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

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May 20, 2024

ABFER 11$^{th}$ ANNUAL CONFERENCE

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# Introduction

# Motivation

Prospect theory has become a prominent alternative utility framework that describes investors' decision-making under uncertainty

- Barberis and Thaler (2003); Barberis (2013)

Initially, it was developed to explain choices in the *laboratory*, from which they derived a set of important parameters to govern the framework

- Kahneman and Tversky (1979); Tversky and Kahneman (1992);

However, these parameters are rarely confronted with choice outcomes outside of the laboratory, largely due to the scarcity of data

- existing field studies rely on prices, an outcome variable of market equilibrium (Barberis, Mukherjee, and Wang 2016; Baele, et al. 2019)
- choices and prices do not always "agree" (Bossaerts, Fattinger, Frans and Yang (2022))

# This Paper

Our logic is simple:

$$\textit{flows} \Longrightarrow \textit{choices} \Longrightarrow \textit{preferences}.$$

- We examine the link between mutual funds' prospect theory values and fund flows
    - flows represent the aggregate choices of investors
    - prospect theory values are based on the standard parameters from the laboratory
- We test whether prospect theory explains individual investors' buy and sell decisions of mutual funds
    - granular evidence based on account-level transactions
- Taking a revealed preference approach, we estimate the prospect theory parameters through a discrete choice model

# Overview of Our Findings

**We provide strong support for prospect theory using choice outcomes in the market**

- under a standard set of parameters, funds with higher prospect theory value attract significantly larger future flows
- we also find corroborative evidence using account-level data
- our field-based estimates (the revealed preference parameters) align well with previous experiment-based estimates

# Overview of Our Findings

**Prospect theory offers a new framework for understanding flows**

- as it has incremental predictive power over existing drivers
  - alphas which proxy for manager skills
  - expected utility value based on power utility
  - extrapolation measurements
  - salience measurements
  - maximum or skewness of fund returns
  - MorningStar Ratings
- compared to existing drivers, prospect theory is a well-established psychologically realistic framework

# Overview of Our Findings

**Prospect theory captures the non-fully rational aspect of mutual fund flows**

- the predictive power is stronger among retail funds and broker-sold funds
- the effect is stronger during periods of high investor sentiment while drops during recessions
- flows driven by prospect theory significantly predict under-performance of funds

# Prospect Theory and Measure Construction

## Prospect Theory — Background

History:

- The original Prospect Theory: Kahneman and Tversky (1979)
- Cumulative Prospect Theory (CPT): Tversky and Kahneman (1992)
    - overcome some limitations in the original version
    - we use CPT.

Two steps of decision-making under prospect theory (Barberis et al (2016)):

1. Representation
    - the decision maker constructs a representation of the contingencies and outcomes relevant to the decision.
2. Valuation
    - the decision maker assesses the value of each prospect and chooses accordingly.

# Prospect Theory — Representation

Assumption of prospect theory: investors form a mental representation of gains and losses when evaluating risks

In the mutual fund context: investors mentally represent a fund by the distribution of its past returns over the past 60 months

- to most investors, past returns is good and easily accessible proxy for future return
- past performance is an important information source for mutual fund investors
    - other information is limited for funds: no “fundamental” information
- we use last 60 months, as typical price charts on MorningStar website go back on average five years at the monthly frequency

# Prospect Theory — Representation

The representation of distribution is as follows:

$$(r_{-m}, \frac{1}{60}; \ldots; r_{-1}, \frac{1}{60}; r_1, \frac{1}{60}; \ldots; r_n, \frac{1}{60})$$

- we assign an equal probability of $\frac{1}{60}$ to each past monthly return
- $r_i$ are sorted ascendingly: $r_{-m}$ is the most negative return and $r_n$ is the most positive return

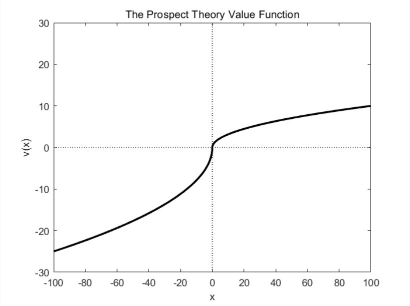
# Prospect Theory — Value Function

Prospect Theory Value (TK) is computed as:

$$TK = \sum_{-m}^{n} \pi_i v(x_i)$$

$v(\cdot)$ is the *value function*:

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



# Prospect Theory — Decision Weights

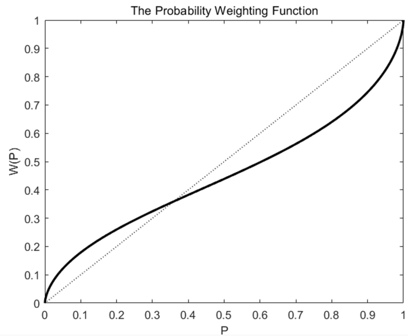
$\pi_i$ is known as *decision weights*

$$\pi_i = \begin{cases} w^+(p_i + \ldots + p_n) - w^+(p_{i+1} + \ldots + p_n) & 0 \le i \le n \\ w^-(p_{-m} + \ldots + p_i) - w^-(p_{-m} + \ldots + p_{i-1}) & -m \le i \le 0 \end{cases}$$

*$w^+(\cdot)$ and $w^-(\cdot)$ are functions to transform probabilities*

$$w^+(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{1/\gamma}}, w^-(P) = \frac{P^\delta}{(P^\delta + (1-P)^\delta)^{1/\delta}}$$

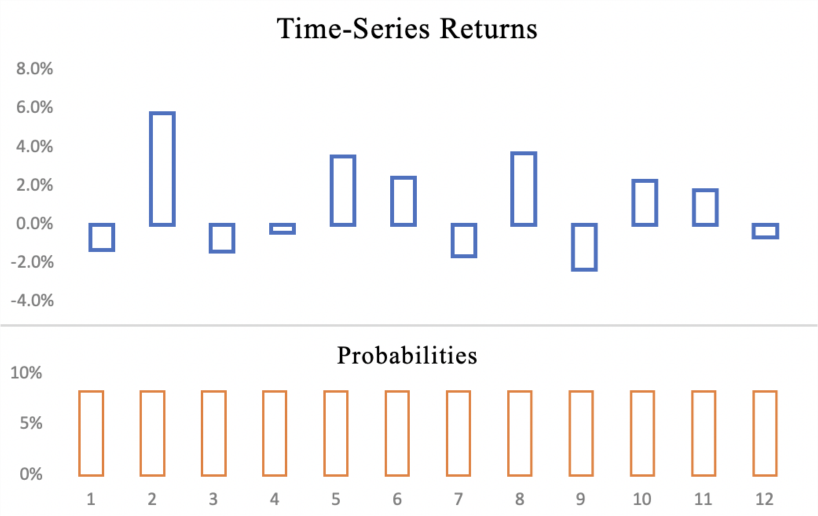
*where $\alpha$, $\gamma$, $\delta \in (0,1)$ and $\lambda > 1$*



# Prospect Theory — Parameters

- Reference Point = risk-free rate
  - a common choice in the literature
  - other reference points also work: zero, market return, and fund style averages
- Other parameter values: $(\alpha = 0.88, \lambda = 2.25, \gamma = 0.61, \delta = 0.69)$
  - originally estimated by Tversky and Kahneman (1992)
  - sensitivity analysis shows our results are robust

# Prospect Theory — A Simple Example



# Prospect Theory — A Simple Example

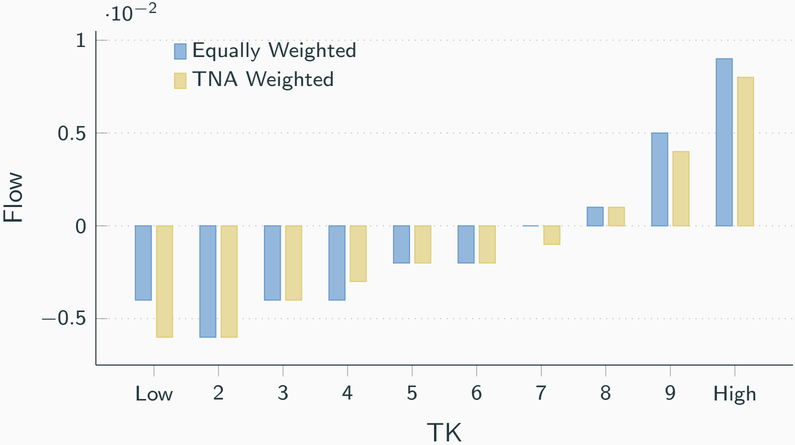
# Baseline Results

# Sample

- Mutual fund data drawn from CRSP
- Sample period: 1981 to 2022
- Brokerage data from Odean
- Share classes aggregated following Berk and van Binsbergen (2015)

| | mean | p50 | sd |
|---|---|---|---|
| Flow | -0.002 | -0.005 | 0.034 |
| TK | -0.033 | -0.031 | 0.019 |
| Age | 17.440 | 14.000 | 11.637 |
| TNA | 1533.457 | 258.500 | 5799.611 |
| Expense Ratio | 0.013 | 0.012 | 0.013 |
| Turnover Ratio | 0.822 | 0.540 | 2.015 |
| CAPM Alpha | -0.086 | -0.095 | 0.510 |

# Prospect Theory Value and Fund Net Inflows




- The "low", "high", and "H-L" are statistically significant at 1%.

# Baseline Results

Prospect theory (TK value) significantly predicts future mutual fund flows

| | Dependent Variable: *Flow* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| TK | 0.604*** | 0.343*** | 0.307*** | 0.383*** |
| | (26.89) | (12.88) | (10.24) | (11.27) |
| *performance controls* | | ✓ | ✓ | ✓ |
| *risk loadings controls* | | | ✓ | ✓ |
| *fund characteristics controls* | | | | ✓ |
| Adjusted R-Squared | 0.124 | 0.128 | 0.130 | 0.138 |
| N | 871,549 | 861,927 | 861,927 | 859,562 |
| Fund FE | Yes | Yes | Yes | Yes |
| Date FE | Yes | Yes | Yes | Yes |
| Controls | No | Yes | Yes | Yes |

# Baseline Results — Cont'd

| | Dependent Variable: *Flow* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| TK | 0.604*** | 0.343*** | 0.307*** | 0.383*** |
| | (26.89) | (12.88) | (10.24) | (11.27) |
| Cumulative Returns(60m) | | 0.006*** | 0.007*** | 0.008*** |
| | | (6.16) | (6.61) | (7.05) |
| CAPM Alpha | | 0.001 | 0.002** | 0.002* |
| | | (1.06) | (2.28) | (1.91) |
| Market Loading | | | -0.001 | -0.003 |
| | | | (-0.53) | (-1.56) |
| SMB Loading | | | 0.003*** | 0.001 |
| | | | (2.99) | (0.88) |
| HML Loading | | | 0.000 | 0.000 |
| | | | (0.10) | (0.14) |
| MOM Loading | | | -0.010*** | -0.008*** |
| | | | (-8.43) | (-6.32) |
| FF4 R Squared | | | | -0.001 |
| | | | | (-0.59) |
| Return Volatility | | | | 0.114*** |
| | | | | (3.91) |
| Ln(Age) | | | | -0.013*** |
| | | | | (-13.01) |
| Ln(TNA) | | | | -0.003*** |
| | | | | (-16.30) |
| Expense Ratio (t-1) | | | | 0.001 |
| | | | | (0.04) |
| Turnover Ratio (t-1) | | | | 0.000 |
| | | | | (1.35) |
| Adjusted R-Squared | 0.124 | 0.128 | 0.130 | 0.138 |
| N | 871,549 | 861,927 | 861,927 | 859,562 |
| Fund FE | Yes | Yes | Yes | Yes |
| Date FE | Yes | Yes | Yes | Yes |

# Which Feature of Prospect Theory Plays a Role?

We investigate the standalone explanatory power of each feature of prospect theory on mutual fund flows

- To focus on one feature, we shut down other features.
- all three features contribute to the predictive power

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

# Alternative Data — Account Level Evidence

We use Odean's data to provide account-level evidence.

Panel A. TK and Holdings

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

Panel B. TK and Transactions

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

# Revealed Preference Analysis

Now, we estimate the parameters directly from mutual fund flows

- we capture investor's choice of mutual funds using discrete choice models
- when making investment decisions, investors select a fund $i$ from the "product space" of all funds.

We write down the investor's indirecty utility function as:

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

The probability of an investor selecting fund $i$ is determined as $Prob_i = e^{\delta_i} / \sum_{j=0}^{J} e^{\delta_j}$

# Revealed Preference Analysis

We link the probability of selecting fund $i$ to the "market share" of fund $i$

$$s_i = f_i / \sum_{j=0}^{J} f_j$$

where $f_i$ is the inflows to fund $i$

Then estimate the discrete choice model based on market shares of inflows using MLE:

Estimation of Parameters

| | description | mean | s.e. | Literature |
|---|---|---|---|---|
| $\alpha$ | Curvature of the value function | 0.745 | 0.061 | $[0.5, 0.95]$ |
| $\lambda$ | Loss aversion | 1.824 | 0.110 | $[1.31, 2.25]$ |
| $\gamma$ | Probability weighting in gain region | 0.110 | 0.028 | $(0, 1)$ |
| $\delta$ | Probability weighting in loss region | 0.228 | 0.041 | $(0, 1)$ |

Lab-based Parameters:$\alpha = 0.88, \lambda = 2.25, \gamma = 0.61, \delta = 0.69$

# A New Framework for Mutual Fund Flows

# Controlling for Expected Utility

We directly compare prospect theory and expected utility in explaining future fund flows

- for preference, we take the power utility with a risk aversion coefficient $\theta$ of 0.88.[1]
- we then calculate:

$$EU = \sum_{t=1}^{60} \frac{1}{60} u(r_i) \text{ ,where } u(r) = \frac{(1+r)^{1-\theta}}{1-\theta}$$

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

[1] This parameter is consistent with the $\alpha$ in TK calculation.

# Other Behavioral Theories

- *Extrapolation* follows Barberis, Greenwood, Jin and Shleifer (2015)
- *Salience* follows Bordalo, Gennaioli, and Shleifer (2013) and Cosemans and Frehen (2021)
- *Max Return* is the maximum value of a fund's monthly returns from the past 60 months, from Akbas and Genc (2020).
- Morningstar Rating comes from Morningstar Direct.

# Other Behavioral Theories

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

# Bounded-rational Drivers of Fund Flows

# Institutional vs. Retail Investors

The predictive power of prospect theory is stronger for retail investors

- Institutional = TNA in institutional share classes > 75%
- Retail = TNA in retail share classes > 75%

| | Dependent Variable: *Flow* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| TK | 0.383*** | 0.390*** | 0.368*** |
| | (11.27) | (11.36) | (10.50) |
| Institutional × TK | | -0.033** | |
| | | (-2.22) | |
| Institutional | | -0.000 | |
| | | (-0.32) | |
| Retail × TK | | | 0.024* |
| | | | (1.95) |
| Retail | | | -0.001 |
| | | | (-1.51) |

# Investor Sophistications

Prospect theory predicts fund flows stronger for the funds dominated by less sophisticated investors

- **broker/direct sold ≈ less/more sophisticated clientele** (Barber, Huang and Odean, 2016 among others)

| | Dependent Variable: *Flow* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| TK | 0.383*** | 0.363*** | 0.392*** |
| | (11.27) | (10.51) | (11.51) |
| Broker Sold × TK | | 0.038*** | |
| | | (3.22) | |
| Broker Sold | | 0.001 | |
| | | (1.10) | |
| Direct Sold × TK | | | -0.036*** |
| | | | (-2.76) |
| Direct Sold | | | -0.004*** |
| | | | (-5.41) |

# TK and Future Returns

Are investors making the "right" choices by picking the funds with high TK value?

We decompose flow into 2 components by projecting flows on past TK: $Flow_{i,t} = a + bTK_{i,t-1} + u_{i,t}$.

- expected: the fitted flow $= \hat{flow}$
- unexpected: the residual flow $= \mu$

Then we regress future fund performance (four-factor alpha) on these components respectively.

# TK and Future Returns — Cont'd

Panel A: TK and Fund Performance

| | (1)<br>1 Month | (2)<br>3 Months | (3)<br>12 Months |
|---|---|---|---|
| TK | -0.014 | -0.053 | -0.380 |
| | (-0.39) | (-0.52) | (-1.13) |

Panel B: TK-Driven Flows and Fund Performance

| | (1)<br>1 Month | (2)<br>3 Months | (3)<br>12 Months |
|---|---|---|---|
| $\widehat{flow}$ | -0.001** | -0.003* | -0.008 |
| | (-2.07) | (-1.87) | (-1.56) |

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

| | (1)<br>1 Month | (2)<br>3 Months | (3)<br>12 Months |
|---|---|---|---|
| $u$ | 0.006*** | 0.009*** | 0.010** |
| | (5.62) | (4.27) | (2.31) |

# Concluding Remarks

## Summary

- Prospect Theory aligns with the choices of mutual fund investors
    - aggregate
    - individual
    - structural estimation
- Prospect theory offers a new framework for understanding flows, as it has incremental predictive power over
    - alphas, EU, extrapolation measure, salience theory, max returns, and MorningStar Ratings
- Prospect theory reflects the irrational aspect of fund flows
    - stronger among funds dominated by retail and less sophisticated investors
    - stronger during high sentiment period
    - TK-Driven fund flow predicts lower future performance– dumb money effect

# Prospect Theory and Investor Sentiment

Prospect theory predicts fund flows more strongly for the funds during episodes of high investor sentiment

- Sentiment index from Baker and Wurgler (2006)
- Recession Dummy from NBER

| | Dependent Variable: *Flow* | |
|---|---|---|
| | (1) Investor Sentiment | (2) NBER Recessions |
| TK | 0.082** | 0.084*** |
| | (2.55) | (2.70) |
| TK × High Sentiment | 0.074* | |
| | (1.71) | |
| High Sentiment | 0.002* | |
| | (1.67) | |
| TK × Recession | | -0.099** |
| | | (-2.15) |
| Recession | | -0.007*** |
| | | (-3.62) |

# TK and Return Moments

Prospect theory implies a type of "mean-variance-skewness" preferences

TK Values and Characteristics of Past Fund Return Distributions

| | Dependent Variable: *TK* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Cumulative Returns(60m) | 0.022$^{***}$ | | | 0.011$^{***}$ |
| | (86.39) | | | (34.27) |
| Return Volatility | | -0.499$^{***}$ | | -0.510$^{***}$ |
| | | (-31.53) | | (-35.88) |
| Skewness | | | 0.009$^{***}$ | 0.006$^{***}$ |
| | | | (20.24) | (15.68) |

- The negative coefficient of Volatility is due to loss aversion.
- The positive coefficient of Skewness is due to probability weighting.

# Alternative Flow Measures — Buys and Sells

We look at new subscriptions and redemption separately.

- from SEC filings, starting 2003
- more accurate measures of money flow in and out of mutual funds

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

- TK predicts subsequent inflows positively and significantly
- The outflow result is not significant
  - outflows are less sensitive to past bad performance than inflows to past good performance (Sirri and Tufano, 1998)