007. Daily mutual fund flows and redemption policies. *Journal of Banking & Finance*, **31** 3822–3842.

Gruber, Martin J. 1996. A another puzzle: The growth of actively managed mutual funds. *Journal of Finance*, **51** 783–810.

Hartzmark, Samuel M, Abigail B Sussman. 2019. Do investors value sustainability? a natural experiment examining ranking and fund flows. *The Journal of Finance*, **74** 2789–2837.

Huang, Jennifer, Clemens Sialm, Hanjiang Zhang. 2011. Risk shifting and mutual fund performance. *The Review of Financial Studies*, **24** 2575–2616.

Huang, Jennifer, Kelsey Wei, Hong Yan. 2007. Participation costs and the sensitivity of fund flows to past performance. *Journal of Finance*, **62** 1273–1311.

Ippolito, Richard. 1992. Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. *Journal of Law and Economics*, **35** 45–70.

Ivković, Zoran, Scott Weisbenner. 2009. Individual investor mutual fund flows. *Journal of Financial Economics*, **92** 223–237.

Jain, Prem C, Joanna Shuang Wu. 2000. Truth in mutual fund advertising: Evidence on future performance and fund flows. *The Journal of Finance*, **55** 937–958.

Jordan, Bradford, Timothy Riley. 2015. Volatility and mutual fund manager skill. *Journal of Financial Economics*, **118** 289–298.

Kacperczyk, Marcin, Clemens Sialm, Lu Zheng. 2005. On the industry concentration of actively managed equity mutual funds. *The Journal of Finance*, **60** 1983–2011.

Kaniel, Ron, Robert Parham. 2017. WSJ category kings–the impact of media attention on consumer and mutual fund investment decisions. *Journal of Financial Economics*, **123** 337–356.

Kumar, Alok, Alexandra Niessen-Ruenzi, Oliver G Spalt. 2015. What's in a name? mutual fund flows when managers have foreign-sounding names. *The Review of Financial Studies*, **28** 2281–2321.

Li, Bin, Shivaram Rajgopal, Mohan Venkatachalam. 2014. R^2 and idiosyncratic risk are not interchangeable. *The Accounting Review*, **89** 2261–2295.

Lou, Dong. 2012. A flow-based explanation for return predictability. *Review of Financial Studies*, **25** 3457–3489.

Madrian, Brigitte, Dennis Shea. 2001. The power of suggestion: Inertia in 401(k) participation and savings behavior. *Quarterly Journal of Economics*, **116** 1149–1187.

Malkiel, Burton G, Yexiao Xu. 2002. Idiosyncratic risk and security returns. *Working Paper*.

Merton, Robert C. 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance*, **42** 483–510.

Pastor, Lubos, Robert Stambaugh, Lucian Taylor. 2015. Scale and skill in active management. *Journal of Financial Economics*, **116** 23–45.

Rakowski, David. 2010. Fund flow volatility and performance. *Journal of Financial and Quantitative Analysis*, **45** 223–237.

Sapp, Travis, Ashish Tiwari. 2004. Does stock return momentum explain the "smart money" effect? *The Journal of Finance*, **59** 2605–2622.

Sensoy, Berk. 2009. Performance evaluation and self-designated benchmark indexes in the mutual fund industry. *Journal of Financial Economics*, **92** 25–39.

Sialm, Clemens, Laura Starks, Hanjiang Zhang. 2015. Defined contribution pension plans: Stick or discerning money? *Journal of Finance*, **70** 805–838.

Sirri, Erik, Peter Tufano. 1998. Costly search and mutual fund flows. *Journal of Finance*, **53** 1589–1622.

Solomon, David H, Eugene Soltes, Denis Sosyura. 2014. Winners in the spotlight: Media coverage of fund holdings as a driver of flows. *Journal of Financial Economics*, **113** 53–72.

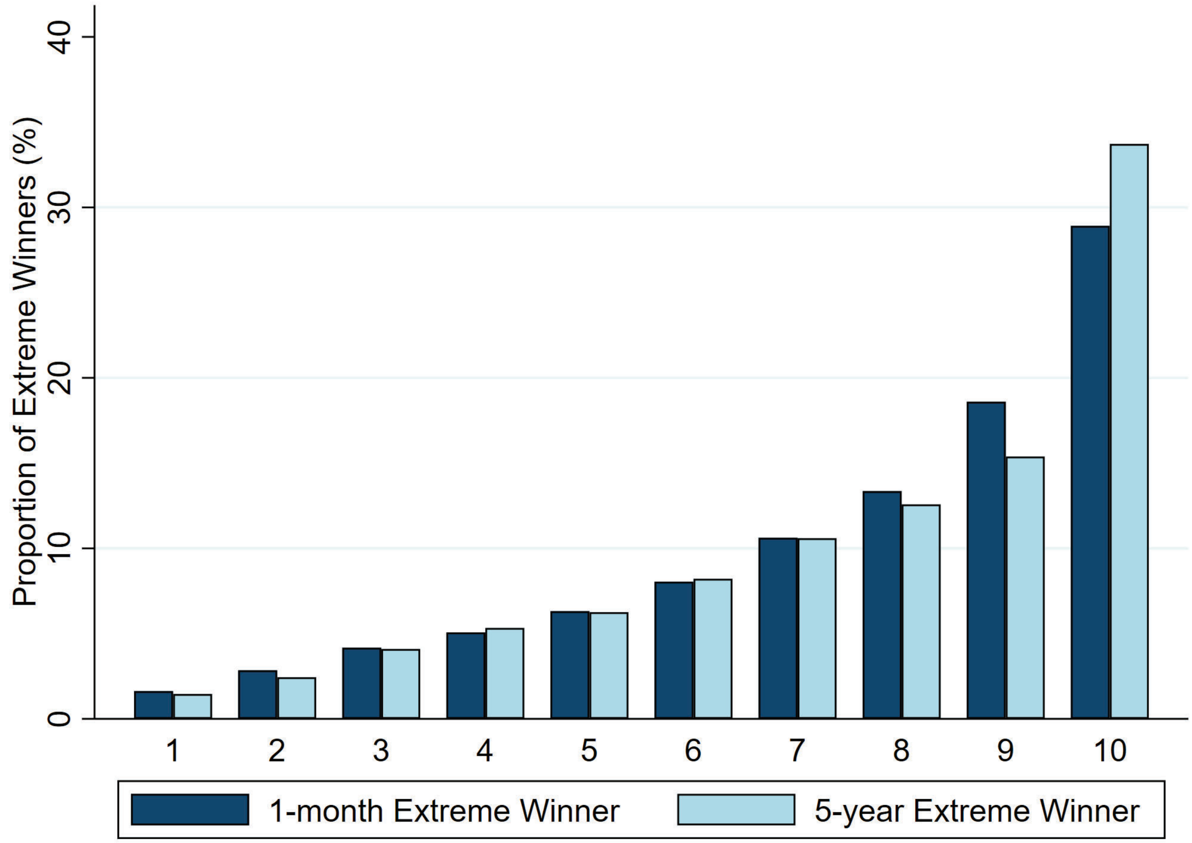

Figure 1
The Proportion of Extreme Winners by Idiosyncratic Volatility Decile
This figures plots the proportion of mutual funds within an idiosyncratic volatility decile (10 is the highest IV decile) that are classified as *extreme winners*. Each month we sort funds into deciles based on past 12 month idiosyncratic volatility. We then report the fraction of funds within each decile that are in the top 10% of past one-month or past five-year returns.

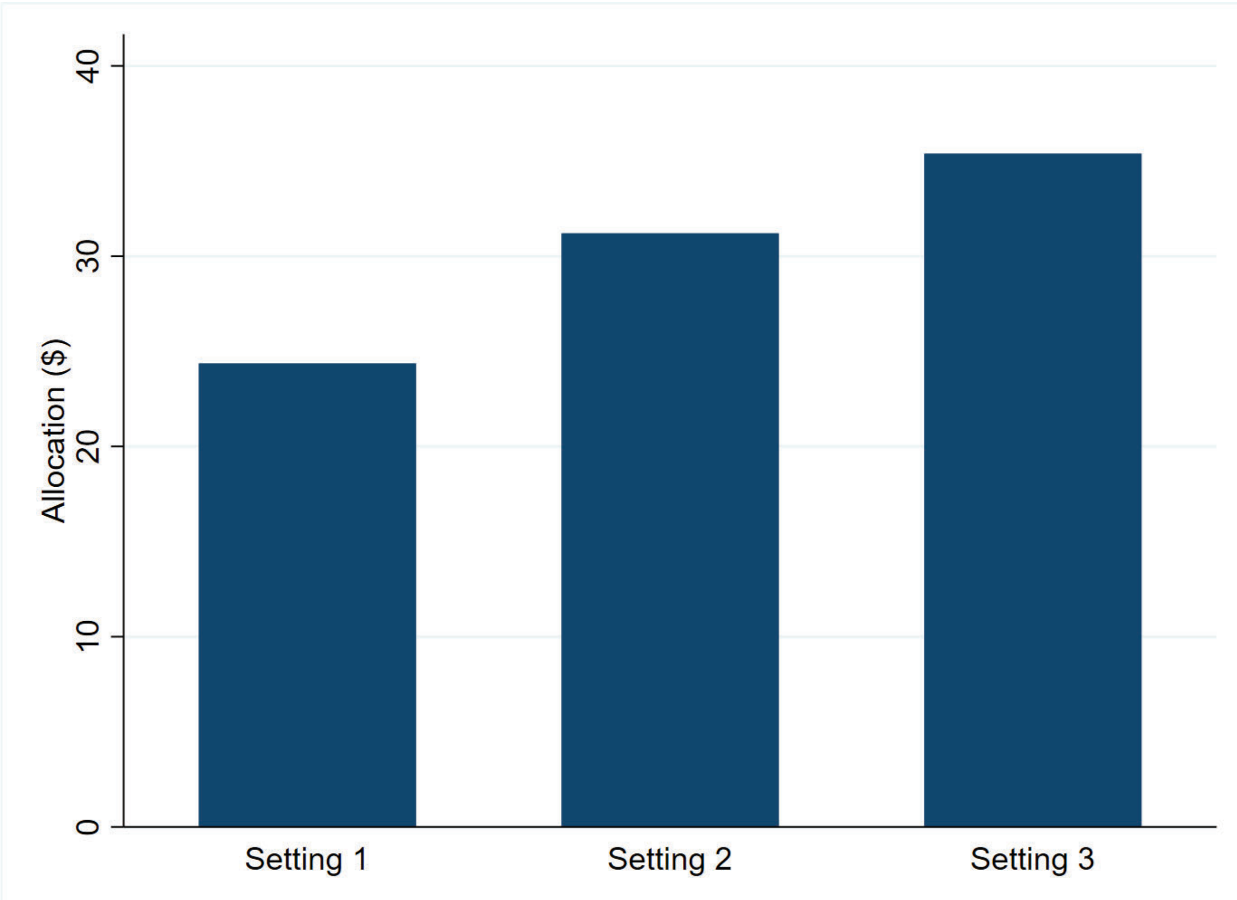

Figure 2
MTurk Worker Allocation to High IV Funds
Workers on Amazon Mechanical Turk (MTurk) are asked to allocate $100 across three funds. This table reports the average percentage of capital that MTurk workers allocate to the fund with the highest IV across three different settings. In Setting 1 investors are given information on six fund characteristics: fund size, fund age, expense ratio, fund turnover, past one-year return, and IV. The funds are similar along the first five characteristics but differ significantly with respect to IV. Setting 2 augments Setting 1 by including the funds' returns over the prior one month, three months, three years, and five years. Past returns are simulated from a market model where all funds have an alpha of zero, a beta of one, and an IV as given in Setting 1. Setting 3 augments Setting 2 by including an additional line (in bold) that reports whether a given fund has the highest three-year and five-year return. Additional details on the experimental design are available in Section 4.3.2 and Section IA.6 of the Internet Appendix.

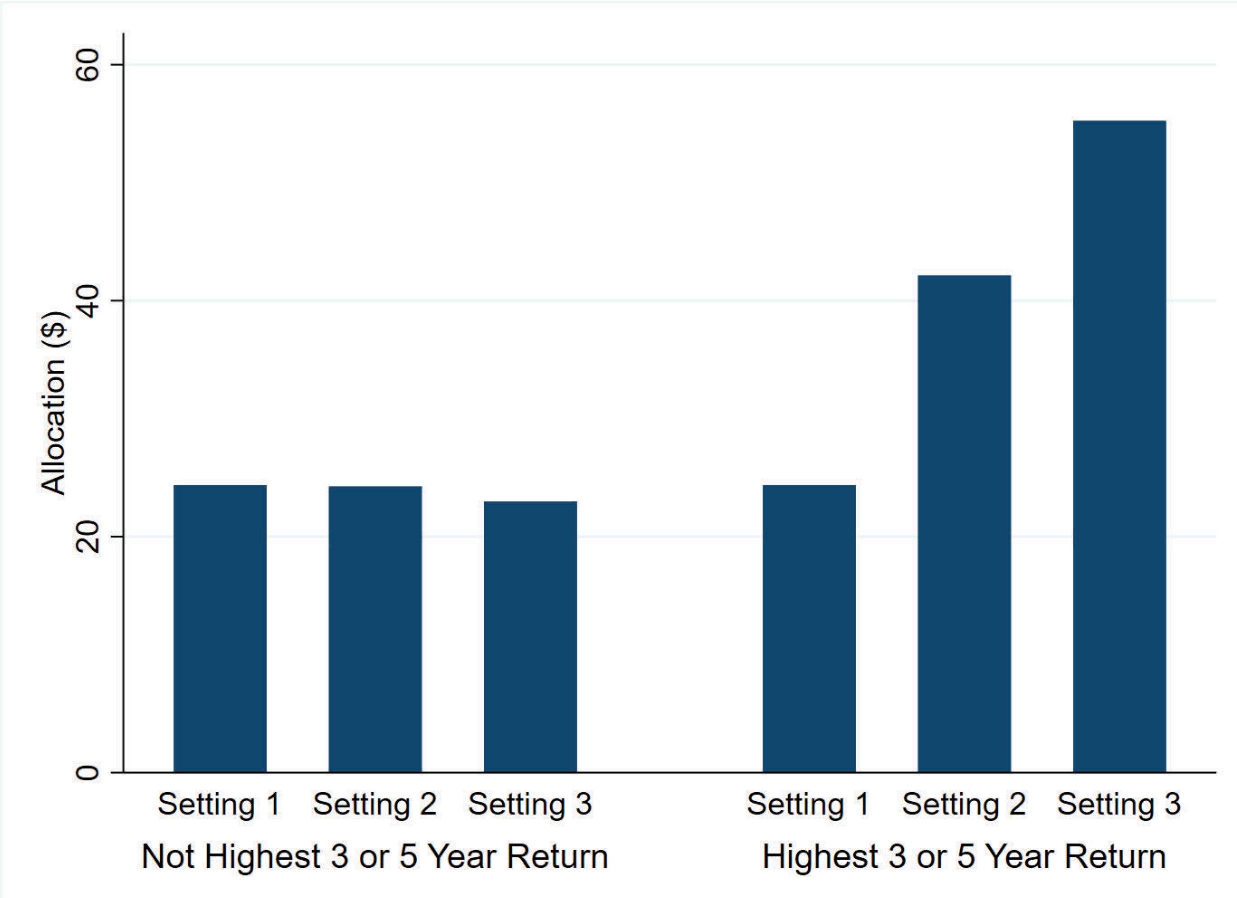

Figure 3
MTurk Worker Allocation to High IV Funds: Conditional on Past Performance
This figure repeats the analysis in Figure 2 conditional on past three-year and five-year performance. Past three-year and five-year performance is simulated from a market model where all funds have an alpha of zero, a beta of one, and the fund's IV. We report the results separately for the sample of simulations where the high IV fund has either the highest three-year return or the highest five-year return (or both) and the sample of simulations where the high IV fund has neither the highest three-year nor the highest five-year return. Additional details on the experimental design are available in Section 4.3.2 and Section IA.6 of the Internet Appendix.

Table 1
Summary Statistics

This table provides summary statistics for the sample of active, equity fund managers used in this study. We aggregate (TNA-weighted) multiple share classes to form one "fund" observation. The sample includes 2,481 unique funds and 204,072 fund-month observations over the December 1999-December 2012 time period. Variable definitions are reported in the Appendix.

Panel A: Fund Summary Statistics

	Mean	Median	10%	90%	Std. Dev.
Family TNA ($MM)	48,100	7,340	268	120,000	111,000
Total TNA ($MM)	1,540	319	45	3,040	5,650
Age (months)	177	136	53	323	151
Expense Ratio	1.21%	1.19%	0.76%	1.73%	0.42%
Turnover Ratio	83.37%	63.76%	17.00%	168.00%	78.19%
Load Fund	0.68	1.00	0.00	1.00	0.47
Return (prior 12 months)	7.65%	9.72%	-24.14%	32.71%	23.26%
Standard Deviation (prior 12 months)	5.07%	4.71%	2.43%	8.07%	2.43%
Idiosyncratic Vol. (prior 12 months)	1.19%	0.92%	0.43%	2.18%	0.98%
Systematic Vol. (prior 12 months)	4.86%	4.51%	2.28%	7.80%	2.37%
Carhart Alpha (annual)	-0.48%	-0.72%	-9.72%	8.88%	9.84%
New Share Class	0.01	0.00	0.00	0.00	0.10
12b-1 Fees	0.19%	0.10%	0.00%	0.52%	0.22%
Closed	0.06	0.00	0.00	0.00	0.24
Star Fund	0.12	0.00	0.00	1.00	0.32
% of Assets Retail Only	40.21%	0.00%	0.00%	100.00%	49.03%
% of Assets Institutional Only	9.16%	0.00%	0.00%	0.00%	28.84%

Panel B: Flow Summary Statistics

	Mean	Median	10%	90%	Std. Dev.
Net flow	0.41%	-0.02%	-1.63%	2.62%	3.69%
Inflow	4.19%	2.66%	0.96%	6.50%	9.03%
Outflow	3.78%	2.72%	1.36%	4.94%	7.86%

Panel C: Flow Correlations

	Net flow (%)	Inflow (%)
Inflow (%)	0.62	
Outflow (%)	-0.15	0.68

Table 2

Summary Statistics by Idiosyncratic Volatility (*IV*)

This table reports summary statistics for funds partitioned based on past 12 month *IV*. Low *IV* consists of funds in the bottom 20% of past 12 month *IV*, High *IV* consists of funds in the top 20% of past 12 month *IV*, and Middle *IV* consists of the remaining 60% of funds. For each group, we report the mean and medians for a number of variables. Variable definitions can be found in the Appendix. The sample includes 204,072 fund-month observations over the December 1999-December 2012 time period.

	Means			Medians		
	Low 20% IV	Middle 60% IV	High 20% IV	Low 20% IV	Middle 60% IV	High 20% IV
Family TNA ($MM)	48,768	38,638	76,091	10,576	6,386	7,476
Total TNA ($MM)	2,483	1,469	811	470	311	246
Age (months)	195	174	164	138	134	137
Expense Ratio (%)	1.04	1.22	1.33	1.03	1.20	1.32
Standard Deviation (lag)	4.32	4.90	6.35	4.19	4.58	5.69
Standard Deviation (lead)	4.33	4.91	6.33	4.20	4.61	5.57
Carhart Alpha (lag) (annual)	-0.90%	-0.65%	0.23%	-1.05%	-0.76%	0.21%
Carhart Alpha (lead) (annual)	-1.12%	-1.02%	-0.60%	-1.13%	-0.92%	-0.48%
Sharpe Ratio (lag)	0.17	0.17	0.16	0.21	0.20	0.18
Sharpe Ratio (lead)	0.16	0.16	0.15	0.20	0.19	0.16
Avg. Net Flow (lead)	-0.1%	0.1%	0.2%	-0.4%	-0.4%	-0.6%
Std. Dev. Net Flow (lead)	2.3%	2.7%	4.0%	1.5%	1.8%	2.4%
Avg. Inflow (lead)	2.3%	3.0%	5.0%	1.4%	1.6%	2.1%
Avg. Outflow (lead)	2.5%	2.9%	4.8%	1.8%	2.1%	2.7%

Table 3
Idiosyncratic Volatility and Fund Flows

This table presents the estimates of panel regressions, where the dependent variable is the fund's monthly net flow, inflow, or outflow. To allow for non-linearity in performance sensitivity, we follow Sirri and Tufano (1998) and use a piecewise linear specification. See Section 3.1 for a detailed description. All independent variables, except past returns, are standardized to have mean zero and variance one. All independent variables are lagged one period except style-level flows, which are estimated contemporaneously. Definitions of all variables are available in the Appendix. In brackets, we report t-statistics computed from standard errors clustered by fund. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively. Each model has 204,072 observations.

	(1) Net flow	(2) Inflow	(3) Outflow	(4) Net flow	(5) Inflow	(6) Outflow
Ret Low	5.59***	1.20	-4.51***	5.07***	0.82	-4.18***
	[8.74]	[1.08]	[-4.16]	[8.01]	[0.94]	[-5.70]
Ret Mid	2.54***	1.76***	-0.74***	2.15***	1.41***	-0.76***
	[27.26]	[14.94]	[-7.56]	[24.84]	[15.26]	[-11.81]
Ret High	7.61***	10.06***	2.58***	7.11***	8.56***	1.39***
	[15.71]	[13.20]	[4.42]	[16.18]	[16.56]	[4.57]
Systematic Vol.	-0.11***	-0.12	0.04	0.14***	0.40***	0.28***
	[-2.67]	[-0.58]	[0.19]	[2.92]	[3.80]	[3.02]
Idiosyncratic Vol. (IV)	0.08***	0.84***	0.84***	0.11***	0.21***	0.11**
	[3.13]	[3.05]	[3.10]	[2.75]	[3.27]	[2.03]
Log Age	-0.57***	-0.61***	-0.06	-1.89***	-1.60***	0.27**
	[-18.09]	[-11.22]	[-1.22]	[-13.76]	[-9.16]	[2.05]
Log Size	-0.08**	-0.31***	-0.25***	-1.21***	-1.28***	-0.08
	[-2.26]	[-3.41]	[-3.18]	[-11.31]	[-8.56]	[-0.81]
Log Family Size	0.04	-0.05	-0.07	0.31**	0.72***	0.43***
	[1.18]	[-0.46]	[-0.65]	[2.15]	[3.87]	[2.96]
Turnover Ratio	0.02	1.95***	1.93***	0.08	0.52***	0.44**
	[0.64]	[4.75]	[4.74]	[1.53]	[2.85]	[2.51]
Expense Ratio	-0.21***	-0.48***	-0.25**	0.04	-0.12	-0.14
	[-6.32]	[-4.19]	[-2.28]	[0.46]	[-0.89]	[-1.23]
Load Fund	0.03	0.53***	0.50***	-0.04	-0.76***	-0.71***
	[0.50]	[3.17]	[3.28]	[-0.26]	[-3.14]	[-3.65]
New Share Class	0.73***	1.35***	0.64***	0.43**	0.91***	0.50***
	[3.81]	[5.69]	[3.69]	[2.32]	[4.15]	[3.58]
Closed	-0.77***	-0.91***	-0.11	-1.13***	-1.21***	-0.10
	[-10.09]	[-6.57]	[-0.90]	[-8.82]	[-7.49]	[-0.95]
Style Flows	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	-	-	-	Yes	Yes	Yes
R^2	5.7%	12.8%	14.1%	13.5%	44.4%	57.5%

Table 4
Idiosyncratic Volatility, Fund Flows, and Future Performance

This table presents the estimates of panel regressions where the dependent variable is fund performance defined as either the return of the fund in excess of the risk-free rate (*Excess Return*) or the Carhart (1997) four-factor alpha (*Carhart Alpha*), and the independent variables include *IV*, *Inflows*, *Outflows*, and other fund characteristics. All independent variables are lagged one month relative to the dependent variable, and they are standardized to have mean zero and variance one. Definitions of variables are available in the Appendix. In brackets, we report t-statistics computed from standard errors clustered by time. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively. Each model has 198,359 observations.

	(1) Excess Return	(2) Carhart Alpha
Idiosyncratic Vol. (IV)	0.06	0.04
	[0.70]	[0.37]
Inflow	0.02	0.00
	[0.65]	[0.21]
Outflow	-0.04	-0.03
	[-1.17]	[-1.48]
Log Age	0.03*	0.01
	[1.78]	[0.62]
Log Size	-0.08***	-0.02
	[-2.80]	[-0.92]
Log Family Size	0.03*	0.01
	[1.86]	[0.76]
Turnover ratio	-0.02	-0.01
	[-0.70]	[-0.45]
Expense Ratio	-0.03**	-0.02
	[-2.19]	[-1.21]
Time Fixed Effects	Yes	Yes
Style Fixed Effects	Yes	Yes
R^2	0.778	0.081

Table 5
Response of Fund Flows to Components of Fund Returns

This table reports estimates from panel regressions of monthly fund net flows, inflows, or outflows on the lagged components of a fund's return. The components of fund returns include the fund's alpha and the returns attributable to the factor loadings. In Panel A, we include market beta, size, value, momentum, and LIVH (the *IV* factor) (see regression equation (5) in the text). In Panel B, we include market beta, size, value, RMW (a profitability factor), and CMA (an investment factor). Returns due to factor loadings of a fund are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's estimated factor loading. The regression also includes a fund's systematic and idiosyncratic volatility estimated over the prior 12 months as well as all of the control variables included in Table 3. Definitions of all variables are available in the Appendix. In brackets, we report t-statistics computed from standard errors clustered by fund. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively. Each model has 199,188 observations.

Panel A: IV Factor

	(1) Net flow	(2) Inflow	(3) Outflow	(4) Net flow	(5) Inflow	(6) Outflow
Alpha	1.45***	1.27***	-0.16**	1.26***	1.09***	-0.17***
	[24.81]	[13.90]	[-2.26]	[23.21]	[16.24]	[-3.51]
Ret from MKT	-0.10*	0.14	0.22	-0.10*	-0.02	0.06
	[-1.70]	[0.70]	[1.05]	[-1.77]	[-0.27]	[0.84]
Ret from SMB	0.72***	0.34	-0.36*	0.49***	0.79***	0.23*
	[8.58]	[1.49]	[-1.76]	[5.60]	[5.18]	[1.72]
Ret from HML	0.55***	0.54***	0.01	0.49***	0.32***	-0.16**
	[10.00]	[4.26]	[0.05]	[9.02]	[3.54]	[-2.15]
Ret from UMD	1.00***	0.46***	-0.54***	1.01***	0.60***	-0.41***
	[13.93]	[2.86]	[-3.65]	[14.33]	[5.51]	[-4.64]
Ret from LIVH	0.86***	0.63***	-0.25	0.82***	0.76***	-0.09
	[8.54]	[3.30]	[-1.36]	[8.35]	[5.62]	[-0.85]
Systematic Vol.	-0.21***	-0.07	0.17	-0.08*	0.25***	0.35***
	[-4.86]	[-0.39]	[0.90]	[-1.72]	[2.59]	[3.99]
Idiosyncratic Vol. (IV)	0.02	0.86***	0.91***	0.05	0.16**	0.12**
	[0.96]	[3.11]	[3.40]	[1.42]	[2.45]	[2.15]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	-	-	-	Yes	Yes	Yes
R^2	6.2%	12.9%	13.8%	13.5%	44.8%	57.2%

Panel B: Profitability and Investment Factor

	(1) Net flow	(2) Inflow	(3) Outflow	(4) Net flow	(5) Inflow	(6) Outflow
Alpha	1.38***	1.12***	-0.24***	1.24***	1.03***	-0.20***
	[25.61]	[12.24]	[-3.22]	[24.68]	[16.51]	[-4.44]
Ret from MKT	0.18**	0.48*	0.26	0.12*	0.13	-0.01
	[2.44]	[1.68]	[0.91]	[1.70]	[1.31]	[-0.14]
Ret from SMB	0.73***	0.40*	-0.33*	0.44***	0.67***	0.14
	[8.62]	[1.91]	[-1.75]	[4.96]	[4.65]	[1.11]
Ret from HML	0.61***	0.45***	-0.14	0.53***	0.36***	-0.17***
	[11.21]	[4.37]	[-1.50]	[9.59]	[4.77]	[-2.83]
Ret from RMW	0.77***	1.01***	0.24	0.68***	0.68***	-0.01
	[9.16]	[5.81]	[1.60]	[8.17]	[5.59]	[-0.14]
Ret from CMA	1.05***	0.19	-0.85**	0.88***	0.34	-0.53***
	[10.63]	[0.55]	[-2.57]	[9.59]	[1.64]	[-2.66]
Systematic Vol.	-0.30***	-0.20	0.13	-0.13***	0.20**	0.33***
	[-6.97]	[-1.00]	[0.68]	[-2.63]	[1.97]	[3.71]
Idiosyncratic Vol. (IV)	0.03	0.88***	0.92***	0.08**	0.19***	0.13**
	[1.36]	[3.19]	[3.44]	[2.13]	[3.09]	[2.39]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effects	-	-	-	Yes	Yes	Yes
R^2	6.0%	12.8%	13.9%	13.4%	44.7%	57.2%

Table 6
Idiosyncratic Volatility, Fund Flows, and Salient Returns

This table reports estimates of panel regressions where the dependent variable is the fund's monthly inflow, or outflow, respectively. Specifications 1-4 report the estimates of equation (1) after limiting the sample to funds with a five-year return history. Specifications 5-8 augment Specifications 1-4 by adding controls for returns over the prior one month, three months, three years, and five years. We control for all past returns using the piecewise linear model of Sirri and Tufano (1998). The regressions include all the variables from Table 3, but in the interest of brevity, only the coefficients on IV and the measures of past returns are tabulated. Definitions of variables are available in the Appendix. In brackets, we report t-statistics computed from standard errors clustered by fund. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively. Each model has 161,560 observations.

	(1) Inflow	(2) Outflow	(3) Inflow	(4) Outflow	(5) Inflow	(6) Outflow	(7) Inflow	(8) Outflow
Idiosyncratic Vol. (IV)	0.79***	0.78***	0.14**	0.10*	0.54**	0.72***	0.07	0.10**
	[3.35]	[3.47]	[2.32]	[1.96]	[2.19]	[3.09]	[1.30]	[2.02]
Ret Low (12 month)	0.55	-5.14***	0.94	-4.00***	-0.26	-2.70***	-0.86	-2.60***
	[0.47]	[-4.52]	[1.00]	[-4.92]	[-0.26]	[-2.70]	[-0.93]	[-3.40]
Ret Mid (12 month)	1.53***	-0.78***	1.16***	-0.85***	0.40***	-0.54***	0.35***	-0.47***
	[12.96]	[-7.58]	[12.04]	[-11.76]	[2.86]	[-4.14]	[3.49]	[-5.74]
Ret High (12 month)	9.08***	2.28***	7.68***	1.08***	5.66***	1.96***	5.30***	1.41***
	[11.43]	[3.79]	[14.65]	[3.67]	[8.78]	[3.93]	[11.14]	[4.68]
Ret Low (1 month)					-0.47	-4.00***	1.28**	-1.75***
					[-0.49]	[-4.41]	[2.03]	[-4.17]
Ret Mid (1 month)					-0.03	-0.11*	0.02	-0.05
					[-0.35]	[-1.86]	[0.34]	[-0.99]
Ret High (1 month)					3.93***	1.05***	2.71***	-0.28
					[7.22]	[2.63]	[7.71]	[-1.47]
Ret Low (3 month)					-0.23	-2.46***	0.56	-1.28**
					[-0.28]	[-3.12]	[0.90]	[-2.25]
Ret Mid (3 month)					-0.02	-0.22***	-0.02	-0.21***
					[-0.30]	[-3.29]	[-0.32]	[-4.00]
Ret High (3 month)					4.21***	1.32***	3.47***	0.65**
					[7.21]	[3.03]	[7.38]	[2.25]
Ret Low (3 year)					-1.98	-3.87***	-0.25	-1.93**
					[-1.33]	[-2.71]	[-0.27]	[-2.29]
Ret Mid (3 year)					1.10***	-0.31**	0.97***	-0.30***
					[5.90]	[-1.97]	[6.91]	[-2.60]
Ret High (3 year)					2.67***	0.08	3.04***	0.27
					[3.71]	[0.15]	[5.41]	[0.69]
Ret Low (5 year)					-2.95	-2.54	-0.47	-1.10
					[-1.50]	[-1.35]	[-0.43]	[-1.11]
Ret Mid (5 year)					1.65***	0.51**	1.17***	-0.54***
					[7.43]	[2.56]	[6.73]	[-3.92]
Ret High (5 year)					1.89**	-0.81	2.36***	-1.74***
					[2.20]	[-1.22]	[2.84]	[-2.75]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Fixed Effect	-	-	Yes	Yes	-	-	Yes	Yes
R^2	12.2%	14.2%	44.5%	58.0%	13.2%	14.4%	46.1%	58.1%

Table 7

Idiosyncratic Volatility, Fund Flows, and Salient Returns: Experimental Evidence

This table examines how IV influences capital allocations (i.e., inflows) in an experimental setting. Workers on Amazon Mechanical Turk (MTurk) are asked to allocate \$100 across three funds. In Specifications 1-3, the table reports estimates from regressions of dollar allocations on a dummy variable equal to one if the fund has the highest IV (*High IV*), the highest past one-year returns (*High Ret1Y*), and the highest fees (*High Fees*). Specification 4 adds dummy variables equal to one if the fund has the highest return over the past one month (*High Ret 1M*), past three months (*High Ret 3M*), past three years (*High Ret 3Y*), past five years (*High Ret 5Y*), and the highest return in both the past three years and past five years (*High Ret 3Y and 5Y*). We report the results separately for three different experimental settings. In *Setting 1* investors are given information on six fund characteristics: fund size, fund age, expense ratio, fund turnover, past one-year return, and IV. The funds are similar along the first five characteristics but differ significantly with respect to IV. *Setting 2* augments *Setting 1* by including the funds returns over the prior one month, three months, three years, and five years. Past returns are simulated from a market model where all funds have an alpha of zero, a beta of one, and an IV as given in *Setting 1*. *Setting 3* augments *Setting 2* by including an additional line (in bold) that reports whether a given fund has the highest three-year and five-year return. Additional details on the experimental design are available in Section 4.3.2 and Section IA.6. In brackets, we report t-statistics computed from standard errors clustered at the survey level. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

	(1) Setting 1	(2) Setting 2	(3) Setting 3	(4) Setting 3
Intercept	\$32.81***	\$31.35***	\$29.11***	\$22.61***
	[28.06]	[24.28]	[21.62]	[15.28]
High IV	-\$6.63***	\$0.54	\$5.94***	-\$3.35*
	[-5.68]	[0.29]	[2.37]	[-1.70]
High Ret 1Y	\$13.24***	\$6.78***	\$6.05***	\$2.55
	[5.56]	[2.82]	[2.54]	[1.20]
High Fees	-\$3.64***	-\$1.37	\$0.68	\$0.68
	[-3.84]	[-1.40]	[0.67]	[0.67]
High Ret 1M				-\$1.87
				[-1.01]
High Ret 3M				\$4.82***
				[2.25]
High Ret 3Y				\$7.47***
				[3.37]
High Ret 5Y				\$15.04***
				[5.13]
High Ret 3Y and 5Y				\$9.71***
				[3.32]
Observations	2,924	2,964	2,904	2,904
R^2	15.30%	1.99%	1.04%	25.04%
Δ High IV (Relative to Setting 1)		\$7.17***	\$12.57***	\$3.28
		[3.32]	[4.77]	[1.51]

Table 8
Idiosyncratic Volatility and Fund Flows- Cross-Sectional Predictions

This table reports estimates of panel regressions where the dependent variable is the fund's monthly net flow, inflow, and outflow, respectively. The regression includes all the variables from Table 3 and also interacts all the variables with a conditioning variable (CV). The conditioning variables are constructed to be positively correlated with the importance of fund salience as a driver of fund flows. The conditioning variables in Panels A through F are: *Small*, an indicator equal to one if the fund is not in the top quintile of fund size; *Young*, an indicator equal to one if the fund is not in the top quintile of fund age, *Low Marketing*, an indicator equal to one if the fund is not in the top quintile of marketing expenditures, defined as 12b-1 fees + 1/7 of the load; *Non-Star Fund*, an indicator equal to one if none of the fund's share classes ranked as 5-star by Morningstar; *Open*, an indicator equal to one if the fund is not closed to new investors; and *Retail* an indicator equal to one if all share classes within the fund are retail, and zero if all the share classes are institutional. Definitions of all variables are available in the Appendix. In brackets, we report t-statistics computed from standard errors clustered by fund. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively. In Panels A-E, each model has 204,072 observations. In Panel F, each model has 100,754 observations.

		Net Flow	Inflow	Outflow
Panel A: Fund Size				
	IV	0.07**	0.09	0.06
		[2.27]	[1.38]	[1.15]
	IV × Small	0.03	0.93***	0.96***
		[0.65]	[3.03]	[3.24]
Panel B: Fund Age				
	IV	0.05**	0.21***	0.21***
		[2.00]	[4.09]	[4.28]
	IV × Young	0.05	0.89**	0.87**
		[1.19]	[2.49]	[2.50]
Panel C: Marketing Expense				
	IV	-0.08	0.15	0.33***
		[-0.72]	[1.09]	[3.89]
	IV × Low Marketing	0.16	0.75**	0.56**
		[1.50]	[2.51]	[2.11]
Panel D: Morningstar Rank				
	IV	-0.08	0.15	0.33***
		[-0.72]	[1.09]	[3.89]
	IV × Non-Star Fund	0.16	0.75**	0.56**
		[1.50]	[2.51]	[2.11]
Panel E: Accepting New Funds				
	IV	0.03	0.06	0.06
		[0.35]	[0.32]	[0.44]
	IV × Open Fund	0.05	0.79***	0.79***
		[0.57]	[2.73]	[2.90]
Panel F: Institutional/Retail				
	IV	-0.05	0.09	0.27**
		[-0.45]	[0.56]	[1.99]
	IV × Retail	0.07	1.00**	0.88**
		[0.61]	[2.38]	[2.21]

Table 9
Idiosyncratic Volatility, Google Search, and Fund Flows

In this table we examine the relation between idiosyncratic volatility, Google search, and fund flows. In Specification 1, the dependent variable is the Log (1+*Search*), a measure of the fund's monthly search frequency as reported by Google Trends. In Specifications 2-4 and 5-7, the dependent variable is the fund's monthly net flow, inflow, and outflow, respectively. The regressions include all the variables from Table 3, but for brevity their coefficients are unreported. Variable definitions are reported in the Appendix. In brackets, we report t-statistics computed from standard errors clustered by fund. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively. In Model 1 there are 164,738 observations, and in Models 2-7 there are 136,527 observations.

	(1) Log(1+Search)	(2) Net Flow	(3) Inflow	(4) Outflow	(5) Net Flow	(6) Inflow	(7) Outflow
Idiosyncratic Vol. (IV)	0.66***				0.05	0.68***	0.66***
	[10.99]				[1.63]	[2.81]	[2.85]
Log (1+Search)		0.22***	0.41***	0.21***	0.21***	0.26***	0.06
		[6.77]	[6.31]	[3.71]	[6.26]	[3.61]	[0.91]
Ret Low	-3.34***	5.74***	-0.72	-6.62***	5.93***	2.22***	-3.68***
	[-5.15]	[8.08]	[-0.64]	[-6.49]	[8.39]	[2.49]	[-3.92]
Ret Mid	0.50***	2.34***	1.56***	-0.74***	2.33***	1.53***	-0.79***
	[6.72]	[24.04]	[15.48]	[-8.96]	[23.93]	[15.25]	[-9.52]
Ret High	2.87***	6.66***	10.08***	3.68***	6.51***	7.93***	1.50***
	[7.93]	[13.47]	[11.45]	[4.51]	[12.76]	[10.96]	[2.76]
Log Size	1.90***	-0.03	-0.31***	-0.31***	-0.02	-0.21***	-0.20***
	[30.17]	[-0.76]	[-3.96]	[-4.69]	[-0.53]	[-2.32]	[-2.54]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	34.0%	4.4%	10.1%	11.8%	4.4%	10.8%	12.8%

Table 10
Attention-Based Trading and Investor Holding Period

This table sorts households into quintiles based on the total fraction of their mutual fund purchases that are classified as *attention based*. We classify a purchase as *attention based* if the purchase was in the top 5% of returns in the current month, past month, or past year. For each household, we also report the average percentile rank of the *IV* across all purchased funds (*IV Percentile Rank*), the average turnover of their holdings (*Household Turnover*), and the fraction of purchases that are at least partially reversed in the subsequent three months or twelve months. This table reports the average values across each quintile. We also report the difference between the top and bottom quintile and the *t*-statistic testing whether the difference is zero. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively. The sample includes 16,456 households that trade at least five equity-oriented mutual funds through a large discount brokerage over the January 1991 through November 1996 sample period.

Attention Based Trading Group	Attention Based Buys	IV Percentile Rank	Houselhold Turnover	Fraction of Purchases Reversed within 3 months	Fraction of Purchases Reversed within 12 months
1	0.00%	40.50%	84.84%	5.12%	18.10%
2	8.50%	47.12%	117.06%	7.07%	25.80%
3	18.26%	51.27%	116.83%	9.46%	27.96%
4	34.09%	56.51%	147.80%	12.90%	35.79%
5	62.44%	65.15%	184.87%	19.55%	45.97%
5-1	62.44%***	24.65%***	100.03%***	14.43%***	27.87%***
	[232.83]	[55.35]	[29.27]	[25.95]	[30.44]

Table 11
Idiosyncratic Volatility and Liquidity Management

This table reports estimates of panel regressions where the dependent variable is the fund's *IV*, defined as the standard deviation of the fund's residuals from the Carhart (1997) four-factor model over the previous 12 months. The independent variables of interest are *Redemption Fee*, a dummy variable equal to one if the has a short-term redemption in place, and *Count of Funds in Family*, the number of funds in the fund family. We also include all of the fund characteristics from Equation 1 except SV, IV, and style level flows. All independent variables are measured in $t-12$. In brackets, we report t-statistics computed from standard errors clustered by fund. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively. Each model has 148,272 observations.

	(1) IV	(2) IV
Redemption Fee	0.310***	0.044**
	[7.73]	[2.39]
Count of Funds in Family	0.109***	0.010
	[5.67]	[0.33]
Ret Low	-3.639***	-0.130
	[-14.66]	[-1.23]
Ret Mid	0.187***	0.032***
	[10.84]	[2.92]
Ret High	3.501***	0.385***
	[11.12]	[5.95]
Log Age	0.063***	-0.102***
	[3.72]	[-3.90]
Log Size	-0.059***	0.077***
	[-4.18]	[4.19]
Turnover Ratio	0.054**	-0.001
	[2.32]	[-0.06]
Expense Ratio	0.146***	0.006
	[6.62]	[0.44]
New Share Class	-0.018	0.000
	[-0.79]	[0.01]
Load Fund	-0.063**	0.002
	[-2.14]	[0.08]
Closed	0.078*	0.017
	[1.68]	[0.81]
Time Fixed Effects	Yes	Yes
Fund Fixed Effects	-	Yes
R^2	25.2%	76.4%