Reference-Dependent Preferences and Mutual Fund Flows*

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Abstract

In this paper, we use the well-documented mutual fund flow-performance relationship to infer investors' preferences under global risk aversion (GRA) and reference-dependent preferences (RDP). Our methodology yields preference parameter values that maximize the explanatory power of the expected utility of returns on fund flows under the two frameworks. We provide evidence that RDP outperform the GRA framework in explaining mutual fund flows. Our results indicate that mutual fund investors exhibit loss aversion and have differential attitudes toward risk over losses (risk-seeking) and over gains (risk-averse) when evaluating fund performance. Furthermore, we show that our results apply more strongly to retail compared to institutional funds.

Keywords: Reference-dependent preferences, loss aversion, prospect theory, mutual fund flows.

JEL classification: G11, G23, G40.

1 Introduction

Under the expected utility framework with global risk aversion (GRA), agents penalize risk over the entire spectrum of returns. Yet, a growing strand of literature shows that investors' attitudes toward risk may depart significantly from the predictions of GRA. For instance, recent studies document that stocks with high return volatility or high beta underperform those with low volatility or low beta, suggesting that, on some occasions, there is a demand for risk.[1] Reference-dependent preferences (RDP) provide an alternative way of modeling investor behavior that has the potential to address these puzzling phenomena in financial markets.[2]

Under the RDP framework, investors can exhibit differential preferences over gains and over losses. Kahneman and Tversky (1979, 1992) show that individuals exhibit loss aversion and, more importantly, they appear to be risk-averse over gains, but they become risk-seeking over losses. However, most empirical evidence on RDP comes from experimental settings, reflecting the challenges of identifying investors' preferences from market data (Campbell (2000)).

In this study, we examine the relevance of RDP using market data from mutual fund flows, a broad financial market where 45% of U.S. households invest.[3] We infer investors' preferences using the well-documented flow-performance relationship in mutual funds (Ippolito (1992); Chevalier and Ellison (1997)). Specifically, we consider how investors evaluate fund performance under the GRA and RDP frameworks as depicted from their flow allocations. Our methodology infers investors' preferences in two steps. In the first step, we estimate the expected utility of returns (i.e., the certainty equivalent) under a wide range of plausible parameter values for the GRA and RDP utility functions. Then, we include the expected utility of returns in Fama and Macbeth (1973) (FM) regressions of fund flows and find the parameter values that best explain net flow allocations. Thus, our inferred parameters have maximal explanatory power over investors' responses to fund performance within each preference framework.

Under the GRA framework, our method yields a relative risk aversion coefficient (θ) of 1.65, which is closer to risk aversion estimates from consumption-based asset pricing models and labor

[1] See Ang et al. (2006, 2009), Blitz and van Vliet (2007), Baker et al. (2011), and Frazzini and Pedersen (2014).

[2] See Shefrin and Statman (1985), Odean (1998), Grinblatt and Han (2005), Frazzini (2006), and Barberis and Xiong (2009) on how RDP can account for the disposition effect, Benartzi and Thaler (1995), Barberis et al. (2001) for the equity premium puzzle, and Ingersoll and Jin (2013), Wang et al. (2017), An et al. (2020) for the lack of a positive risk-return relation for stocks as well as the negative risk premium for idiosyncratic risk and lottery preferences.

[3] See 2018 Investment Company Factbook (`https://www.ici.org/pdf/2018_factbook.pdf`).

supply data (Hansen and Singleton (1982); Epstein and Zin (1991); Chetty (2006)) compared to values imposed by widely used benchmarks (e.g., Morningstar). Allowing investors to have differential attitudes toward risk over gains and over losses, under the RDP framework, we find evidence in support of loss aversion. Fund flows are best explained with a loss aversion coefficient greater than one ($\lambda = 1.45$), suggesting that mutual fund investors care more about losses than gains. Furthermore, our results indicate that mutual fund investors are risk-seeking over losses and risk-averse over gains, consistent with the findings of Kahneman and Tversky (1992) in experimental settings. Specifically, we find that mutual fund flows are best explained by diminishing sensitivity parameters less than one, which correspond to a mild degree of curvature for the utility function that is concave over gains ($\alpha = 0.85$) and convex over losses ($\beta = 0.9$).

Next, we use these parameter values to compare the ability of the two preference frameworks to explain mutual fund flows. In standardized Fama-MacBeth regressions, we find that the expected utility of returns under RDP can explain fund flows significantly better than GRA, suggesting that investors do not always penalize risk when evaluating fund performance. Specifically, a one standard deviation increase in the certainty equivalent under RDP (GRA) leads to a 1.274% (1.256%) increase in monthly fund flows. The difference in flow response between the two preference measures is both economically and statistically significant. For instance, a 1% difference in the expected utility of returns under RDP and GRA, controlling for excess returns, corresponds to a 2.5% (= 0.698/0.28) increase in monthly flows. More importantly, when we include both variables in the same regression, the certainty equivalent under RDP subsumes its GRA counterpart, suggesting that the latter does not have any additional explanatory power on mutual fund flows.

With the same methodological setting, we also examine retail and institutional funds separately. Under the GRA framework, we find a similar degree of risk aversion for retail and institutional funds ($\theta_R = 1.65$, $\theta_I = 1.60$). However, when we allow for differential attitudes toward risk under RDP, we document a stark difference between the two groups. Retail mutual fund investors appear to be risk-averse over gains ($\alpha_R = 0.85$) and risk-seeking over losses ($\beta_R = 0.90$), in line with our full sample results. By contrast, for institutional funds the risk-seeking behavior over losses is all but absent ($\beta_I = 1.00$), consistent with past findings that institutional investors evaluate fund performance differently compared to their retail peers (Del Guercio and Tkac (2002); Salganik-Shoshan (2016)). Consequently, the RDP framework loses much of its appeal for institutional funds, suggesting that our full-sample results are driven mainly by retail funds. As a result, the evidence in favor of RDP is stronger in the first half of our sample period (1994–2005), in which 70% of the funds are classified as retail, compared to the second half (2006–2020), in which the portion of retail funds steadily declines.

In additional tests, we examine the role of nonlinear probability weighting (Kahneman and Tversky (1992)), but we do not find evidence that mutual fund investors significantly overweight extreme outcomes. Our methodology yields probability-weighting parameters (γ, δ) very close to one, which only marginally affect the explanatory power on fund flows. This finding is not surprising, given that our sample consists of large, well-diversified portfolios for which extreme outcomes are less likely to occur compared to individual securities (Barberis et al. (2016)).

The findings in our main analysis are robust to a wide array of specifications. We obtain similar results using panel regressions and in out-of-sample tests, where we infer preference parameters and estimate the expected utility of returns in non-overlapping periods. Our findings also remain qualitatively unchanged with different performance evaluation horizons, alternative reference points to separate gains and losses, and the alternative fund flow definition of Spiegel and Zhang (2013) that is based on changes in market shares. Finally, our baseline results remain strongly robust in the presence of performance measures (alphas) from widely-used asset pricing models (CAPM, 3-factor and 4-factor Fama-French models) and controls for Morningstar ratings.

Our paper contributes to the growing literature on the relevance of RDP to model investor behavior. Following the seminal work of Kahneman and Tversky (1979, 1992), many studies structurally estimate agents' preferences with experimental data.[4] Additional important work on the field uses data from settings such as betting (Golec and Tamarkin (1998); Jullien and Salanié (2000); Snowberg and Wolfers (2010); Andrikogiannopoulou and Papakonstantinou (2019)) and insurance markets (Cohen and Einav (2007); Syndor (2010); Barseghyan et al. (2013)). Blackburn and Ukhov (2006) and Kliger and Levy (2009) find strong support for a reference-dependent utility function using stock returns and option prices. More recently, Barberis et al. (2016) show that investors evaluate the past distribution of individual stocks according to prospect theory.

Our findings are consistent with contemporaneous work on the relevance of RDP for mutual fund investors (Gu and Yoo (2021); Guo and Schönleber (2021); Han et al. (2021)). However, our

[4]See Starmer (2000) and Barseghyan et al. (2018) for a review.

paper differs from these studies in two important ways. First, our methodology infers preference parameters from the flow-performance relationship instead of adopting the parameter estimates of Kahneman and Tversky (1992) from laboratory experiments. We show that these parameters values are crucial for assessing the (relative) ability of the RDP framework to explain mutual fund flows, suggesting that its role may be understated in other studies. Second, we focus on the ability of RDP to explain mutual fund flows relative to GRA preferences, rather than risk-adjusted performance measures (alphas). The reason is that comparing expected utility to risk-adjusted returns is more restrictive and less informative, since alphas correspond to specific asset pricing models (e.g., CAPM assumes global risk aversion). In line with this view, we show that alphas from widely-used asset pricing models are subsumed by the expected utility of returns under both RDP and GRA, when included in the same regression.

Our study is closely related to work that examines how investors evaluate mutual fund performance and allocate their flows. Early studies find that mutual fund investors chase raw returns (Ippolito (1992); Chevalier and Ellison (1997); Sirri and Tufano (1998)). More recently, Berk and van Binsbergen (2016) and Barber et al. (2016) provide evidence that investors use the capital asset pricing model (CAPM) to evaluate performance and allocate flows, ignoring additional factors. Polkovnichenko et al. (2019) and Artavanis et al. (2019) show that mutual fund investors are sensitive to downside risk. We extend this line of inquiry by examining the relevance of the RDP framework for mutual fund flows and show that mutual fund investors exhibit loss aversion and differential attitudes toward risk over losses and gains.

Finally, this paper contributes to the literature on the differences between institutional and retail fund investors. Del Guercio and Tkac (2002) find that fiduciary pension fund clients evaluate fund managers based on risk-adjusted performance and punish poorly performing funds, in contrast to other mutual fund investors. Evans and Fahlenbrach (2012) document that institutional investors are more sensitive to high fees and poor risk-adjusted performance, reflecting their greater monitoring abilities. Salganik-Shoshan (2016) show that the convex return-flow relationship exists only among retail funds and that institutional fund investors use quantitatively more sophisticated criteria. Consistent with the findings of Barberis et al. (2016), our results suggest that RDP is more relevant for retail investors, who exhibit differential responses over gains and losses, whereas the risk-seeking behavior over losses is all but absent for institutional funds.

2 Reference-Dependent Preferences

2.1 The Global Risk Aversion (GRA) Framework

Under the global risk aversion (GRA) framework, individuals maximize their expected utility from final wealth or consumption levels with a concave utility function. The most commonly used utility function in portfolio theory is power utility that exhibits constant relative risk aversion and takes the form

$$U^{GRA}(1+r;\theta) = \frac{(1+r)^{1-\theta}-1}{1-\theta}, \tag{1}$$

where r is the investment return and $\theta \geq 0$ is the relative risk aversion coefficient.[5]

Hansen and Singleton (1982) and Epstein and Zin (1991) find θ to be around 1 by estimating a consumption-based model, while Chetty (2006) provides similar estimates with a different approach using labor supply data. Conversely, Mehra and Prescott (1985) argue that investors should have an implausibly large θ to account for the high excess returns of U.S. equities under the GRA framework.

2.2 The Reference-Dependent Preference (RDP) Framework

The reference-dependent preference (RDP) framework allows investors to have differential attitudes toward risk over gains and losses and can account for some puzzling empirical results that the GRA framework cannot explain. For example, previous studies find that the relationship between risk and return is much flatter than predicted by the CAPM (Black (1972); Fama and French (1992)) or is even reversed (Haugen and Heins (1975)). More recently, Ang et al. (2006, 2009), Blitz and van Vliet (2007), Baker et al. (2011), and Frazzini and Pedersen (2014) show that stocks with high volatility, beta, or idiosyncratic risk earn lower returns, creating "perhaps the greatest anomaly in finance" according to Baker et al. (2011).

Under the RDP framework, utility is defined over gains and losses measured relative to a reference point, and the utility function takes the form

[5]The power utility function reduces to log utility for $\theta = 1$, while $\theta = 0$ implies risk neutrality.

$$U^{RDP}(r;\alpha,\beta,\lambda) = \begin{cases} r^{\alpha} & \text{if } r \geq 0 \\ -\lambda(-r)^{\beta} & \text{if } r < 0 \end{cases}, \tag{2}$$

where λ is the coefficient of loss aversion, and α and β govern risk preferences in the domain of gains and losses (coefficients of diminishing sensitivity).

Kahneman and Tversky (1992) observe that individuals are more sensitive to losses compared to gains, which induces a kink in their utility function ($\lambda > 1$). Furthermore, they find that experiment participants are risk-averse over gains but risk-seeking over losses.[6] To account for this behavior, they propose an S-shaped utility function that is concave over gains and convex over losses ($\alpha, \beta < 1$).

The past literature has applied RDP to address asset pricing anomalies such as the disposition effect (Shefrin and Statman (1985); Odean (1998); Grinblatt and Han (2005); Frazzini (2006); Barberis and Xiong (2009)) and the equity premium puzzle (Benartzi and Thaler (1995); Barberis et al. (2001)). More recently, Ingersoll and Jin (2013) show that a dynamic model with RDP can explain the flattening of the risk-return trade-off and the negative risk premium for idiosyncratic risk. Consistent with RDP, Wang et al. (2017) find a positive risk-return relation for stocks trading at a gain but a negative risk-return relation for stocks trading at a loss. An et al. (2020) show that anomalies related to lottery preferences exist only among stocks where investors have lost money and argue that RDP can drive lottery preferences. Finally, Lian et al. (2018) use RDP to explain greater risk taking when interest rates are low.

2.3 Comparison of GRA and RDP: An Example

We illustrate the difference between the two frameworks with an example. Figure 1 presents monthly excess returns from August 2001 to July 2004 for two funds, BlackRock Mid Cap Value Opportunities and Diamond Hill Long-Short. The two funds have almost identical monthly mean excess returns (0.3%) and volatility (5.7%), but differ in their return distributions over gains and losses. Specifically, the returns of the BlackRock fund have similar volatility over losses and gains

[6] Specifically, experiment participants prefer a sure gain of \$50 over a 50% chance of gaining \$100, suggesting risk-averse behavior over gains, yet they turn to risk-seeking behavior over losses, as they prefer a 50% chance of losing \$100 over a sure loss of \$50.

(3.6% vs. 3.0%), whereas in the case of Diamond Hill, gains are relatively stable but losses are quite volatile (2.4% vs. 5.7%).

If investors are globally risk-averse (or risk-neutral), they will be indifferent between these two funds. On the other hand, if agents have reference-dependent preferences, the expected utility of returns under the RDP framework can differ significantly between the two funds. In our example, applying the parameter values we use in our main analysis ($\theta = 1.65$, $\lambda = 1.45$, $\alpha = 0.85$, $\beta = 0.9$) yields exactly the same expected utility for the two funds under GRA, whereas the expected utility of Diamond Hill returns is 0.4% higher under the RDP framework. Thus, if investors exhibit risk aversion toward gains and risk-seeking behavior toward losses, they will prefer Diamond Hill—with relatively stable gains and more volatile losses—over BlackRock.

In this paper, we compare the ability of the two frameworks to explain mutual fund flows. In terms of our example, we examine whether Diamond Hill receives significantly more flows than BlackRock, even though the two funds perform similarly under the GRA framework.

3 Data and Sample

Our sample includes actively managed, domestic equity funds from the CRSP survivor-bias-free mutual fund database. We remove foreign equity, sector equity, fixed income, and mixed funds using the CRSP objective codes in the database.[7] We also filter out index funds and exchange traded funds (ETFs) based on index fund or ETF flag or based on a fund name containing a string associated with index funds or ETFs. Additionally, we remove target-date funds from the sample by using the target year in the fund's name.

We obtain monthly fund returns, total net assets (TNA), and fund characteristics from CRSP. The sample period is from January 1991, when monthly TNAs first become available, to November 2020. We merge different share classes of a fund[8] and define monthly fund flow F_{it} following Sirri and Tufano (1998) as follows:

[7] CRSP objective codes are constructed using objective codes from three different sources (Wiesenberger, Strategic Insight, and Lipper) in order to provide continuity in style classifications. Detailed information can be found at http://www.crsp.com/products/documentation/crsp-style-code

[8] We sum the TNA of each share class to obtain a fund's TNA. Fund age is defined as the age of the oldest share class. We calculate the value-weighted averages of monthly return, expense ratio, and turnover ratio across share classes. The fund objective is defined based on the largest share class of the fund.

$$F_{it} = \frac{TNA_{it} - (1 + R_{it})TNA_{it-1}}{TNA_{it-1}}, \tag{3}$$

where TNA_{it} is total net assets under management for fund i at the end of month t, and R_{it} is the total return in month t.[9]

We exclude funds with TNA less than \$15 million in a given month and monthly flows less than -90% or more than 1000% to avoid outliers and to mitigate incubation bias (Evans (2010)). We also winsorize fund flows at 1% and 99% levels. We require a fund to have 37 (36+1) monthly returns available in order to calculate the expected utility of returns, and the next month's flow. The final sample contains 3,979 funds from 847 distinct fund families over a testing period of 324 months. Following Benartzi and Thaler (1995) and Barberis et al. (2001), we use the risk-free rate as the reference point to separate gains from losses, which implies that individuals frame gains and losses with respect to the opportunity cost of investing in the risk-free asset.

Table 1 provides the summary statistics for the funds in our sample. All statistics are first calculated in the cross section each month and then averaged across time. Panel A shows that the average fund has an age of 13.8 years and \$1,298 million in TNA, with a much smaller median (\$281 million), reflecting a positive skew in fund size. Average and median monthly fund flow is negative (-0.13% and -0.4% respectively). The average expense and turnover ratios are 1.2% and 85%, respectively. Finally, the majority of the funds (73%) charge either front-end or back-end loads for at least one share class. The median fund in our sample has a monthly volatility of 4.63%, and positive expected utility of returns under the GRA (0.42%) and RDP (0.46%) frameworks.

4 Empirical Results

4.1 Flow Regressions on Return and Risk

In this section, we motivate the relevance of reference-dependent preferences by examining mutual fund investors' responses to return and risk. Early literature on mutual funds focuses mostly on the

[9] We consider an alternative definition of fund flows following Spiegel and Zhang (2013) in robustness tests (section 4.7). Also, we obtain qualitatively similar results when we apply the Berk and Tonks (2007) fund flow correction:

$$F_{it} = \frac{TNA_{it} - (1 + R_{it})TNA_{it-1}}{(1 + R_{it})TNA_{it-1}}$$

return-chasing behavior of investors and documents only a weak negative relationship between fund flows and risk (Sirri and Tufano (1998); Barber et al. (2005); Spiegel and Zhang (2013); Clifford et al. (2013)). To examine whether investors' responses to risk—in the form of fund flows—depend on recent fund returns, we compare the following Fama and Macbeth (1973) regressions:

$$F_{it} = a + b_1 \cdot Return_{i,t-1} + b_2 \cdot Risk_{it-1} + c \cdot X_{it-1} + FO_i + \epsilon_{it} \tag{4}$$

$$F_{it} = a + b_1 \cdot Return_{i,t-1} + b_{21} \cdot Risk_{it-1} \cdot Gain_{it-1} + b_{22} \cdot Risk_{it-1} \cdot Loss_{it-1} + c \cdot X_{it-1} + FO_i + \epsilon_{it} \tag{5}$$

where F_{it} is the monthly fund flow, $Return_{i,t-1}$ is the buy-and-hold excess return over the past 12 months ($t-12$ to $t-1$), and $Risk_{it-1}$ is the monthly excess return volatility estimated over the previous 36 months. Regressions also include a vector of control variables X_{it-1} and fund objective fixed effects (FO_i) based on CRSP objective codes.[10]

The parameter of interest is b_2 in regression (4), which depicts the fund flow response to risk. In specification (5), we examine risk responses for funds that overperformed (b_{21}) and underperformed (b_{22}) the risk-free rate over the past year, separately. For this reason, we interact $Risk_{it-1}$ with the dummy variable $Gain_{it-1}$ ($Loss_{it-1}$), which takes the value of one if the fund has achieved positive (negative) excess returns over the past year, and zero otherwise.[11]

Table 2 provides the results of regressions (4) and (5), after standardizing all continuous independent variables to allow for a direct comparison of their economic significance. The results are consistent with the well-documented return-chasing behavior of mutual fund investors. A one standard deviation increase in excess returns over the previous year leads to a highly significant 1.38% increase in monthly fund flows. Also consistent with the past literature, our findings suggest that investors only slightly punish risk (column 1). A one standard deviation increase in return volatility leads to a 0.13% decrease in fund flows, which is marginally significant (t-stat -1.71).

However, when we examine risk in conjunction with return, we find that investors facing gains and losses react very differently to risk. In column 2, a one standard deviation increase in volatility

[10] The control variables include logarithms of fund size and age, turnover and expense ratios, a load dummy indicating whether any of the fund's share classes charge front-end or back-end loads, and the logarithm of fund family size.

[11] It is not clear over which horizon investors evaluate the performance of their investments. In our study, we use a one-year horizon following the literature on the mutual fund flow-performance relationship (Sirri and Tufano (1998); Chevalier and Ellison (1997)), and Benartzi and Thaler (1995) who suggest that one year is a plausible period for investors to evaluate their returns and determine whether they have made losses or gains.

leads to a 0.36% (t-stat -4.59) decrease in flows for funds with recent gains, but it increases flows for funds that have suffered recent losses by 0.25% (t-stat 3.39). Furthermore, the pattern remains intact and significant when we control for convexity in the performance-flow relationship using piecewise linear regressions, similar to Sirri and Tufano (1998) (columns 3 and 4). In column 4, a one standard deviation increase in volatility leads to a 0.38% (t-stat -4.01) decrease in flows for funds with recent gains, but it increases flows for funds with recent losses by 0.15% (t-stat 2.33).

Collectively, these results are consistent with the existence of RDP and support the hypothesis that investors respond to risk very differently depending on past fund performance, similarly to the findings of Wang et al. (2017) on common stocks. Retrospectively, our results provide an explanation for the weak relationship between fund flows and risk documented in the past literature; Table 2 shows that the pooling of positive and negative responses of fund flows to risk over losses and gains can average out the overall effect of risk to marginally significant levels.

So far, we have considered the return and risk components of performance separately, which provides only a rough approximation of how investors evaluate performance. Nevertheless, the negative response of fund flows to risk following gains and the positive response following losses motivates a further investigation of the relevance of RDP for mutual fund investors.

4.2 Inferring Risk Preference Parameters from Flows

In this section, we infer risk preference parameter values under the GRA and RDP frameworks using the well-documented mutual fund flow-performance relationship. The past literature collectively finds a strong flow-performance relationship that is robust to the measure of performance. Here, we infer investors' preferences by examining the explanatory power of expected utility of returns—under the GRA and RDP frameworks—on mutual fund flows.

Our methodology includes two steps. In the first step, we calculate the expected utility of returns (i.e., the certainty equivalent) under GRA and RDP for plausible values of the risk preference parameters. For both frameworks, we use excess returns over the risk-free rate for the past 36 months using equal weights for each observation (i.e., objective probabilities).[12] We calculate the certainty equivalent under GRA as the expected value of equation (1) with θ values ranging from

[12] We examine the case of probability weighting in Section 4.6. In robustness tests (Section 4.7), we also consider zero and market returns as alternative thresholds for separating gains from losses, and excess returns over the past 24 or 48 months.

-1 to 5 in increments of 0.05. Similarly, we calculate the certainty equivalent under RDP as the expected value of equation (2) for different values of parameters λ, α, β. Specifically, we let λ take values from 0.5 to 2.5, and α and β range from 0.4 to 1.2, both in increments of 0.05.

In the second step, we include the expected utility of returns, estimated for different parameter values, in Fama and Macbeth (1973) (FM) regressions:

$$F_{it} = a + b \cdot EU(r)_{i,t-1} + c \cdot X_{i,t-1} + FO_i + \epsilon_{it}, \tag{6}$$

where F_{it} is the monthly fund flow, $EU(r)_{i,t-1}$ is the expected utility of (excess) returns over the past 36 months under GRA or RDP, and $X_{i,t-1}$ is a vector of control variables. We include fund objective fixed effects (FO_i) and standardize all continuous independent variables.

We infer the value of risk preference parameter(s) within each framework by maximizing the explanatory power of the expected utility of returns on fund flows, as measured by the average adjusted-R^2. In other words, we hypothesize that the risk parameters values that explain fund flows best are the closest to describing investors' preferences within that framework.

Our main methodological approach uses standardized Fama and Macbeth (1973) regressions for three reasons. First and foremost, FM regressions focus on the cross section of funds and isolate the effect of market-wide factors. Second, this specification is more robust to time-varying flow-performance sensitivity compared to panel regressions (Franzoni and Schmalz (2017), Ben-David et al. (2022)). Finally, FM regressions place equal weights on each period, which avoids overweighting (later) periods with a larger number of funds. It is important to note that our results remain strongly robust when we use panel (instead of FM) regressions (Table A4).

First, we examine the relationship between mutual fund flows and the certainty equivalent of returns under the GRA framework for different values of parameter θ. For instance, if investors were risk-neutral and simply chased raw returns, we would expect fund flows to be best explained with a zero degree of risk aversion within the GRA framework. Figure 2 plots the explanatory power of the expected utility of returns on fund flows (i.e., average adjusted R^2) for different θ values. We find that mutual fund flows are explained best with a degree of risk aversion (θ) of 1.65, which is closer to estimates from consumption-based asset pricing models (Hansen and Singleton

(1982), Epstein and Zin (1991)) and labor supply data (Chetty (2006)), and significantly lower compared to parameter values imposed by widely used benchmarks (e.g., Morningstar).[13]

Next, we examine the fund flow-performance relationship under RDP to infer parameters λ, α, and β. Figure 3 plots our results in the three-dimensional parameter space, where the explanatory power is represented by color. If investors cared equally about gains and losses, fund flows would be best explained with a coefficient of loss aversion (λ) equal to one. Instead, we find that investors exhibit loss aversion, as they put more weight on losses than they do on gains with $\lambda = 1.45$. Even though our method is different, it is worth noting that our coefficient of loss aversion is close to estimates from more recent experimental studies (Schmidt and Traub (2002), Harrison and Rutstrom (2009)) and field or market data studies (Andrikogiannopoulou and Papakonstantinou (2019), Kliger and Levy (2009)), which find λ to be between 1.40 and 1.50. This value is also significantly lower than the estimate of Kahneman and Tversky (1992) in their experiments ($\lambda = 2.25$), consistent with the view that real-market investors may be less loss-averse than the general population (Barberis (2018)).

Additionally, Figure 3 shows that both diminishing sensitivity parameters α and β are below one, which implies that investors are risk-averse over gains ($\alpha = 0.85$) but risk-seeking over losses ($\beta = 0.90$). Figure 4 plots the RDP utility function that corresponds to parameter values inferred from fund flows ($\alpha = 0.85$, $\beta = 0.90$, and $\lambda = 1.45$). As depicted in the graph, the utility function has the characteristic S-shape proposed by Kahneman and Tversky (1979), suggesting that mutual fund investors are risk-seeking over losses (convex part) and risk-averse over gains (concave part).

A closer inspection of Figures 2 and 3 reveals the importance of risk parameter values in assessing the ability of a preference framework to explain mutual fund flows. First, we observe that the relative performance of RDP compared to GRA does not depend mechanically on the number of preference parameters in each framework. For example, Figure 3 depicts the parameter space (in blue-yellow color) for which the ability of RDP to explain mutual fund flows decreases to levels lower than the GRA framework (Figure 2). Second, applying parameter estimates from experimental settings to market data may underestimate the performance of the RDP framework to the extend that investors' preferences deviate from those of experiment participants. For instance,

[13] The Morningstar risk-adjustment methodology imposes $\theta = 3$ (see https://www.morningstar.com/content/dam/marketing/shared/research/methodology/771945_Morningstar_Rating_for_Funds_Methodology.pdf).

Figure 3 shows that using the parameter values of Kahneman and Tversky (1992) from laboratory experiments ($\lambda = 2.25$, $\alpha = \beta = 0.88$) yields significantly lower explanatory power for the expected utility of returns compared to the results of our methodology.

4.3 Comparison of Risk-Adjusted Returns with GRA and RDP

Here, we examine how the GRA and RDP frameworks fare in explaining mutual fund flows, using the parameters we inferred in the previous section ($\theta = 1.65$ and $\alpha = 0.85$, $\beta = 0.90$, $\lambda = 1.45$). Additionally, we consider the average excess return (Exret) as a performance measure that investors would use if they were risk-neutral.[14] We use FM regressions of next month's fund flows on the expected utility of excess returns over the past 36 months (as in (6)), and we standardize all performance measures to allow for a direct comparison of the coefficients.

Table 3 presents our results. Column 1 shows that a one standard deviation increase in excess returns leads to a 1.236% increase in monthly fund flows, while the respective increase in the GRA certainty equivalent ($\theta = 1.65$) leads to a higher response; 1.256% (column 2). Column 3 shows that a one standard deviation increase in the expected utility of returns under RDP ($\lambda = 1.45$, $\alpha = 0.85$, $\beta = 0.90$) leads to an even higher increase of 1.274% in monthly fund flows. Columns 4 and 5 indicate that the difference is statistically significant; when we include all measures in the same regression, the expected utility of returns under RDP subsumes all competing variables and remains strongly significant.[15] Furthermore, RDP perform significantly better than GRA in predicting flows in the Barber et al. (2016) 10x10 pairwise comparison test (Table A2).

The stronger response of fund flows to RDP compared with GRA is also economically significant. To assess economic significance more precisely, we include the difference in the expected utility between the two frameworks controlling for excess returns (Column 6). The coefficient of the difference is positive and highly significant; a 1% difference in expected utility between the two frameworks (RDP-GRA) corresponds to a 2.5% increase in monthly fund flows.[16] In terms of our example in Section 2.3, our results suggest that Diamond Hill would receive 1% ($= 0.698 \cdot 0.4\%/0.28\%$) more flows than BlackRock over the next month.

[14] Note that preferences under GRA with $\theta = 0$ or under RDP with $\lambda = \alpha = \beta = 1$ also correspond to risk neutrality. Since our analysis focuses on cross-sectional tests, excess returns can be regarded as equivalent to raw or market-adjusted returns.

[15] Our results remain qualitatively unchanged when we include lagged flows in the regression (see Table A1).

[16] A one standard deviation increase in RDP-GRA ($\sigma = 0.28\%$) corresponds to a 0.7% increase in monthly flows.

Collectively, our findings suggest that investors evaluate mutual fund performance according to a process that is more in line with the RDP rather than the GRA framework. In other words, our results support the view that mutual fund investors exhibit loss aversion and differential risk preferences toward losses and gains.

4.4 Retail versus Institutional Investors

So far, we have treated mutual fund investors as a homogeneous group. However, different investor groups may assess fund performance differently. For instance, Del Guercio and Tkac (2002) and Salganik-Shoshan (2016) show that institutional investors use risk-adjusted returns (e.g., Jensen (1968)'s alpha) to evaluate funds, while retail investors simply chase raw returns. Furthermore, Barberis et al. (2016) find stronger support for prospect theory among stocks that are more heavily traded by individuals (i.e., small-cap), suggesting that RDP may be better suited to describe the preferences of retail investors.

In this section, we examine retail and institutional funds separately using the same methodology as previously. We classify a fund as institutional (retail) if more than 75% of its TNA are held in an institutional (retail) share class based on CRSP institutional (retail) fund flag or share class name.[17] Funds with significant portions of TNA in both retail and institutional share classes are excluded from the current analysis (19% of the sample).[18] Figure 5 shows how the two groups evolve through time; institutional funds account for a small portion of the sample in early years, but almost half of the fund population by the end of our sample period.

Table 4 presents our results on retail and institutional funds separately. In Panel A, we repeat the regression analysis of fund flows on return and risk (as in Section 4.1). In line with our previous results, we find that risk is weakly related to fund flows (columns 1 and 3) implying that mutual fund investors do not care about risk. However, once we interact risk with the recent performance of retail funds (column 2), we find that flows are significantly negatively related to risk over gains

[17]CRSP institutional (retail) fund flags are based on the Lipper categorization method, according to which a fund share class is classified as Institutional if it has a minimum investment requirement of at least \$100,000 and if its shares are distributed to or through an institution (see Salganik-Shoshan (2016)). Also, CRSP institutional (retail) fund flags are available from 1999 onward. For years prior to 1999, we backfill this information whenever it is available. Additionally, we categorize funds with names containing "Class I," "Class Y," "Class X," "Class K," "Institutional," "Inst," "Trust Class," "Premier Class," and "Fiduciary Class" as institutional, and funds with names containing "Retail" and "Ret" as retail.

[18]We obtain qualitatively similar results when we restrict our sample to purely institutional or retail funds (i.e., with 100% of assets held in respective share classes).

and significantly positively related to risk over losses. Thus, retail investors not only care about risk but also treat risk differentially over gains and losses. For institutional funds, flows are significantly negatively related to risk following recent gains, but the positive flow-risk relationship that we observe in retail funds is all but absent (column 4).

Panel B reports the preference parameter values that maximize the explanatory power of the expected utility of returns on flows for the two subsamples. Both retail and institutional investors exhibit mild levels of risk aversion under the GRA framework ($\theta_R = 1.65$, $\theta_I = 1.60$). However, under the RDP framework the two groups appear to approach risk differently. While both types of investors exhibit loss aversion and are risk-averse over gains ($\alpha_R = 0.85$, $\alpha_I = 0.9$), only retail investors exhibit risk-seeking behavior over losses ($\beta_R = 0.9$, $\beta_I = 1$), consistent with the results in Panel A. Consequently, the RDP framework loses much of its appeal in explaining flows for institutional funds. In Panel C, we compare the ability of the two frameworks to explain mutual fund flows for the two groups. We find that the RDP explain fund flows significantly better, but only in the case of retail investors; the RDP coefficient is larger and it subsumes its GRA counterpart when both are included in the same regression (columns 1-3). By contrast, the incremental ability of RDP to explain fund flows better than GRA is insignificant for institutional funds (columns 4-6).

Overall, our findings here suggest that our baseline results are mainly driven by retail funds, in line with the insights of Barberis et al. (2016) that the predictions of prospect theory hold more strongly among stocks that are more heavily traded by individual investors (e.g., small-cap).

4.5 Subperiod Analysis

Actively managed mutual funds went through significant changes over our sample period. Figure 5 shows that the number of mutual funds in the industry increased sharply in the first half of the sample period (Dec.1993–Nov.2005), when retail funds account for up to 70% of the sample. During the second subperiod (Dec.2005–Nov.2020), the relative population of institutional funds increased gradually, accounting for half of our sample in later years.

Here, we investigate how these advances in the mutual fund industry affect our results. Table 5 (Panel A) presents the results from fund flow regressions on return and risk for the two subperiods separately. The positive fund flow response to risk following losses is particularly strong in the first subperiod (coef: 0.378, t-stat: 3.30), whereas it becomes marginally significant in the second (coef: 0.141, t-stat: 1.67). This result is consistent with institutional funds—for which the positive response to risk over losses is all but absent (Table 4)—making up a larger portion of the sample in the second subperiod.

Panel B reports the risk preference parameter values that maximize the explanatory power of the expected utility of returns on flows for the two subperiods. In the first subperiod, we find risk-seeking ($\beta = 0.90$) and risk-averse behavior ($\alpha = 0.75$) toward losses and gains, respectively, in line with our baseline results. However, the results for the second subperiod indicate a significantly weaker degree of diminishing sensitivity, with the respective coefficient for both losses and gains being very close to one ($\alpha = \beta = 0.95$). Furthermore, while the flow response to the certainty equivalent under RDP is stronger in both subperiods (Panel C), the difference between the coefficients is smaller in the second half of our sample.

Overall, our results here indicate that the ability of the RDP framework to better explain mutual fund flows is stronger in the first subperiod, when retail funds dominate the sample. In additional tests, we confirm that the RDP framework performs better in both subperiods for retail funds, but not for institutional funds (see Table A3).

4.6 Probability Weighting

Under cumulative prospect theory (Kahneman and Tversky (1992)), in addition to the reference-dependent utility function with loss aversion in (2), agents can overweight extreme outcomes through probability weighting. That is, instead of objective probabilities, agents use probability weights (π_j) of the form:

$$\pi_j = \begin{cases} \omega^+(p_j + ... + p_n) - \omega^+(p_{j+1} + ... + p_n) & \text{for } 0 \leq j \leq n \\ \omega^-(p_{-m} + ... + p_j) - \omega^-(p_{-m} + ... + p_{j-1}) & \text{for } -m \leq j < 0 \,, \end{cases} \tag{7}$$

where the outcomes (i.e., returns) are sorted by index j from $-m$ to n with m negative (loss) and n positive (gain) outcomes.

The transformation of objective probabilities (p_j) to probability weights π_j involves the use of the probability-weighting (PW) functions:

$$\omega^+(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}} \quad \text{and} \quad \omega^-(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}} \;, \tag{8}$$

where γ and δ are PW parameters for gains and losses, respectively. From (7) and (8), it follows that PW parameter values equal to unity ($\gamma = \delta = 1$) imply no probability weighting. Parameter values below one indicate overweighting of extreme outcomes, with heavier overweighting of the tails the lower the values of γ and δ (see Barberis (2018)).

In our analysis so far, we have used equal weights for each observation in the 36-month performance evaluation horizon ($p_j = 1/36$). Here, to investigate whether investors overweight extreme returns, we examine how accounting for probability weighting affects the performance of the expected utility of returns in explaining fund flows.

Table 6 presents our results. The first column reports our baseline results without probability weighting (as in Table 3); the coefficient of the certainty equivalent under RDP is 1.274 and highly significant ($Adj.R^2 = 11.4\%$). In column 2, we allow for probability weighting by jointly inferring the vector of RDP (λ, α, β) and PW (γ, δ) parameters using our methodology.[19] The inclusion of PW does not have a significant impact on the RDP parameters; fund flows are best explained with RDP utility parameters similar to before ($\lambda = 1.5$, $\alpha = 0.8$, $\beta = 0.9$) with the small differences being mainly due to the wider grids used in this test. Our results indicate that fund flows are best explained with probability weighting parameters $\gamma = \delta = 0.9$, but the improvement in flow response and explanatory power are marginal at best; the coefficient of the expected utility of returns with PW increases by just 0.005 ($Adj.R^2 = 11.5\%$).

To better understand the role of probability weighting in explaining mutual fund flows, we perform two additional tests. First, we infer PW parameters *given* the parameter values from our baseline analysis ($\lambda = 1.45$, $\alpha = 0.85$, $\beta = 0.90$); in this test, we let γ and δ take different values between 0.4 and 1.2 in finer increments of 0.05. We find that fund flows are best explained for $\gamma = 0.95$ and $\delta = 0.95$ (column 3), parameter values that are even closer to unity. The improvement in fund flow response and explanatory power with respect to our baseline results is negligible. In column 4, we repeat the analysis by calculating the expected utility of returns

[19] To circumvent the computational challenges arising from the number of parameters to consider, we use wider grids for RDP parameters and set the PW parameters to be equal (γ=δ). Specifically, we let λ take values from 0.5 to 2.5 in increments of 0.25, and α, β, and $\gamma = \delta$ range from 0.4 to 1.2 in increments of 0.1.

only with PW (i.e., setting $\lambda = \alpha = \beta = 1$). The flow response and the explanatory power of the expected utility of returns just with PW decrease significantly compared to our baseline (Diff: -0.029, $Adj.R^2 = 10.96\%$). Collectively, these two conditional tests suggest that the incremental contribution of probability weighting in explaining mutual fund flows is low.

In the last column of Table 6, we report results under the parameter values of Kahneman and Tversky (1992) from laboratory experiments ($\lambda = 2.25$, $\alpha = \beta = 0.88$, $\gamma = 0.61$, $\delta = 0.69$), that are also used in recent studies (Gu and Yoo (2021); Han et al. (2021); Guo and Schönleber (2021)). Under these parameters values, explanatory power ($Adj.R^2 = 8.7\%$) and the coefficient of the certainty equivalent (coeff= 1.05) decrease dramatically to levels even lower than the case of risk neutrality (see column 4). These results reaffirm the importance of the risk parameter values in accessing the performance of preference frameworks, and are consistent with the argument that applying parameter values from experiments to market data may underestimate the role of RDP for real-world investors.

Overall, our findings do not support the view that mutual fund investors overweight extreme outcomes. However, the obvious caveat here is that our sample consists of large, well-diversified portfolios, for which extreme outcomes may be too scarce—relative to individual securities (Barberis et al. (2016))—to have a substantial impact. Therefore, even though our findings do not contradict probability weighting in general, we find little support for it in the context of the mutual fund market.

4.7 Robustness Tests

In this section, we examine the robustness of our main results on the relevance of RDP for mutual fund investors to alternative specifications and methodologies. Our baseline analysis uses FM regressions to access and compare performance of preference frameworks. We obtain qualitatively similar results using panel regressions, which is another common methodological approach in the literature; the expected utility of returns under RDP commands a larger flow response, increases explanatory power, and subsumes all competing variables while remaining highly significant (Table A4). Our results are also robust in out-of-sample tests, where infer parameter values and estimate the expected utility of returns in non-overlapping periods. Specifically, in the second column of Table 7, we infer risk preference parameters from annual-rolling estimation periods and then use them to calculate the expected utility of returns over the following year. The results are qualitatively similar to our baseline with respect to both risk preference parameters (Panel A) and the relative ability of the two frameworks to explain fund flows (Panel B).

Next, we examine whether the choice of the reference point that separates gains and losses has an effect on our results. In our main analysis, we use the risk-free rate as the reference point, but here we also consider the zero return and the market return as possible alternatives.[20] Additionally, we consider different horizons for the estimation of expected utility of returns, since there is no consensus in the literature regarding the time frame that investors use to evaluate fund performance.[21] Our baseline analysis uses 36 monthly returns to calculate the expected utility of returns. Here, we also consider performance evaluation horizons of 2 and 4 years. Finally, we use the Spiegel and Zhang (2013) specification of fund flows, defined as changes in market shares, as a way to account for the convexity in the flow-performance relationship (Sirri and Tufano (1998)).[22] Columns 3 to 7 in Table 7 report the results of these robustness tests. The RDP parameter values remain relatively stable across various alternative specifications (Panel A), indicating the existence of loss aversion ($\lambda > 1$) and differential risk responses over gains and losses ($\alpha, \beta < 1$). Furthermore, the expected utility of returns under RDP consistently commands a larger flow response and provides higher explanatory power compared to its GRA counterpart (Panel B). Importantly, when both variables are included in the same regression the certainty equivalent of returns under RDP subsumes the GRA coefficient and remains highly significant in all specifications (Panel C).

Finally, in our main analysis we focus on the relative ability of RDP and GRA preferences in explaining mutual fund flows because they are two comparable frameworks. By contrast, a comparison between risk-adjusted returns (alphas) and the expected utility of returns is more

[20] In an average month, 59% of the funds in our sample overperform the monthly risk-free rate, while 61% and 46% have returns over zero and market return, respectively.

[21] Early studies that focus on the return-chasing behavior of investors use a one-year horizon (e.g., Sirri and Tufano (1998), Chevalier and Ellison (1997)), whereas more recent studies that examine risk-adjusted returns use a longer time period (e.g., Barber et al. (2016); Berk and van Binsbergen (2016)). Morningstar evaluates the performance of a fund using 3, 5, or 10 years of data depending on data availability.

[22] Spiegel and Zhang (2013) argue that the convexity in the flow-performance relationship is caused by heterogeneous responses of investors, and it disappears when fund flows are defined as changes in market shares:

$$F_{it}^{SZ} = \frac{TNA_{it}}{\overline{TotalTNA_t}} - \frac{TNA_{it-1}}{TotalTNA_{t-1}}$$

where $TotalTNA_{t-1}$ is the sum of the TNA of all funds in the sample as of month $t-1$ and $\overline{TotalTNA_t}$ is the sum of the TNA of the same funds that existed in $t-1$ as of t.

restrictive and, thus, less informative. The reason is that alphas correspond to specific asset pricing models, which become redundant when we consider broader preference frameworks (e.g., the CAPM model assumes global risk aversion), while their performance crucially depends on the relevance of their factors (see Barber et al. (2016); Berk and van Binsbergen (2016)). Nevertheless, we examine whether risk-adjusted returns can affect our baseline results, since they appear as performance benchmarks in recent studies (Gu and Yoo (2021); Guo and Schönleber (2021); Han et al. (2021)). In Table 8, we include CAPM, 3- and 4-factor alphas in our main specification. Consistent with the view that preference frameworks render risk-adjusted returns less informative, all alpha coefficients are subsumed by the expected utility of returns not only under RDP but also under GRA framework (columns (6) and (7)).Furthermore, in line with our baseline results, the RDP coefficient subsumes all the rival coefficients when all variables are included in the same regression (column (8)).[23]

5 Conclusion

Reference-dependent preferences provide an alternative way to model investor behavior, allowing for loss aversion and differential attitudes toward risk over gains and losses. While most of the work on RDP is conducted in experimental settings, recent studies demonstrate the relevance of RDP for real-world investors (Barberis et al. (2016)). To this end, our study provides evidence on the relevance of RDP using market data from flow allocations of mutual fund investors.

In this paper, we use a novel methodology to infer preference parameter values from mutual fund flows. Then, we use these parameters to evaluate the ability of the RDP and GRA frameworks to explain mutual fund flows. Our findings highlight the importance of these parameter values when evaluating preference frameworks, suggesting that adopting values from different settings (e.g., laboratory experiments) may understate preference framework performance. We find strong empirical evidence in support of both loss aversion and differential attitudes toward risk over losses (risk-seeking) and gains (risk-averse), suggesting that mutual fund investors exhibit reference-dependent preferences. These results apply more strongly to retail funds, consistent with the views of Barberis et al. (2016) regarding the relevance of prospect theory for retail investors.

[23] In untabulated results, our baseline findings also remain strongly robust in the presence of controls for Morningstar ratings (Evans and Sun (2021); Ben-David et al. (2022)).

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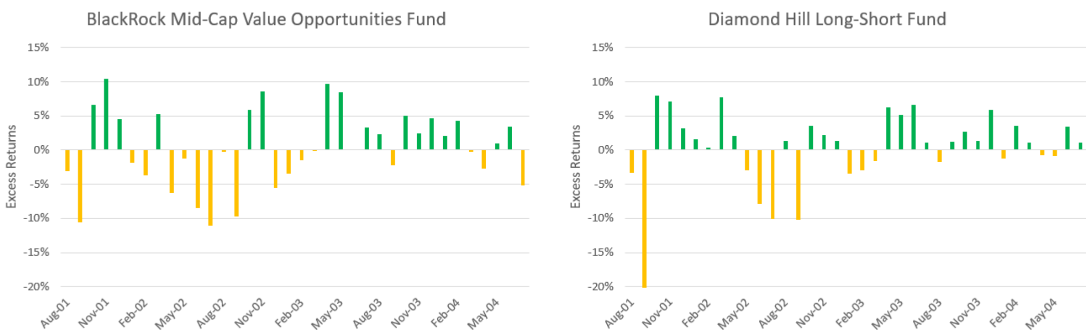
Figures

Figure 1: Example - Monthly Excess Returns of Two Funds



$\mu = 0.3\%$, $\sigma = 5.7\%$

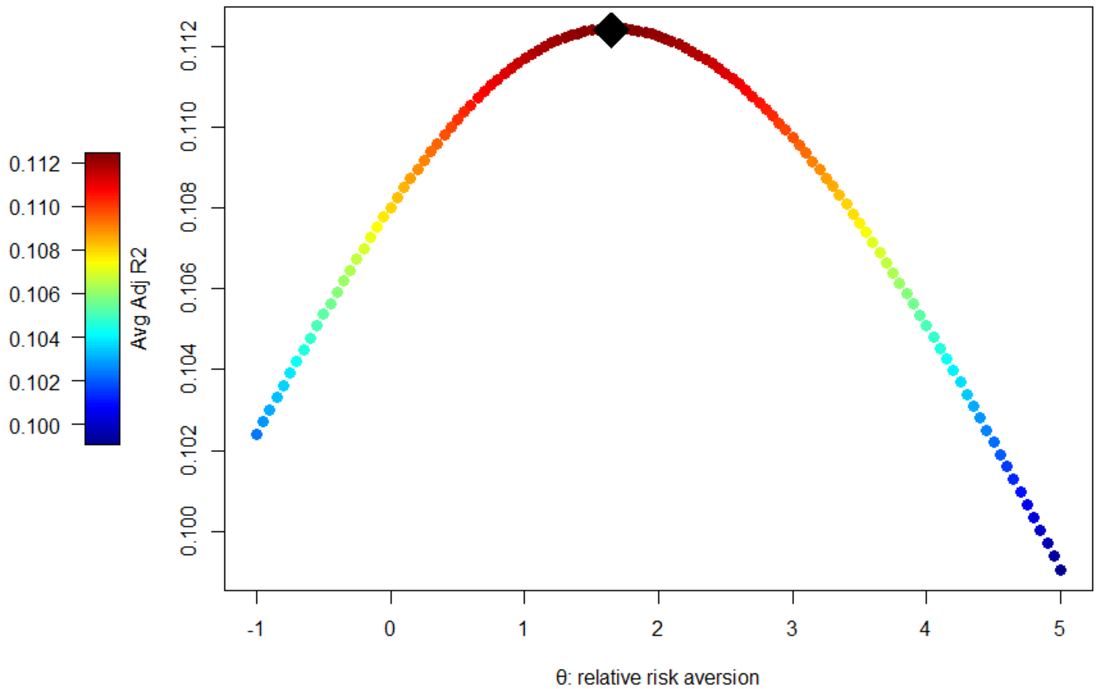
$EU(r)_{GRA} = 0\%$, $EU(r)_{RDP} = -0.4\%$

$\mu = 0.3\%$, $\sigma = 5.7\%$

$EU(r)_{GRA} = 0\%$, $EU(r)_{RDP} = 0\%$

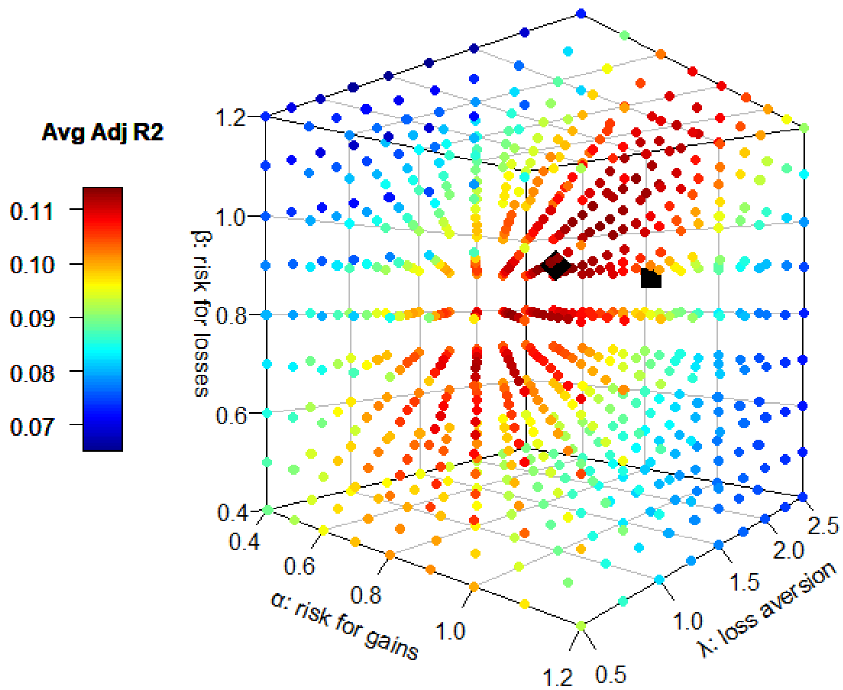
This figure presents monthly returns in excess of the risk-free rate for two sample funds, BlackRock Mid Cap Value Opportunities and Diamond Hill Long-Short, from August 2001 to July 2004. The expected utility of returns under GRA is calculated as the expected value of equation (1) with θ=1.65. The expected utility of returns under RDP is calculated as the expected value of equation (2) with λ=1.45, α=0.85 and β=0.90.

Figure 2: Explanatory Power of Expected Utility of Returns under GRA



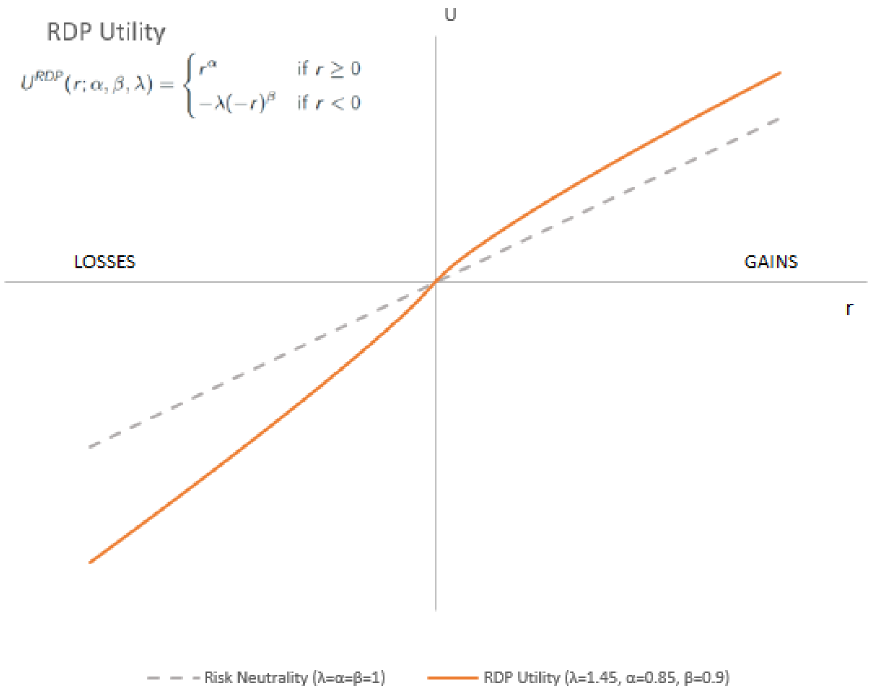
This figure plots average adjusted R^2 of FM regressions (6) of fund flows on expected utility of returns under GRA for different θ values. The expected utility of returns is calculated as the expected value of the utility function in Equation (1) for θ values from -1 to 5 in increments 0.05 using 36 months of excess returns. The black diamond depicts maximal average explanatory power of FM regressions (Adj.R^2=11.2%) that corresponds to $\theta = 1.65$.

Figure 3: Explanatory Power of Expected Utility of Returns
under Reference-Dependent Preferences



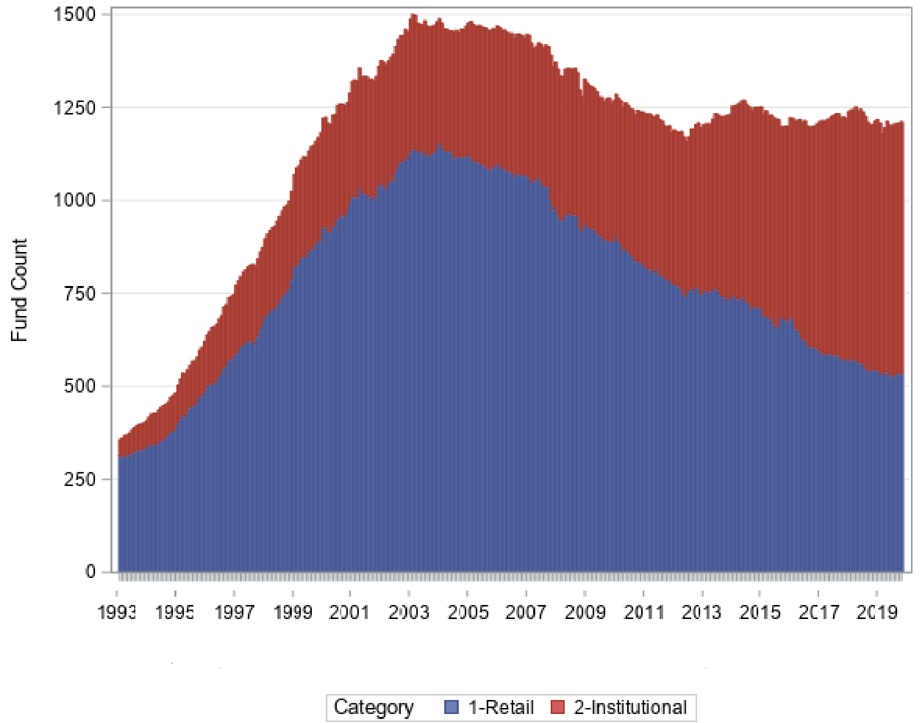
This figure plots average adjusted R^2 of FM regressions (6) of fund flows on expected utility of returns under RDP for different combinations of λ, α and β values. The expected utility of returns is calculated as the expected value of the utility function in Equation (2) for varying λ (from 0.5 to 2.5 in increments of 0.05), α and β (from 0.4 to 1.2 in increments of 0.05) values using 36 months of excess returns. The magnitude of the average adjusted R^2 is represented by color in three parameter dimensions. The figure only displays average adjusted R^2 for λ values in increments of 0.25, and α and β values in increments of 0.1 for better visualization. The black diamond depicts maximal average explanatory power of FM regressions (Adj.R^2=11.4%) that corresponds to parameter values $\alpha = 0.86, \beta = 0.90, \lambda = 1.45$. The black square depicts the average explanatory power of FM regressions (Adj.R^2=10.1%) that corresponds to the Kahneman and Tversky (1992) parameter values $\alpha = \beta = 0.88, \lambda = 2.25$.

Figure 4: Reference-Dependent Utility Function Inferred from Fund Flows



This figure plots the utility function that corresponds to parameter values λ=1.45, α=0.85 and β=0.90 (solid line) and the linear utility function (dashed line) that corresponds to risk neutrality.

Figure 5: Retail versus Institutional Funds in the Sample over Time



This figure presents the number of retail and institutional funds in the sample from December 1993 to November 2020. A fund is classified as a retail (institutional) fund if more than 75% of its TNA is held in a retail (institutional) share class based on CRSP retail (institutional) fund flag or share class name. Funds with significant portions of TNA in both retail and institutional share classes are excluded.

Tables

Table 1: Summary Statistics

Panel A: Fund Characteristics

Variable	Mean	StdDev	Q1	Median	Q3
Monthly Flow	-0.13%	3.95%	-1.50%	-0.40%	0.88%
Size (\$mil)	1,297.72	4672.47	88.42	280.72	940.83
Age (years)	13.80	10.18	7.09	11.34	16.97
Expense Ratio	1.19%	0.41%	0.94%	1.16%	1.43%
Turnover Ratio	84.54%	135.03%	34.00%	61.80%	103.52%
Load	0.73	0.44	0.45	1.00	1.00
Family Size	27,698.97	64,668.40	968.69	6,686.41	21,801.15

Panel B: Fund Return and Risk

Variable	Mean	StdDev	Q1	Median	Q3
Loss	0.30	0.25	0.18	0.27	0.40
Risk	4.63%	1.16%	3.89%	4.40%	5.26%
Exret	0.63%	0.43%	0.36%	0.61%	0.89%
GRA	0.42%	0.43%	0.16%	0.42%	0.69%
RDP	0.45%	0.70%	0.02%	0.46%	0.89%

This table presents sample summary statistics of fund characteristics, return, and risk from December 1993 to November 2020. Monthly fund flow is the percentage change in TNA after adjusting for the fund's total return. Load is a dummy variable that takes the value of 1 if any share class of a fund charges front- or back-end loads. Loss is a dummy variable that equals 1 if the cumulative return of the fund over the previous 12 months is less than the risk-free rate. Risk is the standard deviation of the monthly excess returns over the previous 36 months. Exret return is the mean excess return over the past 36 months. Expected utility of returns under GRA and RDP are calculated as the expected value of utility functions in (1) with θ=1.65 and in (2) with λ=1.45, α=0.85, and β=0.90, respectively, using excess returns over the past 36 months. All statistics are first calculated for the cross section in a given month, and time series averages of the monthly statistics are reported.

Table 2: Fama-MacBeth Regressions of Fund Flows on Return and Risk

	(1)	(2)	(3)	(4)
Return	1.381***	1.395***		
	(17.89)	(18.47)		
Return Low			0.374***	0.377***
			(19.01)	(17.75)
Return Mid			0.625***	0.630***
			(10.51)	(10.70)
Return High			0.670***	0.670***
			(17.32)	(17.31)
Risk	-0.130*		-0.167**	
	(-1.71)		(-2.54)	
Risk x Loss		0.246***		0.151**
		(3.39)		(2.33)
Risk x Gain		-0.359***		-0.375***
		(-4.59)		(-4.01)
LogAge	-0.413***	-0.410***	-0.414***	-0.412***
	(-17.28)	(-17.33)	(-17.82)	(-17.76)
LogSize	0.045	0.042	0.047	0.046
	(1.51)	(1.38)	(1.65)	(1.63)
Expense	0.045	0.049	0.037	0.041
	(1.21)	(1.31)	(0.96)	(1.08)
Turnover	-0.048**	-0.044**	-0.051**	-0.045**
	(-2.15)	(-1.97)	(-2.23)	(-1.97)
LogFamilySize	0.088**	0.092**	0.092**	0.094**
	(2.16)	(2.27)	(2.30)	(2.38)
Load	0.139***	0.139***	0.144***	0.141***
	(4.10)	(4.06)	(4.00)	(3.96)
Fund Obj FEs	Yes	Yes	Yes	Yes
Avg Adj R^2	0.116	0.119	0.117	0.119
Observations	460,923	460,923	460,923	460,923

This table presents the results of Fama and Macbeth (1973) regressions of fund flows on return and risk in Equations (4) and (5). Return is the cumulative return of the fund over the previous 12 months in excess of the risk-free rate. Loss (Gain) is a dummy variable that equals 1 if the return is negative (positive). Risk is the standard deviation of the monthly excess returns over the previous 36 months. Columns 3–4 presents results of a piece-wise linear specification, where funds are divided into three groups based on their return (bottom 20%, middle 60%, top 20%) as in Sirri and Tufano (1998). All continuous independent variables are standardized. T-statistics reported in parentheses are calculated with Newey and West (1987) standard errors with 12 lags. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 3: Fama-MacBeth Regressions of Fund Flows on Expected Utility of Returns

	(1)	(2)	(3)	(4)	(5)	(6)
Exret	1.236***				0.102	0.602***
	(21.12)				(0.40)	(5.30)
GRA		1.256***		-0.066	-0.128	
		(20.95)		(-0.31)	(-0.39)	
RDP			1.274***	1.335***	1.284***	
			(20.99)	(6.41)	(5.39)	
RDP-GRA						0.698***
						(6.57)
LogAge	-0.340***	-0.324***	-0.310***	-0.310***	-0.310***	-0.315***
	(-13.95)	(-13.00)	(-12.52)	(-13.19)	(-12.94)	(-13.56)
LogSize	-0.095**	-0.099**	-0.102**	-0.105**	-0.108***	-0.105***
	(-2.27)	(-2.34)	(-2.46)	(-2.55)	(-2.68)	(-2.59)
Expense	0.003	0.044	0.061	0.059	0.055	0.046
	(0.07)	(1.06)	(1.43)	(1.41)	(1.30)	(1.11)
Turnover	-0.019	0.013	0.032	0.028	0.028	0.024
	(-0.71)	(0.53)	(1.29)	(1.12)	(1.28)	(1.02)
LogFamilySize	0.110**	0.109***	0.107***	0.111***	0.108***	0.108***
	(2.55)	(2.63)	(2.65)	(2.77)	(2.73)	(2.65)
Load	0.184***	0.158***	0.155***	0.156***	0.162***	0.168***
	(4.97)	(4.27)	(4.35)	(4.40)	(4.75)	(4.80)
Fund Obj FE	Yes	Yes	Yes	Yes	Yes	Yes
Avg Adj R^2	0.108	0.112	0.114	0.116	0.120	0.117
Observations	460,923	460,923	460,923	460,923	460,923	460,923

This table presents the results of Fama and Macbeth (1973) regressions of fund flows on expected utility of returns (Eq. 6). Expected utility of returns with GRA and RDP are calculated as the expected value of utility functions in (1) with θ=1.65 and in (2) with λ=1.45, α=0.85, and β=0.90 using the past 36 months' excess returns. Exret is the mean excess return over the past 36 months. All continuous independent variables are standardized. T-statistics reported in parentheses are calculated with Newey and West (1987) standard errors with 12 lags. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 4: Retail and Institutional Funds

Panel A: FM Regressions on Return and Risk

	Retail Funds		Institutional Funds	
	(1)	(2)	(3)	(4)
Return	1.362***	1.373***	1.108***	1.131***
	(14.42)	(14.64)	(14.30)	(15.32)
Risk	-0.121		-0.111	
	(-1.62)		(-1.63)	
Risk x Loss		0.223***		-0.144
		(3.06)		(-1.42)
Risk x Gain		-0.356***		-0.217**
		(-4.37)		(-2.14)
Controls	Yes	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes	Yes
Avg Adj R^2	0.141	0.144	0.068	0.071
Observations	254,471	254,471	118,535	118,535

Panel B: Risk Parameters Inferred with Subsamples

	Retail Funds	Institutional Funds
GRA theta	1.65	1.60
RDP lambda	1.45	1.60
RDP alpha	0.85	0.90
RDP beta	0.90	1.00

Panel C: FM Regressions on Expected Utility of Returns

	Retail Funds			Institutional Funds		
	(1)	(2)	(3)	(4)	(5)	(6)
GRA	1.194***		-0.224	1.109***		0.571
	(15.77)		(-0.94)	(19.11)		(1.17)
RDP		1.220***	1.438***		1.101***	0.542
		(15.71)	(6.07)		(19.25)	(1.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes	Yes	Yes	Yes
Avg Adj R^2	0.129	0.132	0.135	0.072	0.072	0.075
Observation	254,471	254,471	254,471	118,535	118,535	118,535

Panel A reports results from FM regressions of fund flows on return and risk (as in (4), (5)) separately for retail and institutional funds. Panel B reports risk preference parameters that maximize the explanatory power of the expected utility of returns on fund flows. Panel C reports results from FM regressions in (6) of fund flows on expected utility of returns with GRA and RDP with the parameters values of Panel B. A fund is categorized as an institutional (retail) fund if more than 75% of its TNA is held in an institutional (retail) share class based on CRSP institutional (retail) fund flag or share class name.

Table 5: Subperiod Analysis

Panel A: FM Regressions on Return and Risk

	Dec93-Nov05		Dec05-Nov20	
	(1)	(2)	(3)	(4)
Return	1.640***	1.660***	1.173***	1.182***
	(13.06)	(13.90)	(23.69)	(25.09)
Risk	-0.054		-0.191**	
	(-0.42)		(-2.21)	
Risk x Loss		0.378***		0.141*
		(3.30)		(1.67)
Risk x Gain		-0.251**		-0.445***
		(-2.00)		(-4.81)
Controls	Yes	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes	Yes
Avg Adj R^2	0.144	0.146	0.094	0.097
Observations	158,283	158,283	302,640	302,640

Panel B:Risk Parameters Inferred with Subsamples

	Dec93-Nov05	Dec05-Nov20
GRA theta	1.65	1.70
RDP lambda	1.65	1.35
RDP alpha	0.75	0.95
RDP beta	0.90	0.95

Panel C: FM Regressions on Expected Utility of Returns

	Dec93-Nov05			Dec05-Nov20		
	(1)	(2)	(3)	(4)	(5)	(6)
GRA	1.438***		0.018	1.109***		0.476
	(15.10)		(0.05)	(23.09)		(1.56)
RDP		1.476***	1.460***		1.115***	1.114***
		(15.85)	(4.58)		(23.05)	(3.01)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes	Yes	Yes	Yes
Avg Adj R^2	0.134	0.136	0.139	0.096	0.098	0.099
Observations	158,283	158,283	158,283	302,640	302,640	302,640

Panel A reports results from FM regressions of fund flows on return and risk as in Table 2 separately for subperiods Dec93–Nov05 and Dec05–Nov20. Panel B reports risk preference parameters that maximize the explanatory power of the expected utility of returns on fund flows. Panel C reports results from FM regressions in (6) of fund flows on expected utility of returns with GRA and RDP with the parameters values of Panel B.

Table 6: Probability Weighting and Reference-Dependent Preferences

	(1) Only RDP	(2) PW and RDP	(3) PW given RDP	(4) Only PW	(5) KT (1992)
RDP lambda	1.45	1.50	**1.45**	**1.00**	**2.25**
RDP alpha	0.85	0.80	**0.85**	**1.00**	**0.88**
RDP beta	0.90	0.90	**0.90**	**1.00**	**0.88**
PW gamma	**1.00**	0.90	0.95	1.00	**0.61**
PW delta	**1.00**	0.90	0.95	0.95	**0.69**
Coefficient	1.274	1.279	1.275	1.245	1.050
Avg Adj R^2	0.114	0.115	0.115	0.109	0.087

This table presents the RDP and PW parameter values that maximize the explanatory power of expected utility of returns on mutual fund flows, the coefficient of expected utility of returns and the average adjusted-R^2 of Fama-MacBeth regressions (6) for the reported parameter values. Parameters in bold indicate fixed (set) values. Column (1), reports the baseline results without PW. In column (2), PW and RDP parameters are jointly inferred by maximizing the explanatory power of the expected utility of returns on fund flows. Column (3) infers PW parameters given the RDP parameter vector in the baseline results. Column (4) infers PW parameters without RDP. Column (5) uses the preference parameter values of Kahneman and Tversky (1992). Column (2) uses a wider grid for parameters: λ from 0.5 to 2.5 in increments of 0.25, and α, β, $\delta = \gamma$ from 0.4 to 1.2 in increments of 0.1. Columns (1), (3) and (4) use a finer grid for all inferred parameters in increments of 0.05.

Table 7: Robustness Tests

Panel A: Inferred Risk Parameters

		Estimation	Reference Point		Performance Horizon		Flow
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	OutSample	Zero	Market	2 years	4 years	ΔMktShr
GRA theta	1.65	1.70	1.65	1.10	1.45	1.55	1.15
RDP lambda	1.45	1.44	1.45	1.60	1.55	1.45	1.35
RDP alpha	0.85	0.85	0.85	0.80	0.80	0.90	0.90
RDP beta	0.90	0.88	0.90	0.95	0.90	0.95	0.95

Panel B: Coefficients of Expected Utility of Returns and Average Adjusted R-squared

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GRA Coeff	1.256	0.170	1.256	1.241	1.306	1.151	0.716
Avg Adj R^2	0.1124	0.1043	0.1124	0.1086	0.1165	0.1008	0.0706
RDP Coeff	1.274	0.179	1.273	1.251	1.324	1.166	0.721
Avg Adj R^2	0.1144	0.1061	0.1144	0.1094	0.1185	0.1025	0.0714
Observations	460,923	409,164	460,923	460,923	503,499	419,538	460,923

Panel C: FM Regressions on Expected Utility of Returns under GRA and RDP together

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GRA	-0.066	-0.043	-0.033	-0.095	-0.176	-0.091	-0.023
	(-0.31)	(-0.19)	(-0.15)	(-0.28)	(-0.66)	(-0.33)	(-0.04)
RDP	1.335***	1.218**	1.302***	1.344***	1.495***	1.246***	0.737**
	(6.41)	(5.35)	(6.06)	(3.67)	(5.63)	(4.93)	(2.44)

Panel A reports risk preference parameters that maximize the explanatory power of the expected utility of returns for fund flows. Panel B reports coefficients of expected utility of returns under GRA and RDP, estimated with the parameters in Panel A, and the average adjusted-R^2 of Fama-MacBeth regressions (6) of fund flows. Panel C reports results of regression (6) that includes both certainty equivalents under GRA and RDP. Column (2) presents results of out-of-sample tests in which parameters are inferred with annually rolling 6-year windows and then the expected utility of returns is calculated over the next 12 months. Columns (3) and (4) use the zero and market return as alternative reference points to separate gains from losses. Columns (5) and (6) use alternative performance horizons of 2 and 4 years for the estimation of the expected utility of returns. Column (7) uses the Spiegel and Zhang (2013) definition of fund flow, defined as the change in market share.

Table 8: Fama-MacBeth Regressions of Fund Flows on Expected Utility of Returns and Alphas

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha 4F	1.065***					2.191	2.140	2.168
	(23.15)					(1.32)	(1.30)	(1.31)
Alpha 3F		1.078***				-1.761	-1.674	-1.741
		(18.93)				(-1.05)	(-1.01)	(-1.04)
Alpha CAPM			1.198***			0.211	-0.031	0.077
			(21.21)			(1.21)	(-0.21)	(0.45)
GRA				1.256***		0.713***		-0.222
				(20.95)		(5.17)		(-1.02)
RDP					1.274***		0.913***	1.061***
					(20.99)		(7.10)	(4.88)
LogAge	-0.315***	-0.320***	-0.307***	-0.324***	-0.310***	-0.295***	-0.290***	-0.290***
	(-12.34)	(-12.81)	(-13.76)	(-13.00)	(-12.52)	(-12.54)	(-12.30)	(-12.57)
LogSize	-0.058*	-0.083**	-0.080**	-0.099**	-0.102**	-0.112***	-0.114***	-0.114***
	(-1.73)	(-2.33)	(-2.31)	(-2.34)	(-2.46)	(-3.08)	(-3.11)	(-3.11)
Expense	0.055	0.037	0.043	0.044	0.061	0.054	0.064	0.061
	(1.53)	(1.11)	(1.03)	(1.06)	(1.43)	(1.33)	(1.56)	(1.53)
Turnover	0.041	0.006	0.018	0.013	0.032	0.025	0.034	0.031
	(1.24)	(0.18)	(0.55)	(0.53)	(1.29)	(1.17)	(1.59)	(1.42)
LogFamilySize	0.120***	0.120***	0.123***	0.109***	0.107***	0.114***	0.110***	0.112***
	(2.90)	(2.85)	(3.05)	(2.63)	(2.65)	(2.97)	(2.92)	(2.96)
Load	0.147***	0.164***	0.139***	0.158***	0.155***	0.156***	0.156***	0.159***
	(3.95)	(4.29)	(3.98)	(4.27)	(4.35)	(4.46)	(4.45)	(4.55)
Fund Obj FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg Adj R^2	0.099	0.101	0.106	0.112	0.114	0.129	0.130	0.131
Observations	460,923	460,923	460,923	460,923	460,923	460,923	460,923	460,923

This table presents the results of FM regressions of fund flows on expected utility of returns and alphas, as in Equation (6). The CAPM, 3-factor, and 4-factor alphas of Fama and French (1993) and Carhart (1997) models are estimated as the regression intercepts of the fund's excess return on the respective set of factors on a rolling 36-month window. Expected utility of returns with GRA and RDP is calculated as the expected value of utility functions (1) with θ=1.65 and (2) with λ=1.45, α=0.85, and β=0.90 using the past 36 months' excess returns as before. All independent variables are standardized. T-statistics reported in parentheses are calculated with Newey and West (1987) standard errors with 12 lags. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Appendix

Table A1: Fama-MacBeth Regressions of Fund Flows on Expected Utility of Returns and Lagged Fund Flows

	(1)	(2)	(3)	(4)	(5)
Exret	0.800***				0.063
	(20.40)				(0.36)
GRA		0.817***		-0.019	-0.060
		(20.62)		(-0.13)	(-0.28)
RDP			0.830***	0.848***	0.820***
			(20.87)	(6.24)	(5.31)
LagFlow	1.381***	1.368***	1.363***	1.359***	1.351***
	(28.73)	(29.41)	(29.77)	(29.73)	(29.84)
LogAge	-0.192***	-0.182***	-0.174***	-0.174***	-0.175***
	(-13.20)	(-12.47)	(-11.83)	(-12.49)	(-12.16)
LogSize	-0.108***	-0.111***	-0.113***	-0.115***	-0.117***
	(-3.68)	(-3.72)	(-3.83)	(-3.92)	(-4.04)
Expense	0.004	0.030	0.042	0.040	0.039
	(0.15)	(1.14)	(1.50)	(1.47)	(1.37)
Turnover	-0.016	0.004	0.016	0.014	0.014
	(-0.89)	(0.26)	(0.96)	(0.83)	(0.97)
LogFamilySize	0.099***	0.099***	0.098***	0.100***	0.098***
	(3.31)	(3.43)	(3.46)	(3.58)	(3.53)
Load	0.123***	0.107***	0.106***	0.106***	0.110***
	(4.54)	(3.96)	(4.01)	(4.03)	(4.35)
Fund Obj FE	Yes	Yes	Yes	Yes	Yes
Avg Adj R^2	0.225	0.227	0.229	0.229	0.231
Observations	460,923	460,923	460,923	460,923	460,923

This table presents the results of FM regressions of fund flows on the expected utility of returns and lagged fund flows from previous month. Expected utility of returns under GRA and RDP is calculated as the expected value of the utility functions (1) with θ=1.65 and (2) with λ=1.45, α=0.85, and β=0.90 using the past 36 months' excess returns. Exret is the mean excess return over the past 36 months without any risk adjustment. All continuous independent variables are standardized. T-statistics reported in parentheses are calculated with double-clustered standard errors by fund and month. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table A2: Pairwise Comparisons of Expected Utility of Returns in Predicting Fund Flows

10x10 Horse Race of Expected Utility of Returns

	Off-diagonal coefficient differences	
Winning/ Losing	GRA	Exret
RDP	3.71	10.57
	(0.000)	(0.000)
GRA		6.15
		(0.000)
Observations	460,923	

This table compares different performance measures (i.e., expected utility of returns) in predicting fund flows by applying the 10x10 model horse race, similar to Barber et al. (2016). Every month, funds are assigned to a decile rank based on two different performance measures, and the following regression is estimated:

$$F_{it} = a + \sum_{m=1}^{10} \sum_{k=1}^{10} b_{mk} D_{mk,it-1} + c \cdot X_{it-1} + FO_i + \epsilon_{it} \quad (9)$$

where $Dmk, it-1$ is a dummy variable that takes the value of 1 if fund i in month $t-1$ is in the m^{th} decile based on the performance measure M and the k^{th} decile based on the performance measure K. The dummy variable for $m = 5$ and $k = 5$ is excluded to estimate the equation. We test whether $\sum_{m \neq k} b_{mk} - b_{km} = 0$ (i.e., whether a fund receives significantly more flows when it ranks better based on the performance measure M compared to the performance measure K). For each pairwise comparison, the sum of 45 off-diagonal coefficient differences is reported together with its p-value in parentheses.

Table A3: Suberiod Analysis of Retail and Institutional Funds

Panel A: Retail Funds

	Dec93-Nov05	Dec05-Nov17
GRA theta	1.60	1.80
RDP lambda	1.75	1.40
RDP alpha	0.70	0.90
RDP beta	0.90	0.90
GRA Coeff	1.439	0.996
RDP Coeff	1.490	1.066
Observations	110,041	144,429

Panel B: Institutional Funds

	Dec93-Nov05	Dec05-Nov17
GRA theta	1.90	1.35
RDP lambda	1.75	1.35
RDP alpha	0.85	0.95
RDP beta	1.05	1.00
GRA Coeff	1.250	1.001
RDP Coeff	1.241	0.997
Observations	32,805	85,730

This table reports the risk preference parameters that maximize the explanatory power of returns under GRA and RDP, along with the coefficients of the certainty equivalent from FM regressions in (6) with the reported parameter values, for retail (Panel A) and institutional (Panel B) funds separately for the subperiods Dec93–Nov05 and Dec05–Nov20.

Table A4: Panel Regressions of Fund Flows on Expected Utility of Returns

	(1)	(2)	(3)	(4)	(5)
Exret	1.078***				0.065
	(30.478)				(0.688)
GRA		1.096***		-0.053	-0.119
		(30.778)		(-0.458)	(-0.811)
RDP			1.113***	1.165***	1.17***
			(29.951)	(9.326)	(9.373)
LogAge	-0.384***	-0.373***	-0.358***	-0.358***	-0.358***
	(-19.892)	(-19.639)	(-18.986)	(-18.962)	(-18.952)
LogSize	-0.014	-0.02	-0.027	-0.027	-0.027
	(-0.659)	(-0.913)	(-1.233)	(-1.23)	(-1.261)
Expense	-0.014	0.026	0.046*	0.047**	0.044*
	(-0.624)	(1.102)	(1.941)	(1.993)	(1.897)
Turnover	0.000	0.026	0.039*	0.039*	0.038*
	(-0.018)	(1.323)	(1.914)	(1.932)	(1.891)
LogFamilySize	0.058**	0.062***	0.063***	0.063***	0.063***
	(2.528)	(2.749)	(2.819)	(2.822)	(2.811)
Load	0.124***	0.098**	0.096**	0.095**	0.097**
	(3.057)	(2.447)	(2.395)	(2.392)	(2.432)
Fund Obj FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Avg Adj R^2	0.102	0.107	0.110	0.110	0.110
Observations	460,923	460,923	460,923	460,923	460,923

This table presents the results of *panel regressions* of fund flows on the expected utility of returns under GRA and RDP with month fixed effects. Expected utility of returns under GRA and RDP is calculated as the expected value of the utility functions (1) with θ=1.85 and (2) with λ=1.55, α=0.85, and β=0.90 (parameter values that maximize the explanatory power in *panel regressions*) using the past 36 months' excess returns. Exret is the mean excess return over the past 36 months without any risk adjustment. All continuous independent variables are standardized. T-statistics reported in parentheses are calculated with double-clustered standard errors by fund and month. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.