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Beyond Returns: The Impact of Price Path Convexity on Mutual Fund Flows

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Abstract

Do mutual fund investors rely on sophisticated analysis, or do they chase intuitive signals? This paper uncovers a compelling new factor influencing investor behaviour: price path convexity. We find that mutual fund flows respond positively to convexity, a measure capturing the trajectory of a fund's net asset value (NAV). A one-standard-deviation increase in convexity leads to a 0.34% rise in mutual fund flows, with this effect doubling to 0.69% when fund returns are smooth. The relationship holds across both active and passive funds and is particularly strong among less sophisticated investors. Our results offer new insights into capital allocation decisions and underscore the power of simple yet influential performance signals in mutual fund investing.

JEL Classifications: G10; G23; G40; G41

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

1. Introduction

Earlier finance literature assumes 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 capital accordingly (e.g. Berk and Green, 2004; Berk and van Binsbergen, 2016; Barber, Huang, and Odean, 2016; Franzoni and Schmalz, 2017). More recent studies show that mutual fund investors rarely engage in sophisticated learning either due to limited financial sophistication (Ben-David et al., 2022) or because they derive minimal benefits 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 assess managerial skill and make capital allocation decisions.

In this paper, we argue that price path — the historical movement of a mutual fund's net asset value (NAV) — contains valuable information readily available to investors, thus affecting their capital allocation decisions. The history of a mutual fund's NAV, i.e. price path, is usually presented on fund management company websites, brokerage platforms, and third-party professional information vendors, typically depicted alongside historical returns. However, past returns and Morningstar ratings do not fully capture how a fund's NAV has evolved over time. Past returns reflect how a fund's NAV has changed over a given period by comparing the closing NAV to the beginning NAV of the period. And Morningstar rating is based on returns aggregated over the sample period. Neither of these metrics captures the NAV trajectory, that is, how the NAV has travelled within return intervals[2]. Prior research suggests that information contained in the

[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.

price trajectory 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, Grosshans and Zeisberger (2018) find that investors prefer the stock first falling in value over the stock first rising in value by examining how investors react to different stock price paths with equal returns over a given period.

Measuring price path quantitatively is challenging, since its shape varies significantly across different funds and time periods. In this paper, we adopt the price path convexity measure from Gulen and Woeppel (2024), where it is originally used to measure extrapolative expectations of stock returns. The convexity of price path is an easily perceivable and informative performance signal to investors. In our context, the price path convexity is measured as the average value of the closing and beginning NAVs over a given period (e.g., five years), minus the average of all monthly NAVs, then scaled by the average monthly NAV of the period. A positive convexity indicates 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 convexity indicates 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 flow-rating) relation in mutual funds primarily focus on cross-sectional difference. These studies show that mutual funds with higher past returns or ratings receive more inflows[3]. Price path convexity, however, captures an overlooked dimension of performance signal: the trajectory of a fund's NAV, which depicts how a fund's recent return is compared to its distant return. This dimension is likely a determinant of

[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.

fund flows because investors not only chase trend (Bailey, Kumar, and Ng, 2011) but also pay attention to how asset returns are achieved (Grosshans and Zeisberger, 2018).

Our empirical analysis documents a statistically and economically significant positive impact of price path convexity on mutual fund flows. A one-standard-deviation increase in convexity leads to an average 0.34% increase in monthly mutual fund flows, with this effect doubling to 0.69% when fund returns are smooth. Robustness tests confirm that this relationship holds across alternative measures and time horizons. Even when controlling for Morningstar ratings and employing market-share-adjusted flow measurements, the impact of convexity remains significant. Our findings suggest that price path convexity provides additional information beyond fund ratings and is not merely a variation of the convex flow-performance relationship found in prior studies (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Fant and O'Neal, 2000; Huang, Wei, and Yan, 2007).

We conduct several analyses to consolidate the underlying mechanism of investors' response to price path. First, we examine how the perceived informativeness of price path affects the flow-convexity relation. We employ the volatility of returns during the convexity measurement period as a proxy for the perceived informativeness, as volatile past returns make investors relying less on information embedded in the past returns (Huang, Wei, and Yan, 2022). 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 is high. In mutual funds with less volatile returns, a one-standard deviation increases in the convexity, on average, leads to a 0.69% increase in monthly mutual fund flows.

Second, we investigate whether the flow-convexity relation is driven by investors' preference for individual stocks or extrapolation behaviour documented in the stock market (Da, Huang, and Jin, 2021). Investors who prefer high-convexity stocks might invest in mutual funds rather than purchasing them individually. To rule out this clientele effect, we retrieve quarterly mutual fund holdings data and construct portfolio-level convexity measures for each fund. We include these measures in our baseline regression and find that the flow-convexity relation cannot be explained by extrapolating behaviour in the stock market. The results demonstrate the direct signalling role of the fund price path.

Thirdly, we examine whether the flow-convexity relation reflects sophisticated investor learning as suggested by earlier literature such as Berk and Green (2004), Berk and van Binsbergen, (2016) and Barber, Huang, and Odean, (2016), or naïve performance chasing according to Ben-David et al., (2022) or Schwarz and Sun (2023). 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 passive fund samples and document similar impact of price path convexity on fund flows. In addition, we adopt mutual fund expense ratio, turnover ratio, dividend payout, and CRSP's flag of retail funds as proxies for investor sophistication. We show that the flow-convexity relation is more pronounced for funds with more unsophisticated investors. Finally, we investigate whether convexity predicts future fund performance. We find that funds with high convexity do not outperform in the future, regardless of whether the performance is measured by net return or alphas from different asset pricing models. This result reinforces the notion that the flow-convexity relation reflects naïve performance chasing rather than rational learning.

This paper provides new insights into mutual funds investor's capital allocation process. Prior studies such as Berk and Green (2004), Berk and van Binsbergen (2016), and Barber et al. (2016) impliy investors are rational agents who employ asset pricing models to learn managerial skills, on contrast, 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 (Del Guerciao and Tkac 2008; Ben-Rephael, Kandel, and Wohl, 2012; Greenwood and Shleifer, 2014; Reuter and Zitzewitz, 2021; Ben-David et al., 2022). We also show that responding to simple performance signals however does not deliver abnormal returns to unsophisticated investors.

This paper also contributes to the literature by introducing price path convexity as a determinant of investors' capital allocation. 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 heterogenous preference (Wang and Young, 2020; Han, Sui and Yang, 2023). Our paper adds to this strand of literature by demonstrating that price path convexity, a long-overlooked performance signal, which measures the trajectory of mutual fund performance, affects mutual fund flows significantly.

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 essential 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 and demonstrates that price paths of funds significantly affect unsophisticated 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 baseline results and robustness tests. Section 4 investigates the mechanism of the impact of price path convexity on fund flows. Section 5 concludes.

2. Methodology and data

2.1 Price path signals

Existing literature typically assumes that mutual fund investors are rational agents with a significant degree of financial literacy, enabling them to engage in sophisticated learning about investment skill. For example, in Berk and Green (2004), mutual fund investors assess managerial skill based on alpha and allocate capital to funds with a positive alpha. Similarly, Pástor and Stambaugh (2012) suggest that mutual fund investors recognize the presence of decreasing returns to scale in active mutual funds and incorporate this understanding into their learning process.

However, given that the majority of mutual fund investors are households[4], empirical evidence provides a different perspective. According to Lusardi and Mitchell (2007), most households are not financially educated and show little understanding about basic investment concepts like compounding returns, risk, diversification, and inflation. Using a survey of individual investors, Choi and Robertson (2020) find that retail investors learn skills from mutual fund past returns and do not understand the well-documented diseconomies of scale in the active fund management industry[5]. Moreover, several studies have documented investors' simplistic decision-making behaviour, including their susceptibility to sentiment (Ben-Rephael et al., 2012; Greenwood and Shleifer, 2014) and sales channels (Bergstresser et al., 2008), as well as their tendency to chase past performance naïvely (Chevalier and Ellison, 1997). Furthermore, mutual fund investors heavily rely on fund ratings (Del Guercio and Tkac, 2008; Evans and Sun, 2021;

[4] According to information from the 2022 Investment Company Institute (ICI) Fact Book (available at https://www.ici.org/system/files/2023-05/2023-factbook.pdf), over 88% of equity mutual fund shares were held by households at 2022. 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.

Reuter and Zitzewitz, 2021; Ben-David et al., 2022) and respond to advertisements in the 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 base their capital allocation decisions on simple signals like past returns and fund ratings rather than advanced performance measures like, 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 evolution of a mutual fund's price path. Intuitively, the visual representation of an NAV path conveys information beyond what returns and ratings reflect, as these do not capture how the fund's price evolves over time. To illustrate this, we present hypothetical price paths for two mutual funds in Figure 1. Panel A shows two funds that generate the same overall return of zero but experience different 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 declines, whereas Fund Y's NAV decreases initially and then recovers. Panel B presents a scenario where both funds achieve a positive return over the period; however, Fund X's return slows down in the latter half, while Fund Y's return accelerates. Despite having identical overall returns, investor responses to these two funds are likely to differ due to the distinct information embedded in their price paths.

[Insert Figure 1 here]

In reality, price paths are far more complex than the hypothetical cases in Figure 1. Their shapes can vary significantly across funds and time periods, making them challenging to quantify with a single measure. In this paper, we focus on a simple yet meaningful aspect of price path by using convexity, following the approach of Gulen and Woeppel (2024). 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. We then calculate the average of all month-end NAVs within these period, defined as P_{avg}. For inclusion in our sample, a fund must have at least three years of observations within the five-year window. 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 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). Conversely, a negative 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 provides a continuous and dynamic perspective, capturing information beyond what is reflected in returns and ratings.

2.2 Fund flows

We use fund flows to measure investors' allocation of capital among mutual funds. We follow the literature to calculate the net flow into fund *i* in month *t*, denoted by $Flow_{i,t}$, as follows:

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

In Eq. 2, $TNA_{i,t}$ is the total net asset of fund *i* at the end of month *t*, and $r_{i,t}$ is the net return of fund *i* in month *t*.

2.3 Sample description

Our initial sample consists of all US mutual funds in the Center for Research in Security Prices (CRSP) Survivor Bias-Free Mutual Fund Database, covering the period from 1980 to 2023. We focus our analysis on domestic actively managed equity funds. Following Kacperczyk, Sialm, and Zheng (2008) and Doshi, Elkamhi, and Simutin (2015), we select the funds 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, G-I, GCI, IEQ, LTG, MCG, SCG. All these codes are available in the CRSP mutual fund database. We exclude international funds, balanced funds, sector funds, bond funds, money market funds, target date funds[6], passive funds (including ETFs), and leveraged and inverse funds[7]. Our final sample includes 527,524 fund-month observations, covering the period from 1980 to 2023, and comprises a total of 3,806 unique actively managed mutual funds.

We obtain fund returns, expenses, NAVs, investment objectives, and other fund characteristics from the CRSP mutual fund database. Most funds have multiple share classes, which primarily differ in the fee structure and the target clientele. We consolidate 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 calculate their TNA-weighted averages 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.

[6] 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.

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

We also match our sample with the Morningstar database using CUSIP and TICKER identifiers. We extract historical fund ratings spanning from 1980 to 2023, labeled as "Morningstar Overall Rating". The 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 52% of the unique funds and over 56% of the observations.

In our extended analysis, we use samples of passive funds and sector funds to infer the mechanism behind investors' response to price path convexity. We follow the methodologies of Dannhauser and Pontiff (2019) and Ben-David et al. (2022) to identify passive funds in the CRSP Mutual Fund database, with slight modifications to their approaches. A fund is classified as a passive fund if it meets at least one of the following criteria: (1) it is identified by a relevant keyword in its name[8], or (2) it is flagged as passive by CRSP[9]. We define sector funds using CRSP target codes (*crsp_obj_cd* = "EDS*"). All 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. On average, mutual funds in our sample have net flows equivalent to -0.2% to their TNAs, with a standard deviation of 5.7%. The average and median TNAs of mutual funds are about $1,222.6 million and $313.1 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 discrepancy arises because the estimation of price path convexity over a five-year window inherently excludes funds that have

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[8] If the CRSP fund name contains the following strings: SP, DOW, Dow, DJ, ETF, ETN or if the lowercase version of the CRSP fund name contains: index, idx, indx, composite, nyse, nasdaq, s&p, s and p, s & p, ishares, exchange traded, exchange-traded, 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.

[9] If the CRSP index_fund_flag equal to D or B, or et_flag is not missing.

existed for less than five years. Nonetheless, this bias is expected to have a negligible impact on assessing how convexity affects mutual fund flows[10].

[Insert Table 1 here]

[10] We also conduct robustness tests where we calculate the price path convexity over one-year and three-year windows. The results still hold.

3. The impact of price path convexity on mutual fund flows

3.1 What information does price path convexity capture?

The extant flow-performance literature typically focuses on the cross-section heterogeneity of funds (e.g. Chevalier and Ellison, 1997, Sirri and Tufano, 1998, Bergstresser and Poterba, 2002, Del Guercio and Tkac, 2008, and Reuter and Zitzewitz, 2021). These studies find that funds with better performance receive higher inflows. We begin our empirical analysis by showing that price path convexity captures the key information examined in prior studies with potentially additional insights that may have been overlooked.

First, we regress convexity on past annual returns to show that price path convexity captures the history progression of fund performance. *Return* $[-t_1, -t_2]$ denotes the cumulative return between month t_1 and t_2 prior to the month when convexity is estimated. The coefficients are positive and statistically significant in the first two columns, where we regress convexity on the most recent annual returns, suggesting that better recent returns lead to a higher convexity. By contrast, in columns 3 to 5, the coefficients are negative and statistically significant when convexity is regressed on distant annual returns. 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. In column 7, we include a set of observable price path characteristics, including the standard deviation of monthly returns (*Volatility*), skewness of monthly returns (*Skewness*), maximum value of monthly return (*Maximum*), the distance between the highest NAV and current NAV (*End_to_Highest*), the distance between the current NAV and lowest NAV (*End_to_Lowest*), and the fraction of time that the NAV is below the initial NAV (*Loss_Domain*) during the period the convexity is calculated. Convexity is significantly correlated with most variables. Specifically, a high convexity corresponds to a price path marked by lower volatility, higher skewness, a stronger recovery from its lowest NAV, and a larger loss interval, together adding a marginal increase to explanatory power R^2.

Overall, high convexity implies an improving price trajectory, where recent and distant returns accounting for a substantial portion of the explanatory power (R^2=0.779). Additionally, convexity encompasses further observable characteristics of the price path, as shown in our regression results, while also likely capturing some unobservable or omitted aspects.

[Insert Table 2 here]

Then, we use a 5x5 double sorting method to examine whether the trajectory of funds' NAV complements the cross-sectional fund heterogeneity in explaining the differences in mutual fund flows. We sort our sampled funds into 25 return-convexity groups based on their returns over the past year and the price path convexity measures, then report the average fund flow for each group in Table 3. Consistent with previous flow-performance studies, the results in Table 3 show that high-return fund quintiles attract more fund flows than low-return quintiles. The fund flow of the highest return quintile is at least 1.75% 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 1.57%, compared to an average fund flow of 0.33% of funds with the bottom 20% convexity (the lowest convexity quintile). The difference of 1.25% in flows between these groups is both statistically and economically significant. Similar results are observed for other return quintiles[11].

[Insert Table 3 here]

[11] In untabulated results, we also conduct a 10x10 double sorting on 1-year return and convexity, 5x5 double sorting on 3-year(5-year,6-month,3-month,1-month) return and convexity. The results are consistent.

In summary, the results in this section show that price path convexity captures a historical 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 Baseline results

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

$$Flow_{i,t} = \alpha + \beta Convexity_{i,t-1} + \sum_{j=1}^{k} \gamma Controls_{i,t-1}^{k} + w_i + \mu_t + \varepsilon_{i,t} \quad (3)$$

where $Flow_{i,t}$ is the net capital flow to fund *i* at time *t* estimated using Eq. (2) and $Convexity_{i,t-1}$ is the convexity measure for fund *i* at time *t-1* using Eq. (1). $Controls_{i,t-1}$ are a series of control variables that may affect mutual fund flows, including fund-level characteristics like fund annual returns in each year of the five-year window (*Return [-t_1, -t_2]*), the natural logarithm of fund TNA (*Log TNA*), the natural logarithm of fund age (*Log Age*), turnover ratio (*Turnover*), expense ratio (*Expense*), and price path characteristics defined in Table 1. We control for fund fixed effect (w_i) and year-month fixed effect (μ_t) and cluster standard errors at both fund level and year-month level to address the potential concern of within-fund and within-time correlations of the regression residuals. The average impact of convexity on fund flows is captured by β. Table 4 reports the baseline regression results.

[Insert Table 4 here]

In Table 4, column 1 reports the regression results without any controls and fixed effects. The results show that funds with higher convexity attract more net flows than funds with lower convexity. Fixed effects are added in column 2, and fund-level control variables are further included in column 3. Results in both columns support a positive impact of convexity on fund flows. Column 4 reports the results of the baseline regression model with fixed effects and the full set of control variables. The results show that a one-standard-deviation increase in the convexity is associated with a 0.34% increase in fund flow. The results are robust when we use Fama-MacBeth regressions with Newey and West adjusted t-statistic 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 because 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 et al., 2022). Lastly, the adjusted R^2, 14.1%, 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 (*MS Rating*) as an additional control variable[12]. The coefficient on convexity is still positively significant at 1%.

To summarize, our baseline results document an economically meaningful positive impact of convexity on mutual fund flows after controlling for a set of fund-level and price path characteristics. Consistent with Grosshans and Zeisberger (2018), the results imply that mutual fund investors not only chase return values, 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. These findings shed light 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

[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 40%. Instead, we include it in a separate regression where necessary throughout this paper.

(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.

3.3 Robustness check

In this section, we conduct a series of 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 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 the past one year and past three years[13], respectively. 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

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

measures of 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 ratings. 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[15].

$$AC(1) = \frac{P_0 + P_5 - 2 \times P_{2.5}}{2 \times P_{2.5}} = \frac{\frac{P_5 - P_{2.5}}{P_{2.5}} - \frac{P_{2.5} - P_0}{P_{2.5}}}{2} \quad (4)$$

$$AC(2) = \frac{P_5 - P_{2.5}}{P_{2.5}} - \frac{P_{2.5} - P_0}{P_0} = \triangle Ret \quad (5)$$

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

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

[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).
[15] The positive magnitude of a one-standard-deviation increase in the alternative measure does not exceed that of our original measure.

to heterogeneity in the fractional specification of fund flows and implies a linear flow-performance relation. Suppose the documented flow-convexity relation is merely a variation of the convex flow-performance relation; it should then vanish 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. 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 here]

4. Mechanism investigation

Our empirical analysis has shown that mutual fund investors rely on signals from the price path for capital allocation decisions. Specifically, funds with high convexity tend to attract higher net flows in subsequent periods. But why might investors favour this particular price path shape? Experimental literature suggests that this preference may be influenced by recency bias, reference point effect, and personal satisfaction, etc. Recency bias and reference points affect investors' perception of assets return and risk (Nolte and Schneider, 2018; Borsboom and Zeisberger, 2020), while satisfaction may impact their utility function (Grosshans and Zeisberger, 2018).

In this section, rather than directly testing these channels, we build on these insights to propose several testable hypotheses. Our aim is to support our primary findings and enhance understanding of how mutual fund investors respond to price path information. We thus re-examine the flow-convexity relation under different levels of signal reliability, within different fund types, and across different investor groups. We also explore its link to stock market extrapolation and assess whether convexity can produce abnormal returns.

4.1 Reliability of price path and the flow-convexity relation

In this subsection, we investigate how the documented flow-convexity relation interacts with the reliability of 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 seems more (less) reliable to investors. We proxy the reliability of price path by the volatility of fund returns. Volatile past returns are signals of non-persistence and noises, and make investors rely less on information embedded in past performance (Huang et al., 2022). We augment our baseline regression by interacting price path convexity with volatility of returns and report our results in Table 7.

[Insert Table 7 here]

In column 1 of Table 7, *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.

It is worth noting that the aggregate coefficient on convexity in column 2 is 0.055. It suggests that, for mutual funds with low return volatility, a one-standard-deviation increase in the convexity is associated with a 0.69% increase in fund flow. This doubles the average impact of convexity on mutual fund flow observed in our entire sample. Overall, our results in this subsection reveal that mutual fund investors rely on signals from price path to make their investment decisions, and their reliance on such signals varies with the reliability of price path.

4.2 Ruling out clientele effect

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 extrapolative investors rather than mutual fund investors' response to performance signals.

To address this concern, we retrieve quarterly mutual fund holdings data from the Thomson

Reuters database and calculate the convexity for each of the stocks in the same way as we calculate the convexity for the fund. Then, we define two variables that measure the fund portfolio convexity. The first variable, *Cov_Stock (max)*, is the convexity of the stock with the highest price path convexity in the fund's most recently disclosed portfolio. The second variable, *Cov_Stock (weighted)*, is the weighted average convexity of the stock in the fund's most recently disclosed portfolio. We include these two variables as additional controls and repeat our baseline regression. If the flow-convexity relation reflects the clientele effect, then we would find that this relation no longer exists after adding these controls. We report our results in Table 8.

[Insert Table 8 here]

In Table 8, column 1 presents the regression result where we regress fund flows on the convexity and *Cov_Stock (max)*, with fixed effects only. Column 2 presents the regression result where we regress fund flows on the convexity and *Cov_Stock (weighted)*, again with fixed effects only. In column 3, we include both portfolio convexity measures in the regression. In column 4, we incorporate a full set of controls and fixed effects. In column 5, we add Morningstar ratings as an additional control. In all cases, the coefficient on the fund convexity remains positive and statistically significant[16]. To summarize, the results in Table 8 indicate that the mutual fund flow-convexity relation reflects investors' response to fund performance itself rather than stock market extrapolation.

4.3 Results on other funds

Investors' response to fund performance can be attributed to either mutual fund investors' sophisticated learning about alpha, as suggested by the literature (e.g. Berk and Green, 2004;

[16] We remove the recent annual return in these specifications due to its high collinearity with *Cov_Stock (weighted)*, which could affect the direction of *Cov_Stock (weighted)*'s coefficient. However, including it does not impact the *Convexity* coefficient.

Barber, Huang, and Odean, 2016; Franzoni and Schmalz, 2017), or investors' naïve performance chasing, as proposed Ben-David et al. (2022). In the same spirit as Ben-David et al. (2022), we examine the flow-convexity relation in passive funds to investigate which alternative the flow-convexity reflects. If the flow-convexity relation reflects investors' sophisticated learning, then the flow-convexity relation should not be observed in passive funds, because there is little or no investment skill for investors to learn about in passively managed funds[17]. We estimate the baseline specification given by Eq. 3 for passive funds and report the results in Table 9.

[Insert Table 9 here]

In Table 9, column 1 reports the regression result for the baseline specification using a sample of passive funds. The coefficient on convexity is positive and statistically significant. In column 2, we run the baseline specification using a sample of sector funds. The coefficient on convexity again is positive and statistically significant. Our results thus suggest that investors also value the convexity when choosing passively managed funds, and our results support the notion that the flow-convexity relation is due to naïve performance chasing behaviour of unsophisticated investors.

4.4 Cross-sectional analysis on investor sophistication

The results in the previous subsection indicate that the flow-convexity relation reflects performance-chasing behaviour by unsophisticated mutual fund investors. If this is the case, we will observe that the relation is more pronounced in mutual funds with more unsophisticated investors. To test this hypothesis, we augment our baseline specification and interact the convexity with variables that proxy the level of investor sophistication, including expense ratio, turnover,

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

dividends, and retail funds. We report the results in Table 10.

[Insert Table 10 here]

In column 1 of Table 10, we use turnover ratio as a proxy for the level of investor sophistication. *High_turnover* is a dummy variable that takes one if the fund's turnover ratio is above the 25th percentile, and zero otherwise. In column 2, we use expense ratio as a proxy for the level of investor sophistication. *High_expense* is a dummy variable that takes one if the fund's expense ratio is above the 25th percentile, and zero otherwise. Turnover ratio and expense ratio are commonly used in the literature as proxies for investor sophistication (e.g. Gil-Bazo and Ruiz-Verdú, 2009; Bailey et al., 2011; Huang et al., 2022). In column 3, the proxy for investor sophistication is dividend. *High_div* is a dummy variable that takes one if the fund's dividend ratio is above the 25th percentile, and zero otherwise. Harris et al. (2015) show that unsophisticated investors prefer mutual funds with high dividends. In column 4, we leverage CRSP's identification of retail funds. *Retail* is a variable that takes one if the fund is flagged as a retail fund, and zero otherwise. For funds with multiple share classes with different retail flags, *Retail* is the TNA-weighted average of those share classes.

In the first three columns, investors of any funds that are identified as high-turnover funds, high-expense funds, or high-dividend funds are more likely retail investors and thus unsophisticated. We use the 25th percentile as the cut-off point because it is consistent with the empirical evidence that most mutual fund investors are households[18]. Consistent with our expectation, we find that all interaction terms between the unsophistication indicators and price path convexity are positive and statistically significant. The results suggest that the flow-convexity

[18] As presented in footnote 4, over 88% of equity mutual fund shares were held by households in 2022, and about 79% of the assets of all mutual funds were held by households. In addition, according to Morningstar's identification of retail funds, there are about 24.38% funds in our sample identified as pure institutional funds (i.e. funds without any share class identified as retail).

relation is more pronounced in funds with more unsophisticated investors. Hence, the flow-convexity relation is most likely driven by naïve performance chasing.

4.5 Performance predictability of convexity

A naïve performance chasing strategy is unlikely to generate superior performance. In this subsection, we conduct a univariate analysis to examine whether investors achieve better investment outcome through investing in high-convexity mutual funds.

Each month, we sort funds into quintiles by price path convexity. Then, we estimate future fund performance, measured by net return, the CAPM alpha, and the Carhart 4-Factor alpha, for each fund group in the next two months. We compute the difference in future fund performance between the group with the highest convexity and the group with the lowest convexity and report the results in Table 11.

[Insert Table 11 here]

Panel A of Table 11 reports the fund performance in the next month. The results show no significant variation across the convexity groups, regardless of how performance is measured. The difference in fund performance between the highest convexity group and the lowest convexity group is also statistically insignificant. In the presence of diseconomies of scale, the results in Panel A may reflect the diminishing impact of additional flows on fund performance documented in the previous literature (e.g. Chen et al., 2004; Yan, 2008; Zhu, 2018). To rule out this concern, we examine fund performance in the second month in Panel B and obtain similar results.

To summarize, our results in this subsection show that convexity does not predict future fund performance. Investors who rely on price path convexity in their capital allocation among mutual funds are unlikely to achieve better investment outcomes. Hence, the flow-convexity relation reflects naïve performance chasing by unsophisticated investors.

5. Conclusion

Recent studies show that mutual fund investors are of limited financial sophistication, and they tend to follow simple performance signals. They do not engage in sophisticated learning about mutual fund skill, as early theoretical and empirical studies in this field suggested. Instead, they focus on 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 trajectory, which is an important, simple and easily accessible performance signal. We find that a one-standard-deviation increase in price path convexity leads to a 0.34% increase in mutual fund flows on average and this impact rises to 0.69% when fund returns are smooth. The positive relation between price path convexity and mutual fund flows is robust to different horizons and alternative measures.

In addition, we show that the flow-convexity relation is weaker when the price path is more volatile. Our further analysis on the convexity of mutual fund holdings reveals that the flow-convexity relation reflects investors chasing mutual fund performance, rather than using funds as a diversification vehicle to hold high-convexity stocks. The effect of convexity on fund flows also presents in passively managed funds and is more pronounced in mutual funds with more unsophisticated investors. All indications suggest that the flow-convexity relation is driven by naïve performance chasing by investors, and as a result, such performance chasing does not lead to superior future performance.

The empirical findings in this paper contribute to the growing literature on how mutual fund investors, as unsophisticated agents, make their investment decisions. Our findings also have implications for regulators and financial professionals regarding information communication and retail investor protection.

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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.

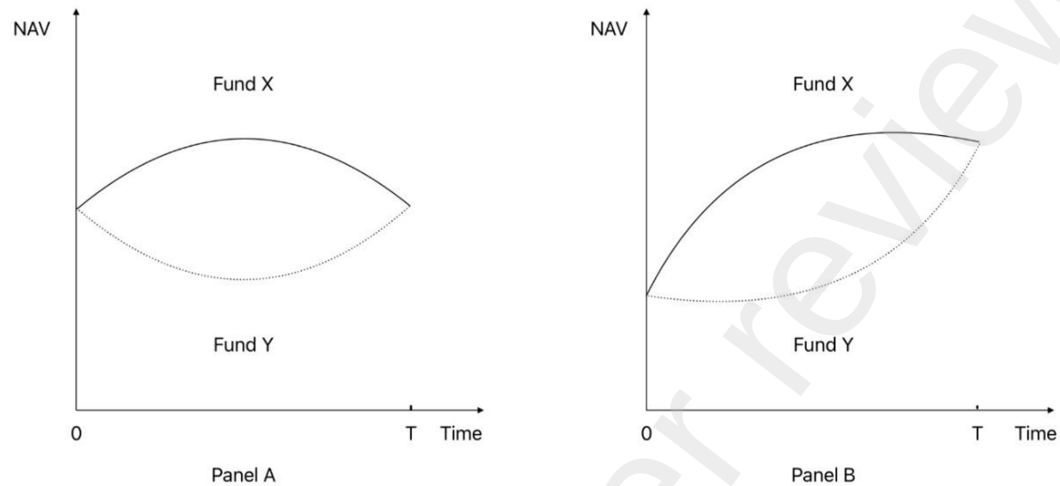

Table 1 Summary Statistics

This table reports the definition and summary statistics of involved variables. Our sample includes 3,806 mutual funds over the period from 1985 to 2023. All continuous variables are winsorized at 1% and 99%.

Variable	N	Mean	Std	P25	P50	P75	Definition
Flow	527524	-0.002	0.057	-0.015	-0.006	0.005	See Equation (1).
Convexity	527524	0.002	0.125	-0.068	-0.003	0.069	See Equation (2).
Return [-1.-12]	527524	0.092	0.191	-0.011	0.096	0.196	Cumulative return from 1 to 12 months prior.
Return [-13.-24]	527524	0.099	0.191	-0.004	0.104	0.203	Cumulative return from 13 to 24 months prior.
Return [-25.-36]	527524	0.108	0.190	0.007	0.110	0.209	Cumulative return from 25 to 36 months prior.
Return [-37.-48]	527524	0.098	0.179	0.003	0.106	0.199	Cumulative return from 37 to 48 months prior.
Return [-49.-60]	527524	0.104	0.180	0.009	0.111	0.204	Cumulative return from 49 to 60 months prior.
TNA	527524	1222.60	2807.20	88.30	313.10	1026.55	Total net assets (TNA) as of quarter-end, in millions.
Month Age	527524	170.58	89.44	99.00	148.00	222.00	Fund age, in months.
Turnover	527524	0.584	0.683	0.120	0.410	0.800	Fund Turnover Ratio, provided by CRSP.
Expense	527524	0.009	0.006	0.006	0.010	0.013	Fund Expense Ratio, provided by CRSP.
Volatility	527506	0.047	0.017	0.036	0.045	0.056	Standard deviation of monthly returns.
Skewness	527506	-0.447	0.482	-0.694	-0.393	-0.157	Skewness of monthly returns.
Maximum	527506	0.118	0.050	0.086	0.111	0.140	Maximum of monthly returns.
End_to_Highest	527506	0.332	0.737	0.032	0.146	0.381	Distance between the highest NAV and current NAV, scaled by current NAV.
End_to_Lowest	527506	0.314	0.163	0.196	0.321	0.432	Distance between the lowest NAV and current NAV, scaled by current NAV.
Loss Domain	527506	0.334	0.318	0.050	0.233	0.583	Fraction of time that the NAV is below the initial NAV

Table 2 The Relation between Convexity and Past Returns

This table reports panel regressions of convexity on other price path characteristics. The variables are defined in Table 1. All the regressions include an intercept, fund fixed effect and year-month fixed effect. Robust standard errors are clustered at both fund level and year-month 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)	(7)
Dependent variable:				*Convexity t+1*			
Return [-1.-12]	0.377***					0.376***	0.219***
	(30.62)					(49.14)	(26.58)
Return [-13.-24]		0.169***				0.142***	0.068***
		(10.20)				(16.86)	(8.61)
Return [-25.-36]			-0.042**			-0.026***	-0.034***
			(-2.11)			(-4.27)	(-5.07)
Return [-37.-48]				-0.223***		-0.187***	-0.148***
				(-12.61)		(-25.63)	(-18.61)
Return [-49.-60]					-0.363***	-0.361***	-0.267***
					(-25.85)	(-33.57)	(-23.55)
Volatility							-0.812***
							(-4.13)
Skewness							0.004*
							(1.82)
Maximum							0.011
							(0.28)
End_to_Highest							-0.001
							(-0.69)
End_to_Lowest							0.339***
							(35.24)
Loss Domain							0.132***
							(30.72)
Cons	-0.033***	-0.015***	0.007***	0.024***	0.040***	0.012***	-0.091***
	(-28.70)	(-8.86)	(3.15)	(13.90)	(27.37)	(4.78)	(-14.88)
Fund FE	Y	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y
N	527524	527524	527524	527524	527524	527524	527506
adj. R2	0.657	0.586	0.568	0.598	0.647	0.779	0.843

Table 3 Double Sorting on Past Return and Convexity

We report the average mutual fund flows of 5×5 double sorting return-convexity groups. We require the number of funds in each group in each month is at least 25. In the last column (row), we report the difference in fund flows between the fund group with the highest convexity (return) and the fund group with the lowest convexity (return). 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.

Mutual Fund Flow t+1						
One-year return Group	*Convexity Group*					
	1 (Low)	2	3	4	5 (High)	High-Low
1 (Low)	-1.41	-1.17	-0.99	-0.92	-0.82	0.59***
	(-18.16)	(-15.81)	(-12.74)	(-8.99)	(-8.74)	(5.95)
2	-0.88	-0.59	-0.52	-0.51	-0.50	0.38***
	(-11.67)	(-9.91)	(-9.09)	(-8.29)	(-4.19)	(2.67)
3	-0.63	-0.31	-0.20	-0.12	-0.19	0.44***
	(-7.46)	(-3.99)	(-3.00)	(-1.96)	(-2.36)	(4.48)
4	-0.25	-0.12	0.13	0.25	0.19	0.44***
	(-2.27)	(-1.40)	(1.74)	(2.66)	(1.84)	(3.23)
5 (High)	0.33	0.81	0.87	1.08	1.57	1.25***
	(2.01)	(4.70)	(6.58)	(8.49)	(9.62)	(8.21)
High-Low	1.75***	1.99***	1.86***	2.00***	2.39***	
	(10.32)	(10.29)	(11.70)	(13.59)	(13.39)	

Table 4 Baseline Results

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

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			*Flow t+1*		
Convexity	0.032***	0.053***	0.026***	0.027***	0.027***
	(11.79)	(14.09)	(7.85)	(7.09)	(6.45)
Return [-1.-12]			0.068***	0.064***	0.060***
			(18.22)	(16.48)	(13.94)
Return [-13.-24]			0.034***	0.030***	0.023***
			(12.43)	(10.47)	(7.66)
Return [-25.-36]			0.033***	0.030***	0.019***
			(14.01)	(12.03)	(7.00)
Return [-37.-48]			0.027***	0.023***	0.018***
			(12.89)	(10.28)	(7.39)
Return [-49.-60]			0.021***	0.017***	0.010***
			(9.93)	(7.72)	(4.00)
Log TNA			-0.006***	-0.007***	-0.007***
			(-18.87)	(-19.42)	(-20.36)
Log Month Age			-0.014***	-0.014***	-0.012***
			(-7.45)	(-7.27)	(-4.81)
Turnover			0.001	0.001**	0.000
			(1.42)	(1.97)	(0.35)
Expense			0.456***	0.450***	0.299***
			(6.50)	(6.43)	(4.31)
Volatility				-0.097*	0.114
				(-1.78)	(1.62)
Skewness				0.000	-0.001
				(0.12)	(-1.54)
Maximum				-0.004	-0.011
				(-0.33)	(-0.73)
End_to_highest				0.001**	0.001
				(2.12)	(0.87)
End_to_lowest				0.010***	0.004
				(3.79)	(1.37)
Loss_domain				-0.006***	-0.003***
				(-5.50)	(-2.80)
MS Rating					0.009***
					(27.42)
Cons	-0.002***	-0.002***	0.082***	0.086***	0.048***
	(-6.73)	(-212.76)	(8.40)	(8.91)	(3.86)
Fund FE		Y	Y	Y	Y
Year-month FE		Y	Y	Y	Y
N	527524	527524	527524	527506	294927
adj. R^2	0.007	0.073	0.141	0.141	0.178

Table 5 Robustness Check: Alternative Convexity Measures

This table reports robustness check regressions of mutual fund flows in the next period on alternative convexity measures. Column 1 presents the regression where we measure convexity using a 1-year window. Column 2 reports the regression where we measure convexity over a 3-year window. Column 3 presents the regression where we use the alternative measure AC1, denoted by Eq. 4. Column 4 presents the regression where we use the alternative measure AC2, denoted by Eq. 5. Column 5 presents the regression where we use the alternative measure AC3, denoted by Eq. 6. In column 6, we construct an orthogonal version of the convexity variable by running monthly cross-sectional regressions of the price path convexity against Morningstar rating. The full set of control variables used in the baseline regression are included but not reported. Robust standard errors are clustered at both fund level and year-month 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)
Dependent variable:			*Flow t+1*			
Convexity 1yr	0.040***					
	(5.59)					
Convexity 3yrs		0.026***				
		(6.29)				
AC1			0.004***			
			(2.77)			
AC2				0.005***		
				(5.10)		
AC3					0.006***	
					(3.86)	
Convexity RES						0.029***
						(6.18)
Cons	0.083***	0.082***	0.083***	0.083***	0.083***	0.070***
	(9.55)	(9.31)	(9.28)	(9.29)	(9.33)	(5.19)
Controls	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y
N	522003	527219	527116	527116	527116	341606
adj. R^2	0.078	0.077	0.077	0.077	0.077	0.093

Table 6 Flow-convexity vs. Convex Flow-performance

This table reports baseline regressions 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 fixed effects. Column 2 presents the regression with fund and year-month fixed effects. Column 3 add a set of fund-level controls. Column 4 presents the regression with the full set of controls (fund-level and price path characteristics) and fixed effects. Column 5 add an additional control for Morningstar fund ratings. Robust standard errors are clustered at both fund level and year-month level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	*Market share-adjusted Flow t+1*				
Convexity	0.002***	0.003***	0.002***	0.001**	0.002***
	(6.12)	(6.41)	(3.78)	(2.36)	(3.88)
Return [-1.-12]			0.005***	0.005***	0.004***
			(7.84)	(6.73)	(5.25)
Return [-13.-24]			0.002***	0.001**	0.001
			(3.46)	(2.52)	(1.31)
Return [-25.-36]			0.002***	0.002***	0.001**
			(4.94)	(3.86)	(2.24)
Return [-37.-48]			0.002***	0.002***	0.002***
			(6.12)	(4.80)	(4.36)
Return [-49.-60]			0.001***	0.001***	0.001***
			(3.82)	(2.75)	(2.85)
MS Rating					0.001***
					(13.06)
Cons	-0.000	-0.000***	0.003***	0.004***	0.002*
	(-0.30)	(-7.55)	(5.04)	(5.37)	(1.91)
Controls (Fund)			Y	Y	Y
Controls (Price Path)				Y	Y
Fund FE		Y	Y	Y	Y
Year-month FE		Y	Y	Y	Y
N	519912	519896	519896	519879	336894
adj. R^2	0.001	0.022	0.033	0.034	0.053

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

This table reports the regression results of the flow-convexity relation conditional on the reliability of information embedded in the price path convexity. Column 1 presents the regression 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 presents the regression 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 lowest quartile, and zero otherwise. Robust standard errors are clustered at both fund level and year-month level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Dependent variable:	*Flow t+1*	
Convexity	0.039***	0.025***
	(9.15)	(6.68)
*High_Vol * Convexity*	-0.021***	
	(-6.95)	
High_Vol	-0.001	
	(-1.15)	
*Low_Vol * Convexity*		0.030***
		(7.54)
Low_Vol		0.001**
		(2.10)
Controls	Y	Y
Fund FE	Y	Y
Year-month FE	Y	Y
N	527506	527506
adj. R^2	0.078	0.078

Table 8 The flow-convexity relation and convexity of fund holdings

This table investigates whether the flow-convexity relation reflects a clientele effect in which investors use mutual fund as a vehicle to chase high-convexity stocks. We define two portfolio convexity measures as *Cov_Stock (max)*, which is the convexity of the stock with the highest price path convexity in the fund's most recently disclosed portfolio, and *Cov_Stock (weighted)*, which is the weighted average convexity of the stock in the fund's most recently disclosed portfolio. In column 1 and 2, we regress the fund flows on these portfolio convexity measures respectively. In column 3, we regress the fund flows on both portfolio convexity measures, with fund and year-month fixed effects. Column 4 presents the regression with the full set of controls and the fixed effects. Column 5 includes Morningstar ratings as a control. Robust standard errors are clustered at both fund level and year-month level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			*Flow t+1*		
Convexity	0.053***	0.049***	0.048***	0.028***	0.028***
	(13.53)	(12.23)	(12.30)	(7.03)	(6.65)
Cov_Stock (max)	0.004***		0.001**	0.001	0.000
	(5.28)		(2.13)	(1.26)	(0.29)
Cov_Stock (weighed)		0.019***	0.017***	-0.015***	-0.017***
		(5.62)	(4.77)	(-4.53)	(-4.43)
MS Rating					0.009***
					(26.80)
Cons	-0.003***	-0.004***	-0.004***	0.080***	0.038***
	(-33.71)	(-19.85)	(-20.74)	(7.68)	(3.36)
Controls				Y	Y
Fund FE	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y
N	425494	429712	425494	425478	308594
adj. R^2	0.054	0.054	0.054	0.077	0.105

Table 9 Results on other funds

This table reports the regression results using samples of other funds over the same period of our active mutual fund sample. Column 1 presents the results with a sample of passive funds. Column 2 presents the results with a sample of sector funds. Robust standard errors are clustered at both fund level and year-month level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)
Dependent variable:	*Flow t+1*	
	in Passive Funds	*in Sector Funds*
Convexity	0.015**	0.017***
	(2.09)	(2.79)
Cons	0.089***	0.150***
	(3.71)	(6.87)
Controls	Y	Y
Fund FE	Y	Y
Year-month FE	Y	Y
N	81,499	95,134
adj. R^2	0.047	0.053

Table 10 Cross-sectional analysis on investor sophistication

This table reports the regression results of the flow-convexity relation conditional on investor sophistication. Column 1 presents the regression of the flow-convexity relation for funds with high turnover ratio. *High_turnover* is a dummy variable that takes one if the fund's turnover ratio is above the 25th percentile, and zero otherwise. Column 2 presents the regression of the flow-convexity relation for funds with high expense ratio. *High_expense* is a dummy variable that takes one if the fund's expense ratio is above the 25th percentile, and zero otherwise. Column 3 presents the regression of the flow-convexity relation for funds with high dividends. *High_div* is a dummy variable that takes one if the fund's dividend ratio is above the 25th percentile, and zero otherwise. Column 4 presents the regression of the flow-convexity relation for retail funds. *Retail* is a variable that takes one if the fund is flagged by CRSP as a retail fund, and zero otherwise. For funds with multiple share classes with different retail flags, *Retail* is the TNA-weighted average of those share classes. Robust standard errors are clustered at both fund level and year-month level. *t*-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Dependent variable:	*Flow t+1*			
Convexity	0.022***	0.018***	0.019***	0.015***
	(5.11)	(4.32)	(4.67)	(3.54)
*High_turnover * Convexity*	0.007**			
	(2.04)			
High_turnover	0.000			
	(0.22)			
*High_expense * Convexity*		0.012***		
		(3.41)		
High_expense		0.001*		
		(1.73)		
*High_div * Convexity*			0.016***	
			(5.47)	
High_div			-0.000	
			(-0.20)	
Retail Convexity*				0.020***
				(5.02)
Retail				0.005**
				(2.46)
Cons	0.086***	0.086***	0.086***	0.084***
	(8.90)	(8.87)	(8.87)	(8.66)
Controls	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
N	527506	527506	527506	527506
adj. R^2	0.078	0.078	0.078	0.078

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

We report the value-weighted and equal-weighted average performance (one-month forward in panel A and two-month forward in panel B) of 10 single sorting convexity groups. Fund performance is measured by net (unadjusted) return, CAPM alpha, and Fama-French-Carhart 4 Factor alpha. 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.

Panel A *Convexity Group*	Value-weighted			Equal-weighted		
	Net Return $_{t+1}$	CAPM Alpha $_{t+1}$	Carhart Alpha $_{t+1}$	Raw Return $_{t+1}$	CAPM Alpha $_{t+1}$	Carhart Alpha $_{t+1}$
1 (Low)	0.77	-0.18	-0.07	0.77	-0.18	-0.09
	(3.42)	(-1.91)	(-0.88)	(3.41)	(-2.09)	(-1.25)
2	0.79	-0.13	-0.09	0.82	-0.10	-0.07
	(3.78)	(-2.14)	(-1.73)	(3.96)	(-1.66)	(-1.43)
3	0.84	-0.03	-0.02	0.85	-0.05	-0.04
	(4.28)	(-0.48)	(-0.41)	(4.24)	(-1.04)	(-1.17)
4	0.92	0.03	0.00	0.90	0.00	-0.03
	(4.60)	(0.52)	(-0.01)	(4.45)	(-0.00)	(-0.55)
5 (High)	0.91	0.01	-0.05	0.93	0.02	-0.05
	(4.09)	(0.15)	(-0.56)	(4.24)	(0.27)	(-0.64)
5-1	0.17	0.23	0.06	0.19	0.24*	0.08
	(1.20)	(1.52)	(0.47)	(1.53)	(1.78)	(0.76)

Panel B *Convexity Group*	Value-weighted			Equal-weighted		
	Net Return $_{t+2}$	CAPM Alpha $_{t+2}$	Carhart Alpha $_{t+2}$	Raw Return $_{t+2}$	CAPM Alpha $_{t+2}$	Carhart Alpha $_{t+2}$
1 (Low)	0.75	-0.17	-0.07	0.75	-0.17	-0.08
	(3.34)	(-1.95)	(-0.91)	(3.39)	(-1.98)	(-1.13)
2	0.80	-0.11	-0.08	0.83	-0.09	-0.05
	(3.86)	(-1.92)	(-1.47)	(3.99)	(-1.52)	(-1.19)
3	0.86	-0.01	0.00	0.84	-0.06	-0.07
	(4.42)	(-0.12)	0.00	(4.22)	(-1.30)	(-1.70)
4	0.93	0.03	0.00	0.93	0.01	-0.02
	(4.47)	(0.40)	(-0.05)	(4.42)	(0.16)	(-0.43)
5 (High)	0.87	-0.04	-0.10	0.88	-0.04	-0.11
	(3.86)	(-0.40)	(-1.05)	(3.98)	(-0.41)	(-1.39)
5-1	0.14	0.17	0.00	0.15	0.17	0.00
	(1.02)	(1.13)	(0.02)	(1.17)	(1.21)	(0.01)