Prospect Theory in the Field: Revealed Preferences from Mutual Fund Flows

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Abstract

Using mutual fund flows, we evaluate prospect theory with choice outcomes in the market. We provide strong support for prospect theory: under a standard set of parameters, funds whose past returns generate higher prospect theory value attract significantly larger future flows; we also find corroborative evidence using account-level data. Taking a revealed preference approach, we estimate the prospect theory parameters through a discrete choice model and find that our field-based estimates align well with previous experiment-based estimates. Moreover, we show that prospect theory offers a new framework for understanding flows, as it has explanatory power over and above existing drivers.

Keywords: Prospect Theory, Revealed Preference, Investor Demand, Mutual Funds

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1 Introduction

Prospect theory has become a prominent alternative utility framework that describes investors' decision-making under uncertainty (Barberis and Thaler (2003); Barberis (2013)). It was initially developed by Kahneman and Tversky (1979) and Tversky and Kahneman (1992) to explain the choices observed in the laboratory, from which they derived a set of important parameters to govern the framework. While these parameters are widely adopted in the subsequent literature to explain various asset pricing phenomena, they are rarely confronted with choice outcomes outside of the laboratory, largely due to the scarcity of data.

In this paper, we examine the relevance of prospect theory for decision-making in the mutual funds market. First, we test whether prospect theory can explain the capital allocations by mutual fund investors. Specifically, we examine the link between mutual funds' prospect theory values under the standard parameters and the fund flows which represent the aggregate choices of investors. Second, we conduct a revealed preference exercise to estimate the preference parameters that best explain the fund flows under prospect theory. Lastly, we explore whether prospect theory provides a new behavioral explanation for mutual fund flows, complementing the existing rational or irrational drivers identified in the literature.

Under prospect theory, investors mentally represent gains and losses associated with each investment choice and evaluate them according to the value function in Tversky and Kahneman (1992) that assigns a prospect-theory value to the given distribution of gains and losses. We adopt the empirical framework developed by Barberis et al. (2016) which relies on the distribution of mutual funds' past returns to represent scenarios of gains and losses. This representation is natural and practical since past returns are readily available across a wide range of investment choices. Moreover, historical fund performance serves as the primary source of information investors use to pick mutual funds.

Prospect theory generates clear predictions for mutual fund flows. According to the theory, investors would prefer to allocate capital to funds with high prospect-theory value. If prospect theory captures the behavior of a significant fraction of mutual fund investors, funds with high prospect-theory values would attract larger investor flows, holding other factors constant. Consequently, our main hypothesis is a positive relation between a fund's prospect-theory value and its fund flows.

To test our hypothesis, we construct a measure, termed "TK" after Tversky and Kahneman, of prospect-theory value for each mutual fund at a given time. Intuitively, TK captures the utility of holding the fund by a prospect-theory investor. Empirically, we use a fund's preceding 60 months' realized returns to *represent* the return distribution.[1] We use the risk-free rate as the reference point to compute the gains and losses.[2] We then feed the adjusted returns into the prospect theory value function to derive the TK value, using the standard prospect theory preference parameters in the literature.

Analyzing a large sample of actively managed equity mutual funds in the US, we find strong and robust evidence for the main hypothesis. Mutual funds with high prospect-theory value experience significantly larger future fund flows. Our main results are based on panel regressions using future flows as the dependent variable and TK values as the independent variable. Our results remain robust after we control for several statistics based on past fund performance, including the cumulative returns over the preceding 60 months, abnormal returns under various factor models, and risk factor loadings. We further examine whether specific components of prospect theory (loss aversion, convexity in the gain region versus concavity in the loss region, and probability weighting) have explanatory power for fund flows. We find that each of these components plays a significant role in explaining future fund flows.

Our analysis of fund-level flows captures the aggregate behavior of mutual fund investors. To provide a more granular analysis, we extend our investigation by utilizing data from a large retail brokerage that covers individual investors' positions and trading records. We test whether prospect theory explains individual investors' buy and sell decisions of mutual funds. Using account-level transactions, we confirm that individual investors are more likely to hold and purchase mutual funds

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[1] Common mutual fund data providers, e.g., Morningstar, display fund performance using graphs. The horizon can vary from one year to as many as ten years, with five years being the most common.

[2] As shown in the Appendix, our results are robust to alternative reference points such as zero, market returns, and style benchmark returns.

with high TK values. This indicates that individual investors, in line with prospect theory, exhibit a preference for funds that offer higher prospect-theory values. Overall, our findings confirm that prospect theory, as captured by the TK measure, plays a significant role in shaping investors' choices of mutual funds at both the aggregate level and individual level.

The analyses so far take the parameters governing the prospect theory preference at the standard values (based on experiments) in the literature. Another question that we seek to answer is what values of prospect theory parameters best fit the mutual fund choices of investors. To answer this question, we conduct a revealed preference analysis of fund choices by estimating a discrete choice model. We find strong loss aversion with a magnitude of 1.824, which falls between the traditional consensus of 2.25 for the loss aversion parameter (Tversky and Kahneman (1992)) and 1.31 proposed in recent lab-based studies (Walasek et al. (2018)). Moreover, by leveraging the variation in loss aversion from our quarter-by-quarter estimation, we document that prior investment performance negatively affects the degree of loss aversion, which supports the key assumption in Barberis et al. (2001).

The estimated probability weighting parameters are 0.11 for the gain region and 0.23 for the loss region. These values are lower than those estimated from lab-based studies, suggesting that mutual fund investors are even more subject to overweighting of small probabilities compared to the laboratory settings. The stronger effect of probability weighting observed in the field aligns with the preferences over lottery-like stocks (Kumar (2009)). Furthermore, we estimate the curvature of the utility function to be 0.745, which is within the common range of findings from lab-based studies. Overall, our revealed preferences analysis provides strong support for the hypothesis that investors exhibit prospect theory preferences when allocating capital among mutual funds.

The vast literature on mutual fund flows has accumulated many determinants of fund flows. We demonstrate TK provides significant incremental explanatory power for mutual fund flows in addition to existing rational and behavioral drivers. When compared with alphas, which reflect managers' skills, we find that TK exhibits distinct predictive power for fund flows. We also compare TK with expected utility value (EU) based on power utility and computed using the preceding 60 months' fund returns. The positive relation between TK and fund flow remains significant in the presence of the EU control. It's worth noting the EU value is also significantly and positively related to future fund flows, indicating that both EU and TK have explanatory power for mutual fund flows. This finding matches our prior as mutual fund flows reflect the aggregate choices of investors, and we expect investors to consist of both expected utility and prospect theory decision-makers.

We further distinguish prospect theory from several behavioral explanations of mutual fund flows. We first compare prospect theory to two prevailing behavioral patterns: return extrapolation and salience theory. We confirm that both have significant explanatory power for mutual fund flows, but the predictive power of prospect theory remains strong after controlling for these two behavioral drivers. This highlights the novel information that prospect theory delivers since all three variables are constructed using past mutual fund performance. Several studies demonstrate that investors often naively follow Morningstar Ratings. Controlling for Morningstar Ratings, we find that TK continues to be a robust and strong predictor of fund flows. The existing literature also relies on the maximum or the skewness of fund returns to capture mutual fund investors' lottery preferences. We show that TK has significant incremental predictive power for mutual fund flows.

Furthermore, we find that the significantly positive relation between TK and fund flows reflects non-fully rational behavior of mutual fund investors. First, the effect of TK on flows is stronger among retail investor-dominated funds and broker-sold funds, which are dominated by less sophisticated investors. This is consistent with the idea that retail and less sophisticated investors are more likely to display prospect-theory preference. Second, the explanatory power of prospect theory for mutual fund flows strengthens during periods of high investor sentiment (as measured by the market sentiment index proposed by Baker and Wurgler (2006)) while it drops significantly during recessions. The significant interactions of investor sophistication and sentiment with the explanatory power of prospect theory for mutual fund flows indicate an element of bounded rationality underlying our main findings.

Finally, we find that although funds with high TK values tend to attract more investor capital, they do not subsequently outperform. In fact, we observe a negative association between TK value and future fund performance, further supporting the "dumb money" interpretation of capital flows to funds with high TK. To delve deeper, we decompose fund flows into a TK-driven component and a non-TK-driven component by projecting fund flows on lagged TK. TK-driven flows significantly and negatively predict future fund performance, while non-TK-driven flows positively predict future fund performance. This suggests that mutual fund flows contain both rational and irrational components. Some investors can pick skilled funds, while other investors simply chase funds with high TK value.

Our paper contributes to the prospect theory literature that tests the theory with market data. Recent work along this line of research includes Barberis et al. (2016), Barberis et al. (2021), Grinblatt and Han (2005) and Baele et al. (2019). A related literature evaluates prospect theory by linking investors' trading decisions to asset returns (An (2016); An et al. (2020); An and Argyle (2021)). Diverging from previous research that primarily relies on market prices, our study emphasizes investors' demand and the choices they make when selecting mutual funds. This distinction is crucial because inferences drawn from choices and prices can differ significantly.[3] Prices, as an equilibrium quantity, can be influenced by factors beyond demand. Consequently, relying solely on market prices may obscure inferences about the underlying preferences of investors. In contrast, choices directly reflect individuals' preferences. Thus, studying choices allows us to uncover and analyze investors' preferences more accurately. Our study provides strong support for prospect theory both at the aggregate level and at the individual level. Furthermore, this study offers estimation of the prospect theory parameters using field data. The preference parameters from our revealed preference analysis confirm the important features of prospect theory preferences. Notably, these estimated parameters fall within a plausible range when compared to the laboratory-based estimates documented in the prior literature.

In addition, our study makes a valuable contribution to the existing literature on mutual fund flows. Since Ippolito (1992), it has been widely recognized that mutual fund investors tend to chase past performance. Recent studies in the flow literature, such as Barber et al. (2016), Berk and

[3] For example, Bossaerts et al. (2022) show that, in a simple two-period dynamic model, prices in a myopic equilibrium are very close to those in a perfect foresight equilibrium, while the choices differ significantly.

Van Binsbergen (2016), Song (2020), and Dannhauser and Pontiff (2019), investigate how different components of past performance affect fund flows. They show that both abnormal returns (alpha) and factor-related returns predict future fund flows. However, this decomposition crucially depends on how investors assess risk, as highlighted in Jegadeesh and Mangipudi (2021). Our research takes a novel approach by examining mutual fund flows through the lens of prospect theory, which provides a psychologically realistic framework. We offer a new behavioral perspective to the flow literature and present empirical evidence supporting the significant incremental explanatory power of prospect theory for mutual fund flows.

Lastly, this study offers new evidence pertaining to the rationality of mutual fund investors. Guided by theory, we show that mutual fund investor behavior in aggregate is consistent with what prospect theory prescribes. Recent studies have also documented instances of non-fully rational behavior of mutual fund investors. For instance, they tend to chase growth stocks and experience poor subsequent performance (Franzoni and Schmalz (2017)); they persistently invest in high-fee mutual funds (Cooper et al. (2021)). Additionally, mutual fund investors blindly follow *Wall Street Journal* rankings (Kaniel and Parham, 2017), Morningstar Ratings (Ben-David et al., 2022; Del Guercio and Tkac, 2008), sustainability rankings (Hartzmark and Sussman, 2019), and are attracted by extreme past returns (Akbas and Genc, 2020). Our study adds to this body of research by highlighting the congruence between mutual fund investors' behavior and the predictions of prospect theory while controlling for other non-fully rational behavior within the mutual fund industry.

In two concurrent studies, Gu and Yoo (2021) and Guo and Schönleber (2022) also document that the fund's TK value is a positive and significant predictor of its future fund flow. Gu and Yoo (2021) contain only some basic findings and does not go in depth or explore the underlying mechanisms as our paper does. Guo and Schönleber (2022) differ from our paper both in focus and some details of the findings. Guo and Schönleber (2022) highlight the role of loss aversion but they do not find empirical support for other features in prospect theory such as probability weighting or concavity/convexity[4], which is in strong contrast to both the original papers (Kahneman and Tversky (1979); Tversky and Kahneman (1992)) and subsequent studies (Barberis (2012); Barberis et al. (2016); Barberis et al. (2021)). We document that each feature of prospect theory independently and importantly contributes to explaining the choices of mutual fund investors. While Guo and Schönleber (2022) report that mutual funds prospect value does not reliably forecast future mutual fund returns, we find a significantly negative relation between prospect theory-driven fund flow and future fund performance. In terms of research focus, they examine the influence of prospect theory on both mutual fund investors and managers, while our study concentrates on mutual fund investors and presents more evidence on non-fully rational behavior among mutual fund investors. Moreover, unlike both papers, our study draws evidence from account-level data. We validate the role of TK value in driving investors' portfolio decisions on mutual funds, thereby providing further support for prospect theory at the micro-level. Furthermore, our paper provides a more extensive analysis by conducting a revealed preference analysis and estimating a set of prospect theory parameters using the mutual fund flow data.

The remainder of the paper is organized as follows. Section 2 provides the theoretical background and measure construction. Section 3 describes the data and sample. Section 4 presents results on the relationship between fund flows and prospect theory values of mutual funds as well as the implied set of prospect theory parameters based on a revealed preference analysis. Section 5 demonstrates the relevance of prospect theory as a new framework for understanding mutual fund flows. Section 6 provides further evidence of the non-fully rational behavior of mutual fund investors. Section 7 reports additional tests regarding the robustness of our findings and the determinants of TK values. Section 8 concludes.

[4]However, an earlier version of their working paper dated April 2021 stated (Page 3) "We analyze the individual building blocks of the prospect theory value (loss aversion, concavity and convexity, and probability weighting) and discover that the concavity and convexity feature, which means that the value function is concave over gains and convex over losses, plays an essential role in mutual fund flow prediction."

2 Prospect Theory Valuation

Following Barberis et al. (2016), we break the decision-making process under prospect theory into two steps: "representation" and "valuation." An investor first forms a mental representation of the distribution of gains and losses for a risky investment. The investor then evaluates this mental representation to assess the attractiveness of the investment.

2.1 Representation

Barberis et al. (2016) propose to use the distribution of a stock's past returns as the representation of its return distribution. In the mutual fund context, past returns are readily available to investors who do not have much additional information about mutual funds. Thus, we posit that mutual fund investors use the distribution of a fund's realized returns to represent possible future return scenarios. Further, we use the distribution of a fund's monthly returns over the preceding five years to represent the future prospect of a fund. This is motivated by Morningstar, one of the major information sources for mutual funds. On its website, Morningstar displays the performance of each mutual fund in a chart, commonly plotting recent fund returns at monthly frequency going back five years.[5]

2.2 Valuation

With the mode of representation in place, we describe the steps to calculate a fund's prospect-theory value (termed "TK") following Tversky and Kahneman (1992). For a given mutual fund with 60 months of past returns, we start by ordering the stock returns in ascending order. We obtain a distribution of gains and losses r (i.e., returns minus reference points) as follows,

$$\left(r_{-m}, \frac{1}{60}; r_{-m+1}, \frac{1}{60}; \ldots; r_{-1}, \frac{1}{60}; r_1, \frac{1}{60}; \ldots; r_{n-1}, \frac{1}{60}; r_n, \frac{1}{60}\right), \tag{1}$$

[5]Our results remain robust for alternative horizons. See Table A2 in the Appendix for details.

where r_{-m} to r_{-1} are losses ordered from the most negative to least negative and r_1 to r_n are gains ordered from the smallest to largest in magnitude. For the results reported in the tables, we use the risk-free rate as the reference point in evaluating gains or losses, following Barberis and Huang (2008). Our results are robust when we use other reference points such as market returns or style average returns.

TK value can then be computed as

$$\begin{aligned} \mathrm{TK} = & \sum_{i=-m}^{-1} v\left(r_i\right)\left[w^-\left(\frac{i+m+1}{60}\right) - w^-\left(\frac{i+m}{60}\right)\right] \\ & + \sum_{i=1}^{n} v\left(r_i\right)\left[w^+\left(\frac{n-i+1}{60}\right) - w^+\left(\frac{n-i}{60}\right)\right] \end{aligned} \tag{2}$$

where $v(\cdot)$, $w^-(\cdot)$, and $w^+(\cdot)$ are defined as follows:

$$v(x) = \begin{cases} x^\alpha & \text{for } x \geq 0 \\ -\lambda(-x)^\alpha & \text{for } x < 0 \end{cases} \tag{3}$$

$$w^+(P) = \frac{P^\gamma}{\left(P^\gamma + (1-P)^\gamma\right)^{1/\gamma}}, \quad w^-(P) = \frac{P^\delta}{\left(P^\delta + (1-P)^\delta\right)^{1/\delta}} \tag{4}$$

The above equation (2) implies decision weights (where π is computed using $w^-(\cdot)$ and $w^+(\cdot)$):

$$\sum_{i=-m}^{n} \pi_i v\left(x_i\right) \tag{5}$$

To compute TK value, we utilize the parameter estimates obtained by Tversky and Kahneman (1992) from experimental data:

$$\begin{aligned} & \alpha = 0.88, \lambda = 2.25 \\ & \gamma = 0.61, \delta = 0.69 \end{aligned} \tag{6}$$

Embodied in the above formulas are the four features of prospect theory: loss aversion, probability weighting, concavity over gains versus convexity over losses, and reference dependence.

3 Data and Sample

3.1 Sample Construction

Our main data source is CRSP's Survivor-Bias-Free US Mutual Fund Database. We focus on equity mutual funds, excluding ETFs/ETNs, variable annuities, and index funds.[6] Our sample spans the period from January 1981 to June 2022. We start our sample period in 1981 to ensure more effective coverage of monthly Total Net Assets (TNA) and return data. Mutual fund data are recorded at the share-class level in CRSP. We aggregate share classes to the fund level following methods described in Berk and Van Binsbergen (2015). Most fund characteristics and performance metrics are value-weighted averages across share classes. Eventually, we select on average 2,698 mutual funds per month for analysis. Fund TNA is the sum of share-class-level TNA, and age is based on the oldest share class. Fund flow, $Flow$, is computed following the standard method,

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})}{TNA_{i,t-1}}, \tag{7}$$

where $r_{i,t}$ denotes the return on fund i during month t and $TNA_{i,t}$ is the TNA value of fund i at the end of month t. Our findings are robust to an alternative measure of fund flows in Huang et al. (2011) computed as $FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+r_{i,t})}{TNA_{i,t-1}(1+r_{i,t})}$. We winsorize fund flows at the 5% and 95% levels.[7] Factor loadings and alphas are computed using a rolling window of past-60-month fund returns.

[6] Our main results are robust for both bond mutual funds and index mutual funds. See Table A4 in the Appendix for details.

[7] We apply this filter to mitigate the impact of measurement errors in fund flows (e.g., Elton et al. (2011) document that the dates on which fund mergers occur often differ from actual merger dates, which may generate extreme flow values). To ensure consistency, we also winsorize the other main variables at the 5th and 95th percentiles. Our main results are robust when we winsorize at the 1% and 99% levels (see Appendix Table A3).

3.2 Summary Statistics

Table 1 Panel A reports the summary statistics of the main variables in our analysis. The summary statistics indicate that we have constructed a large and representative sample of mutual funds. The median fund size in our sample is $258.5 million in total net assets (TNA). Active mutual funds on average experience small outflows and also have negative alphas in our sample period. In Table 1 Panel B, we sort the funds in our sample into five groups each month by fund TK and report the average values of the variables labeled by the rows for each TK quintile. Measures of past performance, such as CAPM alpha, FF4 Alpha, and raw returns, all increase with TK value. High-TK funds also have higher TNA than low-TK funds, while they are similar in age. Most importantly, fund flow increases monotonically with TK value. This hints the presence of a positive relationship between TK value and fund flows.

4 Field Evidence on Prospect Theory

We empirically examine the role of prospect theory in the market through three distinct approaches. First, as mutual fund flows reflect the aggregate choice of mutual fund investors, we establish a connection between TK value and mutual fund flows. This allows us to investigate whether a "representative investor" demonstrates a preference consistent with prospect theory. Second, we delve deeper into the impact of prospect theory on the decision-making process of individual mutual fund investors using trading data at the account level. Moreover, to gain further insights, we employ a discrete choice model and conduct a revealed preference analysis. This enables us to directly infer mutual fund investors' preferences and estimate the prospect theory parameters that best fit the flow data.

4.1 TK and Fund Flows

4.1.1 Portfolio Sorts

Our main hypothesis is that prospect theory describes how investors make their choices among mutual funds: a mutual fund's TK value is positively related to its fund flows. We first use the portfolio sorting approach to test the relationship between TK and fund flows.

For each month from January 1986 through June 2022, we sort funds into deciles based on their TK values in the preceding month. We then examine the average fund flows for each decile in that month, both equal-weighted and value-weighted by the funds' TNA values. This yields a time series of average flows for each decile portfolio of funds sorted by TK. Lastly, we take the average flows over time and compare across deciles. The results are reported in Table 2. From the lowest TK decile to the highest TK decile, we observe a monotonic increase in the average fund flows, ranging from -0.4% to 0.9% when funds are equally weighted (Panel A) and from -0.6% to 0.8% when funds are TNA-weighted (Panel B). The negative (positive) inflows in the low (high) TK funds are both statistically significant. The spread in the monthly fund flow between the highest-TK funds and lowest-TK funds is around 1.4% and also statistically significant.

The results provide initial support for our main hypothesis that prospect theory affects mutual fund investors' decision-making when allocating capital across funds, as funds with high TK value tend to attract significantly greater inflows. Although a univariate analysis provides an intuitive description of the relationship between TK and fund flows, it is not amenable to controlling for many other factors known to affect fund flows. In the following section, we employ regression analysis to control for various known determinants of fund flows.

4.1.2 Baseline Regression

We now conduct regression analyses to test our main hypothesis. Our main econometric specification is a panel regression with fixed effects (Pástor et al., 2015).[8] Specifically, we estimate

[8] In untabulated results, we confirm that TK's predictive power remains robustly positive when we use Fama-MacBeth regressions.

the following regression model:

$$Flow_{i,t} = bTK_{i,t-1} + cX_{i,t-1} + \phi_i + \eta_t + \epsilon_{i,t}. \tag{8}$$

The dependent variable, $Flow_{i,t}$, represents the flow of mutual fund i in month t. Fund flows result from mutual fund investors' buying and selling decisions, i.e., the aggregate choices of mutual fund investors for each fund. Our variable of interest is $TK_{i,t-1}$, which measures a fund's prospect-theory value based on preceding-60-month returns by the end of the period $t-1$. $X_{i,t-1}$ is a vector of control variables that have been documented to predict fund flows.

Performance measures. The most important set of controls are fund-performance measures. Previous literature has documented extensive evidence that good past fund performance draws capital inflows from investors. We consider several types of performance measures. The first is cumulative fund returns in the preceding 60 months, which is a basic performance measure that investors can easily obtain. Since TK value is a nonlinear function of the preceding 60-month returns, we control for cumulative returns in the preceding 60 months to show that TK value contains additional information. The second performance measure is the fund alpha estimated using CAPM or Fama-French-Carhart four-factor model (Fama and MacBeth (1973); Fama and French (1992); Fama and French (1993); Carhart (1997)). Alphas are known to predict future fund flows. Recently, several papers (e.g., Berk and Van Binsbergen (2016) and Barber et al. (2016)) have shown that CAPM alpha outperforms alphas under more complicated factor models in explaining fund flows. Lastly, we control for factor loadings on *mktrf*, *smb*, *hml*, and *umd* because investors respond to the portion of fund performance that is attributable to these factors (Barber et al. (2016)).[9]

Other Fund Characteristics. In addition to fund performance measures, we include a battery of fund characteristics that investors might consider when selecting funds, including R-squared from the Four-Factor Model, fund age, size, expense ratio, and turnover ratio. We also control for fund-return volatility, which could diminish investors' ability to learn about fund-manager skills

[9]To estimate the alphas and factor loadings, we use fund returns over the previous 60 months, which aligns with the estimation for TK. The results are similar if we use other estimation windows, such as 36 months.

(Huang et al., 2022).

Fixed Effects. We include two fixed effects in equation (8): fund fixed effects, ϕ_i, and time fixed effects, η_t. By including fund fixed effects, we control for unobserved heterogeneity among mutual funds that is constant over time, such as time-invariant fund skills (Pástor et al., 2015) and dis-economy of size (Zhu, 2018). Moreover, fund fixed effects allow us to identify important within-fund variations over time.

We estimate the regression model in equation (8) using fund flows as the dependent variable. By regressing flows on TK, we test whether prospect theory can explain investors' choices in aggregate. Table 3 presents the regression results. In all specifications, we include both fund and date fixed effects.[10] All standard errors are two-way clustered at the fund and date levels. Column (1) reports the result of the univariate regression with TK as the only regressor, indicating a strong and positive relationship between TK and future fund flows, with a coefficient of 0.604 and a t-statistic of 26.89. The univariate regression result corroborates the sorting results reported in Table 2. When we add performance measures as control variables in Columns (2) and (3) of Table 3, TK remains positive and significant. Column (2) controls for the cumulative returns over the preceding 60 months and CAPM alpha.[11] The results are quantitatively similar if we use the alpha from the Fama-French-Carhart four-factor model (Carhart, 1997). In column (3), we additionally control for factor loadings under the Fama-French-Carhart four-factor model. Thus, prospect theory value provides distinct information about what drives fund flows above and beyond fund performance.

Table 3 column (4) includes additional fund characteristics as controls. The TK measure continues to be positive and significant, with a coefficient of 0.383 and a t-stat of 11.27. In economic terms, for an average fund in our sample with a TNA of $1,533 million, a one-standard-deviation increase in TK maps into $11.16 million in fund flows. We find that larger and older funds experience lower future flows, which is consistent in general with the theory of dis-economy of size. Other characteristics, such as expense ratios, turnover ratios, and fund activeness, are

[10] Our results are robust when including either fund fixed effects only or date fixed effects only.

[11] The CAPM alpha's coefficient is positive and significant when we regress future flows on CAPM alpha alone, which is consistent with previous literature.

nonsignificant in the presence of TK value.

Overall, the findings reported in Table 3 strongly support our hypothesis. Prospect theory offers significant incremental explanatory power for fund flows beyond existing determinants including traditional performance measures and fund characteristics.

4.1.3 Dissecting TK: Which Features of Prospect Theory Play a Role?

Prospect theory synthesizes four behavioral traits associated with individual decision-making—reference dependence, loss aversion, concavity/convexity, and probability weighting. *Reference dependence* involves selecting the appropriate benchmark (i.e., reference point) for calculating gains and losses. There is a lack of clear theory guidance regarding the specification of the reference point. In the main analysis, we use the risk-free rate as the reference point, a common choice in this literature. Our results remain robust to these alternative reference points, such as market returns, style averages, and zero.[12] *Loss aversion* suggests that an individual is more sensitive to losses than to gains of the same magnitude. *Concavity/Convexity* describes the feature that the prospect theory value function, $v(\cdot)$, is concave over gains but convex over losses. *Probability weighting* involves a situation in which an individual uses transformed probabilities when evaluating a gamble. The main consequence of probability weighting under prospect theory is inflated probability of tail events.

To gain insights about how these individual features affect mutual fund investor choices, we construct alternative prospect-theory values that focus on only one feature by turning off others. We achieve this by applying alternative parameters to equation (2). To construct the prospect-theory value with the loss-aversion component only, we use the parameter set $(\alpha, \gamma, \delta, \lambda) = (1, 1, 1, 2.25)$, instead of $(0.88, 0.61, 0.69, 2.25)$ in the original TK. Similarly, the prospect theory value featuring only concavity/convexity is computed using parameters $(\alpha, \gamma, \delta, \lambda) = (0.88, 1, 1, 1)$. The prospect theory value with probability weighting only is calculated using parameters $(\alpha, \gamma, \delta, \lambda) = (1, 0.61, 0.69, 1)$.

[12]See Table A5 in the Appendix.

We re-estimate the baseline regression equation (8) using loss aversion, concavity/convexity, and probability weighting individually in place of TK and report the results in the first four columns of Table 4. In the fifth column, we repeat the analysis under our main specification with TK. Columns (1) through (3) report the regression results for each feature individually. All the coefficients are positive and statistically significant. In column (4), we horse-race all three separate features in one regression and find that each feature still has strong predictive power for fund flows. We conclude that each element of prospect theory has a significant and independent contribution to the explanatory power of prospect theory for fund flows.

Barberis et al. (2016) find that probability weighting is the primary driver for explaining the cross-section of expected stock returns. In their setting, if the probability-weighting feature is turned off, the standalone predictive power of loss aversion and concavity/convexity drops markedly. The discrepancy between the two sets of results is attributable to the different outcome variables used in the two papers. Expected stock returns, the outcome variable in Barberis et al. (2016), are jointly determined by investor preferences and other variables. By using a direct measure of investors' choices, a simpler outcome variable, this paper can potentially provide a sharper test of investor preference.

4.2 Account-Level Evidence

Flows at the fund level, aggregated across investors, help us identify the general pattern that would indicate whether a "representative investor" in mutual funds displays a preference that is consistent with prospect theory. In this section, we use individual account-level positions and transaction data from a large retail brokerage to test whether investors display prospect-theory preferences.[13] The account-level tests provide us with more granular examinations of our hypothesis. We first estimate the following regression,

$$AmtHeld_{i,j,t} = \beta TK_{j,t-1} + \gamma X_{j,t} + \lambda_i + \eta_t + \varepsilon_{i,j,t}, \tag{9}$$

[13] See Barber and Odean (2000) for more details about the data.

where $AmtHeld_{i,j,t}$ is investor i's amount of holdings in fund j on date t. We compute two measures of holdings: dollar amount held as a proportion of the overall account value, or as a proportion of a fund's TNA. $X_{j,t}$ is a set of fund-level control variables, including fund size, turnover ratio, expense ratio, past performance, and factor loadings. λ_i and η_t are individual (account) and date (year-month) fixed effects. By including account- and date-fixed effects, we explore variations within an account on a given date across multiple funds. This enables us to determine how TK values of funds affect investors' allocation decisions.

In addition to holdings, we also examine whether investors' trading patterns fit the description of prospect theory. We estimate a model that is similar to (9), but with an alternative dependent variable, "NetBuy",

$$NetBuy_{i,j,t} = \beta TK_{j,t-1} + \gamma X_{j,t} + \alpha_i + \eta_t + \varepsilon_{i,j,t}, \tag{10}$$

where $NetBuy_{i,j,t}$ is the net amount that investor i traded in fund j in month t. $TK_{j,t}$ is the TK value for fund j in month $t-1$. Similar to holdings, we consider two transaction measures: the ratio of dollar amount of trading to the account value or to the fund size.

Panel A of Table 5 reports the results of regression (9). For both holding measures, we find a positive and significant coefficient of TK. Thus, individual investors' portfolio choices are consistent with prospect theory. In terms of economic magnitude, the coefficient of column (1) indicates that one standard deviation increase in TK value would boost the investor's holding of that fund in their portfolio by 7%. Panel B reports the results of regression (10). The coefficient of TK is consistently positive and significant, suggesting that prospect theory value has a robust and significant explanatory power for individual investors' mutual fund choices. Using the coefficient in column (1) as an example, an investor would invest 1.1% more of their account value in a fund when the fund's TK increases by one standard deviation. Overall, the findings based on individual investors' portfolio decisions regarding mutual funds are consistent with the patterns we document using fund-level flow data.

4.3 Revealed-preference Analysis

Thus far, our computation of TK value has been based on the following parameters:

$$\alpha = 0.88, \lambda = 2.25$$
$$\gamma = 0.61, \delta = 0.69$$

While these parameters are widely utilized in the finance literature (Barberis et al. (2016)), it is important to note that they are estimated based on laboratory settings and may not fully capture the preferences of real-world investors. The fund flow data lend us the opportunity to conduct a *revealed preference* analysis based on the field data. To this end, we employ a discrete choice model to determine which set of parameter values from prospect theory best explains the investment choices made by mutual fund investors.

4.3.1 A Discrete Choice Model

Specifically, investors in our discrete choice model are presented with a "product space" consisting of $J+1$ funds. Each fund is assigned an index value i, ranging from 0 to J. Fund 0 is the baseline category, proxied by the Vanguard index fund (Roussanov et al. (2021)). The remaining J funds are a collection of actively managed domestic equity funds, each indexed from $i = 1$ to J. When making investment decisions, investors select a fund i from both the index fund 0 and the remaining J active funds. Their choices are guided by the following utility function:

$$\delta_i = bTK_i(\theta, R_i) + c_k \sum_k x_i^k + e_i \tag{11}$$

Here, the TK value of fund i, denoted as TK_i, is jointly determined by prospect theory parameters $\theta = [\alpha, \lambda, \gamma, \delta]$ and the historical returns R_i of fund i. The characteristics of fund i, such as its size, turnover ratio, and expense ratio, are denoted by x_i^k. The term e_i represents the investor's idiosyncratic utility associated with fund i, which remains unobservable to researchers. We follow the standard industrial organization (IO) literature (Berry (1994)) and assume e_i follows a type I extreme distribution. Consequently, the probability of an investor selecting fund i is determined as $Prob_i = e^{\delta_i} / \sum_{j=0}^{J} e^{\delta_j}$, which is essentially the multinomial logit model.[14]

4.3.2 Estimation

We estimate the model in (11) using investors' choices among the retail equity funds.[15] Specifically, we use the new subscriptions to capture the investor's purchase decision making process. This data is from the CRSP Mutual Fund Database. However, the data quality in the initial years is inadequate, characterized by a substantial number of missing values. As a result, our estimation sample is limited to the quarters from 2013 to 2022 that have more than 1000 non-missing observations.

In each quarter, we observe the inflows (new subscriptions) to each fund, denoted as f_i. This enables us to calculate the quarterly "market share" as $s_i = f_i / \sum_{j=0}^{J} f_j$. Utilizing the market share, we can estimate the parameters θ by maximizing the following likelihood function:

$$\ln L = \ln \prod_{j=0}^{J} Prob_j^{s_j} \tag{12}$$

Specifically, we run a MLE in each quarter based on the above equation. Then we obtain the time series of estimated parameters, $\hat{\theta}_t = [\alpha_t, \lambda_t, \gamma_t, \delta_t]$.

4.3.3 Implied Prospect Theory Parameters from Fund Flows

In Panel A of Table 6, we report the averages, the standard errors, and the confidence intervals of the estimated $\hat{\theta}_t$ over the quarters. Overall, the revealed parameters in the field from our structural model provide strong support for the features of prospect theory. We begin by examining the degree of loss aversion, denoted as λ, which is a prominent feature of prospect theory. The original work

[14] We set the utility of the baseline category as zero, i.e., $\delta_0 = 0$. The probability of choosing the index fund and all other funds can be rewritten as

$$Prob_0 = \frac{1}{1 + \sum_{j=1}^{J} e^{\delta_j}}, \qquad Prob_i = \frac{e^{\delta_i}}{1 + \sum_{j=1}^{J} e^{\delta_j}}$$

[15] We follow the procedure in Roussanov et al. (2021) to exclude institutional funds.

by Tversky and Kahneman (1992) has widely influenced the belief that the degree of loss aversion is approximately 2. However, recent studies based on more representative samples of participants have shown that the true level of loss aversion may be lower than 2. In our findings, the revealed degree of loss aversion from mutual fund flows averages at 1.824, falling between the magnitude of 2.25 suggested in Tversky and Kahneman (1992) and the value of 1.31 reported in recent studies, such as Walasek et al. (2018). Our approach yields an estimate of 0.745 for the parameter α that determines the S-shape of the prospect theory value function. This is in line with the experimental studies that typically produce α estimates ranging from 0.5 to 0.95.

Another important feature in prospect theory is probability weighting. The parameters γ and δ represent the weighting schemes in the gain and loss regions, respectively. According to prospect theory, the values of γ and δ range between 0 and 1, with a smaller magnitude indicating a stronger degree of overweighting tail events. Previous studies (Tversky and Kahneman (1992); Booij et al. (2010)) suggest an estimated value of 0.65 for both parameters. However, our findings indicate an even greater degree of probability weighing in both the gain and loss regions. The estimated mean value for γ is 0.228, approximately a third in magnitude as those reported in previous studies. This suggests that the probability weighting in the loss region, as revealed by mutual fund flow data, is stronger than what has been observed in laboratory settings. Furthermore, the mean value of δ for the gain region is even smaller, suggesting that mutual fund investors exhibit a more aggressive overweighting of tail events in the gain region compared to the loss region. The strong probability weighting parameters from our estimation are consistent with the lottery preferences documented in the previous literature (Kumar (2009)).

In sum, our revealed preference analysis provides further support to the important influence of prospect theory among mutual fund investors, highlighted by the significant loss aversion and strong probability weighting. In the remaining sections, we revert to the prospect theory values of mutual funds under lab-based parameters given in (6), but our findings remain robust if we adopt the parameter estimates obtained above under the revealed preference analysis.

4.3.4 Prior Investment Performance and Loss Aversion

In their seminal theoretical work on aggregate market dynamics, Barberis et al. (2001) highlight the time-varying nature of loss aversion that plays a key role in explaining the equity premium under prospect theory: investors' degree of loss aversion depends on their prior investment performance. After prior gains, investors become less loss averse: the prior gains will cushion any subsequent loss, making it more bearable. Conversely, after a prior loss, investors become more loss averse: after being burned by the initial loss, investors become more sensitive to additional setbacks.[16] Although significant and well-known, there is limited field evidence for this time-varying pattern of loss aversion.

We provide an empirical test by leveraging the variation in loss aversion through our quarter-by-quarter estimation. To proxy for investors' prior gains, we use the market return in the last quarter as it captures the wealth fluctuations at the market-wide level. The first proxy is the market return downloaded from Kenneth French's website, which represents the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. We use returns from the last quarter to predict loss aversion in the current quarter. Based on Table 6 Panel B Column (1), a one standard deviation increase in the quarterly market return (7.288%) significantly decreases the degree of loss aversion by 0.079, which amounts to 71.82% of the standard deviation of loss aversion (calculated as 7.288 / 100 * 1.084 / 0.11). The second proxy is the return of the S&P 500 index. Similarly, we observe a significantly negative relation between last quarter's S&P 500 return and the loss aversion parameter inferred from mutual fund flow. Overall, we provide supportive evidence that prior investment performance affects the degree of loss aversion exactly as assumed in the model of Barberis et al. (2001).

[16]This idea dates back to earlier work such as Thaler and Johnson (1990). They documented that when faced with sequential gambles, people are more willing to take risks if they made money on prior gambles than if they lost. They labeled this pattern as the famous "house money" effect. In a related work, Barberis and Huang (2001) also model the dynamics of loss aversion, but with a focus on the impact of different forms of mental accounting on individual stocks.

5 Prospect Theory: A New Framework for Mutual Fund Flows

In this section, we investigate whether prospect theory can provide new insights about what drives mutual fund flows. Specifically, we compare TK to existing determinants of mutual fund flows under both rational and behavioral theories. We conclude that TK contains novel and robust predictive power beyond the existing predictors, indicating that prospect theory can provide a new framework for thinking about mutual fund flows.

5.1 Controlling for Expected Utility

Our main hypothesis is that investors evaluate mutual fund attractiveness according to the prospect theory. A natural alternative hypothesis is that investors evaluate mutual funds using expected utility (EU) such as the power utility widely studied in the literature. To properly control for and test the possibility that investors evaluate funds according to EU, we derive the utility value under the power utility function using realized returns over the most recent 60 months:

$$EU = \frac{1}{60} \sum_{i=1}^{60} \frac{(1 + r_i)^{1-\theta}}{1 - \theta}, \tag{13}$$

where θ is the relative risk-aversion coefficient. We take the value of 0.88 for θ to be consistent with the risk-aversion coefficient (α) in calculating TK.[17] We then add the estimated EU to our baseline regression model (8). As shown in Table 7, we find that EU also positively predicts future fund flows. The coefficient is 1.628 with a t-statistic of 14.56. This finding suggests that some mutual fund investors display EU preferences. More importantly, both EU and TK possess explanatory power regarding mutual fund flows in bivariate regression (see Table 7 column (3)). As mutual fund flows reflect the collective choices of investors, this suggests that some mutual fund investors have expected utility preferences while others are prospect theory decision-makers.

[17]The results are robust to a wide range of alternative parameter choices.

5.2 Controlling for Other Behavioral Biases

In this section, we differentiate prospect theory from alternative behavioral drivers for mutual fund flows such as return extrapolation, salience theory, max or skewness of returns, and MorningStar ratings. Overall, prospect theory exhibits both novel and robust predictive power for mutual fund flows after controlling for alternative behavioral drivers.

5.2.1 Return Extrapolation and Salience Theory

Greenwood and Shleifer (2014) and Barberis et al. (2015) utilize survey data on beliefs to demonstrate that investors exhibit declining memory, with more recent returns exerting a greater influence on their expected returns compared to distant ones. In line with this, we adopt the memory-decaying structure estimated by Barberis et al. (2015) and quantify return extrapolation as a control variable using a weighted sum of past monthly fund returns, where the weights decline exponentially. Greenwood and Shleifer (2014) also estimate a memory-decaying structure using quarterly returns. We find that the results remain robust under both specifications.

Bordalo et al. (2012) argue that due to cognitive limitations, decision-makers' attention is drawn to the most salient attributes of the options they face. Consequently, these salient attributes are overweighted in their decisions, while nonsalient attributes are often neglected. Cosemans and Frehen (2021) provide empirical evidence for the salience-based asset pricing model of Bordalo et al. (2013). Following these influential studies, we adopt the same methodology to measure the salience of a fund. Specifically, we calculate a weighted sum of its monthly returns over the past 12 months, with the weight reflecting the degree of salience as defined in Bordalo et al. (2013). This ensures that our measurement aligns precisely with the concept of salience in the literature.

We add the return extrapolation and salience measures as controls to the baseline flows regressions (8) and report the results in the first two columns of Table 8. We find that the predictive power of prospect theory remains strong in these alternative regression settings. Return extrapolation and salience measures also have significant predictive power for future mutual fund flows, even after controlling for CAPM alpha as well as prospect theory value. This suggests that extrapolative belief and salience theory also play important roles in decision-making by mutual fund investors, but they can't explain the significantly positive relation between mutual fund flows and prospect theory value. We leave further exploration of this issue to future studies.

5.2.2 Max Returns and Skewness

Akbas and Genc (2020) argue that maximum returns significantly predict future fund flows because investors prefer funds that have extremely positive payoffs or positive skewness. In essence, maximum return and skewness preference are consistent with the probability weighting feature of prospect theory. As we have shown in section 4, however, all features of prospect theory contribute to its explanatory power for mutual fund flows. Hence, we expect TK to remain a significant determinant of fund flows after controlling for maximum past returns. Following Akbas and Genc (2020), we include the maximum style-adjusted returns in the preceding 12 months as an additional control in the fund flows regression. Table 8 column (3) confirms the significant predictive power of max return for fund flows. Consistent with our conjecture, TK is still significantly and positively related to fund flows in the presence of maximum returns. The coefficient of TK only drops slightly in magnitude. Our results also remain robust after controlling for the skewness of the preceding 60 months' returns, as shown in column (4) of Table 8.

5.2.3 Morningstar Ratings

Del Guercio and Tkac (2008) and Ben-David et al. (2022) show that Morningstar Ratings explain mutual fund flows. Morningstar rates funds based on past fund returns. Their approach relies on calculating cumulative risk-adjusted returns in a way that penalizes high volatility.[18] Although prospect theory values are also constructed as a function of past fund returns, there are important differences that distinguish prospect theory from Morningstar Ratings. Prospect theory is deeply rooted in human psychology and contains a rich set of features that describe investor choices under uncertainty. Morningstar Ratings do not capture such features as loss aversion and

[18]The formula for calculating Morningstar ratings is available in the Morningstar manual.

probability weighting.

Therefore, TK value should have additional predictive power after controlling for Morningstar Ratings. We find that this is indeed the case. In column (5) of Table 8, we calculate the average Morningstar Ratings across share classes at the fund level to include as additional controls. Consistent with Ben-David et al. (2022), funds that receive higher ratings from MorningStar attract significantly higher fund flows. Still, a fund's prospect theory value remains both an economically and statistically significant determinant of the future fund flow. In untabulated results, we also create dummies for the five MorningStar ratings and include them in the regression. We find that funds that are awarded five stars by Morningstar tend to experience higher fund flows, while funds awarded only one star will experience lower flows. The predictive power of prospect theory still remains strong in the presence of the MorningStar rating dummies.

Overall, the findings in this section confirm the novelty and robustness of the explanatory power of prospect theory for mutual funds investors' decision-making.

6 Bounded-rational Drivers of Fund Flows

As a psychologically grounded framework, prospect theory is widely recognized for capturing non-fully rational behaviors. In this section, we aim to present further evidence supporting the presence of less-than-fully-rational investor behavior in picking mutual funds within the framework of prospect theory.

6.1 Investor Heterogeneity

Our previous analysis considers all types of funds in aggregate. Mutual funds differ, however, with respect to the distribution channels and investor clientele with different level of sophistication. In this subsection, we investigate the heterogeneous effects of prospect theory on mutual fund investor choices.

6.1.1 Institutional and Retail Funds

Mutual funds are sold in several share classes. Some share classes are sold to institutional investors, while others target retail investors. Empirically, we classify a fund as an institutional (retail) fund if more than 75% of its TNA falls into institutional (retail) share classes. Since institutional investors are less prone to behavioral biases and less likely to be influenced by prospect theory, we expect prospect theory to provide stronger explanatory power when explaining retail fund flows. We test this hypothesis by interacting institutional or retail fund indicators with TK. We present the results in Table 9. For column (1) we repeat the baseline regression associated with Table 3 for comparison purposes. For column (2) we interact TK with the indicator for institutional funds. The coefficient of the interaction term is negative and significant. Similarly, for column (3) we interact TK with the indicator for retail funds and find the interaction term to be positive and significant. These two results are consistent with each other. They suggest a stronger (weaker) effect of funds' prospect theory value on fund flows for funds primarily targeting retail (resp. institutional) investors. This confirms our conjecture that the explanatory power of prospect theory for fund flows depends on the sophistication of the investor clientele.

6.1.2 Distribution Channel

Mutual funds can also differ with respect to their distribution channels. In the US, mutual funds are either sold directly to investors or distributed via intermediaries such as brokers and financial advisors. Previous evidence reveals distinct features of investors across distribution channels. Chalmers and Reuter (2012) find that investors who buy mutual funds through brokers are "younger, less highly educated, and less highly paid." Christoffersen et al. (2013) document that flows to broker-sold funds are influenced by payments from fund companies to brokers. Moreover, Bergstresser et al. (2008) and Guercio and Reuter (2014) both show that broker-sold mutual funds do not seem to provide additional benefits relative to directly sold mutual funds. Based on the extant literature, investors of broker-sold funds appear less sophisticated than investors of directly sold funds. Thus we expect the effect of TK on fund flows to be stronger for broker-sold funds. We classify broker-sold funds following the procedure described in Sun (2014).[19]

The results are reported in Table 10. Column (1) repeats the baseline results. For column (2) we interact the indicator for broker-sold funds with TK and for column (3) we interact the directly sold indicator with TK. The interaction term between the broker-sold dummy and TK is positive and significant, while the interaction term between the directly sold dummy and TK is negative and significant. The results suggest that prospect theory is more powerful at explaining flows of broker-sold mutual funds where investors are less sophisticated. This provides yet more evidence supporting our hypothesis in this subsection.

6.2 Investor Sentiment

The underlying foundations of prospect theory are closely related to judgment heuristics, such as narrow framing, as posited in the psychology literature. To the extent that prospect theory captures non-fully rational behavior, we expect the effect of prospect theory on fund flows to be stronger when investors are more subject to the influence of "animal" spirits. To test this hypothesis, we use the investor sentiment index proposed in Baker and Wurgler (2006). We define episodes of high investor sentiment when the sentiment level exceeds the 75th percentile of the investor sentiment index within the in-sample data. We include an interaction term between TK value and the indicator for high investor sentiment. We anticipate a positive and significant coefficient on the interaction term. Table 11 column (1) shows a positive and significant coefficient for the interaction term, indicating that the predictive power of prospect theory for fund flows intensifies when market sentiment is high.[20] Similarly, in column (2), we include an interaction term between TK value and the NBER recession dummy. We find that the predictive power of TK drops significantly during recessions.

[19] A broker-sold fund holds at least 75% of its TNA in share classes that charge front-end loads, back-end loads, or 12b-1 fees greater than 25 bps. A directly sold fund holds at least 75% of its TNA in share classes that do not charge front-end loads, back-end loads, or 12b-1 fees.

[20] In untabulated results, we find that the positive relations between fund flow and each individual feature of prospect theory (i.e., LA, CC, PW) documented in Table 4 all become stronger (more positive) during periods of high investor sentiment.

6.3 Subsequent Fund Performance

Our main finding so far is that funds with high TK value attract high fund flows, especially for less sophisticated investor clienteles and during periods of high investor sentiment. To dig deeper into the question of whether such mutual fund flows are smart or dumb money, we examine whether investors make wise decisions when investing according to TK. If higher TK values predict superior fund performance, then investors are right to follow such a signal. If the opposite holds, then TK-chasing behavior would be wealth-destroying. To answer this question, we run Fama-MacBeth regressions in which we regress funds' future four-factor alphas on TK value. We check the predictive relation between TK and alphas from multiple horizons of up to 12 months. Table 12 does not lend any support for a significant and positive relation between fund's TK value and future alphas. In fact, there is some evidence that funds with high TK values tend to underperform subsequently.

Fund alpha depends crucially on fund size in addition to managerial skill (Berk and Van Binsbergen, 2015). High TK funds could attract too much fund flows that end up hurting the fund performance due to decreasing returns to scale in deploying managerial skills (Berk and Green, 2004). Thus, we hypothesize that the effect of TK on future fund performance could arise from the price impact of its effect on fund flows. To verify this conjecture, we decompose fund flows into a TK-driven component and a non-TK-driven component by projecting fund flows on lagged TK. We then re-run the Fama-MacBeth regression with future alphas as the dependent variable. As reported in Panel B and C of Table 12, TK-driven flows predict future alphas negatively, while non-TK-driven flows predict future alphas positively. Both results are statistically significant. We conclude that the effect of TK on future fund performance works through flows and TK-chasing behavior is detrimental from the performance perspective. Interestingly, the remaining mutual fund flows (those not driven by prospect theory) seem to be smart money.

7 Additional Tests

7.1 New Subscription versus Redemption

While the fund flow variable captures aggregate mutual fund investor choices, it masks potential differences between inflows and outflows. Chevalier and Ellison (1997) show that inflows are more responsive to good performance than outflows are to poor performance. This hints an important difference may exist when mutual fund investors make purchase and sale decisions.

Using more detailed flow data from the CRSP Mutual Fund Database, we construct monthly inflow and outflow measures using the "new subscription" and "redemption" variables from the database, respectively.[21] Empirically, we scale the dollar amount of new subscription and redemption by the fund size at the previous month's end. We then estimate the regression specified in equation (8) using new subscription or redemption separately as the dependent variable.

Table 13 presents the results. For both new subscription (column (1)) and redemption (column (2)), we estimate the regression with all the control variables included (but for the sake of brevity we do not report their coefficients). Column (1) shows that TK values significantly and positively predict new subscriptions. However, the TK coefficient becomes insignificant when redemption is the dependent variable. It suggests that mutual fund investors are more responsive to funds' prospect theory value in their purchase than in their selling decision.

7.2 Determinants of TK

In previous sections, we have presented evidence that fund flows are positively related to the fund's TK value in the cross-section. Our interpretation is that, when choosing a mutual fund, some investors mentally represent it by its historical return distribution and then evaluate this distribution according to prospect theory. They allocate their capital toward mutual funds that look attractive under prospect theory, thereby generating high flows to funds with high prospect theory value.

[21] These data are collected from SEC mutual fund filings and are therefore available only after 1993. The link table between flow data and fund return data starts only from July 2003.

To better understand which funds tend to have high TK values that attract investor flows, we examine the relationship between TK values and the characteristics of past return distributions, given TK is a nonlinear transformation of past returns. We focus on the first three moments of past return distributions: cumulative returns, return volatility, and return skewness. They have been linked to fund flows in previous studies. Table 14 Panel A reveals how the TK value relates to the three moments of past return distributions. Column (1) indicates a positive relation between a fund's cumulative returns over the last five years and its prospect-theory value. Column (2) shows that high return volatility leads to a lower TK value. The intuition is that loss aversion feature of prospect-theory makes funds with a high standard deviation unattractive. On the other hand, return distributions with high skewness are positively associated with TK values, mainly because of the probability overweighting feature of prospect theory. The relationships remain qualitatively the same when all three moments are included as regressors with TK value as the dependent variable, as shown in column (4).

We further examine the link of the three moments of fund returns to each feature of prospect theory (see section 4.1.3) and report the results in Panel B of Table 14. The cumulative return from the past 60 months is positively related to all three features. Return volatility is negatively associated with loss aversion but positively associated with concavity/convexity and probability weighting. This result reveals that the negative relation between volatility and TK in Panel A is mainly driven by loss aversion. Skewness is positively related to all three features of prospect theory.

8 Conclusion

Investors pick among risky assets based on their assessments of the return distributions via the lense of their preferences or utility functions. Investors' choices provide researchers with valuable insights into the underlying preferences. Building on this rationale, we utilize mutual fund flows to empirically test theories that seek to explain investor behavior. Our focus is on prospect theory.

Widely recognized as a psychologically realistic model of preferences in laboratory environments, prospect theory has garnered growing interest by finance researchers. We provide field evidence on the practical relevance of prospect theory for mutual funds investors. Moreover, we conduct a revealed preference analysis to obtain estimates of the parameters under the prospect theory value function from market participants' choices in mutual funds.

Our empirical findings provide compelling evidence supporting the role of prospect theory in driving investors' choices among mutual funds: funds whose past returns generate higher prospect theory value attract significantly larger future flows. In particular, for an average fund in our sample, with a Total Net Asset of $1,533 million, a one-standard-deviation increase in TK results in a flow increment of $11.16 million. Each feature of prospect theory plays an indispensable role in shaping this predictive pattern. Our account-level evidence corroborates these results. Furthermore, our field-based prospect theory parameter estimates closely match those from experimental studies. This further validates prospect theory's broad relevance in the mutual funds setting.

Our results demonstrate that prospect theory provides a novel framework for understanding mutual fund flows. The predictive power of prospect theory remains robust even after controlling for fund performance measures and other known determinants of flows such as MorningStar ratings. Our findings align well with bounded rational mutual fund investors. Specifically, the effect of prospect theory value on fund flows is more pronounced among retail funds and broker-sold mutual funds where investors are less sophisticated. It is also stronger during periods of high investor sentiment. Additionally, we find the prospect theory-driven flows negatively predicts subsequent fund performance. This highlights a potential "dumb money" effect stemming from investors exhibiting prospect theory preference. Overall, this paper highlights the importance of prospect theory for the capital allocation in the mutual funds market. Similar studies can be conducted to better understand the demand system in other financial markets. Future work could also gain more insights using detailed investor trading data.

Table 1: Summary Statistics

This table presents the summary statistics for the main variables in our analysis. We focus on mutual funds that exist for at least 60 months within our sample, and we aggregate data across share classes to get fund-level monthly observations. In Panel A, we report the summary statistics for the entire sample. In Panel B, we provide the average values of variables for each quintile, based on TK values formed on a monthly basis. The sample spans from January 1981 to June 2022. Definitions of the variables are reported in Table A1.

Panel A: Whole Sample

	mean	p50	sd	min	max
Flow	-0.002	-0.005	0.034	-0.364	0.932
TK	-0.033	-0.031	0.019	-0.093	0.004
Age	17.440	14.000	11.637	-17.000	99.000
TNA	1533.457	258.500	5799.611	0.097	199057.300
Expense Ratio (t-1)	0.013	0.012	0.013	-0.005	1.462
Turnover Ratio (t-1)	0.822	0.540	2.015	0.000	150.910
CAPM Alpha	-0.086	-0.095	0.510	-6.928	4.759
FF4 Alpha	-0.123	-0.116	0.406	-7.382	4.514
Market Loading	0.955	0.980	0.305	-2.881	3.801
SMB Loading	0.148	0.056	0.344	-2.577	2.900
HML Loading	-0.018	-0.020	0.348	-3.048	2.925
MOM Loading	-0.015	-0.012	0.182	-3.347	2.439
FF4 R Squared	0.812	0.883	0.190	-0.070	0.999
Return Volatility	0.050	0.047	0.018	0.000	0.260
Cumulative Returns(60m)	0.547	0.470	0.610	-0.994	15.766

Panel B: Characteristics of High and Low TK Bins

	Low TK	2	3	4	High TK
Flow	-0.007	-0.006	-0.004	-0.001	0.005
TK	-0.050	-0.038	-0.032	-0.027	-0.021
Age	16.570	17.186	17.559	17.955	17.933
TNA	718.650	1075.832	1310.737	1929.821	2634.391
Expense Ratio (t-1)	0.016	0.013	0.012	0.011	0.011
Turnover Ratio (t-1)	1.138	0.873	0.767	0.664	0.669
CAPM Alpha	-0.519	-0.207	-0.066	0.068	0.296
FF4 Alpha	-0.435	-0.203	-0.102	-0.019	0.146
Market Loading	1.036	1.002	0.967	0.934	0.833
SMB Loading	0.236	0.196	0.153	0.088	0.066
HML Loading	-0.115	-0.061	0.001	0.034	0.051
MOM Loading	-0.076	-0.009	0.000	0.001	0.012
FF4 R Squared	0.725	0.813	0.851	0.864	0.808
Return Volatility	0.066	0.052	0.047	0.044	0.040
Cumulative Returns(60m)	0.175	0.441	0.561	0.674	0.884

Table 2: Portfolio Sorts: TK Values and Fund Flows

This table presents the results from portfolio analysis on the relationship between funds' TK values and flows in the subsequent month. The sample spans from January 1981 to June 2022. Each month, we sort funds into deciles based on TK and calculate the average fund flows in the following month across all funds within each decile. We report the time-series averages of the mean values for each decile portfolio. For Panel A, we employ equal weights. For Panel B, we weight the funds by their total net asset value. The t-statistics are computed based on standard errors that are corrected by Newey-West with lags of 12 months.

Panel A: Equally Weighted

	TK Decile										
	Low	2	3	4	5	6	7	8	9	High	H − L
Flow	-0.004	-0.006	-0.004	-0.004	-0.002	-0.002	0.000	0.001	0.005	0.009	0.013
t-stat	(-2.50)	(-4.31)	(-3.69)	(-3.19)	(-2.35)	(-1.72)	(0.26)	(1.74)	(4.77)	(7.85)	(8.50)

Panel B: TNA-Weighted

	TK Decile										
	Low	2	3	4	5	6	7	8	9	High	H − L
Flow	-0.006	-0.006	-0.004	-0.003	-0.002	-0.002	-0.001	0.001	0.004	0.008	0.014
t-stat	(-4.70)	(-4.28)	(-4.30)	(-2.92)	(-2.29)	(-1.63)	(-0.79)	(1.41)	(3.51)	(6.19)	(10.47)

Table 3: Prospect Theory and Fund Flows

This table presents the predictive power of prospect theory in forecasting future fund flows. The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. The dependent variable is fund flow. In column (1), we run a univariate regression with TK as the only regressor. In column (2), we add the cumulative returns and CAPM alpha, both estimated using returns over the preceding 60 months. In column (3), we further control for loadings on factors in the Fama-French-Carhart four-factor model. In column (4), we include additional fund characteristics. In all specifications, we include both fund and date fixed effects. The definitions of variables are presented in Table A1. The sample spans from January 1981 to June 2022.

	Dependent Variable: *Flow*			
	(1)	(2)	(3)	(4)
TK	0.604***	0.343***	0.307***	0.383***
	(26.89)	(12.88)	(10.24)	(11.27)
Cumulative Returns(60m)		0.006***	0.007***	0.008***
		(6.16)	(6.61)	(7.05)
CAPM Alpha		0.001	0.002**	0.002*
		(1.06)	(2.28)	(1.91)
Market Loading			-0.001	-0.003
			(-0.53)	(-1.56)
SMB Loading			0.003***	0.001
			(2.99)	(0.88)
HML Loading			0.000	0.000
			(0.10)	(0.14)
MOM Loading			-0.010***	-0.008***
			(-8.43)	(-6.32)
FF4 R Squared				-0.001
				(-0.59)
Return Volatility				0.114***
				(3.91)
Ln(Age)				-0.013***
				(-13.01)
Ln(TNA)				-0.003***
				(-16.30)
Expense Ratio (t-1)				0.001
				(0.04)
Turnover Ratio (t-1)				0.000
				(1.35)
Adjusted R-Squared	0.124	0.128	0.130	0.138
N	871,549	861,927	861,927	859,562
Fund FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes

Table 4: Prospect Theory Features and Fund Flows

This table presents the predictive power of each individual feature of prospect theory in forecasting future fund flows. The dependent variable is fund flow, and the specifications vary depending on which components of prospect theory are incorporated into prospect-theory values. For explanatory variables in columns (1) through (3), we calculate prospect-theory values using only loss aversion, concavity/convexity, and probability weighting, respectively. In column (4), we include all three independent features in one regression. In column (5), we replicate our main specification and use TK as the explanatory variable. All values are estimated using fund returns from the preceding 60 months. In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in column (4) of Table 3. The sample spans from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*				
	(1)	(2)	(3)	(4)	(5)
LA	0.839***			0.415***	
	(14.17)			(5.77)	
CC		0.974***		0.598***	
		(15.12)		(7.78)	
PW			0.623***	0.233***	
			(9.59)	(3.55)	
TK					0.383***
					(11.27)
Adjusted R-Squared	0.139	0.140	0.137	0.140	0.138
N	859,562	859,562	859,562	859,562	859,562
Fund FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Table 5: Prospect Theory and Mutual Fund Holdings and Transactions: Account-Level Evidence
This table presents the predictive power of prospect theory in explaining mutual fund investors' portfolio decisions. Specifically, we focus on account-level positions and transactions from a large brokerage firm spanning from 1991 to 1996 (see Barber and Odean (2000) for details). The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. The dependent variable in Panel A is the dollar amount of mutual fund holdings in an account scaled by account balances (*Amt Held/Balance*, in percent) or by fund size (*Amt Held/Fund Size*, in basis point). The dependent variable in Panel B is the net dollar amount transacted for a given fund in an account from the preceding month to the current month scaled by the account balance (*NetBuy/Balance*, in percent) or by fund size (*NetBuy/Fund Size*, in basis point). In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in column (4) of Table 3. Standard errors are clustered at the account and date level.

Panel A. TK and Holdings

	(1) Amt Held/Balance (%)	(2) Amt Held/Fund Size (bps)
TK	49.884***	0.458***
	(6.00)	(3.91)
Adj. Rsq.	0.840	0.755
N	1,316,974	1,519,974
Acct FE	Yes	Yes
Date FE	Yes	Yes
Controls	Yes	Yes

Panel B. TK and Transactions

	(1) NetBuy/Balance (%)	(2) NetBuy/Fund Size (bps)
TK	7.412***	0.074***
	(6.31)	(4.97)
Adj. Rsq.	0.094	0.100
N	1,368,438	1,513,620
Acct FE	Yes	Yes
Date FE	Yes	Yes
Controls	Yes	Yes

Table 6: Revealed Preference Analysis: Prospect Theory Parameters from the Field

This table presents the estimated prospect theory parameters based on the discrete choice model using the mutual fund flows data. We estimate the parameters on a quarterly basis. In Panel A, we report the mean, standard deviation, and 99% confidence intervals constructed from the quarterly estimates of the parameters. In Panel B, we use investment performance in the previous quarter to predict loss aversion in the current quarter. We rely on our quarter-by-quarter estimation to obtain the time series for loss aversion. We use market returns in the last quarter as a proxy for prior investment performance. In column (1), we use the market return downloaded from Kenneth French's website, which represents the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. In column (2), we use the return of the S&P 500 index. The t-statistics are based on standard errors corrected by Newey-West with lags of 4 quarters.

Panel A. Estimation of Parameters

	description	mean	s.e.	99% CI
α	Curvature of the value function	0.745	0.061	$[0.576, 0.914]$
λ	Loss aversion	1.824	0.110	$[1.529, 2.119]$
γ	Probability weighting in gain region	0.110	0.028	$[0.034, 0.187]$
δ	Probability weighting in loss region	0.228	0.041	$[0.117, 0.340]$

Panel B. Prior Investment Performance and Loss Aversion

	(1) Loss Aversion(t)	(2) Loss Aversion(t)
Market Return(t-1)	-1.084*	
	(-2.03)	
Return of the S&P 500 Index (t-1)		-1.175**
		(-2.12)
Adjusted R-Squared	0.018	0.018
N	30	30

Table 7: Prospect Theory and Fund Flows: Controlling for Expected Utility

This table compares the predictive power of prospect theory and expected utility in forecasting future fund flows. The values of prospect theory (TK) and expected utility (EU) are both estimated using fund returns from the preceding 60 months. In column (1), we present the predictive power of prospect theory. In column (2), we present the predictive power of expected utility. In column (3), we conduct a horse-race regression incorporating both TK and EU. In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in column (4) of Table 3. The sample spans from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*		
	(1)	(2)	(3)
TK	0.383***		0.137***
	(11.27)		(3.68)
EU		1.628***	1.418***
		(14.56)	(11.38)
Adjusted R-Squared	0.138	0.139	0.140
N	859,562	859,562	859,562
Fund FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Table 8: Prospect Theory and Fund Flows: Controlling for Behavioral Drivers of Fund Flows

This table compares the predictive power of prospect theory and other behavioral drivers of fund flows. The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. The values of return extrapolation (EX) are estimated using fund returns from the preceding 60 months, adopting the memory-decaying structure documented in Greenwood and Shleifer (2014). The values of salience measurement (ST) are based on fund returns in the past 12 months, following Bordalo et al. (2013). The values of max returns (MAX) are based on the maximum value of the market-adjusted fund returns in the past 12 months, as outlined in Akbas and Genc (2020). The values of skewness (Skewness) are based on the distribution of fund returns in the past 60 months. The values of Morningstar Ratings are the average values across share classes at the fund level. In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in column (4) of Table 3. The sample spans the period from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*				
	(1)	(2)	(3)	(4)	(5)
TK	0.247***	0.354***	0.327***	0.295***	0.112***
	(6.70)	(10.59)	(9.80)	(6.58)	(3.25)
Extrapolation	1.177***				
	(15.90)				
ST		0.106***			
		(12.25)			
MAX			9.566***		
			(13.25)		
Skewness				0.002***	
				(3.78)	
MorningStar Rating					0.008***
					(36.25)
Adjusted R-Squared	0.152	0.140	0.141	0.134	0.165
N	859,562	859,562	859,562	522,823	631,401
Fund FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Table 9: Prospect Theory and Fund Flows: Institutional versus Retail Funds

This table presents the heterogeneous predictive power of prospect theory in forecasting flows of funds dominated by different types of investors. The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. We use two variables as proxies for investor types: Institutional, the dummy variable for institutional funds, and Retail, the dummy variable for retail funds. In column (1), we report the baseline regression results. In column (2), we report the result from the regression that includes the dummy variable for institutional funds. In column (3), we report the result from the regression that includes the dummy variable for retail funds. In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in column (4) of Table 3. The sample spans the period from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*		
	(1)	(2)	(3)
TK	0.383***	0.390***	0.368***
	(11.27)	(11.36)	(10.50)
Institutional × TK		-0.033**	
		(-2.22)	
Institutional		-0.000	
		(-0.32)	
Retail × TK			0.024*
			(1.95)
Retail			-0.001
			(-1.51)
Adjusted R-Squared	0.138	0.138	0.138
N	859,562	859,562	859,562
Fund FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Table 10: Prospect Theory and Fund Flows: Effect of Investor Sophistication

This table presents the heterogeneous predictive power of prospect theory in forecasting fund flows dominated by investors with varying levels of sophistication. The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. Following Barber et al. (2016), we utilize two variables to reflect investor sophistication: Broker Sold, a dummy variable for funds distributed mainly through brokers, and Direct Sold, a dummy variable for funds sold directly. In column (1), we report the baseline regression results. In column (2), we present the results of regressions that include the dummy variable for funds distributed through brokers. In column (3), we provide the results of regressions that include the dummy variable for directly sold funds. In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in column (4) of Table 3. The sample spans the period from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*		
	(1)	(2)	(3)
TK	0.383***	0.363***	0.392***
	(11.27)	(10.51)	(11.51)
Broker Sold × TK		0.038***	
		(3.22)	
Broker Sold		0.001	
		(1.10)	
Direct Sold × TK			-0.036***
			(-2.76)
Direct Sold			-0.004***
			(-5.41)
Adjusted R-Squared	0.138	0.138	0.138
N	859,562	859,562	859,562
Fund FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Table 11: Prospect Theory and Fund Flows: Time-varying Predictive Power

This table examines the time-varying predictive power of prospect theory for future fund flows. The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. We consider two indicators for episodes: the investor sentiment indicator proposed in Baker and Wurgler (2006) and the recession indicator (Recession) defined by the NBER. We define a dummy variable for high investor sentiment (High Sentiment) when the sentiment level exceeds the 75th percentile of the investor sentiment index within the in-sample data. In column (1), we report the results of regressions that include the dummy variable for episodes of high investor sentiment. In column (2), we report the results of regressions that include the dummy variable for recession episodes. In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in column (4) of Table 3. The sample spans the period from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*	
	(1) Investor Sentiment	(2) NBER Recessions
TK	0.082**	0.084***
	(2.55)	(2.70)
TK × High Sentiment	0.074*	
	(1.71)	
High Sentiment	0.002*	
	(1.67)	
TK × Recession		-0.099**
		(-2.15)
Recession		-0.007***
		(-3.62)
Adjusted R-Squared	0.113	0.113
N	766,617	766,617
Fund FE	Yes	Yes
Date FE	No	No
Controls	Yes	Yes

Table 12: TK Values and Subsequent Fund Performance

This table presents the results of Fama-MacBeth regressions. The dependent variables are the future fund alphas based on the Fama-French-Carhart four-factor model, with horizons ranging from 1 month to 12 months. The key independent variables are the fund's TK value in Panel A, TK-driven flows in Panel B, and non-TK-driven flows in Panel C. The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. TK-driven flows and non-TK-driven flows are respectively defined as the fitted value ($\widehat{flow}_{i,t}$) and the residual ($u_{i,t}$) from the following cross-sectional regression: $Flow_{i,t} = a + bTK_{i,t-1} + u_{i,t}$. The control variables are identical to those included in column (4) of Table 3. The sample spans the period from January 1981 to June 2022. We report standard errors corrected by Newey-West with lags of 12 months.

Panel A: TK Values and Fund Performance

	(1) 1 Month	(2) 3 Months	(3) 12 Months
TK	-0.014	-0.053	-0.380
	(-0.39)	(-0.52)	(-1.13)
Adj. Rsq.	0.319	0.319	0.359
N	859,592	845,089	782,471
Controls	Yes	Yes	Yes

Panel B: TK-Driven Flows and Fund Performance

	(1) 1 Month	(2) 3 Months	(3) 12 Months
$\widehat{flow}$	-0.001**	-0.003*	-0.008
	(-2.07)	(-1.87)	(-1.56)
Adj. Rsq.	0.309	0.310	0.349
N	843,151	828,864	767,360
Controls	Yes	Yes	Yes

Panel C: Non-TK-Driven Flows and Fund Performance

	(1) 1 Month	(2) 3 Months	(3) 12 Months
u	0.006***	0.009***	0.010**
	(5.62)	(4.27)	(2.31)
Adj. Rsq.	0.310	0.310	0.349
N	843,151	828,864	767,360
Controls	Yes	Yes	Yes

Table 13: Prospect Theory and Alternative Measures of Fund Flows: New Subscriptions and Redemptions

This table compares the predictive power of prospect theory in forecasting future funds' new subscriptions and redemptions. The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. The dependent variables are new subscriptions and redemptions, which are scaled by fund size to reflect fund inflows and outflows, respectively. In column (1), we present the predictive power of prospect theory for future new subscriptions. In column (2), we present the predictive power of prospect theory for future redemptions. In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in column (4) of Table 3. The sample spans from July 2003 to June 2022. Standard errors are clustered at the fund and date level.

	New Subscriptions	Redemptions
	(1)	(2)
TK	0.052***	-0.020
	(3.23)	(-1.42)
Adjusted R-Squared	0.715	0.789
N	359,604	359,604
Fund FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes

Table 14: Determinants of Funds' Prospect Theory Values

This table examines the relationship between funds' prospect theory values and past fund return characteristics. The dependent variables are funds' TK values (Panel A) and funds' prospect theory values with standalone features (Panel B). The explanatory variables include the fund's cumulative returns, return volatility, and skewness. All variables are estimated using fund returns from the preceding 60 months. In all specifications, we include both fund and date fixed effects. The sample spans the period from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

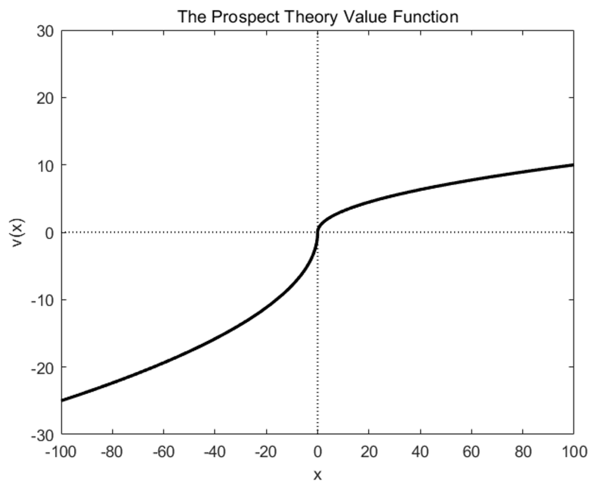
Panel A: TK Values and Characteristics of Past Fund Return Distributions

	Dependent Variable: *TK*			
	(1)	(2)	(3)	(4)
Cumulative Returns(60m)	0.022***			0.011***
	(86.39)			(34.27)
Return Volatility		-0.499***		-0.510***
		(-31.53)		(-35.88)
Skewness			0.009***	0.006***
			(20.24)	(15.68)
Adjusted R-Squared	0.549	0.253	0.217	0.788
N	862,055	862,055	523,446	523,446
Fund FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Controls	No	No	No	No

Panel B: Features of Prospect Theory and Characteristics of Past Fund Return Distributions

	Dependent Variable: *TK Features*		
	(1) Loss Aversion	(2) Concavity/Convexity	(3) Probability Weighting
Cumulative Returns(60m)	0.010***	0.012***	0.005***
	(33.57)	(34.99)	(33.61)
Return Volatility	-0.309***	0.023***	0.036***
	(-32.93)	(3.32)	(6.10)
Skewness	0.001***	0.000*	0.004***
	(4.68)	(1.94)	(20.63)
Adjusted R-Squared	0.772	0.754	0.717
N	523,446	523,446	523,446
Fund FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	No	No	No

Figure 1: Value Function and Probability Weighting Function in Prospect Theory
This figure depicts the value function and probability weighting function in prospect theory. The parameters for each function are based on the estimates reported in Kahneman and Tversky (1979).



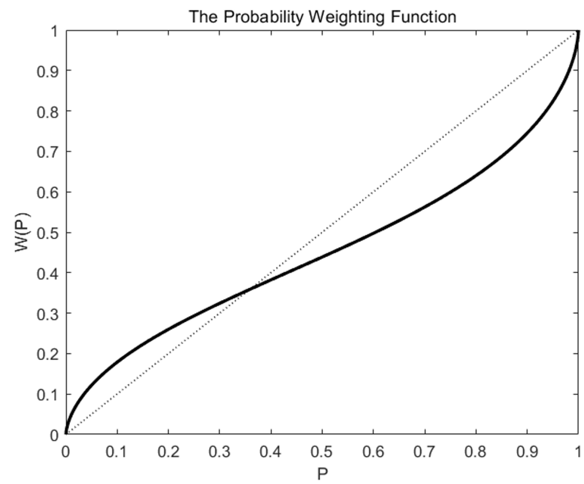


Figure 2: Total Number of Funds Over Time

This figure graphs results indicating how the total number of funds varies over time. We use the CRSP Mutual Fund Database sample, which spans the period from January 1981 to June 2022. We focus on equity funds.

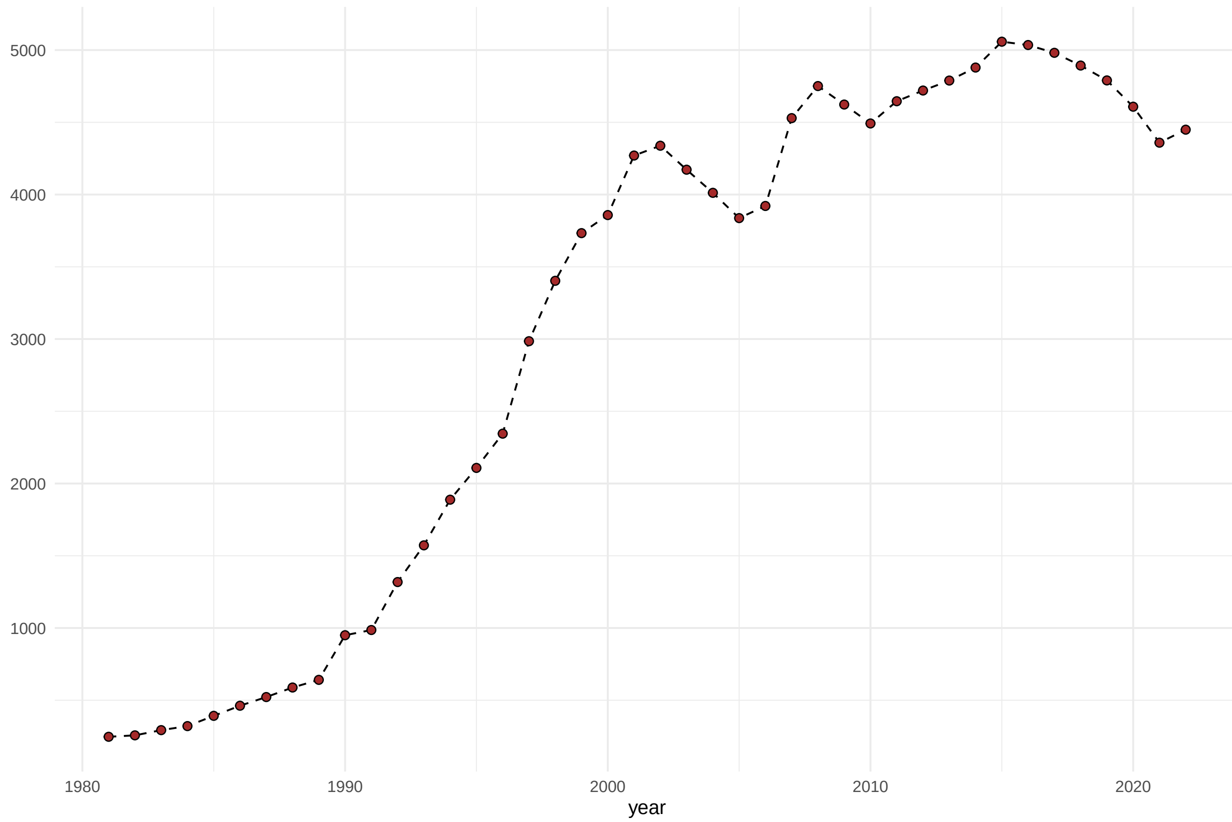


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Table A1: Definition of Variables

This table presents the definitions of the main variables in our study.

Variables	**Description**
Flow	Defined as the percentage growth of new assets, following the fund-flow literature
New Subscriptions	Dollar amount of total new subscriptions in each month scaled by a fund's total net assets at the end of the preceding month
Redemptions	Dollar amount of redemption in each month scaled by a fund's total net assets at the end of the preceding month
TK	Defined as a fund's prospect-theory value based on fund returns in the preceding 60 months. "TK" value represents fund value as specified in Tversky and Kahneman (1992), the paper that first introduced cumulative prospect theory.
LA	Defined as a fund's prospect-theory value, featuring loss aversion while turning off probability weighting and the concavity/convexity feature in the value function.
CC	Defined as a fund's prospect-theory value, featuring concavity/convexity while turning off loss aversion and probability weighting in the value function.
PW	Defined as a fund's prospect-theory value, featuring probability weighting while turning off loss aversion and the concavity/convexity feature in the value function.
CAPM Alpha	The intercept from the time-series regression of monthly fund returns on market excess returns using the preceding-60-months window
FF4 Alpha	The intercept from the time-series regression of monthly fund returns on Fama-French-Carhart 4-factors using the preceding-60-months window
Market Loading, SMB Loading, HML Loading, MOM Loading	The coefficients of Market, SMB, HML, and Momentum factors from the time-series regression of monthly fund returns on Fama-French-Carhart 4-factors using the preceding-60-months window
FF4 R Squared	The R-squared from the time-series regression of monthly fund returns on Fama-French-Carhart 4-factors using the preceding-60-months window
Ln(Age)	Logarithmic form of fund age in years
Ln(TNA)	Logarithmic form of a fund's total net assets
Expense Ratio	A fund's expense ratio
Turnover Ratio	A fund's turnover ratio
Return Volatility	Standard deviation of monthly fund returns in the preceding 60 months
Cumulative Returns(60m)	Cumulative monthly fund returns in the preceding 60 months

Table A2: Prospect Theory and Fund Flows: Constructing TK using Different Windows

This table presents the predictive power of prospect theory in forecasting future fund flows. The dependent variable is fund flow, and the specifications vary depending on the windows used for constructing TK values. For explanatory variables in columns (1) through (4), we calculate TK values by respectively using the fund returns from the preceding 12 months, 24 months, 36 months, and 48 months. In all specifications, we include both fund and date fixed effects. The definitions of variables are presented in Table A1. The sample spans from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*			
	(1)	(2)	(3)	(4)
TK (12 months)	0.268***			
	(20.91)			
TK (24 months)		0.321***		
		(17.97)		
TK (36 months)			0.401***	
			(17.93)	
TK (48 months)				0.392***
				(15.65)
Adjusted R-Squared	0.150	0.145	0.143	0.140
N	859,559	859,562	859,562	859,562
Fund FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table A3: Prospect Theory and Fund Flows: Winsorizing at 1% and 99% Levels

This table presents the predictive power of prospect theory in forecasting future fund flows. We winsorize our main variables at 1% and 99% levels. The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. The dependent variable is fund flow. In column (1), we run a univariate regression with TK as the only regressor. In column (2), we add the cumulative returns and CAPM alpha, both estimated using returns over the preceding 60 months. In column (3), we further control for loadings on factors in the Fama-French-Carhart four-factor model. In column (4), we include additional fund characteristics. In all specifications, we include both fund and date fixed effects. The definitions of variables are presented in Table A1. The sample spans from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*			
	(1)	(2)	(3)	(4)
TK	0.495***	0.227***	0.188***	0.261***
	(24.48)	(9.18)	(6.60)	(7.34)
Cumulative Returns(60m)		0.007***	0.008***	0.008***
		(6.37)	(6.94)	(7.21)
CAPM Alpha		0.002*	0.003***	0.002**
		(1.90)	(3.06)	(2.54)
Market Loading			-0.002*	-0.004**
			(-1.81)	(-2.21)
SMB Loading			0.003***	0.001
			(2.90)	(1.09)
HML Loading			0.000	0.000
			(0.41)	(0.31)
MOM Loading			-0.011***	-0.009***
			(-8.82)	(-7.02)
FF4 R Squared				-0.001
				(-0.58)
Return Volatility				0.102***
				(3.11)
Ln(Age)				-0.013***
				(-13.15)
Ln(TNA)				-0.003***
				(-16.15)
Expense Ratio (t-1)				0.002
				(0.10)
Turnover Ratio (t-1)				0.000
				(1.50)
Adjusted R-Squared	0.122	0.127	0.129	0.137
N	871,549	861,927	861,927	859,562
Fund FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes

Table A4: Prospect Theory and Fund Flows: Bond Mutual Funds and Index Mutual Funds
This table presents the predictive power of prospect theory in forecasting future fund flows, with a specific focus on bond mutual funds and index mutual funds. The values of prospect theory (TK) are estimated using fund returns from the preceding 60 months. Columns (1) and (2) present results for the subsample of bond mutual funds, while columns (3) and (4) present results for the subsample of index mutual funds. In columns (1) and (3), we run a univariate regression with TK as the only regressor. In columns (2) and (4), we include control variables. In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in Table 3. The sample spans the period from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*			
	Bond Mutual Funds		Index Mutual Funds	
	(1)	(2)	(3)	(4)
TK	0.317***	0.460***	0.118**	0.227**
	(3.71)	(5.46)	(2.24)	(2.15)
Cumulative Returns(60m)		0.003		0.004**
		(0.70)		(2.36)
CAPM Alpha		0.015***		0.003
		(5.27)		(1.47)
Market Loading		-0.006		-0.008*
		(-1.24)		(-1.87)
SMB Loading		0.010***		-0.001
		(2.73)		(-0.49)
HML Loading		-0.003		0.000
		(-1.19)		(0.08)
MOM Loading		0.007		-0.003
		(1.52)		(-0.82)
FF4 R Squared		0.001		0.008
		(0.56)		(1.26)
Return Volatility		0.231***		0.357***
		(4.31)		(4.29)
Ln(Age)		-0.014***		0.001
		(-11.97)		(0.22)
Ln(TNA)		-0.002***		-0.007***
		(-8.05)		(-8.75)
Expense Ratio (t-1)		-1.143***		-1.693***
		(-10.18)		(-3.24)
Turnover Ratio (t-1)		0.000		0.000
		(0.19)		(0.74)
Adjusted R-Squared	0.062	0.126	0.049	0.058
N	747,848	511,602	177,707	126,322
Fund FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Table A5: Prospect Theory and Fund Flows: Different Choices of Reference Point

This table presents the predictive power of prospect theory in forecasting future fund flows. The dependent variable is fund flow, and the specifications vary depending on which reference point is used to calculate TK values. For explanatory variables in columns (1) through (3), we respectively use zero, market return, and style return as the reference point. All values are estimated using fund returns from the preceding 60 months. In all specifications, we include both fund and date fixed effects. The control variables are identical to those included in column (4) of Table 3. The sample spans from January 1981 to June 2022. Standard errors are clustered at the fund and date level.

	Dependent Variable: *Flow*		
	(1)	(2)	(3)
TK (risk-free rate)	0.379***		
	(11.24)		
TK (market return)		0.354***	
		(11.09)	
TK (style-adjusted return)			0.490***
			(13.90)
Adjusted R-Squared	0.138	0.138	0.141
N	859,562	859,562	859,562
Fund FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes