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

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Abstract

Using mutual fund flow, we empirically test whether choices made by investors are consistent with preferences implied by prospect theory. Our findings support this hypothesis. When allocating capital to mutual funds, investors evaluate funds based on the past performance distribution and choose the ones that deliver the highest utility according to prospect theory. This predictive relation is robust when we control for a large set of known drivers of fund flows, alternative flow measures, and account-level data. The pattern is more salient among investors more prone to behavioral biases and during times of high-sentiment. Moreover, all the features of prospect theory contribute to the predictive power.

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1 Introduction

Investors decide on which mutual funds to invest in based on their assessment of the risk-reward trade-off. Thus mutual fund flows reveal investors' preferences. Understanding investors' preferences and the way they evaluate risk is a fundamental question in finance. Commonly, the investors preferences are modeled by the expected utility theory. When making risky investments, investors maximize their expected utilities. Thus, the more attractive investment opportunities should deliver higher expected utilities. In the mutual fund context, researchers typically assume investors evaluate risk-reward trade-off using certain asset pricing models such as the Capital Asset Pricing Model. This is equivalent to assuming investors' preferences follow the expected utility, given these models are rooted in the expected utility framework. Recent advancements in behavioral economics and finance challenge the expected utility theory and suggest an alternative — Prospect Theory, developed by Daniel et al. (1979) and Tversky and Kahneman (1992). Prospect theory has found support from both laboratory and empirical settings. In this paper, we assess how closely the prospect theory can describe the mutual fund investors' preferences.

Prospect theory suggests that investors take two steps when making investment decisions: "representation" and "valuation." The "valuation" step follows directly from the value functions in Tversky and Kahneman (1992) that assign prospect theory values to any given distribution of gains and losses. The "representation" step, however, is less straightforward as we do not observe how investors mentally represent the distribution of gains and losses to evaluate risk. To formalize the representation, we adopt the empirical framework developed by Barberis et al. (2016) and rely on the distribution of the mutual funds' past returns. The most obvious reason why investors might adopt this representation is because the past return distribution is an easily accessible proxy for any asset classes. We argue that such representation is particularly suitable for mutual fund investors, because unlike assets such as stocks, mutual funds have limited information besides past performance.

The predictions of prospect theory on mutual fund flow are straightforward. If investors evaluate mutual funds based on their past performance distribution according to prospect theory, then they shall allocate capital to funds with high prospect theory value. That is, prospect theory value predicts future fund flows positively. To test the prediction, we construct a prospect theory measure that captures the utility derived from the mutual funds' past returns. Empirically, we use the fund's past 60 months' returns to *represent* the return distribution.[1] Then we feed the returns into the value functions of the cumulative prospect theory to derive the CPT value. This measure, termed "TK" after Tversky and Kahneman, is the main variable of our interest.

By analyzing a large panel of actively managed equity mutual funds in the US, we find strong and robust evidence for our main prediction. The mutual funds with high prospect theory value experience significantly

[1] Common mutual fund data providers, e.g., Morningstar, display the fund performance using a graph. The horizon can be from one year up to ten years.

larger future net inflows. Our main test is based on panel regressions using the future flows as the dependent variable and the TK value as the independent variable. One obvious concern is that the TK value may proxy for other factors related to the fund's past performance. After all, TK is computed using the past 60 months' fund returns. To alleviate such concern, we control for several statistics based on the past fund performance, including the past returns from the last 60 months, abnormal returns estimated using different versions of factor alphas, and factor loadings. Our results remain robust while controlling these performance-related measures.

To provide robust evidence, we also consider alternative measures of fund flows and control for alternative expected utility values. We examine inflows and outflows separately as the previous literature shows investors have heterogenous responses when making the purchase and sell decisions(Chevalier and Ellison (1997)). We find TK exhibits stronger predictive power to inflows (new subscriptions) than net flows. When considering redemptions as the dependent variable, TK becomes insignificant. This finding aligns with the previous literature that investors are less sensitive when making sell decisions. To explicitly control for expected utility, we derive the utility value from a power utility function using the past 60 months' returns as the return distribution. We find TK remains positive and significant. At the same time, the EU value is also significant and positive. This result matches our priors as we expect the investors are consisted by both rational (EU) and irrational (CPT) decision-makers. Both EU value and TK should have explanatory power to the flows aggregated from two types of investors.

The analysis based on fund level flow depicts the behavior of a ”representative” mutual fund investor because fund flow aggregates the individual buy and sell decisions across investors. To provide a more granular analysis, we utilize the data from a large retail brokerage that covers individual investors' positions and trading records. We identify the account-level mutual fund transaction information and test whether the prospect theory explains the investors' buy and sell decisions of mutual funds. The findings support the hypothesis that CPT explains mutual fund investor decisions in two ways. First, the investors' portfolio holdings positively relate to the fund's TK values. Second, we show that investors tend to buy more in a mutual fund when the fund's TK value is high. (need to provide economic magnitudes).

TK value summarizes all four features of the prospect theory preferences. It is valuable to show which feature is the main driving force. We thus examine the independent predictive power of individual components of the prospect theory value for future fund flows. These components include loss aversion (LA), convexity/concavity (CC), and probability weighting (PW). We find that all the components play significant roles in explaining future fund flows. This result is different from Barberis et al. (2016). They find that when predicting stock returns, the probability weighting is the main driver behind the TK value, while other components (LA and CC) only show marginal predictive power. We attribute these different results to our dependent variable. Unlike return, which is an equilibrium outcome, fund flows are ”choices” that directly map into investor preferences. Since (active) mutual funds are managed portfolios, we look into the portfolio holdings to understand the driving forces behind the fund level TK. We want to know whether a fund has high (low) TK because it holds high (low) TK stocks or because the portfolio adjustments between quarters induced the high TK properties of fund return distributions. We find some weak evidence that high TK funds tend to hold high TK stocks in the future. But the results are not strong and robust enough to fully explain the fund level TK, suggesting that the portfolio adjustments between quarters is also a major driving force.

We identify several channels through which the prospect theory preference can affect fund flows. First, we note that retail and less sophisticated investors should be more likely to fit the prospect theory description. We show that the effect of TK on flow is stronger among retail investor-dominated funds and broker-sold funds, which are dominated by less sophisticated investors. Second, inspired by the findings in Baker and Wurgler (2013) that mutual fund investors' irrational demand comoves with investor sentiment, we document the predictive power of prospect theory becomes stronger when the sentiment index are higher. The predictive power also significantly drops during the recession periods.

Our TK measure is constructed for each month. This means that TK captures the investors' preferences as if they are deciding which fund to invest in each month, which matches more closely to the situation of the new investors. However, the fund flows we observe can come from both new and existing investors. Empirically, we do not observe new investors directly. To account for such limitation, we estimate an AR(1) mode assuming that the existing investors tend to invest in mutual funds persistently through saving plans such as IRA or 401K accounts. We show that our TK measure can explain both the expected component and the unexpected component of fund flow. Alternatively, we use TK's change to explain the fund flow. The change of TK captures how the fund's attractiveness change from time t-1 to t, which maps into the existing investors' preferences. We find the TK's change indeed explains better for existing investors' flow. Lastly, we note that redemptions can only come from existing investors. And the weak result on the redemptions is consistent with our intuition that TK does not match the preferences of the existing investors well.

It is safe to assume capital flows in response to high TK as "dumb money." We find TK value negatively predicts future fund performance, as measured by Fama-French-Carhart Four-Factor Alpha. This finding is consistent with the notion that investors make irrational decisions by oversupplying capital to high TK funds. The result is robust to different predictive horizons up to 48 months. The poor performance confirms that the mutual fund investors have bounded rationality, leading to capital misallocation. Moreover, we estimate a TK-driven flow by projecting the overall flow into TK. The TK-driven flow captures the capital flow in response to TK, and the residual captures flow driven by other factors. We show that TK-driven flow predicts future fund performance negatively while the non-TK-driven flow predicts future fund performance positively.

Lastly, we test several alternative hypotheses that may confound with the prospect theory explanation of fund flows. For example, several studies show that investors follow Morningstar Ratings or respond to past maximum monthly returns. There are also competing behavioral theories. For example, the (over)extrapolation and salience theories also rely on past fund performance. To test against these alternative hypotheses, we run horse races between TK and the empirical measures constructed based on the alternative theories. We find TK remains robust throughout.

Our paper contributes to the prospect theory literature that uses market data to test the theory. Recent work in this line of research include Barberis et al. (2016), Grinblatt and Han (2005) and Baele et al. (2019). Unlike previous literature focusing on prices, we study the choices of mutual fund investors. Choices follow immediately from preferences, thus offering a direct test for the prospect theory. Price is an equilibrium quantity derived from choices through market-clearing conditions and can thus be influenced by trading rules and other frictions. The inferences drawn from choices and prices can be quite different. For example, Bossaerts et al. (2020) show that in a simple two-period dynamic model, the prices from a myopic equilibrium are very close to a perfect foresight equilibrium, while the choices are significantly different.

This study also offers new evidence on the rationality of mutual fund investors. Guided by theory, we show mutual fund investor preferences are consistent with what prospect theory prescribes. Several papers document evidence that mutual fund investors are not rational. For example, Franzoni and Schmalz (2017) show mutual fund investors tend to chase growth stocks and experience poor future performance. Cooper et al. (2020) find that mutual fund investors persistently invest in high-fee mutual funds. Mutual fund investors can also be attracted to Wall Street Journal rankings (Kaniel and Parham, 2017), Morningstar Ratings (Ben-David et al., 2019; Guercio and Tkac, 2008), sustainability rankings (Hartzmark and Sussman, 2019), and past extreme returns (Akbas and Genc, 2020). Different from previous literature, we seek theoretical guidance from the well-established behavioral finance literature to understand the mutual fund flows within a psychologically realistic framework, namely *cumulative prospect theory* (CPT). A vast literature (see Barberis et al. (2016) for a recent survey) shows that when making investment decisions, investors exhibit preferences that are consistent with CPT. One would expect that mutual fund investors may have similar behaviors. Our findings support this view and thus provide a systematic alternative explanation for mutual fund investor behavior.

Lastly, we contribute to the literature to understand mutual fund flows. Since Ippolito (1992), mutual fund investors are known to chase past performance. Recent work in the flow literature (e.g., Barber et al. (2016), Berk and Van Binsbergen (2016), Song (2020), Dannhauser and Pontiff (2020)) studies how different components of past performance affect fund flows. They show that both abnormal returns (alpha) and factor-related returns predict future fund flows. This decomposition, however, crucially depends on how investors evaluate risk (Jegadeesh and Mangipudi (2019)). We offer a new behavioral perspective to the flow literature by documenting prospect theory's incremental explanatory power to mutual fund flows.

The rest of the paper is organized as follows. Section 2 provides the theoretical background. Section 3 describes our data and measure construction. Section 4 and 5 presents the main results and determinants of TK measure. Section 6 and 7 discuss the underlying mechanisms and alternative hypothesis. Section 8 concludes.

2 Prospect Theory Value

Under prospect theory, investors first form a mental representation of the distribution of gains and losses for a risky investment. Then, they evaluate this mental representation to assess the attractiveness of the investment. Therefore, following Barberis et al. (2016), we break the decision-making process under prospect theory into two steps: "representation" and "valuation."

2.1 Representation

In the mutual fund context, the most important deciding factor for an investor is past performance. A large literature documents that mutual fund investors tend to chase past performance (Chevalier and Ellison, 1997; Choi et al., 2010; Sirri and Tufano, 1998). Consistent with the return-chasing behaviors, we posit that mutual fund investors use the distribution of the fund's past returns to represent future fund returns.

The way of representation we suggest above is also consistent with the approach proposed by Barberis et al. (2016). In their paper, they use the distribution of a stock's past returns as the representation of the stock's return distribution. However, unlike the decision-making process of stock investment, where investors have rich supplementary information to rely on, mutual fund investors do not have so much information related to the "fundamental" of a fund. Past return distribution is the primary information source that mutual fund investors depend on, which makes the suggested representation approach more appropriate in the mutual fund context.

To further determine an appropriate frequency and horizon for the past return, we look at one of the major information sources for mutual fund investors: Morningstar, which is a mutual fund research company that provides extensive mutual fund investment information. On its website, Morningstar typically displays mutual fund performance in a chart of wealth change over time. Most of these charts contain returns at the monthly frequency, and a common time window goes back approximately five years. Therefore, we use the distribution of a fund's monthly returns over the past five years as the representation of a fund.

2.2 Valuation

Fixing the representation, we compute the prospect theory value following the cumulative prospect theory (CPT) introduced by Tversky and Kahneman (1992). Here we describe the steps to calculate the prospect theory value (TK). For a given mutual fund with past 60 months returns, we start by ordering the stock returns ascendingly. So we obtain a distribution as

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

where r_{-m} to r_{-1} are the negative returns from the most negative to least. r_1 to r_n are the positive returns from the smallest to largest.

Then, TK value can 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 3 implies decision weights (where π is computed using $w^{-}(\cdot)$ and $w^{+}(\cdot)$:

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

The following parameters are plugged in to compute TK value:

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

Embodied in the above formulas are the four features of prospect theory: loss aversion (LA), probability weighting (PW), reference dependence(RD)[2], and concavity/convexity (CC). We use the returns relative to the risk-free rate as the reference level, following Barberis and Huang (2008). Our results are robust if we use other reference point such as market return or style average return.

3 Data and Sample

3.1 Sample Construction

Our main data source is the CRSP's Survivor-Bias-Free US Mutual Fund Database. We focus on equity mutual funds, excluding ETFs/ETNs, variable annuities, and index funds. We start our sample from 1981[3] for better coverage of monthly Total Net Assets (TNA) and return data. Mutual fund data is recorded at the share class level in CRSP. We aggregate share classes following methods described in Berk and Van Binsbergen (2015). Most of the fund characteristics and performance are weighted averages across share classes using

[2]We use reference dependence only if we use some benchmarks to adjust fund flows.

[3]Since we need to consume 5 years of data to estimate some variables, our analysis starts from 1986.

share class size as weights. In the end, we have 2,698 mutual funds each month on average. Fund TNA is the sum of share class level TNA, and age is from 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 of fund i during month t, and $TNA_{i,t}$ is the total net asset value of fund i at the end of month t. We winsorize fund flows at 1% and 99% level. [4] Factor loadings and alphas are computed using a rolling window of past 60 months return.

3.2 Summary Statistics

Table 1 Panel A reports the summary of statistics on the main variables used in our analysis. Mutual funds in our sample have \$253 Million total net assets on average. Fund experience slightly net outflows and has negative alphas. In table 1 Panel B we sort the sample into five groups at the monthly frequency and report the average values of the variables across TK groups. We notice the performance measures such as CAPM alpha, FF4 Alpha, and raw returns all increase with TK value. High TK funds also manage more assets, while having similar age with low TK funds. Most importantly, net inflow increases monotonically with the TK value.

The summary statistics show that we have a large and representative sample of mutual funds. And the sorting results based on TK value already indicate a positive relation between TK value and fund flows.

4 Prospect Theory and Fund Flows

4.1 Portfolio Sorts

Our main hypothesis is that the prospect theory describes the way investors make their choices among mutual funds: a mutual fund's TK value will predict future flows. A simple way to show the relationship between TK and flow and is through portfolio sorting.

For each month from January 1986 to March 2020, we sort funds into deciles based on the funds' TK values in the last month. Then we examine the average net inflows of each decile in that month, both equal-weighted and value-weighted using the funds' TNA. This yields a time series of monthly net inflows for each TK decile. Lastly, we take the average overtime time to get the average net inflows across deciles. The results are reported in Table 2. From deciles 1 to 10, we observe a monotonic increase of net inflows, from -0.7% to 0.8% when funds are equally weighted (Panel A) and from -0.5% to 0.9% when funds are TNA-weighted

[4] Elton et al. (2011) document that the dates of fund mergers often differ from actual merger date, which introduces a large number of errors into fund returns. This bias in fund returns may lead to extreme values of flows. To mitigate the impact of potential outliers around mergers, some literature filter out the top and bottom 1% of tails of the flow data

(Panel B). Statistically, the negative (positive) inflows in the low (high) TK funds are significant with a t-statistic above 3. The spreads between the highest TK funds and lowest TK funds are around 1.5% and statistically significant.

The results support our main hypothesis that mutual fund investors exhibit prospect theory preferences, as funds with high TK value attract significantly more inflow. The evidence is found both on the positive and negative side and is not affected by fund size. Although the univariate analysis provides an intuitive description of the relationship between TK and fund flows, it falls short in controlling other factors known to affect fund flows. In the following section, we employ rigorous regression analysis to carefully control for other variables that have been shown to predict future fund flows.

4.2 Baseline Regression

We now conduct regression analysis to test our main hypothesis. Our main econometric specification is the panel regression with fixed effects.[5] Specifically, we estimate the following regression model:

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

The dependent variable, $Flow_{i,t}$, is the net inflow of mutual funds in month t. The net inflow is the outcome of mutual fund investors' buy and sells orders, i.e., the aggregate choice of the mutual fund investors for each fund. Our variable of interest is $TK_{i,t-1}$, which measures the prospect theory value of the fund based on the past 60-month returns by the end of the period $t-1$. $X_{i,t-1}$ is a vector of control variables documented to predict fund flows in previous literature.

Performance measures. The most important set of controls are fund performance measures. Previous literature has documented extensive evidence that fund past performance draws capital inflow from investors. We consider several types of performance measures. First, we control the cumulative returns in the past 60 months. This is a basic performance measure that investors can easily get. Moreover, the TK value is essentially a function of the past 60 months returns, albeit motivated by theory. Therefore, to show TK value provides additional information, we control for the cumulative return in the past 60 months. Second, we control for fund alphas estimated using empirical asset pricing models (e.g., CAPM, Fama-French-Carhart Four-Factor Model). Alphas are known to predict fund future flows. Recently, several papers (e.g., Berk and Van Binsbergen (2016) and Barber et al. (2016)) show that CAPM alpha outperforms other predictors. Lastly, we control factor loadings on *mktrf*, *smb*, *hml*, and *umd*. Controlling these loadings is important because Barber et al. (2016) shows that investors respond to the fund performance attributable to these factors. [6]

Other Fund Characteristics. In addition to the performance measures, we include a battery of fund characteristics that investors might care about when picking funds. For example, investors might prefer (or

[5] In untabulated results, we show TK's predictive power remains robustly positive using the Fama-MacBeth regression.

[6] To estimate alpha and loadings, we use 60 months to align the estimation period of TK. The results are similar if we use other estimation windows such as 36 months.

avoid) more actively managed mutual funds. We capture funds' activeness using the R-squared from the Four-Factor Model (Amihud and Goyenko, 2013). We also control for fund return volatility, which could arguably diminish investors' ability to learn about fund manager skills. Lastly, we control for mutual fund characteristics including fund age, size, expense ratio, and turnover ratio.

Fixed Effects.We include two fixed effects in equation (8): fund fixed effect, ϕ_i, and time fixed effect, η_t. By including fund fixed effects, we control for unobserved heterogeneity that is constant over time, such as time-invariant fund skill (Pástor et al., 2015) and the degree of dis-economy of size (Zhu, 2018). Moreover, fund fixed effects allow us to identify important within-fund variations over time. Relying either on within-fund variation or cross-sectional variation can sometimes lead to very different interpretations in the mutual fund context (Pástor et al., 2017). Previous studies on mutual fund flow such as Barber et al. (2016) and Ben-David et al. (2019) only include time fixed effects and focus on cross-sectional variation. We also control for time fixed effects.

We estimate the regression model in equation (8) using fund net inflow as the dependent variable. By regressing the net inflow on TK, we test whether prospect theory can describe the average investor's choice. Table 3 presents the regression results. In all specifications, we include both fund and date fixed effects[7]. All the standard errors are two-way clustered at the fund and date level. Column (1) is the univariate regression with TK as the only regressor. The result shows a strong and positive relation between TK and future fund flows, with a coefficient of 0.613 and a t-statistic of 26.42. The univariate regression result corroborates the sorting result in table 2. In the next columns, we gradually add performance measures as control variables. Column 2 adds the cumulative return of the past 60 months. TK remains positive and significant, indicating that prospect theory's value function (loss aversion) and probability weighting function provides distinct power in explaining mutual fund investor behaviors. Column 3 adds CAPM alpha to the control. Consistent with the previous findings, CAPM alpha positively predicts future fund flows. In the meantime, TK remains positive and significant. The results are quantitatively similar if we use the alpha from the four-factor model (Carhart, 1997). Alphas are typically considered as signals of fund managerial skills that investors learn from past performance (Berk and Green, 2004). Our results provide a plausible alternative interpretation of how past performance may influence investors' decision-making, in addition to the classic learning channel. Specifically, past performance also serves as the mental representation that CPT-type investors rely on to derive their valuations. In column 5, we add other fund characteristics to the performance measures. TK measure continues to be positive and significant with a coefficient of 0.367 and a t-stat of 9.91. In economic terms, for an average fund in our sample, with TNA at $1494 million, one standard deviation increase in TK maps into $10.6 million of net inflows. We find larger and older funds experience lower future inflows, consistent in general with the theory on dis-economy of size. Other characteristics, such as expense ratio, turnover ratio, and fund activeness, are insignificant.

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

Overall, the findings in table 3 strongly support our hypothesis. Prospect theory offers explanatory power for fund flows beyond the traditional performance measures and other fund characteristics based on the neoclassical framework.

4.3 Alternative Flow Measure

While net inflow captures the aggregate choice of mutual fund investors, it necessarily neglects any difference between inflows and outflows. Chevalier and Ellison (1997) show that inflows are more responsive to good performance than outflows to poor performance. Although the evidence is still based on net inflow, it hints that important asymmetry may exist when mutual fund investors make purchase and redemption decisions. Moreover, the net inflow is essentially an estimated measure and thus may suffer from estimation bias.[8]

Using more detailed flow data from CRSP Mutual Fund Database, we construct monthly new subscription and redemption measures for each fund. These data are collected from SEC mutual fund filings and thus are only available after 1993. Specifically, the new subscription (redemption) is equal to the dollar amount of the new subscription (redemption) scaled by the fund size at the previous month-end. Then we estimate the regression specified in equation (8) using new subscriptions and redemption as dependent variables.

Table 4 presents the results. For both new subscriptions (column 1) and redemptions (column 2), we estimate the regression with all the control variables included (but not reported for brevity). In column (1), we find that TK values positively predict new subscriptions. As the mutual fund becomes more attractive under prospect theory, new subscriptions increase significantly. Notably, the coefficients of TK are larger than those seen in 3. When using redemptions as the dependent variable, the TK's coefficient becomes insignificant. This asymmetric pattern is consistent with the previous finding that investors tend to be less responsive to poor performance.

Examining inflows and outflows separately helps us understand through which channels prospect theory influences investor utilities. Kahneman (2000) talks about two distinct ways of driving utilities. The first type is decision utility, which reveals investors' preferences. The second type is experience utility, which investors derive from recalling past experiences in their memories. If prospect theory captures mutual fund investors' decision utility and preferences, then its predictive power on future flows should not depend on whether investors have invested in the fund before. Alternatively, if prospect theory influences investors' choices through experience utility, it plays a role only when investors have traded it in the past.

Our findings support the implications of the decision utility channel. TK value strongly explains funds' inflows — the subscriptions of new investors at the mutual fund level. By definition, these new investors

[8] For example, Huang et al. (2011) argue that the flow should be computed as $FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+r_{i,t})}{TNA_{i,t-1}(1+r_{i,t})}$ instead of the way in equation (7). Although our findings are robust to a different way of computing net inflows.

have no experience in trading the funds. [9] In contrast, the evidence for the experience utility channel seems not obvious. The explanatory power of prospect theory becomes insignificant for redemption that reflects the choices of investors who have already traded the fund in the past.

4.4 Controlling for Alternative Utility Value

Our running assumption is that investors evaluate the attractiveness of mutual funds according to CPT based on the historical return distribution. A natural alternative hypothesis is that investors evaluate mutual funds using the expected utility (EU). So far, none of our control variables are conceptually comparable to the TK value, a utility value derived from CPT value functions. To properly control and test the possibility that investors evaluate funds according to the EU, we derive a utility value of a power utility function specified below

$$EU = \frac{1}{60}\sum_{i=1}^{60}\frac{(1+r_i)^{1-\theta}}{1-\theta}, \tag{9}$$

where, θ is the relative risk aversion coefficient. We take the value of 0.88 to be consistent with the risk aversion coefficient (α) in calculating TK.[10] We then take the estimated EU into our baseline regression model (8) to see whether it has any predictive power of future fund flows. We find EU also positively predicts future fund flows. The coefficient is 1.28 with a t-statistic 9.9. This suggests that expected utility framework describes the investors' preference to a certain degree. More importantly, we find TK remains positive and significant, suggesting the explanatory power of CPT is not absorbed by the expected utility.

4.5 Account Level Evidence

The flows at the fund level, i.e., aggregated across investors, help identify the general pattern on whether a "representative investor" displays preference consistent with CPT when investing mutual funds. However, much of the information at the individual level is necessarily lost In this section, we use account-level transaction data from a large retail brokerage that covers individual investors' positions and trading records. The tests we conduct based on this more granular data provide internal validation of our hypothesis. We utilize both the position and transaction data to test whether investors display prospect theory preferences. We first estimate the following holdings regression:

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

[9]When applying prospect theory to historical histograms, we implicitly assume that decision utility plays a role. That is, investors use past monthly returns to form an expression of future potential gains and losses, and they are NOT required to hold the fund in the past.

[10]The results are robust to different parameter choices.

Where $h_{i,j,t}$ is the holdings of account i for fund j at date t. We compute two types of holdings: the dollar amount proportions to the account size, or the dollar amount proportions to the fund TNA. $X_{j,t}$ is a set of fund-level control variables, including fund size, turnover ratio, expense ratio, past performance, and risk loadings. λ_i and η_t are individual (account) and date (year-month) effects. Including the account and date fixed effects, we explore variations within an account at a given date across different funds, which identifies how the fund-level TK values affect investors' allocation decisions.

In addition to the holdings, we also examine whether investors' trading patterns would fit the description of prospect theory. We estimate a similar model in (10) with a different dependent variable "flow".

$$flow_{i,j,t} = \beta TK_{j,t-1} + \gamma X_{j,t} + \alpha_i + \eta_t + \varepsilon_{i,j,t}, \tag{11}$$

where $flow_{i,j,t}$ is the net dollar amount that investor i traded in fund j in month t. $TK_{j,t}$ is the TK value for fund j in month $t-1$. The results are reported in Table 6. In Panel A, we report the regressions that estimate equation (10). Each column represents a type of holdings measure: the proportion of holdings to account equity, and the proportion of holdings to fund size. In both columns, we observe positive and significant coefficients for TK. The result suggests that the individual investors' portfolio choices are consistent with the prospect theory. Panel B reports the regressions specified in equation (11). We consider two types of transaction measures: the proportion of transacted amount to account equity, and the proportion of transacted amount to fund size. Each measure is considered the dependent variable in each column. Across two columns, TK's coefficients are consistently positive and significant. Overall, the results are consistent with the patterns we document using fund-level flow data. We find the TK value remains robust and significant when explaining individual investors' decision making.

Taken together, the findings so far strongly support our hypothesis that prospect theory describes mutual fund investors' behavior. We show that TK robustly predicts future fund flows both at the fund level and investor level.

5 Dissecting TK

5.1 Which Feature of Prospect Theory Plays a Role?

Prospect theory synthesizes four behavioral traits of individual decision making — reference dependence, loss aversion, concavity/convexity, and probability weighting. *Reference dependence* is about getting the appropriate benchmark for calculating gains and losses. So far the theory does not provide a clear guidance on which reference point researchers should use. In the main analysis, we use the risk-free rate as the reference point, a common choice in this literature. In the tables reported in the Online Appendix, we use reference points such as market return, style averages, or zero. Our results remain robust to these alternative reference points. *Loss aversion* captures the phenomenon that the individual is more sensitive to losses than to gains of the same magnitude. *Concavity/Convexity* describes the fact that the value function in prospect theory, $v(\cdot)$, is concave only over gains but convex over losses. *Probability weighting* describes the situation where the individual uses transformed probabilities when evaluating a gamble. The main consequence of probability weighting is the inflated probability for the tails of any distribution.

To gain insights into how these individual features affect mutual fund investor choices, we construct alternative prospect theory values that focus only on one feature by turning off others. We achieve this by applying different parameters to the equation (3). To construct the prospect theory value contains only the loss aversion component, named LA, 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 (CC) is computed using parameters $(\alpha, \gamma, \delta, \lambda) = (0.88, 1, 1, 1)$. And prospect theory value with only probability weight (PW) is configured using parameters $(\alpha, \gamma, \delta, \lambda) = (1, 0.61, 0.69, 1)$.

We individually estimate our main specification using LA, CC, and PW in place of TK and report the results in table 7 . The last column repeats the main specification. Columns (1) to (3) contain regressions for each feature. The coefficients of all features are positive and significant. The main message is obvious: each element of prospect theory independently contributes to the predictive power of prospect theory on future fund flows.

The evidence here differs from the findings in Barberis et al. (2016), which provides tentative evidence that probability weighting (PW) is the primary driver when explaining the cross-section of stock returns. In their paper, if the feature of probability weighting is turned off, the standalone predictive power of loss aversion and concavity/convexity drops markedly. The discrepancy between the two sets of results may be attributable to the different outcome variables used in the two papers. Barberis et al. (2016) use stock returns to draw inferences on prospect theory. Stock return does not directly capture investors' choices, rather it is the market-clearing outcome of investors' choices. Moreover, inferences on stock return predictability are sensitive to the asset pricing model misspecification problem. In other words, to claim *mispricing*, one needs to fully account for *risk*. Unfortunately, the consensus on a risk-based asset pricing model is yet to be reached. Due to these issues, the test based on stock returns may be contaminated. This paper uses a direct measure of investors' choices and can potentially improve the power to test prospect theory.

5.2 Choice of TK Parameters

Which values of the prospect theory parameters produce the best fit? There is mounting evidence that both in experimental and financial settings, lambda is lower than the estimate of 2.25, while alpha is lower than the estimate of 0.88.[11] To shed some light on this question, we do sensitivity analysis for parameter lambda and alpha. Specifically, we gradually change the values of lambda (alpha), while keeping the values for other parameters as the ones estimated in Tversky and Kahneman (1992)

The left panel in figure 3 report the sensitivity analysis results for alpha. The y-axis represents the

[11] Both 2.25 and 0.88 are estimates obtained in Tversky and Kahneman (1992).

regression coefficients of the modified TK value based on the new set of parameters. As the value of alpha increases and the convexity/concavity becomes more salient, the magnitude of TK predictability also rises. When the value function degenerates to linear as alpha decreases to zero, the coefficient magnitude shrinks, albeit still significant.

The right panel in figure 3 reports the sensitivity analysis results for lambda. Consistent with the recent findings, lower lambda provides a better fit. This indicates that the degree of loss aversion for mutual fund investors may not be as strong as shown in the laboratory.

5.3 Determinants of TK Features

What is exactly about the past fund returns with high TK values that make funds attractive to investors? Conversely, what is the part of the funds with low TK values that is unappealing to investors? To address these questions, we look more closely at the relation between TK values and the characteristics of past returns distributions, specifically, three moments of past return distributions: cumulative returns, return volatility, and skewness.

Panel A of Table 8 presents how the TK value relates to the three moments of past return distributions. In each column, we include control variables as we use in Table 3 and add fund and date fixed effect. Column (1) indicates that funds with high prospect theory values have a high cumulative return, which is consistent with our intuition as prospect theory's value function increases in the payoff. Column (2) implies that high return volatility leads to lower TK values of a fund. We conjecture this is mainly because loss aversion lowers the prospect theory value with a high standard deviation. Return distributions with high skewness are positively associated with TK values, mainly because the probability feature overweights the tails of a positively skewed gamble. The relation remains unchanged if we link TK values to the three moments together, as shown in column (4).

We further connect the three moments to explain each feature of prospect theory in Panel B of Table 8. Three observations stand out. First, all three moments are significant in each TK feature. Second, consistent with our previous conjecture, return volatility negatively relates to TK value partially because of loss aversion: after we turn off loss aversion in Columns (2) and (3), return volatility positively correlates with TK values based on other TK features. Third, the magnitude of skewness is most salient for the TK value based on probability weighting, which validates our intuition about probability weighting.

5.4 TK and Fund Holdings

The mutual fund return distribution is the outcome of the portfolio decisions made by fund managers. Thus there are two potential sources of variations for fund level TK: (1) TK changes at the stock level; and (2) portfolio's TK change due to active management holding stock level TK constant. The first source is the "static" component, which can be isolated by looking into how stock-level TK aggregates into a portfolio-level TK in one period. The second source is the "dynamic" component, which can be inferred by looking into the difference between fund level TK and stock level TK.[12]

To gain insights on how to fund level TK, TK_p^t, and stock level TK, TK_i^t, change over time, we adopt an event window approach. Specifically, for each month t, we sort mutual funds into deciles based on TK_p^t, and then look backward and forward for 12 quarters. For each quarter in the event window, we compute the average fund level TK, and also the average (across funds) of holdings-implied TK at the fund level, $\widehat{TK}_p^t$, which is computed as:

$$\widehat{TK}_p^t = \sum_{i=1}^{I} w_i^t TK_i^t \tag{14}$$

The results are reported in figure 4. The left panel shows the actual fund TK over time. We see a mean-reverting pattern. TK of Decile 10 (1) funds gradually increase (decrease) before the sorting time, then slowly decrease (increase) afterward. Decile 5 funds have stable TK value over time. In general, we observe substantial persistence on fund TK overall. This is expected as it is estimated on a rolling window basis. The right panel displays the holdings-implied TK from equation (14). Compared to the fund level TK, holdings-implied TK shows very little dispersion between Decile 10 and Decile 1 funds. This suggests that the fund level variation of TK is not entirely driven by the changes of TK at individual stocks. Rather, the active portfolio adjustment that we do not observe might be a major contributing factor.

We also investigate whether high TK funds tend to buy high TK stocks in the future. To this end, we run a fund-stock level panel regression by regressing stock level TK in quarter $t+1$ on fund level TK in quarter t, while controlling for the quarter, fund fixed effect, and stock fixed-effect or fund-stock pair fixed effects. The results are presented in table (9). We find fund level TK does not predict stock level TK robustly. This result suggests the fund level TK is not mechanically driven by holding stock TK stocks, highlighting the channel of dynamic trading driving fund TK.

[12] We compute TK for an actively managed portfolio p comprised by a dynamic portfolio with weights $(w_i^\tau, \ldots, w_I^\tau)_{\tau=t-s-1}^{t-1}$ over the period $t-s-1$ to $t-1$ as a function $\mathbf{\Gamma}(\cdot)$:

$$\begin{aligned} TK_p^t &= \mathbf{\Gamma}\left(\sum_i w_i^{t-s-1} R_i^{t-s-1}, \ldots, \sum_i w_i^\tau R_i^\tau, \ldots, \sum_i w_i^{t-1} R_i^{t-1}\right) \\ &\equiv \mathbf{\Gamma}\left(R_p^{t-s-1}, \ldots, R_p^\tau, \ldots, R_p^{t-1}\right) \end{aligned} \tag{12}$$

s is the look-back period, which equals to 60 (months) in this paper. R_i^τ and R_p^τ denote the rate of return for stock i and portfolio p at month τ, and w_i^τ is the portfolio weight of stock i at month τ. Similarly, the stock level TK is expressed as:

$$TK_i^t = \mathbf{\Gamma}\left(R_i^{t-s-1}, \ldots, R_i^\tau, \ldots, R_i^{t-1}\right) \tag{13}$$

Given the function $\mathbf{\Gamma}(\cdot)$ is highly nonlinear, it is difficult to derive the analytical relationship between TK_p^t and TK_i^t.

6 Underlying Mechanism

In addition to our main hypothesis, Prospect theory yields several other testable predictions in the context of mutual funds. We test these predictions in this section.

6.1 Investor Heterogeneity

Our previous analysis considers all types of funds together. However, mutual funds differ in the aspects of clientele and distribution channels. In this subsection, we perform additional analysis and document the heterogeneous effect of prospect theory on mutual fund investors' choices.

6.1.1 Institutional vs Retail Funds

Mutual funds are sold in different share classes. Some share classes are sold to institutional investors, while others are for retail investors. Empirically, we classify a fund as an institutional (retail) fund if more than 75% of its TNA are in institutional (retail) share classes. Intuitively, institutional investors suffer less from behavioral biases and possess more information processing power. Thus, we expect prospect theory to have stronger explanatory power when explaining flows for funds sold to retail investors. We test this intuition by interacting with the institutional or retail fund indicators with TK. Table 10 presents the results. Column (1) repeats the baseline regression in table 3 for comparison purposes. In column (2) we interact TK with the indicator for the institutional fund. The coefficient of the interaction term is negative and significant. Similarly, in column (3) we interact TK with the indicator for the retail fund and find the interaction term positive and significant. These findings confirm our conjecture that prospect theory has different explanatory power of fund flows depending on the mutual fund clientele.

6.1.2 Distribution Channel

In addition to the clientele, mutual funds also differ in distribution channels. In the US, mutual funds are either sold directly to investors or distributed by intermediaries such as brokers and financial advisors. Previous evidence shows that investors in distribution channels have some distinct features. Based on evidence from Oregon University's retirement plan, Chalmers and Reuter (2012) find the investors who buy mutual funds through brokers are "younger, less highly educated, and less highly paid." Focusing on the conflict of interest, Christoffersen et al. (2013) document that flows to broker-sold funds are influenced by the payments made by fund companies to the 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 direct-sold mutual funds. Based on the extant literature, it is safe to presume investors of broker-sold funds are less sophisticated than investors of direct-sold funds. Thus we expect TK to have stronger predictive power for broker-sold fund flows. We classify the broker-sold funds following the procedure described in Sun (2014) [13].

The results are reported in table 11. Column (1) is again the baseline results repeated. In column (2) we interact with the indicator of broker-sold funds with TK and in column (3) we interact with the direct-sold indicator with TK. The interaction term between the broker-sold dummy and TK is positive and significant, while the interaction between the direct-sold dummy and TK is negative and significant. The results are consistent with the hypothesis that prospect theory works better among less sophisticated investors, i.e. investors of broker-sold mutual funds.

6.1.3 Existing Investors vs. New Investors

When calculating TK values, we use the risk-free rate as the reference point, with the implicit assumption that the investor's opportunity set is a risk-free asset contemporaneously. However, this assumption may fit more for new investors and is not appropriate for existing investors. The main reason is that the reference point of existing investors is path-dependent and can be very different from new investors. The concern here is that the documented pattern between TK and future fund flows is mainly driven by new investors. In the following, we address this concern and show our results are robust for both new investors and existing investors.

The approach is to isolate To address this question, we decompose mutual fund flows into two parts by estimating an AR(1) process for fund flows. We define the fitted part of the AR(1) model, the part that can be estimated based on the persistence of flow, as the expected flow. In the literature, persistent mutual fund flows often come from existing investors who set up a regular investment plan for their pension fund. Therefore, we use expected flows to proxy for the flows from existing investors. We define the residual part of the AR(1) model, the part that is not explained by the persistence of flow, as the unexpected flow. We use unexpected flows to proxy for the flows from new investors. We estimate the AR(1) model at the fund level, on a rolling basis, and the rolling window expands as the historical observations accumulate. Therefore, our analysis does not suffer from look-ahead bias.

We hypothesize that the predictive power of TK on future fund flows holds generally for both existing and new investors. Results in Table 12 support our conjecture. In Panel A, we estimate the AR(1) process of net inflows. Columns (1) to (3) present results for existing investors. The predictive power of TK is statistically significant and is not affected when we include FF4-factor-alpha or other controls. Columns (4) to (6) contain results for new investors and the relation between TK and next period fund net inflows is very robust. We then investigate the relation between TK value and inflows from existing and new investors.

[13] A broker-sold fund has at least 75% of the TNA in share classes that charge a front-end load, a back-end load, or a 12b-1 fee greater than 25 bps. A direct-sold fund has at least 75% of the TNA in share classes that do not charge a front-end load, back-end load, or 12b-1 fee.

Different from net inflows, inflows in our sample are constructed based on information on funds' monthly new subscriptions and therefore suffer less from measurement issues. The results, reported in Panel B, indicate that the TK value predicts new subscriptions very well, both for existing and new investors.

To provide more tests for existing investors, we use the change of TK: $\Delta TK_t = TK_t - TK_{t-1}$ as the main variable in the regression to predict future fund flows. The idea is that existing investors are affected by the change of TK from period to period, regardless of the reference point. We find the coefficient of ΔTK_t positive and significant. This result provides further support that prospect theory explains existing investors' behavior as well. (Table 11 Panel B).

6.2 Investor Sentiment

The underlying psychological foundations of CPT are closely related to judgment heuristics such as narrow framing in the psychology literature, some of which serve as the leading explanations for investor irrational regularities. Therefore, as a preference that reflects the "animal" spirit, TK value should have stronger predictive power on mutual fund flows when the market is more sentimental.

To rigorously test our hypothesis, we use the investor sentiment index proposed in Baker and Wurgler (2006) (BW investor sentiment index thereafter), as a measurement for irrationality in the market. This index is constructed using a top-down approach by extracting fluctuations from an array of indicators such as investor surveys, investor trades, dividend premiums, closed-end fund discounts, and mutual fund flows. It lines up fairly well with anecdotal accounts of bubbles and crashes documented in the literature.

We include the interaction term between TK value and the BW investor sentiment index. If the TK value captures the irrational preferences of mutual fund investors, we should anticipate a positive and significant coefficient for the interaction term.

Our findings confirm the conjecture. We report the result from the regressions with the interaction term in Table 13. We see a positive and significant coefficient for the interaction term Column (1), indicating the predictive power of prospect theory on net inflow intensifies when the market sentiment is high. In column(2), we include the interaction term between TK value and the NBER recession dummy. Consistent with our priors, we find the predictive power of TK significantly drops during the recession episodes.

6.3 Implications to Fund Returns

It is then interesting to study whether investors are making wise decisions to invest according to TK. If TK is a strong signal to predict superior fund performance, then investors are right to follow such a signal. However, this may not be the case since prospect theory closely relates to cognitive limitations. We, therefore, expect the TK-chasing behavior is wealth-destroying.

To examine the fund performance implications, we run Fama-MacBeth regressions by regressing funds' future four-factor alphas on the TK value. We do not expect investors to respond to fund performance immediately. Therefore, we compute alphas for multiple horizons of up to 12 months. In Table 14, we show that TK does not significantly predict future alphas, albeit negatively. However, our main hypothesis is that CPT attracts high fund flows — whether TK leads to better or worse future performance is not clear. The future performance is an equilibrium outcome that crucially depends on the managerial skill and current state of fund size (Berk and Van Binsbergen, 2015). That is, TK's impact on fund future performance, if any, should be transmitted through fund flows. To verify this conjecture, we decompose fund flows into a TK-driven component and a non-TK-driven component by projecting future fund flows on TK. Then we re-run the Fama-MacBeth regression on future alphas. As reported in Panel B and C of Table 14, we find the TK-driven flow predicts future alphas negatively, while the non-TK-driven flow predicts future alphas positively. Both results are statistically significant. The results confirm our conjecture that TK predicts future fund performance through flows. And the flows in response to high TK seem to reflect poor choices of mutual funds.

7 Alternative Explanations

In this section, we provide additional analysis to show the robustness of the predictive power of TK. We consider several alternative predictors for fund flows documented in the literature, including the Morningstar ratings, max returns, and skewness of fund returns. Overall, our results remain strong after considering these known drivers of mutual fund flow.

7.1 Return Extrapolation and Salience

We also distinguish prospect theory from other behavior patterns such as return extrapolation and salience. We calculate the measurement for return extrapolation following Barberis et al. (2015) and get the salience measurement following Bordalo et al. (2013).

We include these two measures as additional controls and report our results in the first two columns of Table 15. We find that the predictive power of prospect theory remains strong under different regression settings. In untabulated results, we also show that our findings remain unaffected even if we include recent returns from the past 3 to 12 months as additional controls. This indicates that the prospect theory has additional explanatory power beyond recency bias.

Worth pointing out, return extrapolation and salience also have significant predictive power on future mutual fund flows, even after controlling for CAPM and FF4 alphas. Overall, our findings imply that (1) the predictive power of TK is very robust and (2) patterns documented in behavioral finance literature may also play important role in the decision-making process of mutual fund investors.

7.2 Morningstar Ratings

Guercio and Tkac (2008) and Ben-David et al. (2019) show that Morningstar Ratings explain mutual fund flows. Morningstar rates funds based on their past fund returns. Their approach relies on calculating cumulative risk-adjusted returns in a way that penalizes high volatility.[14] Although prospect theory value is also constructed as a function of past fund returns, it has important differences from the Morningstar Ratings. Prospect theory is deeply rooted in human psychology and contains a rich set of features that describes investors' choices under uncertainty. Morningstar Ratings do not capture these features such as loss aversion and probability weighting.

Therefore, TK value should have additional predictive power after controlling Morningstar Ratings. We find this is indeed the case. In column (3) of Table 15, we include dummies for Morningstar top and bottom ratings as additional controls. Consistent with Ben-David et al. (2019), funds that are labeled as five-stars by Morningstar are expected to have higher inflows, while funds of one-star are going to have lower inflows. However, the explanation of prospect theory remains both economically and statistically strong.

7.3 Max Return

Our results remain robust if we control for other statistical features of past fund returns, such as max return and skewness.

Akbas and Genc (2020) argue that maximum return from the past significantly predicts future fund flows because investors prefer funds with extreme positive payoffs. In essence, maximum return is a measure motivated by prospect theory but only reflects one feature of prospect theory, namely probability weighting. Therefore, the predictive power of max return may partially overlap with the probability weighting. However, as we have shown in section 4, all features of prospect theory contribute to the explanatory power. Hence, we expect TK remain robust after controlling for maximum past return. We compute the maximum monthly return in the past 60 months and control for it in our baseline specification. The result in column (4) of table 15 confirms our conjecture. The predictive power of TK remains unchanged, and the Max Return is no longer significant. Our results also remain robust after controlling for the skewness of the past 60 months' returns. This result is reported in column (5) of Table 15 columns (2) and (3).

8 Conclusion

Investors make decisions to buy or redeem shares from mutual funds based on their assessment of the risk and rewards of fund performance. Researchers can therefore make inferences on the underlying preferences that investors use in this decision-making process. Following this logic, we use mutual fund

[14] The formula for calculating Morningstar rating is available in the Morningstar manual.

flows, the outcome of investor buy and sell decisions, to test theories that describe investor behavior. There are two major paradigms in economics and finance when it comes to understanding investors' choices: rational models based on expected utility theory and behavioral models based on prospect theory. Mutual funds provide a unique setting to test these theories as we can observe investors' choices directly.

Our evidence shows that prospect theory successfully describes how investors allocate money among mutual funds. Moreover, the prospect theory value is robust when we control different ways of measuring fund flows, measures implied by the rational expected utility framework, and rational learning. We also find similar evidence using account-level data.

Consistent with our priors, we find the explanatory power of prospect theory value is stronger among retail and less sophisticated investor dominated funds, and when the investor sentiment is high. We show the fund flow predicted by prospect theory value leads poorer performance in subsequent periods. Our evidence is also robust when confronted with alternative behavioral explanations such as extrapolative beliefs, salience theory, and past extreme returns.

Appendix I: Variable Definitions

Variables	**Description**
Net Inflow	Defined as the percentage growth of new assets, following the fund flow literature
New Subscription	Dollar amount of total new subscription in each month, scaled by the total net assets of the fund at the end of previous month
Rdemptions	Dollar amount of redemption in each month, scaled by the total net assets of the fund at the end of previous month
TK	Defined as a fund's prospect theory value based on fund returns in the past 60 months. "TK" value stands for Tversky and Kahneman (1992), the paper that first introduced cumulative prospect theory.
LA	Defined as a fund's prospect theory value which features loss aversion but turns off probability weighting and the concavity/convexity feature of the value function.
CC	Defined as a fund's prospect theory value which features the concavity/convexity but turns off loss aversion and probability weighting of the value function.
PW	Defined as a fund's prospect theory value which features probability weighting but turns off loss aversion and the concavity/convexity feature of the value function.
CAPM Alpha	The intercept from the time-series regression of fund monthly returns on market excess returns using the past 60-months window
FF3 Alpha	The intercept from the time-series regression of fund monthly returns on Fama-French 3-factors using the past 60-months window
FF4 Alpha	The intercept from the time-series regression of fund monthly returns on Fama-French 4-factors using the past 60-months window
Ln(Age)	Logarithmic form of fund age in years
Ln(TNA)	Logarithmic form of the fund total net asset
Expense Ratio	The expense ratio of the fund
Turnover Ratio	The turnover ratio of the fund
Return Relative to Market	The gap between the fund return and the market return, where the market return follows the definition in Fama and French (1993)
Return Volatility	The standard deviation of the fund monthly returns in the past 60 months
Cumulative Returns(60m)	The cumulative fund monthly returns in the past 60 months
Market Loading	The exposure to the market factor in the past 60 months
SMB Loading	The exposure to the SMB factor in the past 60 months
HML Loading	The exposure to the HML factor in the past 60 months
MOM Loading	The exposure to the MOM factor in the past 60 months
FF4 R-squared	The R-squared from the regression of fund monthly return on Fama-French 4-Factors using the data in the past 60 months
CAPM Beta	The coefficient of market excess return from the time-series regression of fund monthly returns on market excess returns using a the 60-months window

References

Akbas, F. and Genc, E. (2020). Do mutual fund investors overweight the probability of extreme payoffs in the return distribution? *Journal of Financial and Quantitative Analysis*, 55(1):223–261.

Amihud, Y. and Goyenko, R. (2013). Mutual fund's r 2 as predictor of performance. *The Review of Financial Studies*, 26(3):667–694.

Baele, L., Driessen, J., Ebert, S., Londono, J. M., and Spalt, O. G. (2019). Cumulative prospect theory, option returns, and the variance premium. *The Review of Financial Studies*, 32(9):3667–3723.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance*, 61(4):1645–1680.

Barber, B. M., Huang, X., and Odean, T. (2016). Which factors matter to investors? evidence from mutual fund flows. *The Review of Financial Studies*, 29(10):2600–2642.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2015). X-capm: An extrapolative capital asset pricing model. *Journal of financial economics*, 115(1):1–24.

Barberis, N. and Huang, M. (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review*, 98(5):2066–2100.

Barberis, N., Mukherjee, A., and Wang, B. (2016). Prospect theory and stock returns: An empirical test. *The Review of Financial Studies*, 29(11):3068–3107.

Ben-David, I., Li, J., Rossi, A., and Song, Y. (2019). What do mutual fund investors really care about? *Fisher College of Business Working Paper*, (2019-03):005.

Bergstresser, D., Chalmers, J. M., and Tufano, P. (2008). Assessing the costs and benefits of brokers in the mutual fund industry. *The Review of Financial Studies*, 22(10):4129–4156.

Berk, J. B. and Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of political economy*, 112(6):1269–1295.

Berk, J. B. and Van Binsbergen, J. H. (2015). Measuring skill in the mutual fund industry. *Journal of Financial Economics*, 118(1):1–20.

Berk, J. B. and Van Binsbergen, J. H. (2016). Assessing asset pricing models using revealed preference. *Journal of Financial Economics*, 119(1):1–23.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2013). Salience and asset prices. *American Economic Review*, 103(3):623–28.

Bossaerts, P., Fattinger, F., van den Bogaerde, F., and Yang, W. (2020). Asset pricing in a world of imperfect foresight. *Working Paper*.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1):57–82.

Chalmers, J. and Reuter, J. (2012). What is the impact of financial advisors on retirement portfolio choices and outcomes? *Available at SSRN 2078536*.

Chevalier, J. and Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of political economy*, 105(6):1167–1200.

Choi, J. J., Laibson, D., and Madrian, B. C. (2010). Why does the law of one price fail? an experiment on index mutual funds. *The Review of Financial Studies*, 23(4):1405–1432.

Christoffersen, S. E., Evans, R., and Musto, D. K. (2013). What do consumers' fund flows maximize? evidence from their brokers' incentives. *The Journal of Finance*, 68(1):201–235.

Cooper, M., Halling, M., and Yang, W. (2020). The Persistence of Fee Dispersion among Mutual Funds. *Review of Finance*. rfaa023.

Daniel, K., Amos, T., et al. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–291.

Dannhauser, C. D. and Pontiff, J. (2020). Flow. *SSRN Working Paper*.

Elton, E. J., Gruber, M. J., and Blake, C. R. (2011). A first look at the accuracy of the crsp mutual fund database and a comparison of the crsp and morningstar mutual fund databases. In *Investments And Portfolio Performance*, pages 99–114. World Scientific.

Franzoni, F. and Schmalz, M. C. (2017). Fund flows and market states. *The Review of Financial Studies*, 30(8):2621–2673.

Grinblatt, M. and Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of financial economics*, 78(2):311–339.

Guercio, D. D. and Reuter, J. (2014). Mutual fund performance and the incentive to generate alpha. *The Journal of Finance*, 69(4):1673–1704.

Guercio, D. D. and Tkac, P. A. (2008). Star power: The effect of monrningstar ratings on mutual fund flow. *Journal of Financial and Quantitative Analysis*, 43(4):907–936.

Hartzmark, S. M. and Sussman, A. B. (2019). Do investors value sustainability? a natural experiment examining ranking and fund flows. *The Journal of Finance*, 74(6):2789–2837.

Huang, J., Sialm, C., and Zhang, H. (2011). Risk shifting and mutual fund performance. *The Review of Financial Studies*, 24(8):2575–2616.

Ippolito, R. A. (1992). Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. *The Journal of Law and Economics*, 35(1):45–70.

Jegadeesh, N. and Mangipudi, C. S. (2019). What do fund flows reveal about asset pricing models and investor sophistication? *The Review of Financial Studies*.

Kahneman, D. (2000). Evaluation by moments: Past and future. *Choices, values, and frames*, pages 693–708.

Kaniel, R. and Parham, R. (2017). Wsj category kings–the impact of media attention on consumer and mutual fund investment decisions. *Journal of Financial Economics*, 123(2):337–356.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2015). Scale and skill in active management. *Journal of Financial Economics*, 116(1):23–45.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2017). Do funds make more when they trade more? *The Journal of Finance*, 72(4):1483–1528.

Sirri, E. R. and Tufano, P. (1998). Costly search and mutual fund flows. *The journal of finance*, 53(5):1589–1622.

Song, Y. (2020). The mismatch between mutual fund scale and skill. *The Journal of Finance*, 75(5):2555–2589.

Sun, Y. (2014). The effects of index funds and etfs on money management fees. Technical report, MIT working paper.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4):297–323.

Zhu, M. (2018). Informative fund size, managerial skill, and investor rationality. *Journal of Financial Economics*, 130(1):114–134.

Table 1: Summary Statistics

This table presents the monthly summary statistics on mutual funds which exist for at least sixty months. In Panel A, we aggregate multiple share classes to form one "fund" observation. In Panel B, we present the monthly summary statistics on mutual funds of different TK values. We aggregate multiple share classes to form one "fund" observation. The sample horizon spans from January 1981 to March 2020. Definitions for other variables are reported in the Appendix.

Panel A: Whole Sample

	count	mean	p50	sd	min	max
Net Inflow	742087	-0.003	-0.005	0.033	-0.319	0.798
TK	746153	-0.034	-0.031	0.019	-0.094	0.004
Age	733147	17.242	14.000	11.722	1.000	96.000
TNA	745707	1494.184	262.100	5379.968	0.091	173478.750
Expense Ratio (t-1)	745919	0.013	0.012	0.014	-0.005	1.462
Turnover Ratio (t-1)	744580	0.845	0.560	2.091	0.000	150.910
CAPM Alpha	741491	-0.065	-0.079	0.516	-6.928	4.758
FF4 Alpha	741491	-0.113	-0.105	0.420	-7.332	4.429
Market Loading	741491	0.963	0.987	0.308	-2.851	3.835
SMB Loading	741491	0.156	0.067	0.349	-2.658	2.921
HML Loading	741491	-0.026	-0.031	0.357	-3.136	2.843
MOM Loading	741491	-0.015	-0.011	0.190	-3.397	2.499
FF4 R Squared	741491	0.809	0.881	0.193	-0.068	0.999
Return Volatility	737167	0.050	0.046	0.019	0.000	0.260
Cumulative Returns(60m)	737167	0.532	0.447	0.615	-0.994	15.766

Panel B: Characteristics of High and Low TK Bins

	Low TK	2	3	4	High TK
Net Inflow	-0.007	-0.006	-0.004	-0.001	0.005
TK	-0.050	-0.038	-0.032	-0.028	-0.022
Age	16.170	16.874	17.388	17.961	17.814
TNA	729.537	1092.682	1256.537	1870.286	2523.903
Expense Ratio (t-1)	0.016	0.013	0.012	0.011	0.011
Turnover Ratio (t-1)	1.202	0.902	0.784	0.672	0.665
CAPM Alpha	-0.491	-0.181	-0.047	0.085	0.308
FF4 Alpha	-0.439	-0.193	-0.090	-0.006	0.163
Market Loading	1.047	1.015	0.978	0.941	0.832
SMB Loading	0.237	0.209	0.165	0.096	0.073
HML Loading	-0.169	-0.083	-0.000	0.044	0.079
MOM Loading	-0.082	-0.006	0.004	0.001	0.010
FF4 R Squared	0.714	0.814	0.853	0.862	0.801
Return Volatility	0.066	0.052	0.047	0.044	0.040
Cumulative Returns(60m)	0.156	0.434	0.550	0.658	0.858

Table 2: Portfolio Sorts: TK Values and Net Inflows

This table presents the relation between funds' TK values in period t and the net inflows in period $t + 1$. Each month, we sort funds into deciles based on TK and compute the mean values of net inflows across all funds in each decile. We report the time-series averages of the mean values. In Panel A, we use equal weights. In Panel B, we use the total net asset value as the weight to get the mean. The t-statistics are based on standard errors 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
Net Inflow	-0.005	-0.006	-0.005	-0.004	-0.003	-0.002	0.000	0.002	0.005	0.009	0.014
t-stat	(-3.38)	(-4.75)	(-3.79)	(-3.46)	(-2.65)	(-1.83)	(0.07)	(1.71)	(4.70)	(8.07)	(9.31)

Panel B: TNA-Weighted

	TK Decile										
	Low	2	3	4	5	6	7	8	9	High	H − L
Net Inflow	-0.007	-0.006	-0.004	-0.003	-0.002	-0.002	-0.001	0.002	0.004	0.008	0.015
t-stat	(-5.48)	(-4.21)	(-3.95)	(-2.93)	(-2.29)	(-1.65)	(-0.74)	(1.59)	(3.54)	(6.75)	(11.30)

Table 3: TK Values and Fund Net Inflows

This table presents the results from regressions of the fund net inflows in month t on the fund's TK value in month $t-1$. We compare the predictive power of TK to that of CAPM-based alpha estimated based on returns from period $t-60$ to $t-1$. The definitions for the control variables are reported in the appendix. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

	Dependent Variable: *Net Inflow*			
	(1)	(2)	(3)	(4)
TK	0.613***	0.351***	0.317***	0.367***
	(26.42)	(12.17)	(9.62)	(9.91)
Cumulative Returns(60m)		0.007***	0.008***	0.008***
		(6.54)	(7.39)	(7.83)
CAPM Alpha		0.000	0.001	0.001
		(0.47)	(1.59)	(1.43)
Market Loading			-0.001	-0.002
			(-0.62)	(-0.98)
SMB Loading			0.003**	0.001
			(2.41)	(0.64)
HML Loading			-0.001	-0.001
			(-0.88)	(-0.75)
MOM Loading			-0.010***	-0.009***
			(-7.67)	(-6.50)
FF4 R Squared				-0.002
				(-0.86)
Return Volatility				0.076***
				(2.62)
Ln(Age)				-0.012***
				(-11.87)
Ln(TNA)				-0.003***
				(-12.19)
Expense Ratio (t-1)				0.015
				(1.04)
Turnover Ratio (t-1)				0.000
				(0.99)
Adjusted R-Squared	0.131	0.136	0.138	0.145
N	742060	733525	733525	722785
Fund FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Controls	N	N	Y	Y

Table 4: New Subscriptions and Redemptions

This table presents the results from regressions of the fund new subscriptions (scaled by fund size) and redemptions (scaled by fund size) in month t on the fund's TK value. The definitions for the control variables are reported in the appendix. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

	New Subscriptions	Redemptions
	(1)	(2)
TK	0.551***	-0.117
	(3.46)	(-0.92)
Adjusted R Squared	0.613	0.676
N	293,478	290,697
Fund FE	Y	Y
Year FE	Y	Y
Controls	Y	Y

Table 5: Expected Utility and Fund Net Inflows

In this table, we compare the predictive power of prospect theory to that of expected utility estimated based on returns from period $t-60$ to $t-1$. The definitions for the control variables are reported in the appendix. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

	Dependent Variable: *Net Inflow*		
	(1)	(2)	(3)
TK	0.367***		0.137***
	(9.91)		(3.34)
EU		1.496***	1.289***
		(13.02)	(9.96)
Adjusted R-Squared	0.145	0.146	0.147
N	722,785	722,785	722,785
Fund FE	Y	Y	Y
Date FE	Y	Y	Y
Controls	Y	Y	Y

Table 6: Explain account holdings and transactions

This table presents the results based on account-level positions and transactions from a large brokerage firm. We estimate panel regressions using account-level mutual fund holdings (Panel A) and transactions (Panel B). TK is estimated as in previous tables at the fund level. The control variables are the same as in the baseline regression Table (3). Panel A uses dollar amount holdings of mutual funds of an account as dependent variables, scaled by the account balance (*Amt Held/Balance*, in percentages) and fund size (*Amt Held/Fund Size*, in basis points). Panel B's dependent variable is the net dollar amount transacted for a given fund of an account from last month to this month, scaled by the account balance (*Amt Traded/Balance*, in percentages) and fund size (*Amt Traded/Fund Size*, in basis points). All regressions include account and date fixed effects.

Panel A. TK and Holdings

	(1) Amt Held/Balance (%)	(2) Amt Held/Fund Size (bps)
TK	46.869***	0.453***
	(7.88)	(4.17)
Adj. Rsq.	0.853	0.744
N	1,315,375	1,478,800
Acct FE	Y	Y
Date FE	Y	Y
Controls	Y	Y

Panel B. TK and Transactions

	(1) Amt Traded/Balance (%)	(2) Amt Traded/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	Y	Y
Date FE	Y	Y
Controls	Y	Y

Table 7: Different Features of Prospect Theory and Fund Net Inflows

This table presents the results of four regressions. The dependent variable is fund net inflows. The four specifications vary by which components of prospect theory are incorporated into the prospect theory value. In columns (1) to (3), we calculate TK values using only loss aversion, concavity/convexity and probability weighting, respectively. We use these prospect theory components to predict fund net inflows. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

	Dependent Variable: *Net Inflow*		
	(1)	(2)	(3)
LA	0.734***		
	(12.34)		
CC		0.792***	
		(12.78)	
PW			0.719***
			(10.48)
Adjusted R-Squared	0.146	0.146	0.144
N	722,785	722,785	722,785
Fund FE	Y	Y	Y
Date FE	Y	Y	Y
Controls	Y	Y	Y

Table 8: Determinants of TK

This table presents the results of regressing the fund TK value (top) and individual features (bottom) on the fund's cummulative return, return volatility and skewness, all estimated based on returns from $t-60$ to $t-1$. The first three columns present how each individual determinant explains TK. In the column 4, we include all three determinants to explain the TK value. We include control variables and also fund-fixed effect and the year-month-fixed effect in each column. The definitions for the control variables are reported in the appendix. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

	Dependent Variable: *TK*			
	(1)	(2)	(3)	(4)
Cumulative Returns(60m)	0.022***			0.011***
	(80.25)			(30.41)
Return Volatility		-0.478***		-0.504***
		(-28.69)		(-29.22)
Skewness			0.008***	0.006***
			(16.51)	(11.35)
Adjusted R-Squared	0.553	0.246	0.168	0.771
N	737,135	737,135	433,073	433,073
Fund FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y

	Dependent Variable: *TK Features*		
	(1) Loss Aversion	(2) Concavity/Convexity	(3) Probability Weighting
Cumulative Returns(60m)	0.011***	0.012***	0.005***
	(30.28)	(31.31)	(30.80)
Return Volatility	-0.319***	0.015**	0.046***
	(-30.88)	(1.97)	(6.70)
Skewness	0.001***	0.000*	0.004***
	(3.56)	(1.75)	(16.58)
Adjusted R-Squared	0.779	0.758	0.697
N	433,073	433,073	433,073
Fund FE	Y	Y	Y
Date FE	Y	Y	Y
Controls	Y	Y	Y

Table 9: Fund Level TK and Stock Level TK

This table presents the relation between funds' TK values in quarter t and the TK value of stocks held in quarter $t+1$. We switch to the quarterly panel because the holding data of each fund is only available at the quarterly level. The construction of TK value of stocks, the dependent variable in this table, follows Barberis, Mukherjee and Wang (2016). We control for fund-fixed effect and the year-month-fixed effect. The definitions of control variables are included in the appendix. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

	Dependent Variable: *Stock TK*		
	(1)	(2)	(3)
TK	0.095***	-0.003	-0.003
	(8.60)	(-0.12)	(-0.17)
Adj. Rsq.	0.015	0.350	0.382
N	11,016,574	10,697,196	11,016,071
Fund FE		Y	Y
Date FE			Y
Stock FE			Y
Fund-Stock FE		Y	
Controls	Y	Y	Y

Table 10: Prospect Theory: Institutional vs Retail Funds

This table presents the results of regressing fund net inflows on TK and on TK interacted with two variables that proxy for investor types: institutional, the dummy variable for institutional funds, and retail, the dummy variable for retail funds. Column (1) reports regression results based on the full investor sample. Column (2) reports results of regressions that include the dummy variable for institutional funds and Column (3) reports results of regressions that include the dummy variable for retail funds In all columns, we include control variables and add fund-fixed effect and the year-month-fixed effect. The definitions for the control variables are reported in the appendix. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

	Dependent Variable: *Net Inflow*		
	(1)	(2)	(3)
TK	0.367***	0.376***	0.353***
	(9.91)	(10.03)	(9.30)
Institutional × TK		-0.049***	
		(-3.08)	
Institutional Fund		0.000	
		(0.09)	
Retail × TK			0.024*
			(1.71)
Retail Fund			-0.002***
			(-3.10)
Adjusted R-Squared	0.145	0.145	0.145
N	722,785	722,785	722,785
Fund FE	Y	Y	Y
Date FE	Y	Y	Y
Controls	Y	Y	Y

Table 11: Prospect Theory: Investor Sophistication

This table presents the results of regressing fund net inflows on TK and variables that proxy for investor sophistication. We treat funds distributed mainly through brokers as those traded by less sophisticated clienteles while funds directly sold as those traded by more sophisticated investors, as in Barber et al. (2016). Column (1) reports regression results based on the full investor sample. Column (2) reports regression results based on the subsample of funds sold by brokers. Column (3) reports regression results based on the subsample of directly sold funds. Column (4) represents the result of regressing fund net inflows on TK and on TK interacted with the dummy for funds sold by brokers. In all columns, we include control variables and add fund-fixed effect and the year-month-fixed effect. The definitions for the control variables are reported in the appendix. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

	Dependent Variable: *Net Inflow*		
	(1)	(2)	(3)
TK	0.367***	0.347***	0.374***
	(9.91)	(9.18)	(10.05)
Broker Sold × TK		0.037***	
		(2.96)	
Broker Sold		-0.000	
		(-0.72)	
Direct Sold × TK			-0.028**
			(-2.07)
Direct Sold			-0.003***
			(-5.07)
Adjusted R-Squared	0.145	0.145	0.145
N	722,785	722,785	722,785
Fund FE	Y	Y	Y
Date FE	Y	Y	Y
Controls	Y	Y	Y

Table 12: Prospect Theory: Existing Investors

This table presents the predictive power of TK on fund flows for both the existing and new investors. In Panel A, we use the expected component from an AR(1) process of fund flow as the proxy for the flows from existing investors, and use the unexpected component as the proxy for the flows from new investors. The AR(1) process is estimated at a rolling basis, and the rolling window expands as the historical observations accumulate. In Panel B, we use the changes in TK value to measure the demand for existing investors. The definitions for control variables are reported in the appendix. In all columns, we add fund-fixed effect and the year-month-fixed effect. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

Panel A: Expected and Unexpected Flows

	(1) Expected Net Inflows	(2) Unexpected Net Inflow	(3) Expected Inflows	(4) Unexpected Inflows
TK	0.181***	0.186***	0.344***	0.194***
	(9.46)	(7.52)	(2.84)	(3.67)
Adjusted R-Squared	0.316	0.061	0.781	0.029
N	722,785	722,785	291,194	291,194
Fund FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y

Panel B: Changes in TK and Fund Flows

	(1) Net Inflow	(2) New Subscription	(3) Redemptions
Changes in TK	0.736***	0.513***	-0.510***
	(6.88)	(2.87)	(-4.00)
Adj. Rsq.	0.144	0.613	0.676
N	719,169	292,271	289,509
Controls	Y	Y	Y

Table 13: Predictive Power of Prospect Theory in Different Episodes

In this table, we investigate how the predictive power of prospect theory on future fund flows changes over time. In each of the columns, we use a different indicator to interact with the TK value. In column (1), we test how the predictive power is affected by investor sentiment measured by the investor sentiment index proposed in Baker and Wurgler (2006). In column (2), we test the effect of recessions defined by NBER on the predictive power of TK on future fund flows. The definitions for control variables are reported in the appendix. In all columns, we add fund-fixed effect and the year-month-fixed effect. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible.

	Dependent Variable: *Net Inflow*	
	(1)	(2)
	Investor Sentiment	NBER Recessions
TK	0.061*	0.070**
	(1.95)	(2.29)
TK × High Sentiment	0.110***	
	(2.69)	
High Sentiment	0.004***	
	(2.64)	
TK × Recession Dummy		-0.098**
		(-2.11)
Recession Dummy		-0.007***
		(-3.44)
Adjusted R-Squared	0.113	0.113
N	683,278	722,785
Fund FE	Y	Y
Date FE	N	N
Controls	Y	Y

Table 14: TK Values and Fund Performance

This table presents the results from Fama-MacBeth regressions of the future fund returns on the fund's TK-related variables. In Panel A, we use fund's TK value at time t as the predictor. In Panel B and C, we use the TK-driven flow and the NonTK-Driven flow as the predictors, respectively, defined as the fitted value ($\widehat{flow}_{i,t}$) and the residual ($u_{i,t}$) from the following regression: $Flow_{i,t} = a + bTK_{i,t-1} + u_{i,t}$. The horizon of the dependent variable spans from future 1 month to 24 months. The definitions for the control variables are reported in the appendix. The sample horizon spans from January 1981 to March 2020. We report standard errors corrected by Newey-West with lags of 12 months.

Panel A: TK Values and Fund Performance

	(1)	(2)	(3)
	1 Month	3 Months	12 Months
TK	-0.046	-0.150	-0.493
	(-1.33)	(-1.54)	(-1.51)
Adj. Rsq.	0.296	0.298	0.327
N	722,809	718,186	662,758
Controls	Y	Y	Y

Panel B: TK-Driven Flows and Fund Performance

	(1)	(2)	(3)
	1 Month	3 Months	12 Months
$\widehat{flow}$	-0.015**	-0.047**	-0.209**
	(-2.14)	(-2.21)	(-2.15)
Adj. Rsq.	0.286	0.288	0.320
N	722,809	718,186	662,758
Controls	Y	Y	Y

Panel C: NonTK-Driven Flows and Fund Performance

	(1)	(2)	(3)
	1 Month	3 Months	12 Months
u	0.036***	0.056***	0.117***
	(7.34)	(5.50)	(2.85)
Adj. Rsq.	0.291	0.291	0.319
N	722,809	718,186	662,758
Controls	Y	Y	Y

Table 15: Prospect Theory vs Alternative Drivers

This table compares the predictive power of TK with other flow drivers documented in the literature. Column (1) presents the result from a horse race regression between prospect theory and return extrapolation. Column (2) presents the result from a horse race regression between prospect theory and salience theory. Column (3) presents the result from a horse race regression between prospect theory and MorningStar ratings. Column (4) presents the result from a horse race regression between prospect theory and max return. Max Return. Column (5) presents the result from a horse race regression between prospect theory and Skewness. We control for fund-fixed effect and the year-month-fixed effect. The definitions for the control variables are reported in the appendix. The sample horizon spans from January 1981 to March 2020. We report robust standard errors and use two-way clusters whenever possible. Extrapolation; Salience; MorningStar Rating; Max Return; Skewness;

	Dependent Variable: *Net Inflow*				
	(1)	(2)	(3)	(4)	(5)
TK	0.236***	0.463***	0.109***	0.382***	0.237***
	(5.93)	(12.53)	(2.73)	(9.60)	(4.73)
EX	1.202***				
	(15.13)				
ST		-0.058***			
		(-9.72)			
MorningStar Rating			0.007***		
			(28.60)		
Max Return				-0.006	
				(-0.76)	
Skewness					0.003***
					(4.90)
Adjusted R-Squared	0.160	0.146	0.172	0.145	0.148
N	722,785	722,785	427,484	722,785	426,595
Fund FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y

Figure 1

This figure presents the value function and probability weigthing function in the prospect theory. We use the estimates in Tversky and Kahneman (1979) as the parameters for each function.

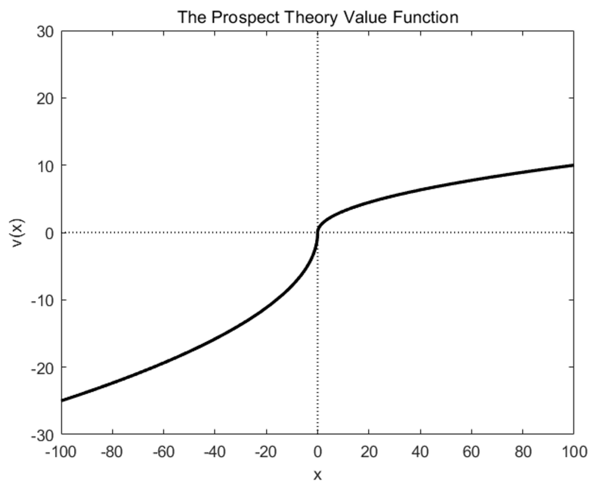

Figure 2: Total Number of Funds Over Time

This figure presents how the total number of funds varies over time. We use the sample from CRSP Mutual Fund Database, ranging from January 1986 to March 2020. We focus on the equity funds.

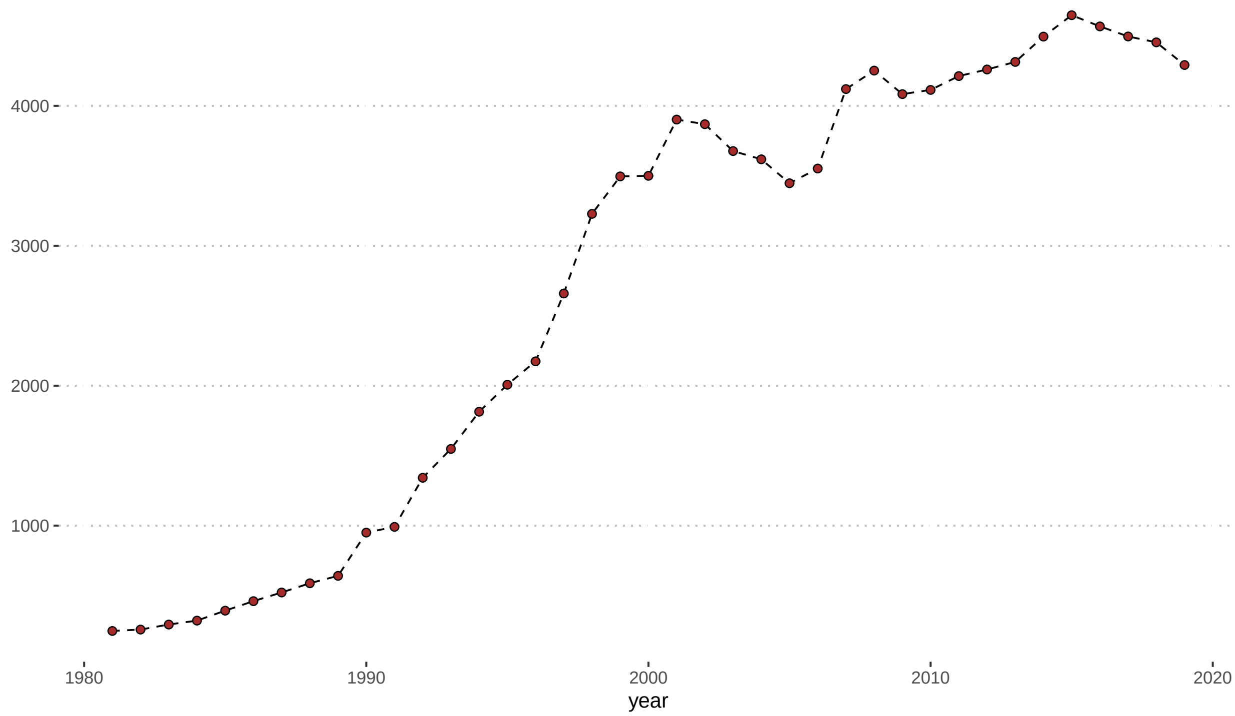

Figure 3: Sensitivity Analysis

This figure presents the sensitivity analysis for the CPT parameter lambda and alpha. In the left panel, we calculate TK with varying values of lambda while fixing other CPT parameters. In the right panel, we calculate TK with varying values of alpha while fixing other CPT parameters. We reestimate the coefficient of TK from the predictive regression in equation (). The dashed vertical line indicates the parameters values estimated in Kahneman and Tversky (1979).

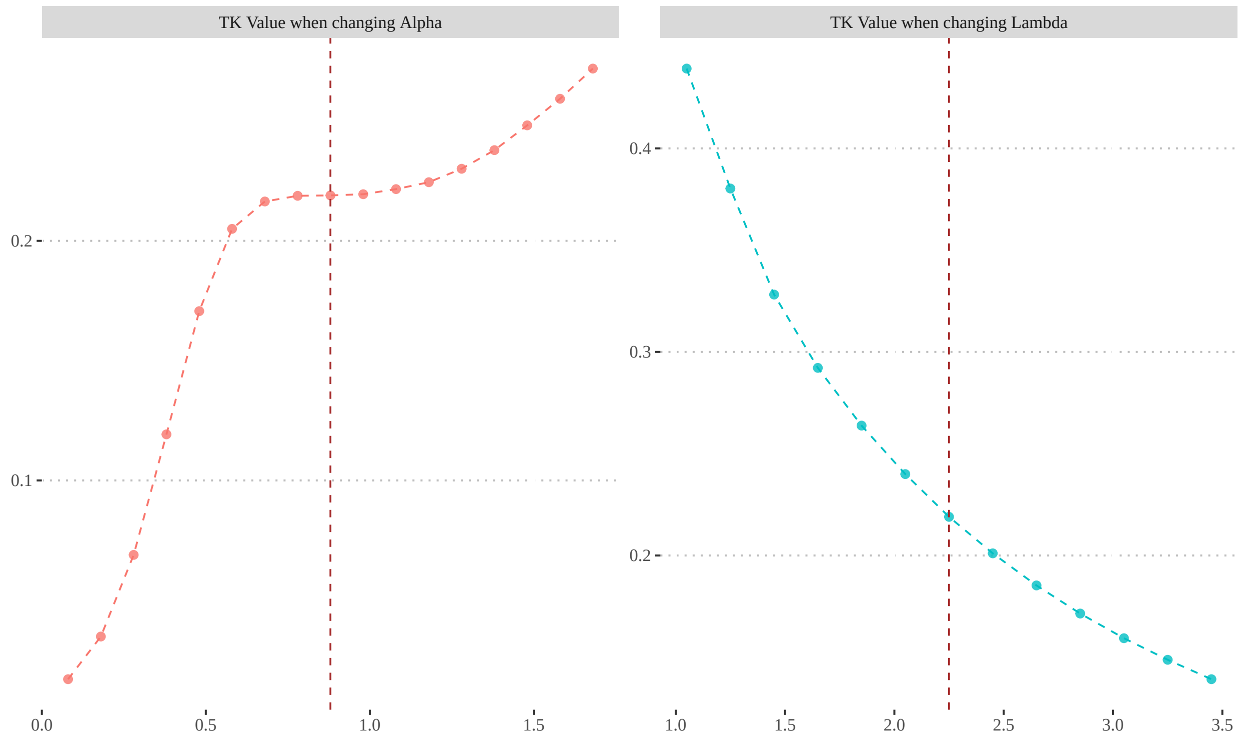

Figure 4: Fund and Stock TK in Event Time

For each month, we sort mutual funds based on their TK into deciles. Then we look backward and forward for 12 months and plot the TK in event time