Search Costs and Investor Demand for Idiosyncratic Volatility

Abstract

We use capital flows into and out of mutual funds to infer investors' demand for idiosyncratic volatility (IV). We find investors are more likely to both purchase and redeem funds with high IV. This pattern is concentrated among funds in the top quintile of IV, and it is stronger among retail investors, non-incumbent investors, and funds with lower visibility. Funds with greater IV have significantly higher Google search volume (SVI), and SVI is also associated with larger inflows and outflows. Our results suggest that limited attention and search costs contribute to investors' demand for IV when trading.

JEL classification: G10, G23

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1. Introduction

In an influential study, Ang, Hodrick, Xing, and Zhang (2006) document a negative relation between idiosyncratic volatility (hereafter IV) and subsequent stock returns.[1] This finding is puzzling since it is in stark contrast to asset pricing theory, which predicts either no relationship or a positive relationship between IV and expected returns. In particular, if markets are complete and frictionless, idiosyncratic risk should not be priced in a correctly specified factor model (Sharpe, 1964 and Lintner, 1965). In contrast, if markets are incomplete and investors must incur costs to diversify, one would expect a positive relation between IV and returns (Merton, 1987).

The existing literature has proposed several possible explanations for the IV puzzle in equities. Consistent with investors preferring risk, several studies suggest that investors' demand for high IV stems from lottery-like preferences (Bali, Cakici, and Whitelaw, 2011; and Boyer, Mitton, and Vorkink, 2010). Other work argues that investors are rational and shun risk, and instead suggest that low IV stocks are actually riskier than high IV stocks (Chen and Petkova, 2012; Fama and French, 2016). A third possible explanation is that the IV puzzle is largely driven by microstructure effects, such as short-term reversals (Fu, 2009; Huang et al., 2009; and Han and Lesmond, 2011) and does not truly capture the preferences of investors.

Motivated by these competing explanations, our study offers a new approach to investigate investors' apparent preference for IV. Specifically, in contrast to the existing literature, which largely relies on equity returns to infer investors' preferences, we directly examine investors' allocation of capital across mutual funds with differing levels of IV. Examining mutual fund flows offers several advantages relative to studying equity returns. First, we can separately study investors' inflows and outflows. This is potentially interesting since

[1]This result also extends to international markets (Ang, Hordick, Xing, and Zhang, 2009) and has generally been confirmed in other studies (see, e.g., Boyer, Mitton, and Vorkink, 2010; George and Hwang, 2011; and Jiang, Xu, and Yao, 2009). However, a few studies argue that the results of Ang et al. (2006) are fragile due to methodological choices (e.g., Bali and Cakici, 2008) or may be driven by microstructure effects (Fu, 2009 and Huang et al., 2009).

most existing studies implicitly assume that investors' preferences for IV should be symmetric for both purchases and sales. Second, analyzing mutual funds allows for clean tests of risk-based explanations since we can infer the risk model that investors use by the fund choices they make (Barber, Huang, and Odean, 2016; and Berk and van Binsbergen, 2016). Finally, by studying quantities rather than prices, we are able to offer an out-of-sample test that abstracts from microstructure effects that can bias tests of equity returns.

We begin by examining the relationship between mutual fund 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 past 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. The result is not simply a manifestation of investors buying last year's extreme winners and selling last year's extreme losers. After dropping funds in the best and worst performing terciles, we continue to find a similar relation between fund flows and past IV. We also find no evidence that IV predicts fund performance, which suggests that our findings cannot be explained by a smart-money effect (Gruber, 1996).

The asymmetric pattern could be consistent with a rational, risk-based explanation. Specifically, if high IV is associated with lower risk, funds experiencing an increase in IV may attract inflows from more risk-averse investors and experience outflows from less risk-averse investors. 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 risks, and examine how flows respond to each of these 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) risk factors (Fama and

French, 2016), we also consider the Fama and French (2015) five-factor model. Using either factor 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. Further, the inclusion of an IV risk factor has virtually no impact on the relationship between gross flows and fund IV.

We conjecture that the asymmetric relationship between IV and fund flows can be better explained as a consequence of search costs and limited investor attention. In particular, there is growing evidence that increases in visibility (or saliency) generate trading (Barber and Odean, 2008; Hartzmark, 2015; Yuan, 2015) and influence mutual fund choice (Barber, Odean, and Zheng, 2005; Huang, Wei, and Yan, 2007; and Kaniel and Parham, 2015). Funds with higher levels of IV are likely to be more salient for at least some investors since high IV funds are more likely to obtain media attention (Sirri and Tufano, 1998; and Kaniel, Starks, and Vasudevan, 2007) and are also more likely to have extreme returns across a wide range of holding periods that investors may consider. For example, we find that relative to the average fund, funds in the top decile of past one-year IV are 240% more likely to be in the top decile of past 5-year returns and 180% more likely to be in the top decile of past 3-month returns. If high IV improves the visibility of the fund among attention constrained investors, who may evaluate fund performance over very different horizons, then high IV funds will tend to experience both more buying and selling activity.

We conduct several tests to evaluate the search cost explanation for investors' tendency to both purchase and sell funds with high IV with greater intensity. First, we expect that the impact of IV on reducing search costs is non-linear and is largely concentrated amongst the subset of funds with very high IV.[2] To test this prediction, we estimate piecewise linear regressions of flows on IV. We find no evidence that IV is related to inflows or outflows

[2]We find that the likelihood of being in the top 10% of past 5-year returns increases by roughly 10 percentage points for funds that move from the first decile to the 8th decile of IV (from 2% to 12%), while the same likelihood increase by 22 percentage points for funds that move from the 8th decile to the 10th decile (12% to 34%).

among funds in the bottom 20% of *IV* or among funds in the middle 60% of *IV*. However, we document a highly significant relationship between *IV* and both inflows and outflows among funds in the top 20% of *IV*. This suggests that the average patterns we document are largely driven by the subset of funds with very high *IV*.

Next, following Huang, Wei, and Yan (2007), we examine whether the documented effects are significantly stronger for less visible funds, where search costs are more pronounced. Consistent with this notion, we find that the impact of *IV* on both inflows and outflows is significantly stronger among smaller funds, younger funds, funds that engage in less marketing, and funds without a 5-star rating by Morningstar. The fact that we find similar patterns for inflows and outflows 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 also find that the relationship between *IV* and inflows and outflows is not present for mutual funds that close to new investors. Thus, the asymmetric pattern we document is driven by new investors who presumably face greater search costs than incumbent investors. Similarly, the impact of *IV* on flows is significantly weaker among institutional funds. Institutional funds cater mostly to defined contribution (DC) plans, where plan participants generally have far fewer investment options[3] and frequently do not deviate from the default allocation (see, e.g., Madrian and Shea, 2001). This finding also suggests plan sponsors, who are likely more sophisticated than the typical mutual fund investor (see, e.g., Sialm, Starks, and Zheng, 2015), are less influenced by *IV* when making decisions on plan offerings.

Our final set of tests use Google's search volume index (*Search*), a common proxy for investor attention (Da, Engelberg, and Gao, 2011), to offer more direct evidence that attention is one channel through which *IV* increases capital inflows and outflows. We show that funds with greater *IV* have significantly higher *Search*. We also document that funds with greater *Search* experience significantly greater inflows and outflows, particularly among funds where search costs are more severe, (e.g., smaller funds, younger funds, and funds open

[3]For example, a 2011 Deloitte survey of DC plan sponsors finds that the median DC plan includes 16 investment options.

to new investors). These results provide further support for the joint hypothesis that 1) IV generates increased investor attention and 2) increased investor attention results in greater capital inflows and outflows.

Our study adds to the literature that seeks to understand investors' apparent preference for IV. Our findings suggest that many existing explanations for the IV puzzle in equities are unlikely to fully explain investors' demand for IV among mutual funds. First, we document systematic patterns between IV and gross flows in a setting that abstracts from microstructure biases. In addition, the finding that demand for high IV funds is significantly stronger in funds with low visibility, coupled with the fact that the IV of mutual funds is substantially less than that of individual stocks, suggests that lottery-like preferences cannot fully explain our findings. Finally, fund flows strongly chase returns attributable to IV tilts, indicating that the majority of the capital does not view IV as a risk factor. Instead, our findings suggest that limited attention and search costs help explain investors' tendency to trade funds with high IV. In particular, funds with high IV are more likely to catch investors' attention, resulting in increased trading and improved investor recognition.

Our findings also contribute to the literature that explores the determinants of mutual fund flows. Several studies have used net flows to conclude that search costs may influence the behavior of mutual funds investors (see, e.g., Sirri and Tufano, 1998; Barber and Odean, 2005; and Huang, Wei, and Yan, 2007). However, none of these studies emphasize the role of IV on the investment decisions of mutual fund investors, presumably because the impact of IV on net flows is relatively small. In contrast, we show that IV is an economically important determinant of both inflows and outflows. This finding highlights the importance of separately examining purchase and redemption decisions when assessing the behavior of mutual fund investors.

Finally, our results also have implications for understanding managerial incentives. For example, it is commonly argued that the convex net flow-performance relationship encourages managers to take on additional IV (see, e.g., Chevalier and Ellison, 1997). Our analysis uncovers a potential cost of increasing IV. In particular, our finding that IV increases both inflows and outflows highlights that increases in IV are associated with increases in the volatility of net flows.[4] This may act as a deterrent to increasing IV since high flow volatility is costly to mutual fund operations (see, e.g., Chordia, 1996; Edelen, 1999; and Rakowski, 2010) and imposes additional externalities (e.g., greater tax liabilities) that may dissuade longer-term investors from holding the fund.

2. A Review of Existing Explanations of the *IV* Puzzle

A number of competing explanations have been developed to explain the puzzling finding that IV is negatively related to future equity returns. While hardly exhaustive, three common explanations include: *risk, lottery-like preferences,* and *microstructure effects.*[5] In this section, we review each of these explanations and discuss their implications for mutual fund investor behavior.

Studies that offer evidence consistent with a risk-based explanation include Ang et al. (2009), Chen and Petkova (2012), and Fama French (2016). Ang et al. (2009) find that the return spread between stocks with high and low IV strongly co-moves across different countries suggesting a broad, not easily diversifiable factor, may be responsible for the IV puzzle. Building off this finding, Chen and Petkova (2012) show that portfolios with high IV have significantly greater exposure to innovations in average stock variance. 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. 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. The mutual

[4]We confirm that high IV funds have more than 75% higher volatility in monthly net flows than low IV funds. Such effects are more dramatic over shorter horizons where inflows and outflows are less likely to offset each other.

[5]Other explanations that do not cleanly fit into these three groups include: Johnson (2004), Jiang, Xu, and Yao (2009), Barberis and Xiong (2012), Rachwalski and Wen (2016), and Stambaugh, Yu, and Yuan (2015).

fund setting offers an ideal laboratory to test this risk-based explanation. In particular, as noted by Barber, Huang, and Odean (2016), mutual fund investors who perceive factor returns to be driven by risk should not react to these returns as if they were alpha. Thus, the risk-based explanation predicts that investors will not chase returns that stems from a funds' exposure to IV risk.

Other studies suggest that the equity IV puzzle can be explained by investors' preference for lottery-like stocks. Barberis and Huang (2008) show that under cumulative prospect theory, investors overweight small chances of large gains, resulting in excess demand, and correspondingly lower expected returns, for stocks with positive skewness. Consistent with this view, controlling for different measures of lottery-like payouts such as maximum daily return over the prior month (Bali, Cakici, and Whitelaw, 2011) or expected idiosyncratic skewness (Boyer, Mitton, and Vorkink, 2010), eliminates or significantly reduces the IV puzzle. It is worth noting, however, that due to diversification the IV of mutual funds is significantly less than that of individual stocks. Accordingly, we would not expect lottery-like preferences to be as important of a determinant of the behavior of mutual fund investors.

Finally, other work argues the IV puzzle is driven by microstructure effects. For example, Fu (2009) and Huang et al. (2009) show that the IV puzzle is no longer significant after controlling for the one-month return reversal effect. Similarly, Han and Lesmond (2011) show that controlling for the impact of liquidity costs on the estimation of IV eliminates the significant negative relationship between IV and returns. Trading frictions are largely absent for mutual funds given the open-end structure, suggesting that any behavior related to mutual fund IV cannot be explained by microstructure effects.

3. Data and Summary Statistics

3.1. 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).[6] 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

[6] 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.

(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.[7]

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 the TNA as reported in CRSP.

Using the merged sample, we combine share classes of a single fund using the Morningstar *Fund ID* variable.[8] 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 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 square root of the difference

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

[8]The gross flow data provided by Morningstar, which is sourced from the SEC Form N-SAR filings, is reported at the fund level rather than the share-class level. Thus, all of our analysis is conducted at the fund level.

between the total return variance and the idiosyncratic return variance.[9] 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.

3.2. *Descriptive Statistics*

Panel A of Table 1 reports summary statistics across the 204,072 fund-month observations. The average fund manages $1.5 billion in assets, has an expense ratio of 1.21%, and earns an annualized four-factor alpha of -0.48%. Most noteworthy for this study is the substantial dispersion in IV among funds. In particular, 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 (as a percentage of beginning-of-month TNA) is 0.09%, but there is considerable variation. At the 10th and 90th percentiles, net flows are -3.04% and 3.39% 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 3.38% (3.29%) of beginning-of-month TNA.[10]

Interestingly, inflows and outflows exhibit a strong positive correlation ($\rho = 0.68$). This is perhaps surprising since presumably many variables have an opposing effect on inflows and outflows. For example, a fund with strong recent performance should attract greater inflows and smaller outflows, inducing a negative correlation. One potential explanation for the positive correlation is a clientele effect. For example, if a subset of investors trade frequently

[9]Much of the asset pricing literature measures IV over the prior month rather than the prior year. We chose to estimate IV at the annual level because the literature on mutual fund flows typically estimates returns and risk at an annual horizon (see, e.g., Sirri and Tufano, 1998; and Huang, Wei, and Yan, 2007). Further, Ang et al. (2006) report that the IV puzzle is slightly stronger when IV is estimated over a 12-month holding period (see their Table 10). Nevertheless, we confirm that our main results are robust to measuring IV over the prior month using daily returns.

[10]We note that 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.

and are attracted to funds with certain characteristics, funds with these characteristics will likely experience both greater inflows and outflows. Thus, examining net flows may conceal many interesting patterns in the data.

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, high IV funds have much larger standard deviations of monthly net flows over the subsequent year. Since flow volatility is associated with increased liquidity-motivated trading (see, e.g., Rakowski, 2010), this finding highlights a potential cost of pursuing high IV strategies. When we decompose net flows into inflows and outflows, 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.

4. Idiosyncratic Volatility (IV) and Fund Flows

4.1. IV and 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.[11] 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 ($RANK_{i,t-1}$ - *Ret Low* - *Ret Mid*) for funds in the top quintile of performance and zero for all other funds. Our model takes on the following general form:

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

In equation (1), 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 $SV_{i,t-1}$ which is the standard deviation of the fund's returns over the previous 12 month less $IV_{i,t-1}$.

$\mathbf{X}_{i,t-1}$ 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 that may influence flows. All specifications include time fixed effects, and in Models 4-6 we also include fund fixed effects. To ease interpretation of the results, we convert all continuous independent

[11] In unreported results, we estimate past performance using alternative horizons (e.g., returns over the prior 24 or 36 months) and alternative risk-adjustments (e.g., CAPM alphas or Carhart (1997) four-factor alphas) and find similar results.

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.[12]

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 that there is a strong relationship between net flows and past performance.[13] 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.[14] 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. We note that 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 both buy and sell a given fund when it experiences an increase in IV.

In Table 4, we examine the robustness of the relation between IV and fund inflows and outflows. In the interest of brevity, in each row we only report the coefficient on IV. For

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

[13]Unlike many prior studies, we find only modest evidence of a convex flow-performance relationship. This finding is consistent with Kim (2013) who finds that the convex flow-performance relationship weakens after 2000.

[14]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.

reference, the first row of Table 4 reports the coefficient and t-statistic on IV from the baseline results reported in Specifications 1 through 3 of Table 3.

One concern is that the relationship between IV and inflows is simply a manifestation of investors buying last year's extreme winners, which naturally tend to have higher IV. Similarly, the positive relation between IV and outflows may reflect investors fleeing from funds with extremely poor performance. To explore this possibility, we re-estimate the baseline results separately for funds in the bottom, middle, and top tercile of past one-year returns. The results, reported in Rows 2 through 4 of Table 4, are inconsistent with extreme return chasing driving our main findings. For example, Row 3 documents a strong positive relation between IV and inflows and outflows even for funds with average performance (i.e., funds in the middle tercile of performance).[15]

Rows 5 through 8 consider several additional robustness checks. First, in Row 5, following Ang et al. (2006, 2009) we redefine IV as the standard deviation of the fund's residuals from the Fama-French (1993) three-factor model using daily returns over the previous calendar month and find very similar results. Second, since many investors may not distinguish between IV and SV (systematic volatility), in Row 6 we replace IV and SV with total volatility.[16] We continue to find that inflows and outflows are both significantly related to total volatility. In Row 7, we repeat our analysis after excluding the month of December and January and continue to find very similar results. This suggests that tax-loss selling and other end-of-year adjustments are unlikely to drive our results. Finally, in Row 8, we document very similar coefficients if we estimate Fama-MacBeth regressions, with Newey-West standard errors, rather than panel regressions.

[15] The patterns in Rows 2 through 4 also indicate that the impact of IV on inflows is attenuated by past performance. One explanation consistent with this finding is that stocks with high IV are more likely to generate increased investor attention resulting in increased buying pressure, but such effects are weaker among funds with stronger annual performance where search costs tend to less severe. An analogous but opposite pattern hold for outflows. Section 5 further explores the role of IV as a means of increasing investor attention, particularly when search costs are more severe.

[16] While much of the asset pricing literature has focused on the IV puzzle, other work highlights the puzzling negative relationship between *total volatility* and returns including Haugen and Heins (1975) and Blitz and Van Vilet (2007).

Since net flows tend to be persistent (see, e.g., Coval and Stafford, 2007 and Lou, 2012), it is also possible that the ability of IV to predict flows is a consequence of IV proxying for past buying or selling pressure. For example, a fund with extreme inflows may have very high returns (and thus high IV) due to price pressure as the fund purchases many of its existing positions. An analogous but opposite pattern could arise for funds with extreme outflows. To explore this possibility, we develop a measure of buying and selling pressure. Specifically, for each fund i and month t, we compute *Buying Pressure* as: Max (0, $NetFlow_{i,t}$). Similarly, we define *Selling Pressure* as: Max (0, $NetFlow_{i,t} \times -1$). Since IV is measured over the prior 12 months, we also sum *Buying Pressure* and *Selling Pressure* over the prior 12 months. In Specification 9 of Table 4 we repeat our baseline specification after including *Buying Pressure* and *Selling Pressure*. We find that the ability of IV to predict both inflows and outflows is reduced, however the estimates remain highly significant.[17] Thus, the ability of IV to predict flows cannot be fully explained by past buying or selling pressure.

We next consider a more general model that allows for a more complex relationship between lagged flows and IV. Specifically, we explore the joint relation between IV, fund inflows, and fund outflows, by estimating the following panel vector autoregression (panel VAR):

$$\mathit{Inflow}_{i,t} = \alpha + \sum_{i=1}^{n} \beta Inflow_{i,t-i} + \sum_{i=1}^{n} \lambda Outflow_{i,t-i} + \sum_{i=1}^{n} \delta IV_{i,t-i} + \gamma \mathbf{X}_{i,t-1} + \epsilon_{i,t} \tag{2}$$

$$\mathit{Outflow}_{i,t} = \alpha + \sum_{i=1}^{n} \beta Inflow_{i,t-i} + \sum_{i=1}^{n} \lambda Outflow_{i,t-i} + \sum_{i=1}^{n} \delta IV_{i,t-i} + \gamma \mathbf{X}_{i,t-1} + \epsilon_{i,t} \tag{3}$$

$$IV_{i,t} = \alpha + \sum_{i=1}^{n} \beta Inflow_{i,t-i} + \sum_{i=1}^{n} \lambda Outflow_{i,t-i} + \sum_{i=1}^{n} \delta IV_{i,t-i} + \gamma \mathbf{X}_{i,t-1} + \epsilon_{i,t} \tag{4}$$

[17] The reduced coefficient is a consequence of the significant contemporaneous correlation between IV and *Buying Pressure* ($\rho = 0.12$) and *Selling Pressure* ($\rho = 0.11$). Controlling for *Buying Pressure* and *Selling Pressure* is appropriate if the contemporaneous correlation is driven by high inflows and outflows causing IV, but conservative if the correlation is driven by higher IV causing greater inflows and outflows.

$Inflow_{i,t}$ and $Outflow_{i,t}$ are defined as in Table 3, while $IV_{i,t}$ is computed as the standard deviation of $fund_i$'s residual returns estimated from the Carhart (1997) four-factor model using daily data during $month_t$.[18] All independent variables, are standardized to have mean 0 and variance 1. Specifications 1-3 of Table 5 report the results for lag length n=1 and Specifications 4-6 report the results for lag length n=3. We choose to report the lag length of 1 for ease of interpretation, and lag length of 3 because this is the optimal lag length as determined by the Akaike Information Criterion (AIC).

The results, using either lag length, yield very consistent patterns. In particular, there is modest evidence that past inflows forecast future IV, consistent with buying pressure causing increased IV. However, there is no evidence that past outflows forecast future IV. More importantly, even after controlling for past inflows and outflows, past IV is a highly significant predictor of future inflows and outflows. The economic magnitudes are also sizeable. For example, Specifications 1 and 2 indicate that a one-standard deviation increase in past one-month IV is associated with a 0.43 percentage point increase in inflows and a 0.34 percentage point increase in outflows.

4.2. Are IV-Induced Capital Flows Informed?

Our results suggests that investors like IV when making purchase decisions, but dislike IV when making redemption decisions. The puzzling positive relation between IV and inflows may be a consequence of investors naturally gravitating towards funds with superior expected performance. Consistent with this view, several recent measures of fund skill including industry concentration (Kacperczyk, Sialm, Zheng, 2005), Active Share (Cremers and Petajisto, 2009), and R^2 (Titman and Tiu, 2011; Amihud and Goyenko, 2013) are all correlated with IV.[19]

[18] Here, we estimate IV at a monthly frequency using daily data to prevent a mechanical relation with lagged values of IV.

[19] The positive correlation between fund characteristics related to IV and fund performance runs counter to the equity literature which finds a negative relation between IV and equity returns. The difference may be attributable to the open-ended structure of mutual funds. For example, consider investors who have lottery-like preferences, resulting in increased demand for both equities and funds with high IV. For equities,

The above explanation would be particularly compelling if: 1) IV is a predictor of fund performance and 2) investor flows can forecast future performance.[20] To explore these possibilities, we estimate the following panel regression:

$$Performance_{i,t} = \alpha_{i,t} + \beta_1 IV_{i,t-1} + \beta_2 Inflow_{i,t-1} + \beta_3 Outflow_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + FE + \epsilon_{i,t}. \tag{5}$$

$Performance_{i,t}$ 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 $Inflow_{i,t-1}$, $Outflow_{i,t-1}$, and $IV_{i,t-1}$, defined as the standard deviation of daily returns in $month_{t-1}$.[21] $\mathbf{X}_{i,t-1}$ 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 6 offer little evidence that IV is associated with superior managerial performance. In particular, 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,

the increased demand should result in higher prices and a lower required rate of return. In contrast, for mutual funds the increased demand will lead to increased fund size, but should have no direct effect on fund prices or subsequent returns.

[20]Existing evidence on whether investors can forecast future performance is mixed. Gruber (1996) finds that net flows forecast returns which he attributes to fund investors being able to predict performance (i.e. a "smart-money" effect), however other studies suggest this relation is driven by return chasing coupled with momentum (Sapp and Tiwari, 2004) or persistent price pressure (Lou, 2012). At the other extreme, Frazzini and Lamont (2008) argue that fund flows represent "dumb-money" and show that flows negatively forecast stock and fund returns over longer horizons.

[21]The calculation of IV using one month of daily returns (Daily IV) differs from IV in our baseline regression which uses 12 months of monthly data (Monthly IV). We report results using Daily IV because subsequent specifications decompose IV, Inflows, and Outflows into their expected and unexpected components using the panel vector autoregression in Table 5 which also relies on Daily IV. The results using Monthly IV are qualitatively similar.

both of which are statistically insignificant.[22] 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 0.03% decrease in excess returns. While the point estimates are directionally consistent with flows forecasting fund performance, the estimates are statistically insignificant and economically small.

In Specifications 3 and 4, we decompose *Inflows* and *Outflows* into their expected and unexpected component based on the panel VAR with lag length equal to 3 (i.e., specifications 4 through 6 of Table 5). This decomposition allows us to separately examine the impact of inflows (or outflows) induced by IV (and other controls) versus the impact of inflows (or outflows) that cannot be explained by our set of controls. Similarly, we decompose IV into its expected and unexpected components estimated from the same panel VAR. We find no evidence that either expected or unexpected IV predicts performance. There is weak evidence that unexpected inflows predict excess returns, although controlling for momentum eliminates this return predictability; and there is no evidence that either expected or unexpected outflows predicts returns. Collectively, the evidence in Table 6 is inconsistent with the view that IV-induced flows are a consequence of smart investors gravitating towards funds with superior future performance.

4.3. Is IV A Risk Factor That Matters To Investors?

Another explanation that is consistent with the asymmetric relationship between IV and inflows and outflows is risk. In particular, if investors view funds with low IV as riskier than funds with high IV, then increases in IV may generate inflows (outflows) from more (less) risk-averse investors. To test this possibility, we follow Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016), and infer the risk model investors use by the fund choices

[22]This finding appears inconsistent with Amihud and Goyenko (2013) who find that selectively, measured are (1-R^2), is a significant predictor of fund performance. We confirm that 1-R^2 is also a significant predictor of fund performance in our sample. Thus, differences in our results stem from significant differences in systematic volatility across funds, which weakens the relation between IV and selectivity (see e.g., Li, Rajgopal, and Venkatachalam, 2014).

they make. Specifically, we assume that investor flows chase perceived past alpha, but do not chase returns that stem purely from taking on perceived risk. Thus, if investors chase returns that are driven by exposure to a particular factor, investors are revealing that they view this return as alpha rather than risk.

We begin by constructing an IV factor, $LIVH$ (low IV minus high IV). The construction of the $LIVH$ factor is similar to the approach outlined in Jordan and Riley (2015), except we sort stocks on IV rather than total volatility. Specifically, when constructing the $LIVH$ factor, we only use the types of US equities commonly held by mutual funds: ordinary shares (CRSP share codes 10 and 11) that trade on the NYSE, NASDAQ, or AMEX. After imposing these filters, we sort stocks into deciles based on the standard deviation of a fund'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 a framework similar to 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 time-series regression using return data from months τ = t-1 to t-60:[23]

$$\begin{aligned} R_{i,\tau} - R_{f,\tau} = \alpha_{i,t} + \gamma_{i,t} YDUM_\tau + \beta_{1i,t}(R_{m,\tau} - R_{f,\tau}) + \beta_{2i,t} SMB_\tau \\ + \beta_{3i,t} HML_\tau + \beta_{4i,t} UMD_\tau + \beta_{5i,t} LIVH_\tau + \epsilon_{i,\tau} \quad (6) \end{aligned}$$

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

[23] 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.

$LIVH_\tau$ is the return on the IV factor. The returns on the market, size, book-to-market, and momentum factors are obtained from Ken French's online data library. 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 (τ = 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:

$$\overline{R_{i,t} - R_{f,t}} = (\widehat{\alpha_{i,t}} + \widehat{\gamma_{i,t}}) + \widehat{\beta_{1i,t}}(\overline{R_{m,t} - R_{f,t}}) + \widehat{\beta_{2i,t}}(\overline{SMB_t}) + \widehat{\beta_{3i,t}}(\overline{HML_t}) + \widehat{\beta_{4i,t}}(\overline{UMD_t}) + \widehat{\beta_{5i,t}}(\overline{LIVH_t}) \quad (7)$$

$\overline{R_{i,t} - R_{f,t}}$ 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.

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

$$Flow_{i,t} = \psi_0 + \psi_1(\widehat{\alpha_{i,t}} + \widehat{\gamma_{i,t}}) + \psi_2\left[\widehat{\beta_{1i,t}}(\overline{R_{m,t} - R_{f,t}})\right] + \psi_3\left[\widehat{\beta_{2i,t}}\overline{SMB_t})\right] + \psi_4\left[\widehat{\beta_{3i,t}}\overline{HML_t})\right] + \psi_5\left[\widehat{\beta_{4i,t}}\overline{UMD_t})\right] + \psi_6\left[\widehat{\beta_{5i,t}}\overline{LIVH_t})\right] + \psi_7 SV_{i,t-1} + \psi_8 IV_{i,t-1} + \gamma\mathbf{X}_{i,t-1} + FE + \epsilon_{i,t} \quad (8)$$

As in equation (1), $Flow_{i,t}$, is either *net flows*, *inflows*, or *outflows*, expressed as a percentage of beginning-of-month TNA for each fund i and month t. $SV_{i,t-1}$, $IV_{i,t-1}$, and $\mathbf{X}_{i,t-1}$ are defined as in equation (1). *FE* includes time fixed effects (in all specifications) and fund fixed effects (in Specifications 4 through 6). The parameter of greater interest is ψ_6, which measures how investors respond to returns due to exposure to the *IV* factor.

Panel A of Table 7 reports the results. Not surprisingly, net flows are strongly related to alpha; a one percentage point increase in alpha is associated with a 1.45 percentage point increase in net flows. We also 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 *IV* risk, 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 and outflows are strongly associated with the fund's *IV* (i.e., ψ_8). In other words, investors' tendency to buy (or sell) funds with high *IV* is not driven by simply chasing funds that earned extreme returns due to their exposure to the *IV* factor.

One concern is that funds with high *IV* may have significant differences in risk exposures that are not fully captured by the *LIVH* factor. For example, Fama and French (2016) show that stocks with high *IV* are associated with companies that are less profitable and invest more aggressively compared to low *IV* stocks. Accordingly, they find that the Fama and French (2015) five-factor model, which adds factors formed on firm profitability (*RMW*) and investment (*CMA*) to the Fama and French (1993) three-factor model, explains a significant portion of the *IV* puzzle in stocks. This finding points to the possibility that more risk-averse mutual fund investors may gravitate towards high *IV* funds because such funds have low exposure to the *RMW* and *CMA* risk factors.

To explore this possibility, we repeat equations (6) through (8), but now replace the *UMD* and *LIVH* factors with the *RMW* and *CMA* factors from Ken French's online data library. The results of this analysis, presented in Panel B of Table 6, 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. In addition, investors continue to be more likely to both buy and sell funds with high *IV* even after the inclusion of the additional risk factors. Collectively, the evidence suggests that flows into (out of) high *IV* funds are unlikely to be entirely driven by investors who simply want to reduce (increase) the risk-level of their portfolio.

5. Search Costs and the *IV* Puzzle

The evidence in Tables 3 through 7 appears at odds with many of the existing explanations for the *IV* puzzle in stocks. For example, if the *IV* puzzle is simply driven by microstructure effects, it is unclear why investors gravitate towards *IV* when purchasing mutual funds. Similarly, if the *IV* puzzle is driven purely by investors having lottery-like preferences, the diversified nature of mutual funds makes them relatively unattractive to investors. Further, it is unclear why investors shun high *IV* funds when making redemption decisions. Finally, our finding that investors appear to chase returns traced to *IV* suggests that most investors do not view returns due to exposure to the *IV* factor as compensation for risk. This is not to say the above explanations do not contribute to fund investor behavior; however, it does suggest that other forces are likely at play.

Another line of reasoning that is consistent with the existing evidence is based on search costs and limited attention. When faced with different options, individuals typically do not pay equal attention to each option, but instead spend more time examining the most salient (i.e., attention-grabbing) option. Funds with higher levels of IV are likely to be more salient for at least some investors since high IV funds are more likely to appear in the media (Kaniel, Starks, and Vasudevan, 2007) and 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, 3 months, 5 years, etc.) that may be more attention grabbing to particular investors.

To get a better sense for the relationship between IV and extreme returns, we sort mutual 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 three months or past five years (extreme winners). We choose the three-month and five-year horizons, as this corresponds to the shortest and longest window reported on Yahoo! Finance when screening for mutual funds. 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 (which reflects a 240% increase relative to the unconditional probability of 10%) and 28% of the time at the three-month horizon.

This finding suggests that high IV funds are more likely to catch the attention of investors who tend to sort funds on past returns over very different horizons. While not all investors will trade funds that catch their attention, it seems likely that funds that catch investors' attention are more likely to be traded. Consistent with this view, Barber and Odean (2008) find that investors tend to be net buyers of stocks with larger one-day returns. They argue that attention-based trading is likely to be more prevalent for purchases, since investors tend to only sell a small subset of all stocks - those they already own.

While limited attention and search costs may have a more pronounced impact on purchase decisions, there is still good reason to believe that funds that catch investors' attention will also experience significantly larger capital outflows.[24] First, even for investors holding

[24]We also note that the positive (albeit economically modest) relationship between IV and net flows in Table 3 is consistent with Barber and Odean's (2008) conjecture that the impact of limited attention should be stronger for purchase decisions.

only a few funds, investors generally need an impetus to sell an existing position. Attention-grabbing extreme returns can be the shock that causes investors to reconsider their current positions. Further, conditional on needing to sell a fund, the "rank effect" documented by Hartzmark (2015) suggests that investors are more likely to sell their extreme winning or losing positions. Finally, if a subset of investors tend to purchase funds with high IV, such investors may also be more likely to sell funds with high IV. In other words, high IV funds may attract a specific clientele of investors who tend to make purchase and redemption decisions based on extreme returns or other attention-grabbing events (e.g., advertising). Thus, the findings that high IV funds experience more purchases and redemptions is consistent with limited attention and search costs influencing investor behavior (hereafter: the search-cost hypothesis). We next examine whether the empirical evidence is consistent with additional implications of the search-cost hypothesis.

5.1. IV and Fund Flows – Piecewise Regressions

The search-cost explanation for the asymmetric relationship between IV and flows points to a possible non-linear relationship between IV and flows. For example, moving from the 1^{st} percentile of IV to the 19^{th} percentile of IV is unlikely to have significant effects on the fund's saliency, since the fund is still unlikely to have extreme returns. In contrast, moving from the 80^{th} percentile of IV to the 99^{th} percentile of IV is likely to have a more dramatic effect, since such funds will be increasingly more likely to be extreme winners or losers over a variety of different return horizons. This view is consistent with the Figure 1 results, which show that the relationship between IV and the likelihood of being an extreme winner is highly convex.

To explore the non-linear relationship between IV and flows, we replace $IV_{i,t-1}$ with an IV rank variable. Specifically, each month we calculate a fractional rank ($RANK_{i,t-1}$) ranging from 0 to 1 for each fund based on the fund's IV. The variable *IV Low* is defined as Min(0.2, $RANK_{i,t-1}$), while *IV Mid* is defined as Min(0.6, $RANK_{i,t-1}$ - *IV Low*). Finally, *IV High* is zero for funds outside the top quintile of performers and equal to ($RANK_{i,t-1}$ - .8) for funds in the top quintile. We conduct an analogous adjustment for $SV_{i,t-1}$. We then estimate the following panel regression:

$$\begin{aligned} Flow_{i,t} = \alpha + \beta_1 RetLow_{i,t-1} + \beta_2 RetMid_{i,t-1} + \beta_3 RetHigh_{i,t-1} \\ + \beta_4 SVLow_{i,t-1} + \beta_5 SVMid_{i,t-1} + \beta_6 SVHigh_{i,t-1} \\ + \beta_7 IVLow_{i,t-1} + \beta_8 IVMid_{i,t-1} + \beta_9 IVHigh_{i,t-1} \\ + \gamma \mathbf{X}_{i,t-1} + FE + \epsilon_{i,t} \end{aligned} \quad (9)$$

where all other variables are defined as in equation (1). The coefficients of interest are β_7 - β_9, which measures the sensitivity of flows to IV for different levels of IV.

Table 8 presents the results. Across all specifications, there is very little evidence that IV is related to fund flows for funds in the bottom 20% of IV or for funds in the middle 60% of IV. However, we document a strong relationship between inflows (or outflows) and IV for funds in the top 20% of IV. In particular, Specifications 2 and 3 indicate that a 10 percentile increase in a fund's IV rank (e.g., moving from the 85th percentile to the 95th percentile) is associated with a 1.02 percentage point increase in inflows and a 1.05 percentage point increase in outflows. Our findings suggest that the relationship between inflows and outflows and IV is driven by funds with the most extreme IV. Since such funds are the most likely to have extreme returns, this pattern is consistent with the search-cost explanation. This result is also consistent with the finding in the equity literature that the IV puzzle is largely driven by the extremely poor performance of stocks in the top quintile of IV (Ang et al., 2006).

5.2. IV and Fund Flows – Interactions with Search Costs

If search costs contribute to the strong relationship between IV and fund inflows and outflows, then the relationship between IV and inflows and outflows should be weaker when search costs are less severe. In this section, we empirically test this prediction using several proxies for search costs.

First, we conjecture that search costs are likely to be less severe for larger funds, older funds, funds that engage in greater marketing (Sirri and Tufano, 1998; Huang, Wei and Yan, 2007), or funds with a five-star rating by Morningstar (Del Guercio and Tkac, 2008). Intuitively, a larger fraction of potential investors are already aware of larger funds, older funds, funds that frequently appear in the media, or funds that have a top rating by Morningstar, and thus extreme returns or other attention-grabbing events are likely to have a less significant impact on the visibility of these funds relative to other funds. We also expect that search costs are less severe for incumbent investors, who already own the fund and thus are already aware of the fund's existence.

Finally, we expect search costs to be less severe for institutional funds, which largely reflect defined contribution (DC) plans. In DC plans, a menu of funds is initially selected by plan sponsors. Plan sponsors, due to their greater sophistication and fiduciary responsibilities, are less likely to have search costs influence their decision to add or remove funds. Within the menu of investment options, IV is likely to be less relevant, since plan participants rarely adjust their pension allocations and generally have far fewer investment options to evaluate.[25]

To examine whether the impact of IV on flows is stronger when search costs are more severe, we estimate equation (1) after including the search cost variable and also interacting the search cost variable with every other independent variable in the model. More specifically,

[25] Studies finding that plan participants often select the default investment options or rarely adjust their allocations include: Madrian and Shea, 2001; Choi et al., 2002; and Sialm, Starks, and Zhang, 2015.

we examine the following panel regression:

$$Flow_{i,t} = \alpha + \beta_1 RetLow_{i,t-1} + \beta_2 RetLow_{i,t-1} \times SC_{i,t-1} + \beta_3 RetMid_{i,t-1} + \beta_4 RetMid_{i,t-1} \times SC_{i,t-1} + \beta_5 RetHigh_{i,t-1} + \beta_6 RetHigh_{i,t-1} \times SC_{i,t-1} + \beta_7 SV_{i,t-1} + \beta_8 SV_{i,t-1} \times SC_{i,t-1} + \beta_9 IV_{i,t-1} + \beta_{10} IV_{i,t-1} \times SC_{i,t-1} + \beta_{11} SC_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + \delta(\mathbf{X}_{i,t-1} \times SC_{i,t-1}) + Time_t + \epsilon_{i,t} \quad (10)$$

where SC is a proxy for search costs and all other variables are defined in equation (1). We exclude fund fixed effects given that the search costs variables often exhibit minimal within-fund variation.[26] In the interest of parsimony, we only report the coefficients on IV and $IV \times SC$.

Panel A of Table 9 reports the results using fund size as a proxy for search costs. We create a dummy variable equal to one if the fund is in the top quintile of fund size, based on the fund's prior month TNA. We use a dummy variable largely for ease of interpretation, and to facilitate comparison with other binary search cost variables (e.g., star fund, institutional fund, and closed fund). We find that the impact of IV on inflows is 1.00% for funds in the bottom four size quintiles, compared to 0.11% (i.e., 1.00% - 0.89%) for funds in the top size quintile. This is consistent with IV being particularly useful in reducing search costs among smaller funds, which tend to have lower visibility. We find that the impact of IV on outflows is also significantly weaker among funds in the top size quintile. This is consistent with a clientele effect, where investors who purchase funds that catch their attention due to the fund's high IV (or variables correlated with high IV including extreme past returns) are also more likely to subsequently sell funds with high IV. This result also parallels the equity literature, which finds that the IV puzzle is weaker among stocks in the largest size quintile (Ang et al., 2006).[27]

[26] Of the search cost 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.

[27] Specifically, Ang et al. (2006) find that the IV puzzle averages 1.23% per month for the smallest four size quintiles compared to 0.26% for the largest size quintile.

In Panels B and C, the search cost proxy is a dummy variable equal to one if the fund is in the top quintile of fund age and fund marketing expenditures, respectively. Following Huang, Wei, and Yan (2007), we measure marketing expenses as the 12b-1 fees + 1/7th of the front-end load. In Panel D, the search cost proxy is a dummy variable equal to one if the fund is rated 5-stars by Morningstar. The results from Panels B, C, and D indicate that the impact of IV on fund inflows (or outflows) is significantly weaker for older funds, funds that engage in greater marketing, and star funds.

Panel E of Table 9 presents results where the search cost measure is a dummy variable equal to one if the fund is closed to new investors. Note that flows in closed funds only reflect the investment decisions of incumbent investors who are already aware of the fund. We find that the relationship between IV and inflows is significantly weaker for closed funds. Similarly, the relationship between IV and outflows is significantly weaker for closed funds. This is perhaps surprising, since outflows for both open and closed funds reflect the investment decisions of incumbent investors. However, the composition of existing investors in open versus closed funds is likely different. In particular, open funds with high IV attract many investors who gravitate towards attention-grabbing funds. These same investors appear prone to quickly selling the fund. Thus, as the fund remains closed, the clientele shifts towards investors who are less likely to be influenced by a fund's past IV when making their redemption decisions.

Finally, Panel F of Table 9 examines whether the results differ for retail versus institutional funds. Specifically, we include an institutional fund indicator which equals one if all the share classes of the fund are classified as institutional by CRSP and zero if all the share classes of the fund are classified as retail.[28] 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. Only

[28] In untabulated analysis, we also define a fund as institutional based on its minimum investment size. Defining a fund as institutional if the minimum investment size is greater than or equal to $10,000 (or $100,000) generates very similar results.

funds with 100% institution or 100% retail are included in Panel F of Table 9. The results confirm that the relationship between IV and flows is stronger among retail-oriented funds. In particular, for retail funds, a one standard deviation increase in IV is associated with a 1.09 percentage point increase in inflows and a 1.14 percentage point increase in outflows. The corresponding estimates for institutional funds are 0.09 and 0.26, neither of which is significantly different from zero. Collectively, the results from Table 9 support the notion that the impact of IV on fund flows is stronger when search costs are more severe.

5.3. IV, Google Search, and Fund Flows

Our evidence is consistent with the views that 1) IV results in increased investor attention, 2) increased investor attention results in greater inflows and outflows, and 3) the impact of increased investor attention on inflows and outflows is greater when search costs are more severe. 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).

5.3.1. Google Search Methodology

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.[29] To increase the likelihood that our search reflects demand for information about mutual funds, we limit the search region to the "United States" and the search category to "Business".[30]

Google defines the $NSVI$ for fund j in month t as: $NSVI_{j,t} = \frac{SearchVolume_{j,t}}{Max(SearchVolume_j)} \times 100$, where $Max(SearchVolume_j)$ is the maximum search volume for fund j over the time period

[29]We search for fund tickers, rather than fund names, because investors may search for the same fund using several variations of its name. For example, a Google search for ticker "FGRIX" is associated with the following search results: "Fidelity Growth & Income Portfolio", "Fidelity Growth & Income Fund", "Fidelity Growth & Income", "Fidelity Growth and Income Pt", etc.

[30]Following, Da, Engelberg, and Gao (2011) we also manually review all tickers and flag tickers that likely have an alternative meaning. As all mutual fund tickers are five letters long and must end in "X", we find only three tickers that likely has an alternative meaning: "FEDEX", "ESSEX", and "FELIX". Results are virtually identical if we exclude these tickers.

of the search. By scaling by $Max(SearchVolume_j)$, *NSVI* abstracts from cross-sectional differences in search volume. For example, a large fund with a maximum monthly search volume of 1,000 and a small fund with a maximum monthly search volume of 10 would both report a maximum *NSVI* of 100. More generally, across all months the large funds' *NSVI* would be understated by a factor of 100 (1000/10) relative to the small funds' *NSVI*.

To circumvent this limitation, we estimate a scaling factor that accurately portrays the relative popularity of each fund.[31] To create the scaling factor for fund j relative to fund k ($Scaling_{j,k}$) we first collect the monthly values of $NSVI_j$ and $NSVI_k$ from two independent searches. We then conduct a joint search for funds j and k. When conducting the joint search, the joint NSVI for $fund_j$ is computed by Google as: $JointNSVI_{j,t} = \frac{SearchVolume_{j,t}}{Max[Max(SearchVolume_j),Max(SearchVolume_k)]} \times 100$. We then compute the scaling factor for $fund_j$ relative to $fund_k$ as: $Scaling_{j,k} = \frac{Max(JointNSVI_{j,t})}{Max(JointNSVI_{k,t})}$.[32] For example, if fund j had a maximum *JointNSVI* of 100 and fund k had a maximum *JointNSVI* of 50, we would multiply all monthly values of $NSVI_j$ by 2 [i.e., (100/50)].

To extend the two-fund example above to the universe of funds, we first sort funds based on TNA, and compute a scaling factor for each fund relative to the next largest fund, resulting in a vector of scaling factors. The smallest fund (fund 1), by construction, has a scaling factor of 1; the second smallest fund (fund 2) has a scaling factor of $Scaling_{2,1}$; the third smallest fund (fund 3) has a scaling factor of $Scaling_{2,1} \times Scaling_{3,2}$, etc.[33] More generally, $ScalingFactor_j = \prod_{k=1}^{j-1} Scaling_{k+1,k}$. The vector has the useful property of allowing us to

[31] Many studies that rely on Google search volume (e.g., Da, Engelberg, and Gao, 2011) focus on within firm variation in search volume and thus are unaffected by the normalization procedure. However, *IV* is highly persistent at the fund-level, and thus focusing on within-fund variation results in significantly less powerful tests. Further, the puzzling negative association between *IV* and future returns is a cross-sectional pattern.

[32] We chose the maximum search volume month for each fund to avoid rounding errors. For example, a fund with zero search volume in a given month would have a value of zero which would not reflect the true ratio.

[33] We choose to compute the scaling factor of fund 3 as $Scaling_{2,1} \times Scaling_{3,2}$, rather than $Scaling_{3,1}$, because as the gap between TNA increases, differences in search volume can differ dramatically, resulting in significant rounding errors.

estimate the popularity of $fund_j$ relative to the smallest fund. To reduce the influence of outliers, we winsorize the scaling factor at the 99th percentile.

Our primary measure of interest is *Search* defined as $NSVI_{j,t}$ multiplied by the scaling factor for fund *j*. We compute a fund-level measure of *Search* by summing the *Search* of each ticker (i.e., share class) of the fund. Our final sample includes 164,378 fund-month Search 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.

5.3.2. Google Search Results

We now turn to testing our three conjectures outlined in Section 5.3. 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 Column 1 of Table 10. 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 roughly 66% increase in *Search*. This finding suggests that funds with greater IV garner greater investor attention.

We next examine whether *Search* forecasts greater inflows and outflows. We re-estimate equation (1) after replacing $IV_{i,t-1}$ with $\text{Log}(1 + Search_{i,t-1})$. Columns 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.[34] We also find that *Search* is significantly positively associated with net flows, consistent with investor attention having a larger effect on buying decisions than selling decisions.

We also re-estimate equation 1 after including both $IV_{i,t-1}$ and $\text{Log}(1+Search_{i,t-1})$. This test examines whether IV and *Search* contain independent information about future flows. Examining inflows (Column 6), we find that both IV and *Search* are incrementally useful in forecasting flows and the difference between the two estimates is not statistically significant. This is consistent with both IV and *Search* containing distinct information about investor attention.[35] However, examining outflows (Column 7), we find that IV remains significantly positive, while *Search* is no longer significantly different from zero. As noted earlier, the positive coefficient on IV is consistent with extreme returns making it more likely that an investor will reconsider his position in the fund. In addition, it increases the likelihood that investors subject to the rank effect bias (Hartzmark, 2015) will sell the fund. The insignificant coefficient on *Search* is consistent with the view that existing investors, who are very familiar with the fund, generally do not need to conduct additional research before selling the fund.

Finally, we examine whether the impact of increased investor attention on inflows and outflows is greater when search costs are more severe. Our approach mirrors equation (10)

[34] 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.

[35] For example, an investor who identifies a high IV fund by sorting on past three-month performance on Yahoo Finance, may simply learn more about the fund by searching within Yahoo Finance (i.e., high IV, but no Search). More generally, *Search* is an imperfect proxy for attention since it is limited to Google searches for the fund ticker. On the other hand, a prominent news story about a fund manager may not be caused by extreme returns, but can lead to significant search volume (i.e., high *Search*, but no IV).

except we replace $IV_{i,t-1}$ with $\text{Log}(1 + Search_{i,t-1})$. Table 11 reports the results for the same six measures of search costs analyzed in Table 9.

We generally find that increased investor attention has a larger effect on inflows and outflows when search costs are more severe. For example, Panel A shows the impact of *Search* on both inflows and outflows is significantly weaker for large funds (i.e., funds in the top TNA quintile). More generally, in 11 out of 12 cases, we find that the impact of *Search* on inflows and outflows is greater when search costs are more severe, and the effect is statistically significant (at a 5% level) in 5 of the 12 cases. Collectively, the results from this section provide more direct evidence that IV is associated with increased investor attention, and confirm that increased investor attention is associated with greater capital inflows and capital outflows, particularly among funds with greater search costs.

6. Conclusion

A growing literature finds that assets with high IV earn low returns, which points to the puzzling possibility that investors prefer assets with high IV. We re-examine 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 investors gravitate towards IV when making purchasing decisions, but flee from IV when making redemption decisions. We find no evidence that purchases or redemptions of funds with high IV are associated with superior returns, which suggests that informed trading cannot explain our findings. We also find that flows chase returns that stem from a fund's exposure to IV risk factors, suggesting that the majority of capital does not view IV as a risk factor.

The above evidence suggests that many existing explanations for the IV puzzle, including risk-based explanations (e.g., Chen and Petkova, 2012) or microstructure biases (e.g., Fu 2009) cannot fully explain investors' demand for IV among mutual funds. Instead, we propose that limited attention and search costs can help explain investors' tendency to both buy and sell funds with high IV more frequently. Intuitively, assets with greater IV are more salient and therefore more likely to catch the attention of investors. Thus, high IV assets are more likely to be purchased by attention-based traders (Barber and Odean, 2008). Attention-based traders are also more likely to sell assets with more extreme returns (Hartzmark, 2015), resulting in the asymmetric pattern where investors gravitate towards IV when making purchasing decisions, but flee from IV when making redemption decisions.

We offer several novel pieces of evidence consistent with limited attention and search costs driving investors' asymmetric demand for IV. First the impact of IV on flows is greater among funds where search costs are more severe including smaller funds, younger funds, funds that engage is less marketing, non-star funds, funds that are not closed to new investors, and retail funds. Second, we find that funds with higher IV garner more investor attention, as measured by Google search volume. Finally, funds with greater investor attention (i.e., funds with larger Google search volume) experience greater inflows and outflows, particularly when search costs are more severe.

Although investors' demand for mutual funds may be driven by different considerations than their demand for individual equities, our findings are consistent with many of the findings from the equity literature. For example, we find that the impact of IV on flows is concentrated in the top quintile of IV. This result is compatible with the equity literature, which finds that the IV puzzle is driven by the extremely low returns of equities in the top quintile of IV (Ang et al., 2006). Similarly, the finding that mutual fund investors' demand for IV is concentrated among retail investors, who presumably face greater search costs, is consistent with the finding that the IV puzzle tends to be stronger among stocks with a less sophisticated investor base (Jiang, Xu, and Yao, 2009).

Given these similarities, the search cost explanation explored in this study may also help explain the IV puzzle among equities. In particular, if IV increases the saliency of mutual funds, it is plausible that IV also increases the saliency of equities, which can result in improved investor recognition and liquidity, and ultimately a lower required rate of return (see, e.g., Amihud and Mendelson, 1986; and Kadlec and McConnell, 1994). In short, while we cannot draw broader conclusions about the role of IV and saliency for individual stocks from this study, the consistencies we observe suggest that exploring this possibility may be a promising area for future research.

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 provides additional details on the NSVI data and the construction of the scaling factor. (Source: Google Trends).

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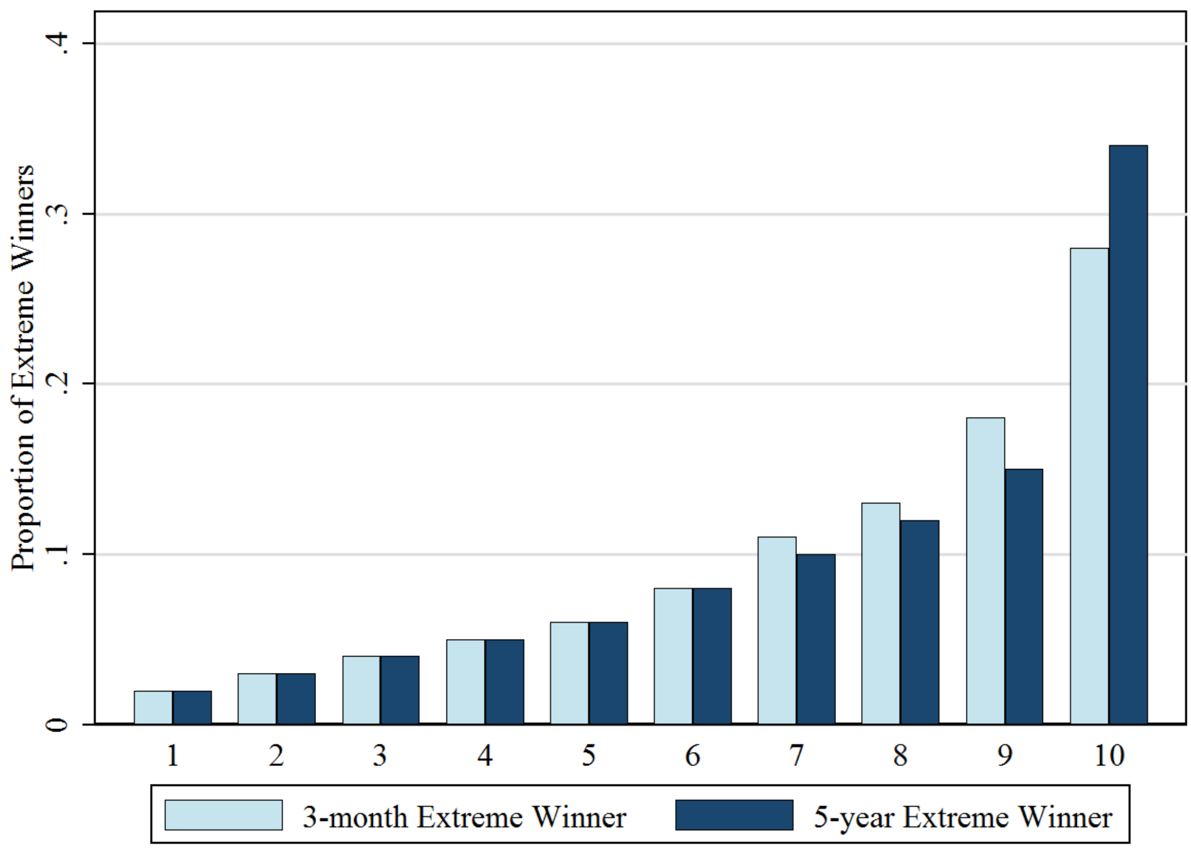

Figure 1
The Proportion of Extreme Winners by Idiosyncratic Volatility Decile
This figures plots the proportion of mutual funds within an idiosyncratic volatility decile that are classified as *extreme winners*. Specifically, each month we sort funds into deciles based on past 12 month idiosyncratic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

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 4.1 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.	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 Net Flow	18.37***			16.77***		
	[8.96]			[8.25]		
Style Inflow		31.06***			28.64***	
		[8.41]			[10.66]	
Style Outflow			8.18***			6.20***
			[6.43]			[7.01]
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 and Fund Flows - Robustness Tests

This table presents the estimates of panel regressions, where the dependent variable is the fund's monthly net flow, inflow, or outflow. Each row represents a unique robustness test based on Models 1-3 of Table 3. We include identical control variables as in Table 3, but only report the coefficient on idiosyncratic volatility for brevity. In brackets we report *t*-statistics. In Rows 1-7 and 9, standard errors are clustered by fund; in Row 8 standard errors are estimated via Fama-MacBeth regressions with a Newey-West (1987) adjustment. ***,**, and * denote statistical significance at the 1%, 5%, and 10% level respectively.

	Net flow	Inflow	Outflow
1. Baseline Specification	0.08***	0.84***	0.84***
	[3.13]	[3.05]	[3.10]
2. Funds in Bottom 1/3 of Performance	0.33***	1.01***	0.76**
	[7.85]	[2.69]	[2.14]
3. Funds in Middle 1/3 of Performance	0.11***	0.85***	0.83***
	[2.29]	[3.89]	[3.93]
4. Funds in Top 1/3 of Performance	-0.13***	0.70***	0.89***
	[-2.82]	[2.86]	[3.54]
5. IV defined as daily residuals from 3-factor model	0.12***	1.01***	0.97***
	[4.32]	[3.18]	[3.08]
6. Replace IV with total volatility	-0.06	0.54***	0.72***
	[-1.59]	[2.71]	[3.67]
7. Exclude December and January	0.08***	0.82***	0.84***
	[3.23]	[2.78]	[2.93]
8. Estimate via Fama-MacBeth	0.00	0.78***	0.76***
	[-0.03]	[10.17]	[9.49]
9. Control for Lagged Buying and Selling Pressure	0.02	0.55**	0.57**
	[1.03]	[2.25]	[2.23]

Table 5
Idiosyncratic Volatility and Fund Flows – Panel VAR

This tables presents the estimates of the following panel vector autoregression (panel VAR).

$$Inflow_{i,t} = \alpha + \sum_{i=1}^{n} \beta Inflow_{i,t-i} + \sum_{i=1}^{n} \lambda Outflow_{i,t-i} + \sum_{i=1}^{n} \delta IV_{i,t-i} + \gamma \mathbf{X}_{i,t-1} + \epsilon_{i,t}$$

$$Outflow_{i,t} = \alpha + \sum_{i=1}^{n} \beta Inflow_{i,t-i} + \sum_{i=1}^{n} \lambda Outflow_{i,t-i} + \sum_{i=1}^{n} \delta IV_{i,t-i} + \gamma \mathbf{X}_{i,t-1} + \epsilon_{i,t}$$

$$IV_{i,t} = \alpha + \sum_{i=1}^{n} \beta Inflow_{i,t-i} + \sum_{i=1}^{n} \lambda Outflow_{i,t-i} + \sum_{i=1}^{n} \delta IV_{i,t-i} + \gamma \mathbf{X}_{i,t-1} + \epsilon_{i,t}$$

Inflow (*Outflow*) is the monthly inflow (outflow) of assets for the fund scaled by the fund's total net assets at the beginning of the month, and IV is computed as the standard deviation of $fund_i$'s residual returns estimated from the Carhart (1997) four-factor model using daily data during $month_t$. $\mathbf{X}$ is the vector of controls from Table 3. Definitions of all control variables are in the Appendix. All independent variables are standardized to have mean 0 and variance 1. Specifications 1 through 3 report the results for lag length n=1 and Specifications 4 through 6 report the results for lag length n=3. 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.

	(1) Inflow	(2) Outflow	(3) IV	(4) Inflow	(5) Outflow	(6) IV
Inflow$_{t-1}$	2.18***	0.46***	0.17**	1.75***	0.24***	0.05
	(22.42)	(8.29)	(2.06)	(20.60)	(5.36)	(0.79)
Inflow$_{t-2}$				0.86***	0.25***	0.07
				(14.68)	(5.95)	(1.08)
Inflow$_{t-3}$				0.63***	0.09***	0.05
				(12.23)	(3.13)	(1.07)
Outflow$_{t-1}$	1.43***	2.85***	0.08	0.45***	1.73***	0.11
	(7.22)	(15.21)	(0.72)	(3.94)	(18.05)	(1.25)
Outflow$_{t-2}$				0.63***	1.17***	-0.02
				(6.99)	(15.13)	(-0.28)
Outflow$_{t-3}$				0.44***	0.92***	-0.16**
				(6.15)	(16.60)	(-2.00)
IV$_{t-1}$	0.43***	0.34***	15.00***	0.15***	0.11***	11.76***
	(5.30)	(4.19)	(48.88)	(3.42)	(3.64)	(36.65)
IV$_{t-2}$				0.13***	0.06***	3.72***
				(3.29)	(2.42)	(10.79)
IV$_{t-3}$				0.09**	0.14***	4.25***
				(2.02)	(4.07)	(33.48)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	194,754	194,754	194,754	182,850	182,850	182,850

Table 6
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*). In specifications 1 and 2 we include $Inflows_{f,t-1}$, $Outflows_{f,t-1}$, and $IV_{f,t-1}$ as defined in Table 5. Specification 3 and 4 decompose $Inflows_{f,t-1}$, $Outflows_{f,t-1}$, and $IV_{f,t-1}$ into their expected and unexpected components based on the panel VAR with lag length equal to 3 (as reported in Specifications 4 through 6 of Table 5). All specifications also control for: *past performance*, Log *age*, Log *size*, Log *family size*, *turnover ratio*, and *expense ratio*. All independent variables 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.

	(1) Excess Return	(2) Carhart alpha	(3) Excess Return	(4) Carhart alpha
Idiosyncratic Vol. (IV)	0.06	0.04		
	[0.71]	[0.37]		
Inflow	0.02	0.01		
	[0.64]	[0.42]		
Outflow	-0.03	-0.03*		
	[-1.24]	[-1.73]		
Expected IV			0.14	0.21
			[0.84]	[1.04]
Unexpected IV			-0.10	-0.23
			[-0.55]	[-0.78]
Expected inflow			0.02	-0.09
			[0.13]	[-1.07]
Unexpected inflow			0.03*	0.01
			[1.73]	[0.55]
Expected outflow			-0.04	0.04
			[-0.36]	[0.62]
Unexpected outflow			-0.02	-0.03
			[-0.80]	[-1.10]
Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Style Fixed Effects	Yes	Yes	Yes	Yes
Observations	198,235	198,235	179,554	179,554
R^2	0.778	0.081	0.798	0.083

Table 7
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.	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.	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 8
Piecewise Idiosyncratic Volatility and Fund Flows

This table presents the results of panel regressions on actively managed, equity funds' flows while allowing investors' sensitivity to risk to be nonlinear. The dependent variable in the model is the fund's monthly net flow, inflow, or outflow. As in Table 3, we allow for non-linearity in performance sensitivity (Sirri and Tufano (1998)), but repeat the analysis for the fund's systematic and idiosyncratic risk. We rank funds each month based on their systematic (SV) and idiosyncratic volatility (IV) over the trailing 12 months. The regression also includes all the control variables reported in Table 3, but the coefficients on these variables are not reported. 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	5.37***	0.66	-4.85***	4.68***	0.25	-4.42***
	[8.42]	[0.60]	[-4.69]	[7.44]	[0.27]	[-5.70]
Ret Mid	2.53***	1.82***	-0.67***	2.13***	1.36***	-0.79***
	[27.38]	[16.31]	[-7.39]	[24.64]	[15.00]	[-12.74]
Ret High	7.73***	10.40***	2.80***	7.14***	8.58***	1.38***
	[15.88]	[14.94]	[5.50]	[16.19]	[16.60]	[4.60]
SV Low	-1.64**	-6.07***	-4.76**	-0.92	-1.75**	-0.73
	[-2.31]	[-2.69]	[-2.19]	[-1.38]	[-2.26]	[-1.55]
SV Mid	-0.30***	-0.44*	-0.05	0.19	0.34**	0.11
	[-2.85]	[-1.82]	[-0.23]	[1.60]	[2.40]	[1.05]
SV High	-1.34***	1.14	2.68**	-0.78*	0.22	1.01*
	[-3.42]	[0.94]	[2.25]	[-1.91]	[0.33]	[1.70]
IV Low	0.71	-0.56	-1.09	-0.88	-0.80	0.00
	[1.22]	[-0.68]	[-1.60]	[-1.54]	[-1.22]	[0.21]
IV Mid	0.23**	0.19	0.19	0.12	0.18	0.09
	[2.18]	[0.87]	[0.98]	[0.99]	[1.44]	[1.11]
IV High	0.42	10.17***	10.49***	0.98*	3.05***	2.22***
	[0.98]	[4.03]	[4.26]	[1.90]	[3.88]	[3.59]
Controls	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%	12.6%	13.9%	13.5%	44.3%	57.5%

Table 9
Idiosyncratic Volatility and Fund Flows - Interactions with Search Costs

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 proxies for search costs (SC). In the interest of brevity, we only report the coefficient on IV and $IV \times$ SC. Panels A, B, and C, measure search costs using fund size, fund age, and a fund's marketing expenditures, defined as 12b-1 fees + 1/7 of the load, respectively. All three search cost variables are dummy variables equal to one if the fund is in the top 20% of the distribution and zero otherwise. In Panels D and E, search costs are measured using a dummy variable equal to one if any share classes within the fund are ranked as 5-star by Morningstar, or if the fund is closed to new investors, respectively. Panel F uses a dummy variable equal to one if all share classes within the fund are institutional funds and zero if all the share classes are retail. Funds that have both retail and institutional funds are omitted from Panel F. 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				
	Idio. Vol.	0.09***	1.00***	1.00***
		[2.92]	[3.11]	[3.18]
	Idio. Vol. × Size	-0.02	-0.89***	-0.91***
		[-0.54]	[-2.95]	[-3.15]
Panel B: Fund Age				
	Idio. Vol.	0.10***	1.10***	1.08***
		[2.94]	[2.95]	[2.97]
	Idio. Vol. × Age	-0.05	-0.89**	-0.87**
		[-1.19]	[-2.49]	[-2.50]
Panel C: Marketing Expense				
	Idio. Vol.	0.06*	0.95***	0.98***
		[1.90]	[2.95]	[3.13]
	Idio. Vol. × Marketing	0.01	-0.75**	-0.81***
		[0.18]	[-2.39]	[-2.72]
Panel D: Star Fund				
	Idio. Vol.	0.08***	0.90***	0.89***
		[3.36]	[3.06]	[3.09]
	Idio. Vol. × Star Fund	-0.16	-0.75**	-0.56**
		[-1.50]	[-2.51]	[-2.11]
Panel E: Closed Fund				
	Idio. Vol.	0.08***	0.85***	0.85***
		[2.96]	[3.01]	[3.08]
	Idio. Vol. × Closed	-0.05	-0.79***	-0.79***
		[-0.57]	[-2.73]	[-2.90]
Panel F: Instituional Dummy				
	Idio. Vol.	0.02	1.09**	1.14***
		[0.52]	[2.53]	[2.73]
	Idio. Vol. × Inst.	-0.07	-1.00**	-0.88**
		[-0.61]	[-2.38]	[-2.21]

Table 10
Idiosyncratic Volatility, Google Search, and Fund Flows

This table we examine the relation between idiosyncratic volatility, Google search, and fund flows. In Model 1, the dependent variable is the Log (1+*Search*), a measure of the fund's monthly search frequency as reported by Google Trends. In Models 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.	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 11
Google Search and Fund Flows - Interactions with Search Costs

This table reports estimates of panel regressions where the dependent variable is the fund's monthly net flow, inflow, and outflow, respectively. The regressions are identical to Table 8, with the exception that we substitute Google Search for idiosyncratic volatility. Panels A, B, and C, measure search costs using fund size, fund age, and a fund's marketing expenditures, defined as 12b-1 fees + 1/7 of the load, respectively. All three search cost variables are dummy variables equal to one if the fund is in the top 20% of the distribution and zero otherwise. In Panels D and E, search costs are measured using a dummy variable equal to one if any share classes within the fund are ranked as 5-star by Morningstar, or if the fund is closed to new investors, respectively. Panel F uses a dummy variable equal to one if all share classes within the fund are institutional funds and zero if all the share classes are retail. Funds that have both retail and institutional funds are omitted from Panel F. 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 136,527 observations. In Panel F, each model has 61,121 observations.

		Net Flow	Inflow	Outflow
Panel A: Fund Size				
	Log (1+Search)	0.20***	0.52***	0.21***
		[3.07]	[6.78]	[3.28]
	Log (1+Search) × Size	-0.13*	-0.45***	-0.14**
		[-1.91]	[-5.31]	[-2.08]
Panel B: Fund Age				
	Log (1+Search)	0.24***	0.44***	0.20***
		[6.02]	[5.60]	[3.02]
	Log (1+Search) × Age	-0.14**	-0.25***	-0.10
		[-2.32]	[-2.40]	[-1.17]
Panel C: Marketing Expense				
	Log (1+Search)	0.18***	0.41***	0.22***
		[5.35]	[5.59]	[3.60]
	Log (1+Search) × Marketing	0.01	-0.14	-0.15*
		[0.15]	[-1.42]	[-1.90]
Panel D: Star Fund				
	Log (1+Search)	0.10***	0.32***	0.22***
		[3.51]	[4.9]	[3.69]
	Log (1+Search) × Star Fund	-0.04	-0.10	-0.06
		[-0.44]	[-0.96]	[-0.85]
Panel E: Closed Fund				
	Log (1+Search)	0.19***	0.41***	0.22***
		[5.63]	[6.07]	[3.87]
	Log (1+Search) × Closed	-0.05	-0.38***	-0.32***
		[-0.72]	[-4.29]	[-3.67]
Panel F: Institutional Dummy				
	Log (1+Search)	0.45**	0.62***	0.16
		[2.19]	[3.14]	[1.14]
	Log (1+Search) × Inst.	-0.28	-0.30	0.01
		[-1.30]	[-1.29]	[0.06]