Prospect Theory and Mutual Fund Flows

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Abstract

We evaluate the hypothesis that investors seek portfolios that display attractive return distributions in terms of Prospect Theory (PT). We consider the mutual fund market in the U.S. as an interesting testbed because fund investors are known to be return-chasing and about a half of U.S. households own mutual funds. Using monthly flow data from 1999-2019, we find that mutual funds attract higher net flows when they have better PT values. We obtain similar results when PT is replaced with Rank-Dependent Utility, a closely related theory that does not require a particular choice of reference points. Our results are consistent with recent evidence that fund flows exhibit heightened sensitivity to extreme performance measures.

JEL classification: D81, G11, G41

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1 Introduction

Prospect Theory (PT) (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) is frequently cited as a theoretical inspiration for empirical studies. As a formal model of decision making under risk, PT places a particular structure on a preference functional that represents the decision maker's evaluation of alternative probability distributions over outcomes. Most empirical studies attribute their motivations to specific aspects of PT, such as loss aversion and reference dependence, but a more holistic use of the PT preference functional has been difficult because researchers rarely observe relevant probability distributions outside laboratory settings.

In an analysis of financial markets, Barberis et al. (2016) make major progress by formulating a two-step model of noise trader behavior. The core idea is that noise traders apply PT to evaluate a financial asset after forming a mental representation of that asset as a probability distribution over its past returns, and re-weight component assets in the classical tangency portfolio according to their PT values. Barberis et al. (2016) find a negative association between risk-adjusted returns and PT values of stocks in several stock markets, in line with the hypothesis that stocks with higher PT values tend to be overweighted, hence overpriced.

Using monthly data from the U.S. mutual fund market, we provide an alternative test of PT-based investment behavior. Instead of re-evaluating the pricing implications, we ask whether investors indeed seek portfolios that have exhibited appealing return distributions under PT. Our empirical setting is attractive because each mutual fund can be seen as an available portfolio choice, mutual funds make up a substantial component of U.S. household portfolios,[1] and mutual fund investors are primarily motivated by investment returns (Choi and Robertson, 2020) rather than potential confounds such as controlling interests in individual companies. We measure each fund's monthly net flow by applying an approach similar to Huang et al. (2011), and estimate multi-way fixed effects models that capture observed and unobserved heterogeneity across funds and fund families. We find that the fund's PT value is a positive predictor of its future net flow, which is consistent with the core assumption of Barberis et al. (2016).

PT is closely related to Rank-Dependent Utility (RDU) (Quiggin, 1982). RDU assumes reference independence but both theories incorporate probability weighting that captures the investor's optimism or pessimism about small probabilities of extreme

[1] According to the 2020 Investment Company Fact Book (https://www.ici.org/research/stats/factbook), 46.4% of all U.S. households owned mutual funds.

outcomes. We find that the fund's PT and RDU values have comparable effects on its future net flow. Thus, while we do not reject PT-based investing, our results are consistent with a broader class of non-standard preferences and also with recent evidence that fund flows exhibit heightened sensitivity to extreme performance measures (Li et al., 2017; Polkovnichenko et al., 2019).

2 Conceptual Framework

Our analysis is motivated by a two-step model of noise trader behavior due to Barberis et al. (2016). In the first step, investors form a mental representation of a stock as a lottery over its possible returns in excess of market returns. Suppose that the lottery is a discrete uniform distribution with support points that capture the excess returns of the stock over the past 60 months. Let $x_1 < x_2 < \cdots < x_{60}$ denote an ordered list of the excess returns where subscript k in x_k indicates its ordinal ranking rather than timing of observation.

In the second step, investors apply a PT preference functional to evaluate the stock's attractiveness. Following Tversky and Kahneman (1992), the PT value of the stock is

$$\mathrm{PT} = \sum_{k=1}^{60} \pi_k \nu[x_k] \tag{1}$$

where $\nu[x_k]$ and π_k denote the utility of excess return x_k and associated decision weight, respectively. The utility is evaluated using a sign-dependent function

$$\begin{aligned} \nu[x_k] &= x_k^\alpha && \text{if} \quad x_k > 0 \\ &= -\lambda |x_k|^\beta && \text{if} \quad x_k \leq 0 \end{aligned} \tag{2}$$

given curvature parameters α and β and loss aversion parameter λ. The decision weight on a gain, *i.e.*, $x_k > 0$, is specified as $\pi_k = \omega^+[P_{x \geq x_k}] - \omega^+[P_{x > x_k}]$, where $\omega^+[P]$ is a probability weighting function (PWF) and $P_{x \geq x_k}$ ($P_{x > x_k}$) is the cumulative probability of excess returns which are weakly (strictly) better than x_k. Given shape parameter γ, the PWF is specified as

$$\omega^+[P] = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^{1/\gamma}}. \tag{3}$$

The decision weight on a loss, *i.e.*, $x_k \leq 0$, is similarly specified as $\pi_k = \omega^-[P_{x\leq x_k}] - \omega^-[P_{x<x_k}]$, where $\omega^-[P]$ is a PWF and $P_{x\leq x_k}$ ($P_{x<x_k}$) is the cumulative probability of excess returns which are weakly (strictly) worse than x_k. $\omega^-[P]$ is functionally identical to $\omega^+[P]$ but has its own shape parameter, δ.

Barberis et al. (2016) map excess return distributions to PT values by assuming that the preference parameters are exogenously given and equal to what Tversky and Kahneman (1992) estimated using lab data: $\alpha = \beta = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$ and $\delta = 0.69$. We follow the same approach. This configuration generates the usual parametric structure associated with PT. The utility function is S-shaped, thereby enhancing risk aversion in the gain domain and risk seeking in the loss domain, and both PWFs are inverse S-shaped, thereby enhancing the fourfold pattern of risk attitudes.

Barberis et al. (2016) formulate a variant of modern portfolio theory that incorporates the PT value of each stock. In the noise trader's portfolio, stocks with relatively high (small) PT values are overweighted (underweighted) in comparison to the tangency portfolio. Thus, risk-adjusted returns of stocks are predicted to vary negatively with their PT values because PT-based overweighting (underweighting) translates into overpricing (underpricing). The authors find evidence supporting this prediction from U.S. and 46 international stock markets.

Instead of retesting the pricing prediction, we conduct an alternative test of the PT-based investment behavior by evaluating its fundamental assumption that investors seek portfolios of stocks which have attractive PT values. We use mutual funds as proxies for possible portfolio choices and investigate whether their net flows vary positively with the PT values of their 60-month excess returns.

To complement this analysis, we also study the association between net flows and the RDU values of fund returns over 60-month horizons. RDU characterizes risk attitudes in terms of utility and probability weighting functions similarly as PT but it does not account for reference dependence, hence different attitudes to gains and losses. RDU is thus less flexible than PT on one hand but on the other hand it does not require a particular choice of reference points against which fund *excess* returns are measured (market returns in our PT analysis). Polkovnichenko et al. (2019) find that an empirical pricing kernel based on RDU can help explain the demand for actively managed funds. As documented in the Online Appendix, we derive the RDU values using the parameters estimated by Harrison et al. (2020).

Table 1: Descriptive Statistics

Variable	Definitions	Obs	Mean	SD
FLOW	growth rate of assets under fund management	531,422	-0.003	0.046
\$-FLOW	dollar growth in assets under fund management (in \$ bn.)	531,422	-0.002	0.052
PT	PT value of fund	531,422	-0.019	0.013
RDU	RDU value of fund	531,422	2.352	0.006
ALPHA_{12}	fund abnormal return over past 12 months	531,422	0.0002	0.007
ALPHA_{36}	fund abnormal return over past 36 months	531,422	0.0003	0.004
ALPHA_{60}	fund abnormal return over past 60 months	531,422	0.0005	0.003
SIZE	natural log of fund total net assets (TNA) in \$ mn.	531,422	5.820	1.827
LOAD	fund load	531,422	0.007	0.012
EXP	fund expense ratio	531,422	0.011	0.005
TURN	fund turnover ratio	531,422	0.714	0.783
AGE	fund age in years since inception in CRSP	531,422	15.593	9.870
$\text{FLOW}_{\text{family}}$	growth rate of assets under family management	431,276	-0.003	0.033
$\text{SIZE}_{\text{family}}$	natural log of fund family TNA in \$ mn.	431,432	8.740	2.523
$\text{EXP}_{\text{family}}$	family expense ratio	431,432	0.010	0.004
$\text{RET}_{\text{family}}$	family gross return	431,432	0.008	0.045
$\text{AGE}_{\text{family}}$	family age in years since inception in CRSP	431,432	24.333	15.332

Notes: Growth rate is equal to $\frac{TNA_t - TNA_{t-1}(1+RET)}{TNA_{t-1}(1+RET)}$ where t indexes months and RET is the gross return between $t-1$ and t. Dollar growth is equal to the numerator divided by 1,000. Each ALPHA_{K} is evaluated using a K-month rolling window regression of the Carhart 4-factor model.

3 Empirical Results

Our data source is the CRSP U.S. Survivorship-Bias-Free Mutual Fund Database, which supplies information on monthly fund returns, total net assets (TNA), fund management structures and other fund characteristics. We apply similar sampling criteria as Huang et al. (2011). Specifically, we focus on actively managed diversified domestic mutual funds and our sample excludes international, bond, money market and index funds. We remove all non-U.S. funds by excluding funds with CRSP investment objective codes that do not start with "ED" (Equity Domestic).[2] Further, to better capture mutual funds which trade mainly in stocks, we select funds that held an average of 70% or more of their assets in common stock. We aggregate share classes into the fund level using a TNA value-weighted approach. Finally, to mitigate small-fund bias, we also exclude funds with TNA less than 5 million dollars. This gives us an unbalanced panel of 4,662 funds and 714 families over 246 calendar months from January 1999 through June 2019. Table 1 reports sample statistics on variables to be used.

[2]The details of CRSP investment objective code can be accessed from http://www.crsp.org/products/documentation/crsp-style-code-0.

Table 2: Fund Flow by Size and PT Terciles

	(a) Mean of FLOW × 100				(b) Median of FLOW × 100			
	Low	Med.	High	High-Low	Low	Med.	High	High-Low
Small	-0.780	-0.576	-0.033	0.747	-0.896	-0.646	-0.375	0.521
	(0.027)	(0.023)	(0.021)	(0.035)	(0.010)	(0.008)	(0.007)	(0.013)
Medium	-0.761	-0.495	0.188	0.949	-0.962	-0.699	-0.343	0.619
	(0.020)	(0.017)	(0.017)	(0.026)	(0.009)	(0.007)	(0.007)	(0.011)
Large	-0.628	-0.340	0.248	0.875	-0.757	-0.489	-0.090	0.666
	(0.015)	(0.012)	(0.013)	(0.020)	(0.007)	(0.006)	(0.007)	(0.010)

Notes: Standard errors in parentheses. All estimates are statistically significant at the 1% level. Small, Medium and Large size terciles are based on TNA. Low, Medium and High PT terciles are based on PT measurement.

Cross tabulations in Table 2 suggest that funds with more attractive PT values indeed display larger net flows. This finding is not confined to smaller funds for which any given dollar amount translates into a larger percentage variation. The left panel reports the mean of net flows for each of 9 cells formed by a double-sorting procedure; we divide the sample into three quantiles based on TNA and subdivide each TNA tercile into three quantiles based on PT. Within each TNA tercile, the difference in means between the top and bottom PT terciles is 0.747 percentage points or greater and statistically significant (p-values < 0.01). The right panel reports qualitatively similar results for the differences in medians.

In Table 3, we use multi-way fixed effects models to study whether the fund's PT value as of month t explains its net flow in month $t + 1$. The first column reports a baseline model that only accounts for the PT value, fund fixed effects and date fixed effects. Since we work with monthly data and the date fixed effects vary across year-month tuples, all models in Table 3, including the baseline specification, implicitly account for fund age which are absorbed by such fixed effects. The estimated coefficient of 0.650 on PT is significant (p-value < 0.01) and suggests that a one standard deviation (SD) increase in PT leads to a 0.184 SD increase in the net flow.

The second column augments the baseline model with fund characteristics observed in month t. Following Li et al. (2017), we control for fund performance over the past 12, 36 and 60 months which is known to be a main determinant of flows. The coefficient on PT remains significant although its magnitude declines by 43% to 0.373. The results

Table 3: Regression of Fund Flow in Subsequent Month

	(1) FLOW	(2) FLOW	(3) FLOW	(4) \$-FLOW	(5) FLOW	(6) \$-FLOW
PT	0.650***	0.373***	0.331***	0.427***		
	(0.027)	(0.028)	(0.029)	(0.051)		
RDU					0.812***	1.167***
					(0.092)	(0.153)
$ALPHA_{12}$		0.435***	0.401***	0.348***	0.404***	0.353***
		(0.019)	(0.019)	(0.025)	(0.019)	(0.026)
$ALPHA_{36}$		1.285***	1.258***	1.262***	1.185***	1.155***
		(0.060)	(0.061)	(0.081)	(0.058)	(0.075)
$ALPHA_{60}$		0.656***	0.675***	0.495***	0.510***	0.179
		(0.087)	(0.091)	(0.140)	(0.100)	(0.174)
Fund controls	No	Yes	Yes	Yes	Yes	Yes
Family controls	No	No	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Family FE	No	No	Yes	Yes	Yes	Yes
Within R^2	0.012	0.034	0.050	0.030	0.051	0.031
N	527,420	527,420	428,710	428,710	428,710	428,710

Notes: We regress one period lead of flows against contemporaneous regressors. Fund-level clustered standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Within R^2 is R^2 of a transformed regression model that eliminates all listed FEs. Fund (family) controls are variables SIZE through AGE ($FLOW_{family}$ through AGE_{family}) in Table 1. Online Appendix reports detailed results.

suggest that one SD increases in the fund's PT and 36-month abnormal return lead to similar changes in its future net flow (0.105 and 0.112 SD increases, respectively).

The third column extends the model further by accounting for family characteristics observed in month t and family fixed effects. The fourth column replaces the dependent variable of the extend model with dollar net flows in month $t+1$. In both specifications, we continue to observe that the effect of PT is positive, significant and similar to that of the 36-month abnormal return.

The final two columns re-estimate the third and fourth columns after replacing PT with RDU. We find that a one SD increase in RDU has comparable effects as the corresponding increase in PT. The goodness of fit in terms of within R^2 remains practically unchanged. RDU is much less known than PT in the empirical finance literature but it appears to deserve more attention as a framework for modeling investor behavior.

4 Conclusions

In a panel study of U.S. mutual funds from 1999 to 2019, we find that the fund's PT value is a positive and significant predictor of its future net flow. We obtain similar results when PT is replaced with RDU. Thus, our results support not only the two-step model of PT-based investment behavior but also a more general notion that investors apply non-standard preferences with probability weighting to evaluate financial asset returns. As probability weighting can amplify decision weights on rare and extreme outcomes, our results are in line with recent evidence that fund flows exhibit heightened sensitivity to extreme performance measures.

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Online Appendix to: Prospect Theory and Mutual Fund Flows

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Appendix A. Rank-Dependent Utility (RDU)

We adapt the two-step model of noise trade behavior by Barberis *et al.* (2016) to evaluate the RDU value of each equity fund. In the first step, investors form a mental representation of the fund as a lottery over its possible returns. Suppose that the lottery is a discrete uniform distribution with support points that capture the monthly returns of the fund over the past 60 months. Denote by $X_1 < X_2 < \cdots < X_{60}$ an ordered list of the returns, where subscript k in X_k indicates its ranking rather than timing of observation. Note that now, the outcome of interest X_k refers to the fund's monthly return *per se* rather than its excess return relative to the market; unlike PT, RDU does not require that outcomes are evaluated relative to some reference point.

In the second step, investors apply a RDU preference functional to evaluate the fund's attractiveness. Following Harrison *et al.* (2020), the RDU value of the fund is

$$\text{RDU} = \sum_{k=1}^{60} \pi_k U[X_k] \tag{A.1}$$

where $U[X_k]$ and π_k denote the utility of X_k and the decision weight on X_k, respectively. To be specific, the utility is evaluated using a constant relative risk aversion (CRRA) function

$$U[X_k] = \frac{(1 + X_k)^{(1-r)}}{(1 - r)} \tag{A.2}$$

where curvature parameter r is equivalent to the Arrow-Pratt coefficient of RRA. The decision weight is given by $\pi_k = \omega[P_{x \geq x_k}] - \omega(P_{x > x_k})$, where $\omega(P)$ is a probability weighting function (PWF) and $P_{x \geq x_k}$ ($P_{x > x_k}$) denotes the cumulative probability of fund returns which are weakly (strictly) better than X_k. The PWF is specified as

$$\omega[P] = \exp[-(-\ln[P])^{\phi}] \tag{A.3}$$

where ϕ denotes a shape parameter such that the PWF displays an inverse-S shape if $\phi < 1$ and an S shape if $\phi > 1$. To operationalize the mapping of return distributions to RDU values, we assume that the r and ϕ parameters are exogenously given and equal to what Harrison *et al.* estimated using data from a field experiment: namely, $r = 0.574$ and $\phi = 0.847$.

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Appendix B. Additional Results

Table B1: Regression of Fund Flow in Subsequent Month

	(1) FLOW	(2) FLOW	(3) FLOW	(4) \$-FLOW	(5) FLOW	(6) \$-FLOW
PT	0.650***	0.373***	0.331***	0.427***		
	(0.027)	(0.028)	(0.029)	(0.051)		
RDU					0.812***	1.167***
					(0.092)	(0.153)
$ALPHA_{12}$		0.435***	0.401***	0.348***	0.404***	0.353***
		(0.019)	(0.019)	(0.025)	(0.019)	(0.026)
$ALPHA_{36}$		1.285***	1.258***	1.262***	1.185***	1.155***
		(0.060)	(0.061)	(0.081)	(0.058)	(0.075)
$ALPHA_{60}$		0.656***	0.675***	0.495***	0.510***	0.179
		(0.087)	(0.091)	(0.140)	(0.100)	(0.174)
SIZE/10		-0.055***	-0.050***	-0.033***	-0.050***	-0.033***
		(0.003)	(0.003)	(0.005)	(0.003)	(0.005)
LOAD		-0.011	-0.003	0.058***	-0.003	0.057***
		(0.012)	(0.012)	(0.020)	(0.012)	(0.020)
EXP		-0.163	-0.176	0.130	-0.169	0.145
		(0.117)	(0.134)	(0.177)	(0.135)	(0.177)
TURN/10		0.011***	0.009***	0.007	0.008**	0.004
		(0.003)	(0.036)	(0.004)	(0.004)	(0.004)
$AGE_{family}/100$			-0.014***	-0.008	-0.014***	-0.008
			(0.005)	(0.005)	(0.005)	(0.005)
$SIZE_{family}/100$			0.151***	-5×10^{-5}	0.159***	0.010
			(0.036)	(0.048)	(0.036)	(0.048)
EXP_{family}			0.493***	0.139	0.533***	0.193
			(0.144)	(0.226)	(0.144)	(0.227)
RET_{family}			0.064***	0.038***	0.062***	0.035***
			(0.006)	(0.006)	(0.006)	(0.006)
$FLOW_{family}$			0.107***	0.075***	0.107***	0.074***
			(0.006)	(0.006)	(0.006)	(0.006)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Family FE	No	No	Yes	Yes	Yes	Yes
Within R^2	0.012	0.034	0.050	0.030	0.051	0.031
N	527,420	527,420	428,710	428,710	428,710	428,710

Notes: We regress one period lead of flows against contemporaneous regressors. Fund-level clustered standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Within R^2 is R^2 of a transformed regression model that eliminates all listed FEs.