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

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Abstract

This paper proposes that a performance signal derived from a mutual fund's price path significantly affects investors' capital allocation decisions. Using convexity to measure the price path shape, we show that mutual fund flows respond positively to this signal. Specifically, on average, a one-standard-deviation increase in the convexity leads to a 0.30% increase in mutual fund flows. The positive flow-convexity relation is robust to alternative convexity measurements and the market-share-adjusted fund flow measurement. In addition, we find that investors respond more conservatively when the price path is volatile, when the uncertainty in the market is high, and when the price path exhibits a large drawdown or loss domain. We show that the flow-convexity relation reflects mutual fund investors' attempt to learn managerial skill. However, this attempt is an ineffective learning as convexity does not lead to better future performance. Our results support the view that mutual fund investors rely on simple performance signals in their capital allocation decisions.

JEL Classifications: G11; G23; D14

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

1. Introduction

Previous studies generally assume 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 argue that price path, defined as the historical movement of a mutual fund's net asset value (NAV), also contains valuable information and is readily 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. However, neither of them captures how the NAV has evolved during the period[2], which is likely material in investors'

[1] Throughout this paper, we refer past returns to past unadjusted returns unless otherwise specified.
[2] Arguably, nor is this information reflected by any sophisticated performance evaluation measures like risk-adjusted returns.

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 in the cross section affects mutual fund flows. They show that mutual funds with better past returns or higher ratings compared to others receive more flows[3]. Price path convexity captures an important dimension of performance signals that extant literature generally overlooked --- trajectory of funds' NAV, depicting 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).

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. Then, 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. 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 the flow-convexity relation still remains statistically and economically significant. Furthermore, we employ an alternative measure of fund flows suggested by Spiegel and Zhang (2013), we find that the flow-convexity relation can't be explained by 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).

[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.

We conduct several analyses to understand 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 the fund level, volatile past returns make investors relying less on information embedded in the past (Huang, Wei, and Yan, 2022). At the market level, market-wide downside shocks divert investors' attention from the historical performance of specific assets (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 the volatility of past returns is low, but weaker when the volatility of past returns or market-level volatility is high.

Second, existing literature suggests that investors with limited information processing abilities tend to focus on salient information (e.g. Hirshleifer and Teoh, 2003; Palomino, Renneboog, and Zhang, 2009). Thus, the impact of price path convexity could be a result of investors attracted by the salient features on the path. We construct three variables reflecting the salient features, namely the distance between the highest price and current price, the distance between current price and the lowest price, and the fraction of time the fund is under water during the estimation window. We find that the flow-convexity relation becomes weaker when the distance between the highest price and current price is greater and when the fund is under water for more time. However, neither of the salient features fully explain the flow-convexity relation.

We further investigate why investors rely on price path convexity in making their mutual fund investment decisions. First, we are interested in whether the flow-convexity relation reflects investor behaviour documented in the stock market. That is, investors extrapolate 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. We decompose price path convexity into convexity from the most recent disclosed portfolio and convexity from trades made by fund managers between disclosure periods, where the latter is associated with managerial skill. We find that investors respond to the latter component only. This finding differentiates our paper from the existing literature in the asset pricing field focusing on stock markets and suggests that mutual fund investors respond to fund performance.

Then we examine whether the flow-convexity relation reflects investors' sophisticated learning as suggested by the strand of sophisticated learning literature (e.g. Berk and Green, 2004), or simplistic performance chasing as suggested by the strand of simplistic chasing literature (e.g. Ben-David et al. 2022). 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. Following this intuition, we re-estimate our baseline specification with an index fund sample and do not find the flow-convexity relation in index funds. Therefore, our results indicate the flow-convexity relation reflect investors' learning, or at least attempt to learn, about managerial skill. However, in our further analysis on the effectiveness of learning through price path, we find that funds with higher convexity do not deliver higher performance in the future, regardless of whether the performance is measured by net return or alphas from different asset pricing models. Therefore, the flow-convexity relation reflects an ineffective learning method by mutual fund investors.

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 have identified 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 trajectory of mutual fund performance, also determines mutual fund flows.

Second, our paper provides new insights into mutual funds investor's capital allocation process. In contrast to prior studies such as Berk and Green (2004), Berk and van Binsbergen (2016), Barber et al., (2016) suggesting investors are rational agents who employ asset pricing models to learn managerial skills, our study finds that investors seem to follow simple signals from the price trajectory. Our result lend support to the recent literature depicting 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).

In addition, this paper contributes to the literature on how 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 empirical evidence from mutual funds and demonstrates that price paths of funds significantly affect retail investors' expectation of future performance. To this end, our paper offers industry implications to practitioners and regulators in financial markets when marketing financial products to different 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 4 concludes.

2. Methodology and data

2.1 Price path convexity and its relation to mutual fund flows

Existing literature 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 to Lusardi and Mitchell (2007), most households are not financially educated and show little understanding about basic investment concepts like compounding, risk, diversification, and inflation. In addition, using a survey to 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), and they are naïve past performance

[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.

chasers (Chevalier and Ellison, 1997, Ben-David et al., 2022). Further 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-mentioned works, 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 such as, alpha, computed from the capital asset pricing model (CAPM).

Apart from past returns and fund ratings as performance signal suggested by Ben-David et al. (2022), another important performance signal is the evolvement of mutual fund's NAV path. This information is readily 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, as a part of the historical performance of funds.

Intuitively, the exhibition of price path embeds more information than what is reflected in return figures 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 of 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. On the other hand, Fund Y's NAV decreases in the first half of the period but then increases in the second half. 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, there is no difference in returns 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 shown in Figure 1. The shape of paths can be of any kind and vary significantly across different funds and time periods. Thus, it is challenging to quantitatively measure the information contained in the price path 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 about how asset returns are achieved (Grosshans and Zeisberger, 2018).

2.2 Fund flows

Fund flows are our main dependent variable that measures how investors allocate capital among mutual funds. 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 US domestic mutual funds in the CRSP mutual fund database covering the period between 1980 and 2023. We focus our analysis on active-managed equity funds, as they provide the most comprehensive and reliable performance data on a monthly basis. Following Kacperczyk et al. (2008) and Doshi et al. (2015), we meticulously filter the funds, specifically including those with Lipper classification codes of EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, or Lipper target codes of CA, EI, G, GI, MC, MR, SG. If Lipper classification and target codes are missing, we include funds with Strategic Insight target codes of AGG, GMC, GRI, GRO, ING, SCG. In the absence of these codes, we select funds with Wiesenberger target codes of G, GCI, IEQ, LTG, MCG, SCG. All these codes are available in the CRSP mutual fund database. Utilizing them for fund selection offers a more rigorous approach than relying solely on CRSP objective codes. We screen styles and fund names to exclude international funds, balanced funds, sector funds, bond funds, money market funds, target date and index funds (including ETFs). Funds that have changed their style since inception are also excluded, even though they constitute a small proportion of the sample. We additionally eliminate a subset of FOFs that do not have their stock proportions within the 80% and 105% range. After meeting the selection criteria and ensuring that control variables are complete, the final sample includes 356,248 fund-month observation data points, covering the period from 1980 to 2023[6], and comprises a total of 2,711 unique actively

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

managed mutual funds.

We also extract Morningstar fund ratings from the Morningstar database. For these funds, we extract their historical ratings spanning from 1980 to 2023, 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.

We follow the methodologies of Dannhauser and Pontiff (2019) and Ben-David et al. (2022) to identify passive index funds in the CRSP Mutual Fund database, with slight modifications to their approaches. 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[8]. We search each fund name to eliminate target date funds[9], leveraged and inverse funds[10]. Fund-level variables are constructed in the same way as in the sample of active funds.

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

[7] Index funds are flagged if index_fund_flag is not missing or 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, composite, nyse, nasdaq, s&p, s and p, s & p, 50, 100, 200, 400, 500, 600, 1000, 1500, 2000, 2500, 3000. These numbers are selected based on major U.S. stock indices. We manually check some funds whose names include 'Morningstar', 'Wilshire', 'Bloomberg', 'FTSE', etc., and find that almost all can be absorbed by existing filters.
[8] Broad ETF products are flagged if et_flag is not missing or the CRSP fund name contains the following strings: ETF, ETN or if the lowercase version of the CRSP fund name contains: ishares, exchange traded, exchange-traded.
[9] Target date funds are flagged if the lowercase version of the CRSP fund name contains: target, retirement, 2010, 2015, 2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 2060, 2065. These numbers are selected based on S&P target date indices.
[10] Inverse and leveraged funds are identified if the lowercase version of their name contains the following strings: inverse, ultra, 1.5x, 2x, 2.5x.

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 an ignorable impact on assessing how convexity affects mutual fund flows. Other characteristics of our sample are consistent with those in recent studies on mutual fund flows.

[Insert Table 1 about here]

3. Empirical results

3.1 What information does price path convexity capture?

Extant flow-performance literature typically focuses on the funds' cross-section heterogeneity (e.g. Chevalier and Ellison, 1997, Sirri and Tufano, 1998, Bergstresser and Poterba, 2002, Del Guercio and Tkac, 2008, and Reuter and Zitzewitz, 2021). They find that funds with better performance receive higher inflows than funds with poorer performance. We begin our empirical results by showing that price path convexity captures a vital piece of information that might have been overlooked by prior studies, i.e. the trajectory of a fund's performance.

First, we conduct a regression analysis to show that price path convexity captures the history progression of funds performance. 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 reports the regression results. The coefficients are positive and statistically significant in the first two columns, where we regress convexity on the most recent annual returns separately. 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 the convexity on the two most 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 the 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 2 about here]

Then, we use a 5x5 double sorting strategy to examine whether the trajectory of funds' NAV complements the cross-sectional fund heterogeneity in explaining the differences in mutual fund flows. We first sort our sampled funds into five groups based on their returns over the past year. Then, within each return quintile, we sort the funds into five groups based on their price-path convexity measurements. 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 attract 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 a non-neglectable differences 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[11].

[Insert Table 3 about here]

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

3.2 The impact of price path convexity on mutual fund flows

In this section, we formally test the impact of price path convexity on mutual 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

[11] 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.

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 the 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 the 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 the 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 the past returns as a result of the performance chasing behaviour 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[12]. The coefficient on convexity is still statistically significant at 1% and positive.

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 return figures, but also pay attention to how the returns are achieved, i.e. the progression path of fund NAVs. A fund with better recent performance would attract more cash flows than a similar 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 historical relative performance in determining mutual fund flows. For a mutual fund that wishes to attract more flows, it is not only important to outperform 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 depict its recent improvements in performance.

[12] 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.

3.3 Robustness check

In this section, we conduct a series robustness tests by repeating our baseline regression with alternative measures of the convexity in the price path and mutual fund flows. 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, nor does it represent the convex flow-performance relation identified in the literature.

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[13]. 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

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

acceleration in financial values used by other studies[14]. 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.

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

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

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

Previous studies document a convex relation 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 relation suggests that as past performance increases, mutual fund flows increase faster than past performance increases. In the context of our study, it is essential to distinguish between the flow-convexity relation and the convex flow-performance relation. As the price path convexity is essentially a second-order polynomial of the price path, one may argue that the documented flow-convexity relation is simply a variation of the convex flow-performance relation.

To rule out this concern, we follow Spiegel and Zhang (2013) and employ the market share-adjusted flow measure as an alternative specification for fund flows. This specification is resilient to heterogeneity in the fractional specification of fund flows

[14] 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).

and implies a linear flow-performance relation. Suppose the documented flow-convexity relation is a variation of the convex flow-performance relation. In that case, 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]

3.4 Price path characeristics and the flow-convexity relation

Our results above indicate that mutual fund investors respond to the shape of price path, which is proxied by the convexity measure. In this subsection, we investigate how the documented flow-convexity relation interacts with other characteristics of the price path.

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[15]. We proxy the reliability of price path by volatilities measured at both the fund level and market level. At the fund level, volatile past returns are signals of performance non-persistence and noises and make investors rely less on information

[15] 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.

embedded in past performance (Huang et al., 2022). At the 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 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.

Extant literature suggests that investors with limited information processing abilities have limited attention, thereby focusing on salient information (e.g. Hirshleifer and Teoh, 2003; Palomino, Renneboog, and Zhang, 2009). It follows that mutual fund investors might be affected by salient features on the path of historical prices, which could be a primary driver for the flow-convexity relation. Therefore, we examine several salient features on the price path that might explain or affect the flow-convexity relation, such as the highest price, whether the price drops below the initial value, and the fraction of time that it is under water. We report the results in Table 8.

[Insert Table 8 about here]

In column 1 of Table 8, we investigate how the flow-convexity relation varies with the distance to the highest price. We construct a variable, *End_to_Highest*, which is the ratio of the higest NAV of a fund in the five-year estimation window to its current NAV. The coefficient on the interaction term is significantly negative, which implies that the flow-convexity relation is much weaker if a fund has dropped significantly from its previous high. This is consistent with Nolte and Schneider (2018) and Grosshans and Zeisberger (2018) in that investors are more unsatisticatory with price path that has dropped from a higher value. In column 2, we investigate whether the flow-convexity relation varies with the distance to the lowest price. We construct a variable, *End_to_Lowest*, which is the ratio of a fund’s current NAV to its lowest NAV in the five-year estimation window to its current NAV. The coefficient on the interaction term is statistically insignificant. In column 3, we investigate how another salient feature, that is the fraction of time the fund is under water, affects the flow-convexity relation. We construct a variable, *Loss_Domain*, which is the number of monthly NAVs that are below the initial NAV divided by 60 (the number of months in a five-year window). The interaction term is statistically significant and negative. The results in Table 8 suggest that investors are more likely to focus on how a fund has lost in value in the past, rather than how it has made gains. This is consistent with the prospect theory that investors are loss aversion. Notably, the coefficient on the convexity remains positive and statistically significant in all conlumns. This indicates that, while the convexity measure captures the salient features on the price path, the salient features themselves do not fully explain why investors respond to price path convexity.

Overall, our results in this subsection support our conjecture that the charactersitics of price path affects the documented flow-convexity relation. This is consistent with our overall argument that investors respond to simple and readily available performance signals and allocate their capital accordingly.

3.5 Further investigation on investors' reponse to price path convexity

Our analysis has shown that price path is an important performance signal used by mutual fund investors in their capital allocation decision. What remains unaddressed so far is why investors use this signal. In this subsection, we aim to answer this question.

Recent studies in asset pricing reveal that investors form their expectations of 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 (i.e. a clientele effect). Therefore, one may concern that the documented mutual fund flow-convexity relation simply reflects the clientele effect induced by extrapolating investors rather than mutual fund investors' response to performance signals.

To address this concern, we estimate the two components of price path convexity as follows. First, we retrieve quarterly mutual fund holdings data from the Thomson Reuters 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[16]. 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 9.

[Insert Table 9 about here]

In Table 9, 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 evidence against that mutual fund investors simply chase the convexity of mutual fund portfolio holdings. A 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

[16] 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 our baseline specification with the convexity gap and find a positive impact of the 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 the 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 9 indicate that the mutual fund flow-convexity relation does not reflect the extrapolation in the stock market, but investors' response to fund performance.

Investors' response to fund performance can be attributed to either 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 to investigate which alternative the flow-convexity reflects. 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[17]. We estimate the baseline specification given by Eq. 3 for the index fund sample and report the results in Table 10.

[Insert Table 10 about here]

[17] 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.

In Table 10, column 1 reports the regression result for the baseline specification. The coefficient on convexity is insignificant. In column 2, we add Morningstar rating as an additional control. The coefficient on convexity remains insignificant. In sum, the results in Table 10 suggest that the flow-convexity relation is not observed in passive index funds. Therefore, this relation does not imply performance chasing, but investors' attempt to learn about investment skill.

A natural question following the above findings is that do investors successfully learn managerial skill from price path? To answer this question, we conduct a double sorting analysis to examine whether investors achieve better investment outcome through this form of learning. Specifically, in each month, we conduct a 5x5 double sorting on mutual fund return over the past one year and price path convexity[18]. Then, we estimate future fund performance in the next month for each fund group. Within each return quantile, we compute the difference in the future fund performance between the group with the highest convexity and the group with the lowest convexity. We report the results in Table 11. In Panel A, fund performance is measured by net return (not adjusted for any risk factors). The results show that there is no significant variation across the convexity quantiles within the same return group. The difference in net return between the highest convexity quantile and the lowest convexity quantile is also statistically insignificant. In Panel B, fund performance is measured by alpha from the CAPM. Consistent with previous results, the difference in CAPM alpha between the highest convexity quantile and the lowest convexity quantile is statistically insignificant. We observe similar results when we use alpha from the Fama-Frech 3-Factor model (FF3) as a performance measurement in Panel C and alpha from the Fama-French-

[18] Our results remain qualitatively same with a 10x10 sorting.

Carhart 4-Factor model (Carhart) as a performance measurement in Panel D. For the difference in performance between the highest past return quantile and the lowest past return quantile for each convexity quantile, the results in Table 11 show that the difference is generally positive and statistically significant, which is consistent with existing literature that finds performance persistence in mutual funds (e.g. Carhart, 1997; Busse and Irvine, 2006).

To summarize, our results in this subsection show that the flow-convexity relation reflects mutual fund investors' attempt to learn managerial skill. However, learning through past price path does not provide investors with better investment outcome. Collectively, mutual fund learn ineffectively from price path.

4. Conclusion

Recent studies show that mutual fund investors are of limited financial sophistication and they follow simple performance signals. They do not engage in sophisticated learning about mutual fund skill as early theoretical and empirical studies in this field suggest. Instead, 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, 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 the performance of mutual fund, not using mutual funds as a diversification vehicle to buy high-convexity stocks. Our analysis on a passive index fund sample suggests that the flow-convexity relation reflects investors' learning on mutual fund skill. However, this form of learning is ineffective because funds with higher convexity do not deliver better performance in the future.

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.

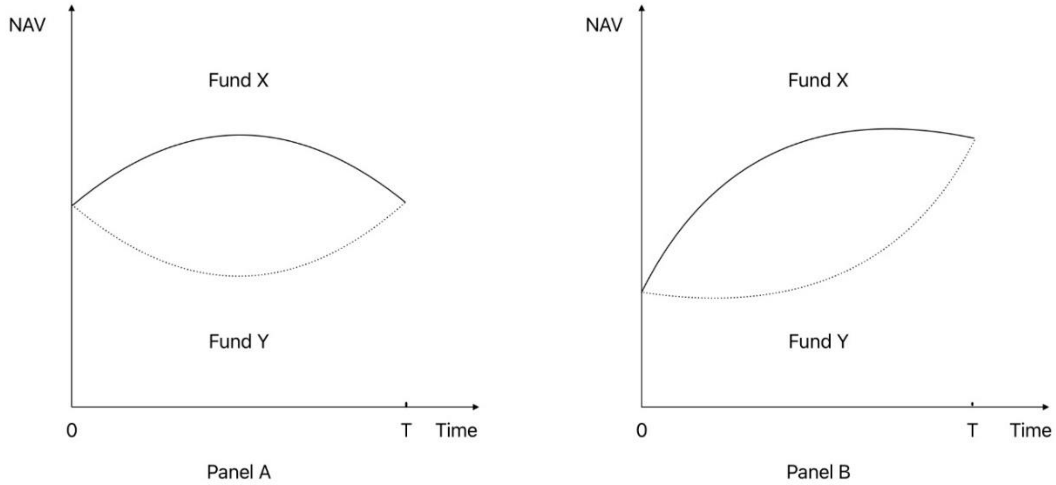

Table 1 Summary Statistics

This table reports the summary statistics of our sample of 2711 mutual funds over the period from 1985 to 2023. 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 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 3 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 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 relation conditional on the reliability of information embedded in the price path convexity. Column 1 reports the regression analysis of the flow-convexity relation 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 relation 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 Salient features and the flow-convexity relation

This table reports the results of regression analyses of the flow-convexity relation conditional on the salient features on the price path. Column 1 reports the regression analysis where we interact price path convexity with the distance to the highest price. *End_to_Highest* the ratio of the highest NAV of a fund in the five-year estimation window to its current NAV. Column 2 reports the regression analysis where we interact price path convexity with the distance to the highest price. *End_to_Lowest* the ratio of a fund's current NAV to its lowest NAV in the five-year estimation window to its current NAV. Column 3 reports the regression analysis where we interact price path convexity with the fraction of time that the fund is under water. *Loss_Domain* is number of month-end NAVs that are lower than the initial NAV of a fund in the five-year estimation window divided by the total number of months in the window (i.e. 60 months). 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)
Convexity	0.039***	0.021***	0.040***
	(4.45)	(3.96)	(5.45)
End_to_Highest	-0.011***		
	(-4.37)		
*End_to_Highest * Convexity*	-0.047***		
	(-4.44)		
End_to_lowest		0.001**	
		(1.99)	
*End_to_lowest * Convexity*		0.001	
		(0.58)	
Loss_Domain			-0.006***
			(-4.66)
*Loss_Domain * Convexity*			-0.016***
			(-3.35)
Controls	Y	Y	Y
Fund and Time FE	Y	Y	Y
N	269483	269483	269483
adj. R2	0.133	0.132	0.133

Table 9 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 10 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	-0.006	0.003
	(-0.73)	(0.21)
Ret_1m	0.301***	0.516***
	(4.49)	(2.68)
Ret_3m	0.120***	0.007
	(3.43)	(0.11)
Ret_6m	0.010	-0.054
	(0.57)	(-1.45)
Ret_12m	0.037***	0.027
	(3.69)	(1.26)
Ret_36m	0.000	-0.009
	(0.02)	(-0.70)
Ret_60m	0.008**	0.008
	(2.22)	(1.06)
Rating		0.007***
		(5.48)
MKT_Loading	-0.019*	-0.038
	(-1.81)	(-1.25)
SMB_Loading	0.001	-0.020
	(0.18)	(-0.94)
HML_Loading	0.005	-0.001
	(0.80)	(-0.06)
MOM_Loading	-0.013	0.025
	(-1.26)	(1.05)
Size	-0.011***	-0.018***
	(-6.00)	(-4.35)
LN(Age)	-0.003	-0.015
	(-0.54)	(-1.56)
Turnover	0.008***	0.011***
	(3.01)	(2.78)
Exp_ratio	-3.275***	-3.002**
	(-4.12)	(-2.38)
Past_Flow	-0.042*	-0.110***
	(-1.95)	(-5.91)
Vol	-0.123	0.058
	(-0.60)	(0.14)
Skew	0.000	-0.008*
	(0.11)	(-1.69)
Max	0.046	0.184
	(0.75)	(1.54)

Ivol	-0.419**	-0.276
	(-2.27)	(-0.55)
Constant	0.103***	0.159***
	(5.06)	(3.56)
Fund and Time FE	Y	Y
N	63896	26316
adj. R^2	0.069	0.082

Table 11 The predictability of price path convexity on future fund performance

In this table, we conduct a 5x5 double sorting of mutual funds on return over past 12 months and convexity and report the average performance for each group. Fund performance is measured by net return in Panel A, CAPM alpha in Panel B, Fama-French 3 Factor alpha in Panel C, and Fama-French-Carhart 4 Facotr alpha in Panel D. Standard errors for testing the difference between high-return/convexity and low-return/convexity groups are adjusted by Newey-West with 3 lags. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Convexity						
Ret_12m	L	2	3	4	H	High-Low	T
				Panel A: Raw Return			
L	0.73	0.64	0.85	0.57	0.75	-0.04	(-0.36)
2	1.00	0.90	0.80	0.84	0.82	-0.13	(-1.44)
3	0.91	0.95	0.89	0.87	1.05	-0.04	(-0.36)
4	1.06	1.05	1.10	0.99	1.00	0.03	(0.30)
H	1.15	1.19	1.15	1.23	1.23	0.04	(0.56)
High-Low	0.41**	0.46***	0.33**	0.51***	0.48***		
T	(2.47)	(2.65)	(2.00)	(3.21)	(2.98)		
				Panel B: CAPM			
L	-0.26	-0.22	-0.17	-0.30	-0.33	-0.03	(-0.23)
2	0.00	-0.06	-0.08	-0.05	-0.14	-0.12	(-1.23)
3	0.03	-0.01	0.00	0.01	0.03	-0.01	(-0.12)
4	0.06	0.12	0.17	0.07	0.12	0.08	(0.80)
H	0.20	0.26	0.25	0.31	0.29	0.05	(0.56)
High-Low	0.43***	0.47***	0.37**	0.55***	0.52***		
T	(2.60)	(2.76)	(2.33)	(3.28)	(3.11)		
				Panel C: FF3			
L	-0.27	-0.24	-0.18	-0.27	-0.29	-0.02	(-0.17)
2	-0.02	-0.08	-0.09	-0.06	-0.14	-0.10	(-1.16)
3	0.04	-0.02	-0.01	0.00	0.04	-0.01	(-0.10)
4	0.06	0.13	0.17	0.09	0.13	0.08	(0.81)
H	0.24	0.27	0.25	0.35	0.32	0.06	(0.71)
High-Low	0.49***	0.52***	0.40**	0.59***	0.57***		
T	(3.05)	(2.99)	(2.56)	(3.64)	(3.51)		
				Panel D: Carhart			
L	-0.09	-0.10	-0.02	-0.18	-0.22	-0.07	(-0.60)
2	0.03	-0.01	-0.03	0.00	-0.09	-0.08	(-0.91)
3	0.02	-0.01	0.00	0.02	0.04	0.02	(0.18)

4	-0.03	0.05	0.09	0.01	0.08	0.11	(1.09)
H	0.10	0.11	0.08	0.17	0.13	0.02	(0.28)
High-Low	0.19	0.23	0.12	0.30**	0.31**		
T	(1.40)	(1.62)	(0.89)	(2.12)	(1.97)		