Beyond returns: The impact of price path convexity on mutual fund flows

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Abstract

In this paper, we investigate how mutual fund investors make capital allocation decisions using a simple performance signal derived from mutual fund's net asset value price path. Using convexity as a measure of the price path character, we show that mutual fund flows respond positively to price path convexity. Specifically, a one-standard-deviation increase in the convexity, on average, leads to a 0.30% increase in mutual fund flows. The positive flow-convexity relationship is robust with alternative price path convexity measures and does not reflect the convex flow-performance relationship documented in previous studies. In addition, we find that investors respond more conservatively when the price path is volatile, and when the uncertainty in the market is high. Moreover, the flow-convexity relation is driven by investors chasing fund performance, but not extrapolating investors chasing recent winning stocks held by mutual funds. An analysis on a passive index fund sample reveals that the flow-convexity relation captures simplistic performance chasing rather than sophisticated learning. Our results support the view that mutual fund investors rely on simple performance signals in their capital allocation decisions.

EFM Classifications: 370; 530

JEL Classifications: G11; G23; D14

Key Words: Mutual funds; Fund flows; Price path; Convexity

1. Introduction

Previous studies generally assume that mutual fund investors are sophisticated and/or Bayesian agents who employ advanced performance evaluation models to assess returns, update their beliefs about managerial skill, and allocate funds accordingly (e.g. Berk and Green, 2004; Berk and van Binsbergen, 2016; Barber, Huang, and Odean, 2016; Franzoni and Schmalz, 2017). On the other hand, recent studies show that mutual fund investors rarely engage in sophisticated learning either because they are of limited financial sophistication (Ben-David et al., 2022) or they do not gain much from such learning (Schwarz and Sun, 2023). In particular, Ben-David et al. (2022) find that mutual fund investors rely exclusively on simple and easily obtainable performance indicators, including past returns[1] and Morningstar ratings, to learn managerial skill and make capital allocation decisions. In this paper, we support the view in Ben-David et al. (2022) that mutual fund investors are simple decision makers. However, we argue that price path, defined as the historical movement of a mutual fund's net asset value (NAV), is also a piece of simple and easily obtainable information available to investors and thus affects their capital allocation decisions.

The history of a mutual fund's NAV, i.e. price path, is available on the fund management company's website and any platforms where the fund is sold (e.g. broker's website) and marketed (e.g. third-party professional information vendor), typically right after the information on historical returns. It embeds information that is not reflected in past returns and Morningstar ratings. Past returns reflect how a fund's NAV has changed over a given period of time by comparing the closing NAV to the beginning NAV of the period. And Morningstar rating is a return-based ranking system.

[1] Throughout this paper, we refer past returns to past unadjusted returns unless otherwise specified.

However, neither of them captures how the NAV has evolved during the period[2], which is likely material in investors' decision making by highlighting specific asset characteristics (Nolte and Schneider, 2018) and influencing investors' risk perception and return beliefs (Borsboom and Zeisberger, 2020). For example, by examining how investors react to different stock price paths with equal returns over a given period, Grosshans and Zeisberger (2018) find that investors prefer the stock first falling in value over the stock first rising in value.

Quantitatively measuring price path is challenging, since its shape can be of any kind and vary significant across different funds and time periods. In this paper, we focus on an easily perceivable, while important, aspect of price path by adopting the price path convexity measure from Gulen and Woeppel (2022), where it is originally used to measure extrapolative expectations of stock returns. For a mutual fund, its price path convexity is measured over a given period of time (i.e. five years) as the average of the closing NAV and the beginning NAV of the period, minus the average of all monthly NAVs, and divided by the average monthly NAV of the period. A positive price path convexity suggests that the fund has experienced return acceleration (i.e. low returns followed by high returns) or return reversal (i.e. negative returns followed by positive returns). In contrast, a negative price path convexity suggests that the fund has experienced return slowdown (i.e. high returns followed by low returns) or return reversal (i.e. positive returns followed by negative returns).

Previous studies examining flow-performance (or rating) relation in mutual funds naturally focus on how performance difference on the cross section affects mutual fund flows. They show that mutual funds with better past returns or higher ratings

[2] Arguably, nor is this information reflected by any sophisticated performance evaluation measures like risk-adjusted returns.

compared to others receive more flows[3]. Price path convexity captures an important dimension of performance signals that extant literature generally overlooked --- time-series relative performance, i.e. how a fund's recent return is compared to its distant return. This dimension is likely a determinant of fund flows because investors chase trend (Bailey, Kumar, and Ng, 2011) and care how asset returns are achieved (Grosshans and Zeisberger, 2018).

Our empirical analysis uses an active mutual fund sample from 1980 to 2022 from the Center for Research in Security Prices (CRSP) Survivors Bias-Free Mutual Fund Database. We employ a fixed-effect regression model to identify how mutual fund flows respond to price path convexity after controlling for a set of variables that may affect fund flows. We document an economically and statistically significant positive impact of price path convexity on mutual fund flows. Specifically, a one-standard deviation increases in the convexity, on average, leads to a 0.30% increase in mutual fund flows.

We conduct a series of robustness tests to further confirm the documented flow-convexity relation. First, the relation is robust when we add Morningstar rating as an additional control. Second, we re-estimate the convexity over three- and ten-year estimation windows (the baseline regression uses a five-year window). The results show that the impact of convexity on mutual fund flows is still significant when the convexity is measured in both alternative windows. Third, we develop alternative measures of convexity that may capture different shapes of price path which might not well captured by the original one in Gulen and Woeppel (2022). The results show that

[3] For example, see Chevalier and Ellison (1997), Sirri and Tufano (1998), Bergstresser and Poterba (2002), for flow-performance relation, and Del Guercio and Tkac (2008), Reuter and Zitzewitz (2021) for flow-rating relation, among others.

the flow-convexity relationship remains statistically and economically significant. Finally, we employ the market share-adjusted measure from Spiegel and Zhang (2013) as an alternative way to measure fund flows and show that the flow-convexity relation differs from the convex flow-performance relation found in previous studies (e.g. Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Fant and O'Neal, 2000; Huang, Wei, and Yan, 2007).

We further examine the underlying mechanism of investors' use of price path convexity. First, the extent to which investors rely on price path convexity, as a piece of performance signal, is likely to be affected by fund-level and market-level uncertainties. At fund level, volatile past returns make investors less relying on information embedded in past performance (Huang, Wei, and Yan, 2022). At market level, market-wide downside shocks divert investors' attention from the performance of specific assets to aggregate shocks (Peng and Xiong, 2006; Kacperczyk, van Nieuwerburgh, and Veldkamp, 2016). Consistent with this view, we find that the flow-convexity relation is more pronounced when volatility of past returns is low, but weaker when volatility of past returns or market-level volatility is high.

Second, investors' response to price path convexity may be explained by two channels. One is investors extrapolating past returns to select stocks (Da, Huang, and Jin, 2021). Investors who wish to enjoy the low-cost diversification benefits may invest in mutual funds which hold stocks with high convexity instead of directly purchasing those stocks. The other is investors react to fund performance itself, where the performance is not due to mutual funds' stock selection but portfolio turnover. We construct variables reflecting these channels and find that the flow-convexity relation is primarily driven by fund performance itself, but has little relation to extrapolating investors chasing recent stock winners.

Lastly, we follow Ben-David et al. (2022) and use a passive index fund sample to infer whether the flow-convexity relation represents investor learning about managerial skill or simplistic performance chasing. Ben-David et al. (2022) argue that performance chasing takes place regardless of whether funds are actively or passively managed, while learning is less or not relevant in passively managed funds. Similar to their findings, we document a positive and statistically significant impact of price path convexity on flows to passive index funds. Therefore, the flow-convexity relation suggests that mutual fund investors are pure performance chasers rather than sophisticated learners.

This paper contributes to the literature in the following dimensions. First, it contributes to the longstanding literature on the determinants of mutual fund flows. Prior studies in this strand of literature have identified many determinants of mutual fund flows such as past performance (e.g. Chevalier and Ellison, 1997; Sirri and Tufano, 1998), cosmetic effects (Cooper, Gulen, and Rau, 2005), factor exposures (Barber et al., 2016), fund ratings (Del Guercio and Tkac, 2008; Reuter and Zitzewitz, 2021; Ben-David et al., 2022), macroeconomic conditions (Jank, 2012; Chen and Qin, 2017), tax considerations (Ivković and Weisbenner, 2009), investor risk preference (Wang and Young, 2020). Our paper adds to this strand of literature by demonstrating that price path convexity, which measures the time-series relative performance of mutual funds, also determines mutual fund flows.

Second, our paper contributes to the debate on investor learning in the asset management industry. Some studies in this field suggest that mutual fund investors are sophisticated agents who use advanced methods such as Bayesian updating and various asset pricing models like the capital assets pricing model (CAPM) to learn managerial skill from fund past performance (e.g. Berk and Green, 2004; Berk and van Binsbergen, 2016; Barber et al., 2016; Huang et al., 2022; Schwarz and Sun, 2023). In contrast, other studies show that mutual fund investors, which primarily consist of households, are naïve investors with limited financial literacy and rely on simple and readily available performance signals, such as past returns and fund ratings, to infer managerial skill (Guerciao and Tkac 2008; Ben-Rephael, Kandel, and Wohl, 2012; Greenwood and Shleifer, 2014; Reuter and Zitzewitz, 2021; Ben-David et al., 2022). Our study finds that mutual fund investors allocate capital based on past price path and thus supports the latter view that mutual fund investors rely on simply and readily available signals to make investment decisions.

Third, this paper contributes to the literature on how price path as graphical representation of asset performance affects investors' investment decision. Extant literature in this strand generally uses survey experiments and shows that price paths of stocks play an important role in forming investors' beliefs about future returns and risk (e.g. Mussweiler and Schneller, 2003; Raghubir and Das, 2010; Grosshans and Zeisberger, 2018; Nolte and Schneider, 2018; Borsboom and Zeisberger, 2020). Our study complements this strand of literature with a large empirical dataset of mutual funds and shows that price paths of mutual funds also significantly affect investors' capital allocation in the mutual fund industry. To this end, our paper also provides implications for practitioners and regulators in mutual funds on understanding the investment behaviour of mutual fund investors.

The rest of the paper is organized as follows. Section 2 discusses the measurement of price path convexity, and describes the data and main variables. Section 3 presents the empirical results. Section 5 concludes.

2. Methodology and data

2.1 Price path convexity and its relation to mutual fund flows

Theories regarding capital allocation among mutual funds typically assume that mutual fund investors are rational agents and possess a significant degree of financial literacy to engage in sophisticated learning in mutual fund investment skill. For example, mutual fund investors in Berk and Green (2004) learn about managerial skill from alpha and allocate capital to funds with positive alpha funds. In Pástor and Stambaugh (2012), mutual fund investors are aware of the presence of decreasing returns to scale in active mutual funds and incorporate it into their learning about skill.

However, given that the majority of mutual fund investors are households[4], empirical evidence provides a different clue. According the review of literature by Lusardi and Mitchell (2014), most households are not financially educated and show little understanding about basic investment concepts like compounding, risk, diversification, and inflation. In addition, in a survey of individual investors, Choi and Robertson (2020) show that retail investors learn skill from mutual fund past returns and do not believe the well-documented decreasing returns to scale in the active fund management industry[5]. Moreover, a bunch of studies have documented the simplistic investment decision-making by mutual fund investors, including that their decisions are likely affected by sentiment (Ben-Rephael et al., 2012; Greenwood and Shleifer, 2014) and sales channel (Bergstresser, Chalmers, and Tufano, 2008), that they are naïve past

[4] According to information from the 2014 Investment Company Institute (ICI) Fact Book summarized in Ben-David et al. (2022), over 90% of equity mutual fund shares were held by households between 2000 and 2013. According to the ICI Research Perspective on the Ownership of Mutual Funds and Shareholder Sentiment 2022 (available at https://www.ici.org/system/files/2022-10/per28-09.pdf), about 79% of the assets of all mutual funds were held by households.

[5] For example, see Chen et al. (2004), Yan (2008), Zhu (2018), Reuter and Zitzewitz (2021), Barras, Gagliardini, and Scaillet (2022), Ling, Satchell, and Yao (2023) for evidence on the decreasing returns to scale in actively managed funds at both aggregate and fund levels.

performance chasers (Chevalier and Ellison, 1997, Ben-David et al., 2022), that mutual fund investors rely heavily on fund ratings (Del Guercia and Tkac, 2008; Evans and Sun, 2021; Reuter and Zitzewitz, 2021; Ben-David et al., 2022), and that they respond to advertisements on media (Jain and Wu, 2000; Reuter and Zitzewitz, 2006). Consistent with the above empirical evidence, Ben-David et al. (2022) provide novel evidence that mutual fund investors make capital allocation decisions based on simple signals like past returns and fund ratings instead of advanced performance measures including the simple capital asset pricing model (CAPM) alpha.

In this paper, we unite with Ben-David et al. (2022) in that mutual fund investors infer fund skill through simple and easily obtainable performance signals. Apart from past returns and fund ratings, such performance signals also include the path of mutual fund's NAV. This piece of information is usually available on the fund management company's website, as well as any platforms where the fund is sold (e.g. broker's website) and marketed (e.g. third-party professional information vendor), typically right after the information on historical returns.

More importantly, price path embeds information that is not reflected in past returns and fund ratings. Past returns reflect how a fund's NAV has changed over a given period of time by comparing the closing NAV to the beginning NAV of the period. However, it does not show how the NAV has evolved during the period. To illustrate this, we draw hypothetical price paths for two mutual funds in Figure 1. Panel A shows that the two funds have the same return, zero, but both experience return reversals over the period from time 0 to time T. Fund X's NAV increases in the first half of the period and then decreases in the second half of the period. On the other hand, Fund Y's NAV decreases in the first-half of the period but then increases in the second half of the period. Panel B shows that the two funds have a same positive return over the period, but Fund

X's return slows down in the second half of the period while Fund Y's return accelerates. In either case shown in Figure 1, returns do not differentiate between Fund X and Fund Y, but flows to the two funds are likely different because the information embedded in their price paths are different.

[Insert Figure 1 about here]

In reality, price paths are much more complex than the hypothetical price paths in Figure 1. Their shape can be of any kind and vary significantly across different funds and time periods. Thus, it is challenging to quantitatively measure price paths with a single measure. In this paper, we focus on an easily perceivable, while important aspect of price path using convexity in the same spirit as Gulen and Woeppel (2022). In each month, we retrospectively trace the NAV over a 5-year period. The initial NAV is denoted as P_0, and the ending NAV is labelled as P_5. Subsequently, we calculate the average of all month-end NAVs between these two time points, defined as P_{avg}. In each of the five-year periods, we require a minimum of three years of observations for a fund to be included in our sample. Then, the price path convexity is given by Eq. (1) as follows:

$$Convexity^{5\ years} = \frac{(P_0+P_5)/2-P_{avg}}{P_{avg}} \quad (1)$$

A positive price path convexity suggests that the fund has experienced return acceleration (i.e. low returns followed by high returns) or return reversal (i.e. negative returns followed by positive returns). In contrast, a negative price path convexity suggests that the fund has experienced return slowdown (i.e. high returns followed by low returns) or return reversal (i.e. positive returns followed by negative returns). Thus, price path convexity measures how a fund's recent performance is relative to its distant performance in the five-year period. With this regard, it captures the time-series relative performance, an important dimension of performance signals that previous studies overlooked. This dimension is important in determining mutual fund flows because investors are trend chasing (Bailey, Kumar, and Ng, 2011) and care how asset returns are achieved (Grosshans and Zeisberger, 2018).

2.2 Fund flows

Our main dependent variable that measures how investors allocate capital among mutual funds is fund flows. We follow the literature to calculate the flow to fund *i* in month *t*, denoted by $Flow_{i,t}$, as follows:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + r_{i,t})}{TNA_{i,t-1}} \qquad (2)$$

In Eq. 2, $TNA_{i,t}$ is total net assets (TNA) of fund *i* at the end of month *t*, and $r_{i,t}$ is the net return of fund *i* in month *t*. We restrict our analysis to funds month t flows of more than −90% and less than 1,000%.

2.3 Sample description

We obtain fund returns, expenses, total net assets (TNA), net asset value (NAV), investment objectives, and other fund characteristics from the Center for Research in Security Prices (CRSP) Survivor Bias-Free Mutual Fund Database. Most funds have multiple share classes, which primarily differ in the fee structure and the target clientele. We combine these classes into a single fund. We calculate the TNA of each fund as the sum of the TNAs of its share classes and calculate fund age as the age of its oldest share class. For other fund characteristics, we used a TNA-weighted average across the share classes.

To obtain information on fund holdings, we link the CRSP database to the

Thomson Financial Mutual Fund Holdings using MFLINKS files from the Wharton Research Data Services (WRDS). The holdings database contains stock identifiers, allowing us to link the positions of each fund to CRSP equity files to obtain the market capitalization of each stock on the reported portfolio date.

Our initial sample consists of all mutual funds in the CRSP mutual fund database covering the period between 1980 and 2022. We focus our analysis on domestic equity mutual funds, as they provided the most comprehensive and reliable performance data on a monthly basis. Following Doshi, Elkmahi, and Simutin (2015), we include funds with AGG, GMC, GRI, GRO, ING, and SCG Strategic Insight codes, EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE Lipper codes, and G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG Wiesenberger codes. We screen styles and fund names to exclude international, balanced, sector, bond, money market, and index funds. We also remove funds with flipped styles, accounting for only a small fraction. As a result, our final sample consists of 356,248 fund-month observations for 2711 funds over the period from 1980 to 2022[6].

We also extract Morningstar fund ratings from the Morningstar database. For these funds, we extract their historical ratings spanning from 1980 to 2022, labelled as "Morningstar Overall rating". However, it's noteworthy that rating data only commences from 1985 onwards, and the coverage of funds with available ratings progressively expands year by year. Overall, the rating data covers 66% of the unique funds and over 62% of the samples.

[6] Our empirical analysis actually starts from 1985 because the price path convexity requires a five-year measurement period.

We construct a sample of index funds using the same data source and spanning the same time period as our active fund sample. We follow Dannhauser and Pontiff (2019) and Ben-David et al. (2022) to identify passive index funds in the CRSP Mutual Fund database. Fund-level variables are constructed in the same way as in the sample of active funds. We ensure that the funds extracted do not overlap with our active fund sample. A fund is identified as an index mutual fund if at any point in fund history it is flagged by the (1) name search[7], or (2) a CRSP index fund flag equal to D or B, and (3) is not flagged as an ETF. We search each fund name to eliminate leveraged and inverse funds and delete enhanced index products[8].

2.4 Summary statistics

Table 1 provides summary statistics of the variables used in our study. On average, mutual funds in our sample have net flows equivalent to -0.2% to their TNA, with a standard deviation of 4.9%. The average and median TNA of mutual funds in the sample are about $1103 million and $305.3 million, respectively. The size of mutual funds in our sample is slightly larger than that in other studies such as Doshi et al. (2015), Franzoni and Schmalz (2017), and Huang et al. (2022). This is because the estimation of the price path convexity over a five-year window implicitly rules out funds that have survived for less than five years. Nonetheless, this bias should have ignorable impact on assessing how convexity affects mutual fund flows. Other characteristics of our sample are consistent with those in recent studies related to mutual fund flows.

[7] Index funds are flagged if the CRSP fund name contains the following strings: SP, DOW, Dow, DJ or if the lowercase version of the CRSP fund name contains: index, idx, indx, ind_ (_indicates space), composite, russell, s&p, s and p, s & p, msci, Bloomberg, kbw, nasdaq,nyse, stoxx, ftse, wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, 3000, or 5000.

[8] Inverse and leveraged funds are identified if the lowercase version of their name contains the following strings: plus, enhanced, inverse, 2x, 3x, ultra, 1.5x, 2.5x.

[Insert Table 1 about here]

3. Empirical results

3.1 What information does price path convexity capture?

We begin our empirical results by showing that price path convexity captures an important piece of information that previous studies generally ignored, i.e. the time-series relative performance of a fund. Extant flow-performance literature generally focuses on the cross section (e.g. Chevalier and Ellison, 1997, Sirri and Tufano, 1998, Bergstresser and Poterba, 2002, Del Guercio and Tkac, 2008, and Reuter and Zitzewitz, 2021). In other words, they find that funds with better performance receive higher inflows than funds with poorer performance.

We use a 5x5 double sorting strategy to show that the time-series relative performance complements the cross-sectional fund performance in explaining the difference in mutual fund flows. We first sort our sample funds into five groups based on their return over the past year. Then, within each return quintile, we sort the funds into five groups based on their convexity. We report the average fund flow for each of the 25 return-convexity groups in Table 2. Consistent with previous flow-performance studies, the results in Table 2 show that high-return fund quintiles have more fund flows than low-return fund quintiles. The fund flow of the highest return quintile is at least 2.01% higher than that of the corresponding lowest return quintile. However, there is still non-neglectable difference in fund flows within each return quintile. For example, for the highest 1-year return quintile, the average fund flow of funds with the top 20% convexity (the highest convexity quintile) is 2.55%, compared to an average fund flow of 0.78% of funds with the bottom 20% convexity (the lowest convexity quintile). The difference of 1.57% in flows between these groups is both statistically and economically significant. Similar results are observed for other return quintiles[9].

[Insert Table 2 about here]

Then, we conduct a regression analysis to show that price path convexity captures the time-series relative performance of a fund. Specifically, for each convexity estimated over a five-year window, we calculate the return over periods of [-60, -48], [-48. -36], [-36, -24], [-24, -12], and [-12, 0], where time 0 refers to the month at which the convexity is estimated. Then, we regress convexity on these annual returns with fund and time fixed effects included. Table 3 report the regression results. In the first two columns, where we regress convexity on the most two recent annual returns separately, the coefficients are positive and statistically significant. The results show that better recent returns lead to a higher convexity. In the third column, the coefficient on the annual return over [-36, -24] is statistically insignificant. In the fourth and fifth columns, where we regress convexity on the most two distant annual returns separately, the coefficients are negative and statistically significant. The results show that better distant returns lead to a lower convexity. In column 6, we regress convexity on the past annual returns collectively. The results confirm that better recent returns lead to a higher convexity while better distant returns lead to a lower convexity.

[Insert Table 3 about here]

In summary, the results in this subsection show that price path convexity captures a time-series relative performance, that is, how a fund has performed recently relative to its distant performance. This information well complements the cross-sectional fund performance in explaining the cross-sectional variation in mutual fund

[9] In untabulated results, we also conduct a 10x10 double sorting on 1-year return and convexity. The results are consistent with the 5x5 double sorting.

flows.

3.2 The impact of price path convexity on mutual fund flows

In this subsection, we formally test the impact of price path convexity on mutual fund flows. To capture the impact of convexity on fund flows, we adopt the following fixed-effects regression model as our baseline specification:

$$Flow_{i,t} = \alpha + \beta_1 Convexity_{i,t-1} + \sum_{j=2}^{k} Controls_{j,i,t-1} + w_i + \mu_{ym} + \varepsilon_{i,t} \qquad (3)$$

In model (3), $Flow_{i,t}$ is the net capital flow to the i-th fund at time t estimated using model (2). $Convexity_{i,t-1}$ is the convexity measure estimate for the i-th fund at time t-1 using model (1). $Controls_{j,i,t-1}$ are a series of control variables that may affect mutual fund flows. The control variables include fund flow in the past month (*Past_Flow*) fund past returns over the last month (*Ret_1m*), last three months (*Ret_3m*), last six months (*Ret_6m*), last one year (*Ret_12m*), last three years (*Ret_36m*), and last five years (*Ret_60m*), and fund characteristics including fund size (*Size*), fund age (*Age*), turnover ratio (*Turnover*), expense ratio (*Exp_ratio*), and management fee (*Fee*), and distribution characteristics of fund returns including the realized volatility of fund returns (*VOL*), the skewness of fund returns (*Skew*), the highest value of fund returns (*Max*), and the idiosyncratic risk measured by the Carhart (1997)'s four-factor model (*IVOL*), as well as the factor loadings on the market risk premium (*MKT_Loading*), the value premium (*HML_Loading*), the size premium (*SMB_Loading*), and the momentum (*MOM_Loading*) of the fund's portfolio based the Fama-French-Carhart four-factor model (Fama and French, 1993; Carhart, 1997). Furthermore, we control for fund fixed effect (w_i) and year-month fixed effect (μ_{ym}). We cluster standard errors at both fund level and time level to address the potential concern of within-fund correlations of the regression residuals. The average impact of convexity on fund flows is captured by β_1. Table 4 reports the baseline regression results.

[Insert Table 4 about here]

In Table 4, column 1 reports the regression results without any controls and fixed effects. The results in the column show that funds with higher convexity attract more net capital flows than funds with lower convexity. In column 2 and column 3, we add the fixed effects and the control variables, respectively. The results in both columns support the positive impact of convexity on fund flows. Column 4 reports the results of the baseline regression model with the full set of control variables and fixed effects. The results show that a one-standard-deviation increase in the convexity is associated with a 0.30% increase in the fund flow. The results are robust when we use Newey and West adjusted t-statistic with three lags and when we use weighted least squares estimator. The coefficients on other control variables are generally consistent with earlier studies on mutual fund flows. For example, fund flows respond positively to past returns as a result of the performance chasing by investors (e.g. Sirri and Tufano, 1998; Jain and Wu, 2000). In addition, fund size, age, and expense ratio have significantly negative impact on fund flows (Huang, Wei, and Yan, 2022). Furthermore, flows to mutual funds are smaller if the fund has greater exposure to market risk and weaker exposure to the momentum factor. Lastly, the adjusted R^2, 15.8%, of the baseline regression is comparable to other studies in this field (e.g. Ben-David et al., 2022). In column 6, we include Morningstar fund ratings (*Rating*) as an additional control variable[10]. The coefficient on convexity is still statistically significant at 1% and positive.

[10] We do not include Morningstar rating as a control in our main empirical specification because doing so would shrink our sample size by over 30%. Instead, we include it in separate regressions where necessary throughout this paper.

To summarize, our baseline results suggest an economically meaningful positive impact of convexity on mutual fund flows after controlling for a set of past returns, fund portfolio characteristics, fund characteristics, and return distribution characteristics. Consistent with Grosshans and Zeisberger (2018), the results imply that mutual fund investors not only chase returns, but also pay attention to how the returns are achieved, i.e. the path of fund NAVs. A fund with better recent performance would attract more cash flows than a fund with better early performance, even if both funds have the same performance over the entire evaluation period. This finding sheds lights on the importance of the time-series relative performance in determining mutual fund flows. For a mutual fund that wishes to attract more flows, it is not only important to beat its peers by delivering top-tier returns (Chevalier and Ellison, 1997, Sirri and Tufano, 1998, Bergstresser and Poterba, 2002) and ratings (Del Guercio and Tkac, 2008, and Reuter and Zitzewitz, 2021), but also important to beat itself by delivering better results than in the past.

3.3 Alternative convexity measures

In this subsection, we conduct a series robustness tests by repeating our baseline regression with alternative measures of the convexity in the price path. The purpose of these tests is to confirm that the documented positive impact of convexity on fund flows is not affected by how the price path is measured. The alternative measures consider both the horizon on which the convexity is measured and the reference point at which the convexity is measured. Table 5 reports the results.

[Insert Table 5 about here]

In Table 5, the first two columns investigate the robustness of the impact of convexity on fund flows when the convexity measure (Eq. 1) is estimated over past three years and past ten years, respectively[11]. In either case, the coefficient on the convexity is still significantly positive, confirming that the choice of estimation window does not affect our baseline findings.

In the next three columns, we develop three alternative measures of convexity to account for shapes of price path that may not be fully captured by our primary convexity measure. In column 3, the alternative convexity measure (*AC1*), denoted by Eq. (4), uses $P_{2.5}$, the fund's NAV at the middle point of time in the five-year window, instead of P_{avg}. In column 4, the alternative convexity measure (*AC2*), denoted by Eq. (5), estimates the convexity as the difference in returns between the second half and the first half of the five-year period. This measure is analogue to the measures of acceleration in financial values use by other studies[12]. In column 5, the alternative convexity measure (*AC3*), denoted by Eq. (6), takes the average convexity of the convexities measured in each subperiod of two years within the five-year estimation window. In column 6, we construct an orthogonal version of the convexity variable (*Convexity RES*) by taking the residual from the cross-sectional regression of the price-path convexity against Morningstar rating. Despite the magnitudes, the estimated coefficients on the alternative measures in the last four columns are still significantly positive, supporting a positive impact of convexity on mutual fund flows.

$$AC(1) = \frac{P_0+P_5-2\times P_{2.5}}{2\times P_{2.5}} = \frac{\frac{P_5-P_{2.5}}{P_{2.5}} - \frac{P_{2.5}-P_0}{P_{2.5}}}{2} \qquad \text{Eq. (4)}$$

$$AC(2) = \frac{P_5-P_{2.5}}{P_{2.5}} - \frac{P_{2.5}-P_0}{P_0} = \triangle\, Ret \qquad \text{Eq. (5)}$$

$$AC(3) = \sum_{t=2}^{5} \frac{P_t+P_{t-2}-2\times P_{t-1}}{2\times P_{t-1}} \qquad \text{Eq. (6)}$$

[11] We require that funds must have at least two- (five-) year history of monthly returns in the three- (ten-) year estimation window.

[12] For example, earnings acceleration is commonly measured as the difference in earnings growth rates between consecutive periods (e.g. Cao, Myers, and Sougiannis, 2011; He and Narayanamoorthy, 2020).

3.4 Flow-convexity and the convex flow-performance relation

Previous studies document a convex relationship between mutual fund flows and past performance (e.g. Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Fant and O'Neal, 2000; Huang et al., 2007). The convex relationship suggests that as past performance increases, mutual fund flows increase faster than the increase in past performance. In the context of our study, it is essential to distinguish between the flow-convexity relationship and the convex flow-performance relationship. As the price path convexity is essentially a second order polynomial of the price path, one may argue that the documented flow-convexity relationship is simply a variation of the convex flow-performance relationship.

To rule out this concern, we follow Spiegel and Zhang (2013) and employ the market share-adjusted measure as an alternative specification for fund flows. This specification is resilient to heterogeneity in the fractional specification of fund flows and implies a linear flow-performance relationship. If the documented flow-convexity relationship is a variation of the convex flow-performance relationship, then it should disappear when we use the market share-adjusted fund flows as shown in Spiegel and Zhang (2013). In Table 6, we re-estimate our baseline specification with the market share-adjusted fund flows as the dependent variable. The results show that the coefficient on the convexity remains positive and statistically significant at 1%. The results in Table 6 are robust when we use Newey and West adjusted t-statistics with three lags. Therefore, we confirm that our baseline results are not driven by the heterogeneity in the fractional specification for fund flows, but a robust finding on the impact of price path on fund flows.

[Insert Table 6 about here]

3.5 Reliability of price path and the flow-convexity relation

In this subsection, we investigate whether the reliability of price path in the past prices affects the flow-convexity relation. We conjecture that if investors rely on price path signals to make mutual fund investment decisions, we should observe the flow-convexity relation to be stronger (weaker) when the information embedded in the price path is more (less) reliable to investors[13].

We proxy the reliability of price path by volatilities measured at both fund level and market level. At fund level, volatile past returns are signals of performance non-persistence and noises and make investors less relying on information embedded in past performance (Huang et al., 2022). At market level, extant studies show that mutual investors' decision-making is distinct under different market conditions, such as the level of aggregate risk realizations (Franzoni and Schimalz, 2017) and perceived economic downturns (Chalmers, Kaul, and Philips, 2013). This may be partially because investors tend to pay more attention to aggregate shocks in the market and less attention to the performance of specific assets during periods of market turmoil (Peng and Xiong, 2006; Kacperczyk et al., 2016). To verify our conjecture, we augment our baseline regression by interacting price path convexity with fund-specific and market-wide volatility measures and report our results in Table 7.

[Insert Table 7 about here]

In Table 7, the first two columns report the regression results where we use return volatility as the proxy for the reliability of convexity. In column 1, *High_Vol* is

[13] We do not argue that investors learn rationally from price path. The term "reliability" used in this paper simply refers to the degree of which a naïve investor relies on a performance signal.

a dummy variable that takes the value of one if the volatility of monthly returns over the five-year estimation window is in the highest quartile, and zero otherwise. The coefficient on the interaction term between convexity and the high-volatility dummy is significantly negative. In column 2, *Low_Vol* is a dummy variable that takes the value of one if the volatility of monthly returns over the five-year estimation window is in the highest quartile, and zero otherwise. The coefficient on the interaction term between convexity and the high-volatility dummy is significantly positive. The last two columns of Table 7 report the regression results where we use market-wide volatility measures as the proxies for the reliability of convexity. In column 3, the market volatility is proxied by the implied volatility (VIX) index. The results show that the interaction terms are statistically significant and negative. Column 4 reports the regression results where we interact convexity with the newspaper-based US equity market volatility (*EMV*) index developed by Baker et al. (2019). The results show that the interaction terms are statistically significant and negative.

Overall, our results in this subsection support our conjecture that the reliability of price path affects the documented flow-convexity relation. Investors respond to price path convexity more conservatively if the price path is more volatile or if the aggregate market is of greater uncertainty.

3.6 Which component of price path convexity do investor respond to?

The price path convexity of a mutual fund over a given period is determined by two components. The first is the convexity of the stocks that the fund holds. The second is the convexity resulted from mutual fund itself, primarily due to its portfolio turnover. Recent studies in asset pricing reveal that investors form their expectations on stock returns by extrapolating past returns (Da et al., 2021). Meanwhile, mutual funds periodically disclose their portfolio holdings. Extrapolating investors who wish to enjoy the low-cost diversification benefits may invest in mutual funds which hold stocks with high convexity instead of directly purchasing those stocks. Therefore, one may concern that the documented mutual fund flow-convexity relation simply reflects the extrapolation in stock markets rather than mutual fund investors' react to fund performance.

To address this concern, we estimate the two components of price path convexity as follows. First, we retrieve quarterly mutual fund holdings data from Thomson Reuters mutual fund holdings database. We assume that a mutual fund holds its most recent disclosed stock portfolio until the next calendar quarter when a new stock portfolio is disclosed. In other words, we create a hypothetical portfolio for each fund in which we assume no portfolio turnover between holdings disclosures. Then, we estimate the monthly price history for the hypothetical portfolio and obtain its price path convexity using Eq. 1[14]. The price path convexity of the hypothetical portfolio, which we call holdings convexity, captures the first component of the fund's convexity, i.e. the convexity of the stocks that the fund holds. We measure the second component of the fund's convexity as the difference between a fund's realized price path convexity and the price path convexity of its corresponding hypothetical portfolio, which we call convexity gap. With these two measures, we are able to identify which component that mutual fund investors respond to. We report the results in Table 8.

[Insert Table 8 about here]

[14] Some stocks do not have convexity during certain periods due to insufficient price observations (we require a minimum of three years of observations during any five-year period). In the analysis in this subsection, we drop fund observations if stocks with missing convexity measures account for over 20% value of their hypothetical portfolios. Our results remain qualitatively unchanged if we do not apply the 20% threshold

In Table 8, column 1 presents the regression result where we substitute the convexity in our baseline specification with holdings convexity. The result shows that holdings convexity has a significant negative impact on mutual fund flows, which is an evidence against that mutual fund investors simply chase the convexity of mutual fund portfolio holdings. Similar conclusion can be drawn when we include mutual fund ratings in column 2 as an additional control. In column 3, we substitute the convexity in our baseline specification with convexity gap and find a positive impact of convexity gap on fund flows. The positive impact remains when we control for fund ratings in column 4. In column 5, we regress fund flows on both holdings convexity and convexity gap, with the full set of controls and fixed effects. The coefficient on convexity gap is statistically significant and positive, and its magnitude is similar to the coefficient we find for the flow-convexity relation in the baseline regression. In contrast, the coefficient on holdings convexity is statistically insignificant. The findings remain similar when we control for fund ratings in column 6.

To summarize, the results in Table 8 indicate that the mutual fund flow-convexity relation does not reflect the extrapolation in stock markets. Mutual fund investors allocate capital to funds with high price path convexity in response to fund performance attributed to portfolio turnover.

3.7 Learning or performance chasing?

In this subsection, we further investigate whether the flow-convexity relation reflects mutual fund investors' sophisticated learning on alpha, as suggested by the strand of sophisticated learning literature (e.g. Berk and Green, 2004), or naïve performance chasing, as suggested by the strand of simplistic chasing literature (e.g. Ben-David et al. 2022).

We employ the test of Ben-David et al. (2022) by including an additional sample of index fund. If the flow-convexity relation reflects sophisticated learning, then the flow-convexity relation should not be observed in the index fund sample, because there is little or no investment skill for investors to learn about for passively managed index funds[15]. We estimate the baseline specification given by Eq. 3 for the index fund sample and report the results in Table 9.

[Insert Table 9 about here]

In Table 9, column 1 reports the regression result for the baseline specification. The coefficient on convexity is positive and statistically significant. In column 2, we add Morningstar rating as an additional control. The result remains qualitatively unchanged. In sum, the results in Table 9 suggest that the flow-convexity relation is still observed in passive index funds. Therefore, this relation does not imply investors' learning about investment skill, but simply reflects a performance chasing by mutual fund investors.

[15] Following Ben-David et al. (2022), we do not argue that passive index fund managers do not possess skill. However, returns, or price path, of a passive index fund is predominantly determined by the performance of the index being tracked. The skill of a passive index fund manager primarily affects tracking error or transaction costs, which marginally affects the fund's performance.

4. Conclusion

This paper is built on the view that mutual fund investors are of limited financial sophistication and chase signal performance signals. They do not engage in sophisticated learning about mutual fund skill as suggested by early theoretical and empirical studies in this field. Rather, they value past returns, learn from third-party ratings, and can be affected by market sentiment and media attention.

In this paper, we provide additional evidence that mutual fund investors make capital allocation decisions based on price path, which is an important, simple and easily accessible performance signal. We find that a one-standard deviation increase in the price path convexity leads to a 0.30% increase in mutual fund flows on average. The positive relation between price path convexity and mutual fund flows is robust to different measurement horizons and alternative price path convexity measures.

Moreover, consistent with performance chasing hypothesis, we find that the flow-convexity relation is weaker when uncertainty is high and stronger when uncertainty is low. Our further analysis on the components of convexity reveals that the flow-convexity relation reflects investors chasing performance of mutual fund, not using mutual fund as a diversification vehicle to buying high-convexity stocks. Our analysis on a passive index fund sample reinforces our hypothesis that the flow-convexity relation represents simplistic performance chasing rather than rational learning by mutual fund investors.

Our study suggests that mutual fund investors indeed rely on simple performance signals to form their capital allocation decisions. The empirical findings contribute to the growing literature on how mutual fund investors as unsophisticated agents make their investment decisions. Our findings also have implications for regulators on enhancing retail investor protection and for financial professionals in the investment advisory industry.

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Figure 1 Hypothetical price paths

This figure presents hypothetical price paths for two mutual funds that have same return but with different price paths during a same period. In panel A, two funds have a return of zero from time 0 to time T. In panel B, two funds have a same positive return from time 0 to time T.

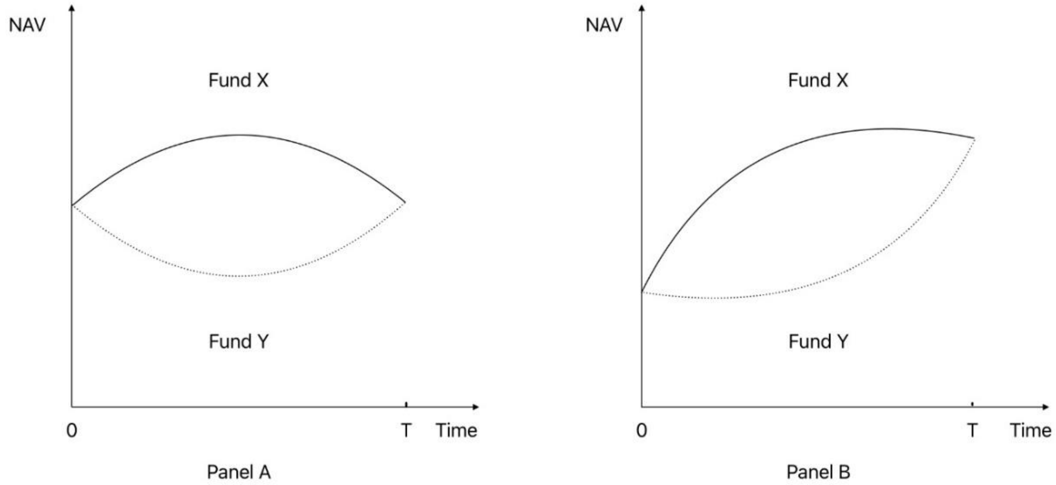

Table 1 Summary Statistics

This table reports the summary statistics of our sample of 2711 mutual funds over the period from 1985 to 2022. All continuous variables are winsorized at 1% and 99%.

Variable	N	mean	sd	p25	p50	p75
Flow	356248	-0.002	0.049	-0.016	-0.005	0.006
Convexity	356248	0.004	0.131	-0.076	-0.001	0.082
Ret_1m	356248	0.007	0.050	-0.019	0.012	0.038
Ret_3m	356248	0.022	0.089	-0.023	0.030	0.074
Ret_6m	356248	0.046	0.132	-0.023	0.054	0.121
Ret_12m	356248	0.098	0.198	-0.010	0.107	0.210
Ret_36m	356248	0.314	0.343	0.106	0.324	0.521
Ret_60m	356248	0.583	0.539	0.160	0.539	0.908
MKT_Loading	356248	0.996	0.148	0.919	1.001	1.077
SMB_Loading	356248	0.249	0.349	-0.046	0.159	0.545
HML_Loading	356248	0.014	0.297	-0.186	0.010	0.208
MOM_Loading	356248	0.009	0.128	-0.064	0.001	0.073
Size	356248	1103.00	2142.00	86.00	305.30	1036.00
Age	356248	13.94	6.81	8.25	12.50	18.33
Turnover	356248	0.743	0.671	0.300	0.560	0.960
Exp_ratio	356248	0.012	0.004	0.009	0.011	0.014
Vol	356248	0.049	0.015	0.038	0.047	0.058
Skew	356248	-0.448	0.458	-0.708	-0.404	-0.151
Max	356248	0.123	0.047	0.091	0.114	0.143
Ivol	356248	0.014	0.007	0.010	0.013	0.017

Table 2 Double Sorting on Past Return and Convexity

In this table, we report a 5×5 double sorting of the mutual funds in our sample. Mutual funds are first sorted into quintiles based on return over the past year. Then, within each return quintile, funds are sorted into quintiles based on convexity. For each group of funds, we report the average fund flows. In the last column, we report the difference in fund flows between the fund group with the highest convexity and the fund group with the lowest convexity. We report the Newey-West t-statistics with 3 lags in the parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Convexity					
1-year return	1 (Low)	2	3	4	5 (High)	5-1
1 (Low)	-1.71	-0.91	-0.93	-0.81	-0.78	0.85***
	(-16.94)	(-4.83)	(-7.32)	(-7.35)	(-3.97)	(5.75)
2	-0.87	-0.63	-0.33	-0.2	0.02	0.74***
	(-6.91)	(-4.34)	(-2.56)	(-1.41)	(0.12)	(3.19)
3	-0.61	-0.17	0.13	0.31	0.01	0.80***
	(-3.98)	(-1.19)	(1.01)	(2.04)	(0.11)	(5.61)
4	-0.15	0.21	0.43	0.63	0.65	0.69***
	(-0.98)	(1.06)	(3.22)	(4.42)	(4.23)	(3.70)
5 (High)	0.78	0.99	1.29	1.54	2.55	1.57***
	(2.87)	(4.41)	(6.86)	(8.84)	(10.25)	(6.47)

Table 3 The Relation between Convexity and Past Returns

This table reports the results of regressions that regress convexity on past returns. For each convexity, whose estimation window is five years, we calculate the rolling return for each year of the five-year window. In columns 1 to 5, we regress convexity on the five annual returns, respectively. In column 6, we regress convexity on all five annual returns. All regressions include fund fixed effect and year-month fixed effect. Robust standard errors are clustered at both fund level and year level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Return $_{-1}$	0.384***					0.386***
	(28.68)					(40.73)
Return $_{-2}$		0.170***				0.143***
		(8.43)				(15.47)
Return $_{-3}$			-0.020			-0.012
			(-0.79)			(-1.62)
Return $_{-4}$				-0.208***		-0.171***
				(-9.13)		(-21.94)
Return $_{-5}$					-0.358***	-0.359***
					(-25.13)	(-32.06)
Constant	-0.034***	-0.014***	0.006**	0.025***	0.043***	0.008***
	(-25.82)	(-6.66)	(2.33)	(10.79)	(27.60)	(2.81)
Fund and Time FE	Y	Y	Y	Y	Y	Y
N	356248	356248	356248	356248	356248	356248
adj. R2	0.726	0.668	0.653	0.675	0.722	0.826

Table 4 Baseline Results

This table reports the results of baseline regressions that regress mutual fund flows in the next period on the price path convexity. Column 1 presents the regression without any control variables and any fixed effects. Column 2 presents the regression with fund, and time (year-month) fixed effects. Column 3 presents the regression with full set of controls. Column 4 presents the regression with the full set of controls, fund and time fixed effects. Column 5 presents the regression with an additional control for Morningstar fund ratings. Robust standard errors are clustered at both fund level and time level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Convexity	0.031***	0.074***	0.014***	0.023***	0.015***
	(9.34)	(13.65)	(3.28)	(4.00)	(4.58)
Ret_1m			0.016*	0.042***	0.048***
			(1.88)	(3.75)	(4.41)
Ret_3m			0.005	0.020***	0.020***
			(0.92)	(3.00)	(2.69)
Ret_6m			0.007*	0.015***	0.013***
			(1.83)	(2.73)	(2.67)
Ret_12m			0.002	0.021***	0.023***
			(0.70)	(6.22)	(8.45)
Ret_36m			0.003*	0.013***	0.007***
			(1.82)	(5.95)	(3.76)
Ret_60m			0.006***	0.014***	0.006***
			(5.67)	(9.75)	(4.83)
Rating					0.007***
					(23.67)
MKT_Loading			-0.012***	-0.014***	-0.007**
			(-5.92)	(-4.39)	(-2.34)
SMB_Loading			-0.003***	0.002	-0.002
			(-4.28)	(1.02)	(-0.89)
HML_Loading			0.002**	-0.003*	-0.002
			(1.97)	(-1.94)	(-1.28)
MOM_Loading			0.009***	0.009***	0.004
			(5.33)	(4.25)	(1.45)
Size			-0.001***	-0.006***	-0.007***
			(-6.25)	(-19.41)	(-19.82)
LN(Age)			-0.006***	-0.012***	-0.010***
			(-13.98)	(-8.20)	(-6.28)
Turnover			-0.001***	0.000	0.000
			(-2.69)	(0.65)	(1.11)
Exp_ratio			-0.164***	-0.552***	-0.804***
			(-3.22)	(-4.08)	(-5.57)
Past_Flow			0.249***	0.195***	0.194***
			(19.27)	(15.55)	(17.17)
Vol			0.108**	0.015	0.178***
			(2.41)	(0.23)	(2.74)
Skew			-0.001	-0.002**	-0.001

			(-1.00)	(-2.40)	(-1.64)
Max			0.001	0.019	0.010
			(0.11)	(1.59)	(0.77)
Ivol			0.140***	-0.031	-0.081
			(3.22)	(-0.47)	(-1.15)
Constant	-0.002***	-0.002***	0.019***	0.061***	0.039***
	(-4.29)	(-80.90)	(9.19)	(12.71)	(7.34)
Fund and Time FE		Y		Y	Y
N	356248	356248	356248	356248	221959
adj. R^2	0.007	0.082	0.096	0.158	0.173

Table 5 Robustness Check: Alternative Convexity Measures

This table reports the results of robustness checks in which we use alternative convexity measures. Column 1 presents the regression where we measure convexity using a 3-year window. Column 2 reports the regression where we measure convexity over a 10-year window. Column 3 presents the regression where we use the AC1, denoted by Eq. 4, as an alternative measure of convexity. Column 4 presents the regression where we use the AC2, denoted by Eq. 5, as an alternative measure of convexity. Column 5 presents the regression where we use the AC3, denoted by Eq. 6, as an alternative measure of convexity. In column 6, we construct an orthogonal version of the convexity variable by running monthly cross-sectional regressions of the NAV-path convexity against Morningstar rating. Standard control variables used in the baseline regression are included but not reported. Robust standard errors are clustered at both fund level and year level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Convexity 3	0.023***					
	(4.49)					
Convexity 10		0.013***				
		(3.93)				
AC1			0.008***			
			(3.00)			
AC2				0.006***		
				(3.67)		
AC3					0.009***	
					(3.64)	
Convexity RES						0.016***
						(4.66)
Controls	Y	Y	Y	Y	Y	Y
Fund and Time FE	Y	Y	Y	Y	Y	Y
N	356204	226238	356248	356248	356248	221959
adj. R^2	0.157	0.122	0.157	0.158	0.157	0.163

Table 6 Flow-convexity vs. Convex Flow-performance

This table reports the regression results where we use the market share-adjusted measure in Spiegel and Zhang (2013) as an alternative specification for mutual fund flows. Column 1 presents the regression without any control variables and any fixed effects. Column 2 presents the regression with fund, and time (year-month) fixed effects. Column 3 presents the regression with full set of controls. Column 4 presents the regression with the full set of controls, fund and time fixed effects. Column 5 presents the regression with an additional control for Morningstar fund ratings. Robust standard errors are clustered at both fund level and year level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Convexity	0.001***	0.005***	0.001***	0.001***	0.001***
	(5.03)	(8.24)	(3.50)	(3.49)	(2.94)
Ret_1m			0.001	0.003	0.003
			(1.02)	(1.07)	(1.02)
Ret_3m			0.000	0.002	0.003*
			(0.23)	(1.07)	(1.66)
Ret_6m			-0.001	0.001	0.001
			(-0.98)	(0.72)	(0.55)
Ret_12m			-0.000	0.002**	0.002**
			(-0.44)	(2.45)	(2.36)
Ret_36m			0.000	0.001**	0.000
			(0.25)	(2.00)	(0.67)
Ret_60m			0.000***	0.001***	0.001***
			(3.20)	(5.40)	(2.91)
Rating					0.000***
					(12.23)
MKT_Loading			-0.001***	-0.000	-0.000
			(-2.62)	(-0.87)	(-0.63)
SMB_Loading			-0.000	0.000*	0.000
			(-0.54)	(1.94)	(0.71)
HML_Loading			0.000***	0.000	0.000*
			(3.20)	(1.52)	(1.77)
MOM_Loading			0.001*	0.001*	0.000
			(1.78)	(1.65)	(0.68)
Size			0.000	-0.000***	-0.000***
			(1.14)	(-4.96)	(-5.41)
LN(Age)			-0.000	-0.000	-0.000
			(-0.31)	(-1.19)	(-0.24)
Turnover			-0.000***	-0.000***	-0.000***
			(-4.60)	(-2.90)	(-2.85)
Exp_ratio			-0.017***	-0.005	0.015
			(-2.79)	(-0.42)	(0.98)
Past_Flow			0.012***	0.009***	0.009***
			(18.81)	(15.86)	(14.04)
Vol			0.003	-0.018	-0.014
			(0.40)	(-1.59)	(-1.12)

Skew			-0.000***	-0.000**	-0.000**
			(-2.69)	(-2.09)	(-2.04)
Max			0.001	0.002	0.005*
			(0.94)	(1.22)	(1.92)
Ivol			0.010*	0.011	0.007
			(1.81)	(1.16)	(0.65)
Constant	0.000	0.000***	0.000	0.002**	-0.000
	(1.63)	(25.14)	(1.08)	(2.49)	(-0.24)
Fund and Time FE		Y		Y	Y
N	346467	346454	346467	346454	215598
adj. R^2	0.002	0.061	0.024	0.088	0.094

Table 7 Reliability of price path and the flow-convexity relation

This table reports the results of regression analyses of the flow-convexity relationship conditional on the reliability of information embedded in the price path convexity. Column 1 reports the regression analysis of the flow-convexity relationship for funds whose return volatility is high during the convexity measurement period. *High_Vol* is a dummy variable that takes the value of one if the volatility of monthly returns over the five-year estimation window is in the highest quartile, and zero otherwise. Column 2 reports the regression analysis of the flow-convexity relationship for funds whose return volatility is low during the convexity measurement period. *Low_Vol* is a dummy variable that takes the value of one if the volatility of monthly returns over the five-year estimation window is in the highest quartile, and zero otherwise. Column 3 reports the regression results conditional on market volatility. *Mkt_Vol* is the implied volatility (VIX) index. Column 4 reports the regression results conditional on market uncertainty. *EMV* is the newspaper-based US equity market volatility index developed by Baker et al. (2019). Robust standard errors are clustered at both fund level and year level. T-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Convexity	0.030***	0.020***	0.043***	0.042***
	(4.46)	(3.94)	(4.99)	(5.48)
*High_Vol * Convexity*	-0.016***			
	(-4.47)			
High_Vol	0.001**			
	(2.36)			
*Low_Vol * Convexity*		0.025***		
		(3.65)		
Low_Vol		-0.000		
		(-0.22)		
*Mkt_Vol * Convexity*			-0.001**	
			(-1.99)	
Mkt_Vol			0.001***	
			(6.47)	
*EMV * Convexity*				-0.001**
				(-2.19)
EMV				0.000***
				(4.90)
Controls	Y	Y	Y	Y
Fund and Time FE	Y	Y	Y	Y
N	356248	356248	355014	356248
adj. R^2	0.158	0.158	0.137	0.134

Table 8 Mutual fund flows and components of price path convexity

In this table, we decompose the price path convexity into two parts. The first component, *Holdings_Convexity*, is the convexity of a hypothetical portfolio comprising a fund's most recently disclosed stock holdings. The second component, *Convexity_Gap*, is the difference between a fund's convexity and its holdings convexity. We substitute the convexity with the two components and re-run the baseline regression. In column 1 and 2, we regress the fund flows on the holdings convexity, without and with Morningstar ratings as a control, respectively. In column 3 and 4, we regress the fund flows on the convexity gap, without and with Morningstar ratings as a control, respectively. In column 5 and 6, we regress the fund flows simultaneously on both components, without and with Morningstar ratings as a control, respectively. Robust standard errors are clustered at both fund level and year level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Holdings_Convexity	-0.014***	-0.009**			0.010	0.003
	(-2.94)	(-2.05)			(1.02)	(0.63)
Convexity_Gap			0.028***	0.015***	0.031***	0.016***
			(3.49)	(4.32)	(2.93)	(3.86)
Rating		0.007***		0.007***		0.007***
		(19.02)		(19.08)		(19.06)
Ret_1m	0.023*	0.034***	0.023*	0.034***	0.022*	0.034***
	(1.89)	(2.93)	(1.92)	(2.93)	(1.87)	(2.92)
Ret_3m	0.032***	0.033***	0.032***	0.033***	0.032***	0.033***
	(4.34)	(4.33)	(4.36)	(4.34)	(4.29)	(4.31)
Ret_6m	0.007	0.003	0.006	0.002	0.005	0.002
	(1.27)	(0.55)	(1.08)	(0.41)	(0.87)	(0.34)
Ret_12m	0.035***	0.031***	0.031***	0.029***	0.029***	0.028***
	(9.32)	(8.72)	(8.18)	(8.44)	(6.94)	(8.04)
Ret_36m	0.022***	0.015***	0.016***	0.011***	0.014***	0.011***
	(9.50)	(6.51)	(7.23)	(5.10)	(4.31)	(4.31)
Ret_60m	0.010***	0.003**	0.014***	0.006***	0.015***	0.006***
	(6.75)	(2.46)	(7.85)	(3.86)	(6.41)	(3.98)
MKT_Loading	-0.017***	-0.009**	-0.018***	-0.009**	-0.018***	-0.009**
	(-3.97)	(-2.28)	(-4.15)	(-2.38)	(-4.17)	(-2.42)
SMB_Loading	0.000	-0.003	0.000	-0.003	0.001	-0.003
	(0.11)	(-1.37)	(0.21)	(-1.32)	(0.25)	(-1.31)
HML_Loading	-0.004*	-0.002	-0.003*	-0.002	-0.003*	-0.002
	(-1.91)	(-1.31)	(-1.74)	(-1.21)	(-1.74)	(-1.22)
MOM_Loading	0.013***	0.003	0.014***	0.004	0.013***	0.004
	(4.59)	(1.04)	(4.94)	(1.19)	(4.77)	(1.13)
Size	-0.006***	-0.007***	-0.006***	-0.007***	-0.006***	-0.007***
	(-14.85)	(-14.68)	(-14.63)	(-14.63)	(-14.62)	(-14.65)
LN(Age)	-0.010***	-0.007***	-0.011***	-0.008***	-0.011***	-0.008***
	(-4.73)	(-3.53)	(-5.31)	(-3.78)	(-5.38)	(-3.79)
Turnover	0.001*	0.001	0.001**	0.001*	0.001**	0.001
	(1.95)	(1.41)	(2.25)	(1.66)	(2.24)	(1.64)
Exp_ratio	-0.487**	-0.733***	-0.503**	-0.741***	-0.509***	-0.742***
	(-2.44)	(-3.75)	(-2.56)	(-3.79)	(-2.63)	(-3.80)
Past_Flow	0.163***	0.158***	0.162***	0.157***	0.162***	0.157***

	(9.89)	(12.15)	(9.81)	(12.10)	(9.83)	(12.10)
Vol	0.052	0.292***	0.074	0.302***	0.078	0.303***
	(0.57)	(3.46)	(0.84)	(3.59)	(0.89)	(3.61)
Skew	-0.002**	-0.002*	-0.003**	-0.002*	-0.003**	-0.002*
	(-2.19)	(-1.85)	(-2.28)	(-1.93)	(-2.30)	(-1.94)
Max	0.032**	0.011	0.031**	0.010	0.030**	0.010
	(2.14)	(0.63)	(2.04)	(0.62)	(2.01)	(0.62)
Ivol	-0.195**	-0.314***	-0.182**	-0.309***	-0.188**	-0.311***
	(-2.35)	(-3.63)	(-2.23)	(-3.58)	(-2.30)	(-3.60)
Constant	0.057***	0.030***	0.058***	0.031***	0.059***	0.031***
	(8.84)	(4.46)	(9.22)	(4.70)	(9.35)	(4.72)
Fund and Time FE	Y	Y	Y	Y	Y	Y
N	204562	130741	204562	130741	204562	130741
adj. R^2	0.136	0.146	0.137	0.146	0.137	0.146

Table 9 Results on passive index funds

This table reports the results of baseline regressions using a passive index fund sample spanning over the same period of our active mutual fund sample. Column 1 presents the regression with the full set of controls, fund and time fixed effects. Column 2 presents the regression with an additional control for Morningstar fund ratings. Robust standard errors are clustered at both fund level and time level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Convexity	0.016**	0.040**
	(2.00)	(2.28)
Ret_1m	0.086***	0.439***
	(3.15)	(2.70)
Ret_3m	0.002	0.037
	(0.15)	(0.65)
Ret_6m	-0.003	-0.085**
	(-0.29)	(-2.00)
Ret_12m	0.011*	-0.016
	(1.67)	(-0.76)
Ret_36m	0.005	-0.000
	(1.26)	(-0.00)
Ret_60m	0.008***	0.014*
	(3.31)	(1.72)
Rating		0.008***
		(6.57)
MKT_Loading	-0.007	-0.016
	(-1.24)	(-0.68)
SMB_Loading	-0.002	-0.012
	(-0.52)	(-0.85)
HML_Loading	0.002	0.010
	(0.57)	(1.02)
MOM_Loading	0.001	0.003
	(0.10)	(0.15)
Size	-0.011***	-0.019***
	(-11.87)	(-5.83)
LN(Age)	-0.010***	0.002
	(-2.86)	(0.19)
Turnover	0.003**	0.014***
	(2.07)	(3.77)
Exp_ratio	-1.353***	-1.906*
	(-3.28)	(-1.77)
Past_Flow	0.007	-0.101***
	(0.44)	(-5.66)
Vol	-0.133	0.072
	(-1.06)	(0.18)
Skew	-0.001	-0.008*
	(-0.48)	(-1.67)
Max	0.046	0.204*
	(1.40)	(1.83)

Ivol	-0.138	-1.114**
	(-0.74)	(-1.99)
Constant	0.103***	0.092***
	(10.17)	(2.64)
Fund and Time FE	Y	Y
N	174279	35209
adj. R^2	0.058	0.072