The Importance of Parameter Values in Prospect Theory: Evidence from Mutual Fund Flows

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Motivation

- Under global risk aversion (GRA), agents penalize risk everywhere
  But there is evidence that investors may demand risk in some cases
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- Prospect theory provides an alternative, more flexible framework with:
  1. Reference dependent preferences (RDP) that include
     (i) Loss aversion
     (ii) Differential attitudes towards risk over gains and over losses
  2. Probability-weighting (over-weighting extreme outcomes)

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     (i) Loss aversion
     (ii) Differential attitudes towards risk over gains and over losses
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- RDP have the potential to address some puzzling phenomena in financial markets (e.g., disposition effect, the equity premium puzzle)

In this Paper

It is very challenging to identify investor's preferences from market data.

Thus, most empirical evidence on RDP comes from experiments

Kahneman & Tversky (1992), Starmer (2000), Barseghyan et al. (2018)

Few studies with market data adopt parameter values from experiments

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In this paper:

1. We use the flow-performance relationship to infer information about investor preferences under GRA & RDP

   We find the parameter vector that maximizes the explanatory power of the expected utility of returns on fund flows

2. Using these parameter values, we evaluate the relative ability of the two frameworks in explaining mutual fund flows

Main Results

1. We find evidence supporting loss aversion and differential risk attitudes toward losses (risk-seeking) and gains (risk-averse) for fund investors

GRA framework:

$\theta = 1.65$

RDP frawework:

$\lambda = 1.45, \alpha = 0.85, \beta = 0.90$

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4. No significant role for probability weighting for mutual fund flows (large, diversified portfolios)

Contribution

1. Relevance of RDP (prospect theory) to model investor behavior using market data

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3. Literature on how mutual fund investors evaluate fund performance

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4. Differences on how retail and institutional investors evaluate performance

   Del Guercio & Tkac (2002), Evans & Fahlenbrach (2012), Salganik-Shoshan (2016), Barberis et al. (2016)

Data & Sample

Actively managed US equity mutual funds from CRSP with 36+1 monthly returns

Exclude sector and target date funds, outliers

Sample: 3,979 funds over 324 months (Dec 1993 - Nov 2020)

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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

The Two Frameworks: GRA and RDP

- The Global Risk Aversion (GRA) framework

  We use power utility with constant relative risk aversion (θ) of the form:

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

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

- The Reference-Dependent Preference (RDP) framework
  Allows for loss aversion (λ) and differential attitudes toward risk ($\alpha,\ \beta$) relative to a reference point (r) that separates gains from losses

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

Motivation: FM regressions of Fund Flows on Return and Risk

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

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

	(1)
Return	1.381***
	(17.89)
Return Low	
Return Mid	
Return High	
Risk	-0.130*
	(-1.71)
Risk x Loss	
Risk x Gain	
Fund Charact.	Yes
Fund Obj FEs	Yes
Avg Adj R^2	0.116
Observations	460,923

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	(17.89)	(18.47)
Return Low		
Return Mid		
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Risk	-0.130*	
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Risk x Loss		0.246***
		(3.39)
Risk x Gain		-0.359***
		(-4.59)
Fund Charact.	Yes	Yes
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	(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)
Fund Charact.	Yes	Yes	Yes	Yes
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Methodology

We infer information about investor's preferences in two steps:

1. We calculate the expected utility of returns under GRA and RDP for a range of plausible parameter values

   Excess returns, 36-month window, equal weights

   GRA: $\theta \in [-1, 5]$, RDP: $\lambda \in [0.5, 2.5]$, $\alpha, \beta \in [0.4, 1.2]$ (0.05 incrememts)

   No probability-weighting (initially); $\gamma, \delta = 1$

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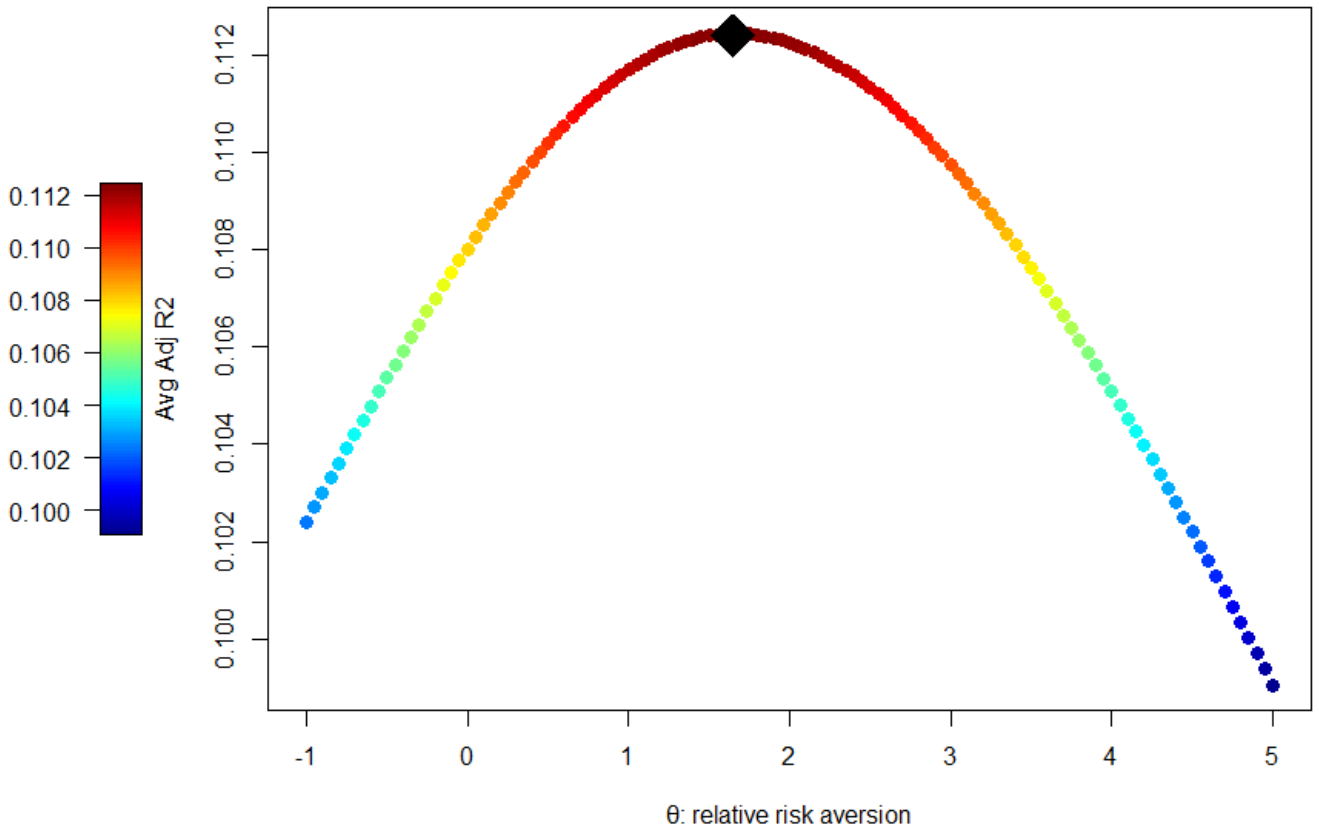
We use Fama-Macbeth regressions for three reasons:

(i) Focus on the cross-section
(ii) More robust to time-varying flow-performance sensitivity
(iii) Place equal weight on each period

Explanatory Power of Expected Utility of Returns under GRA



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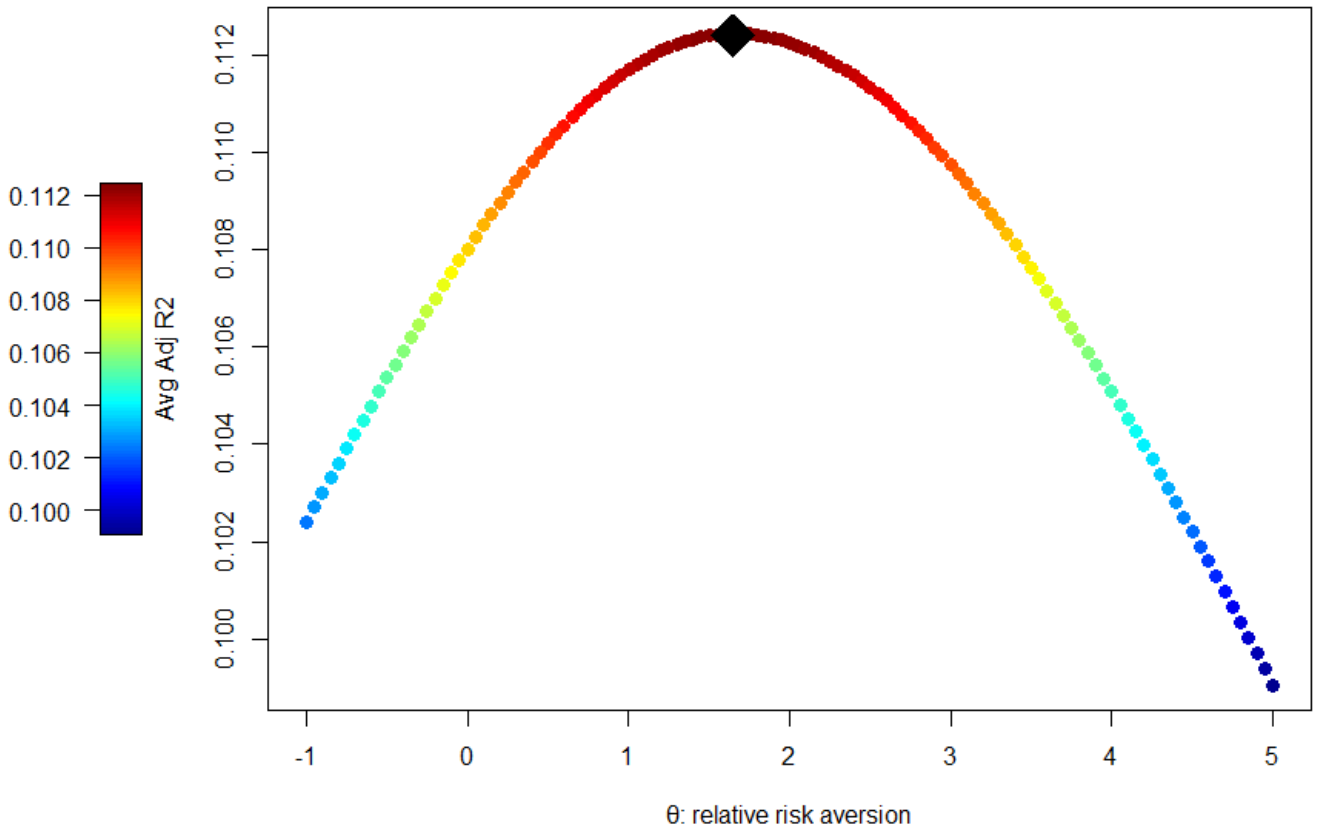

Max explanatory power ($Adj.R^2 = 11.2\%$) for $\theta = 1.65$

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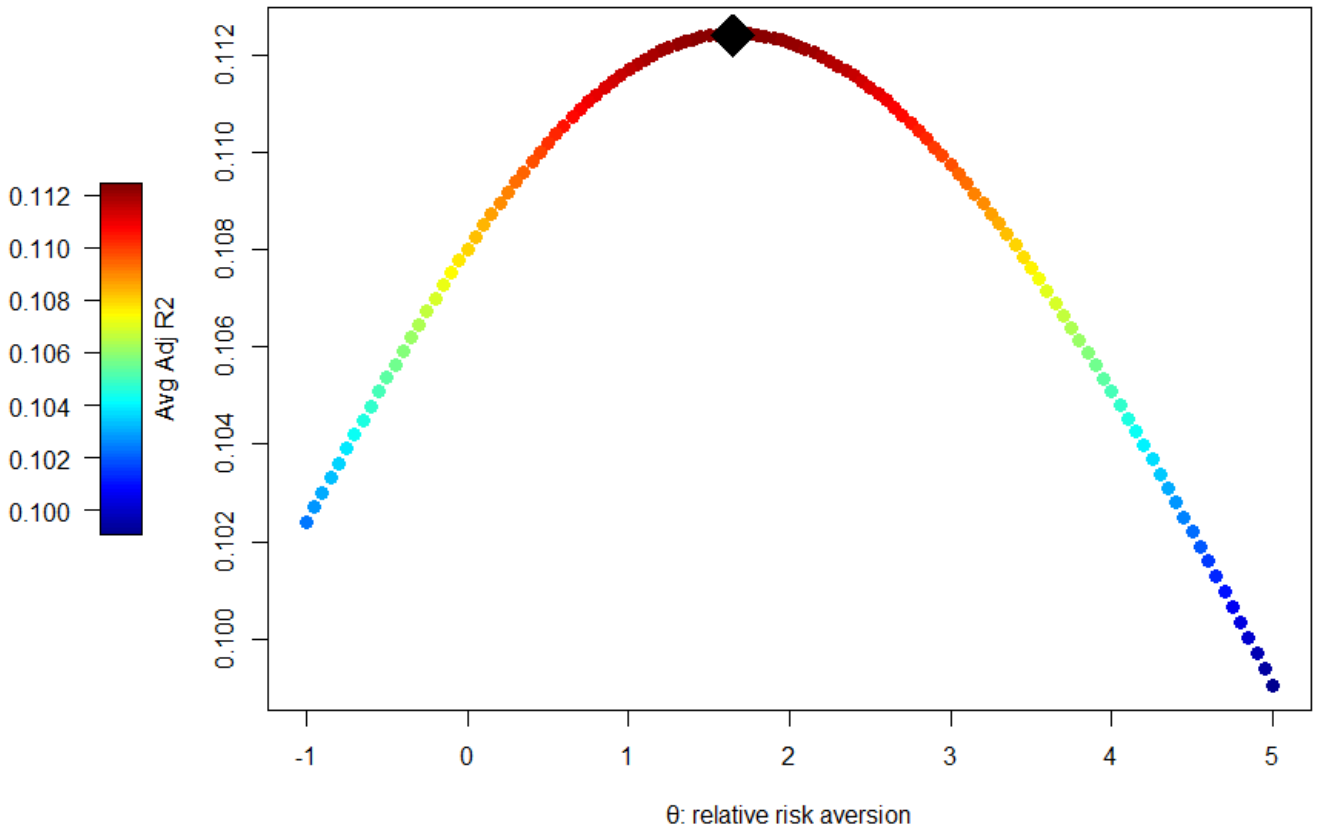
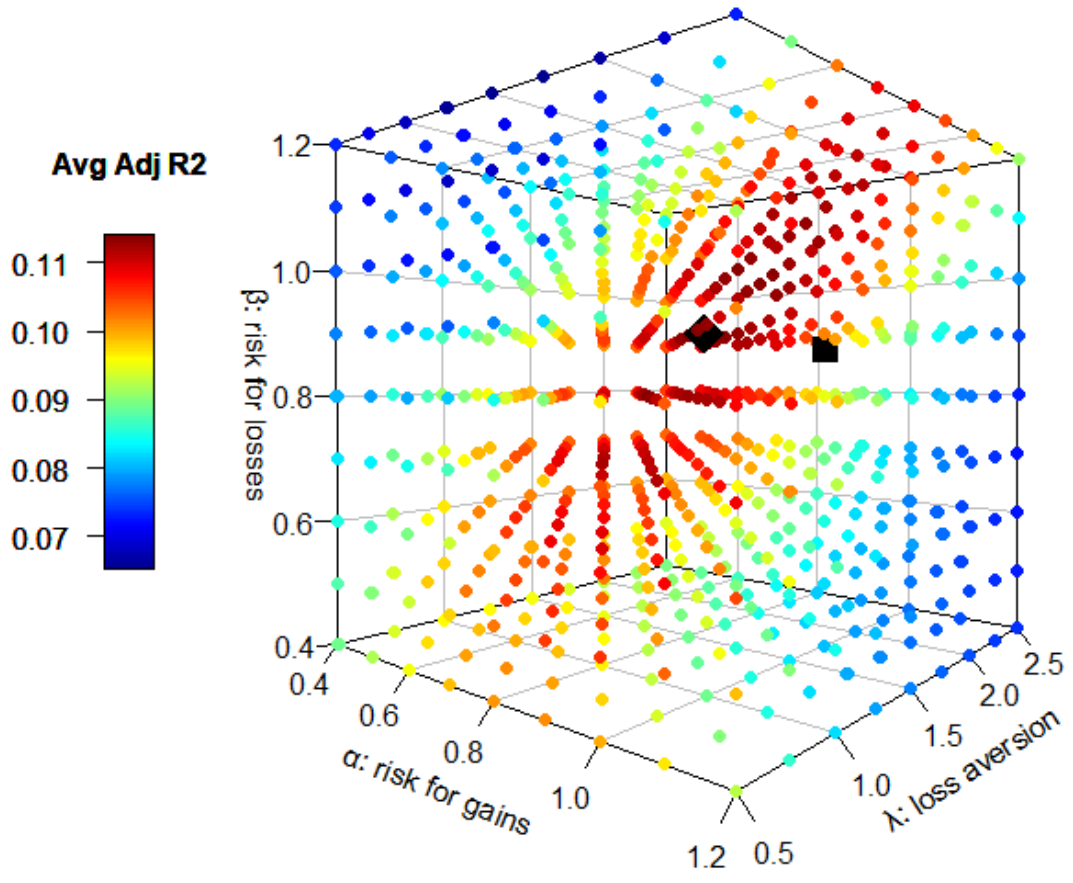


Max explanatory power ($Adj.R^2 = 11.2\%$) for $\theta = 1.65$

Closer to estimates of Hansen & Singleton (1982), Epstein & Zin (1991), Chetty (2006), and significantly lower than Morningstar ($\theta = 3$)

Explanatory Power of Expected Utility of Returns under RDP



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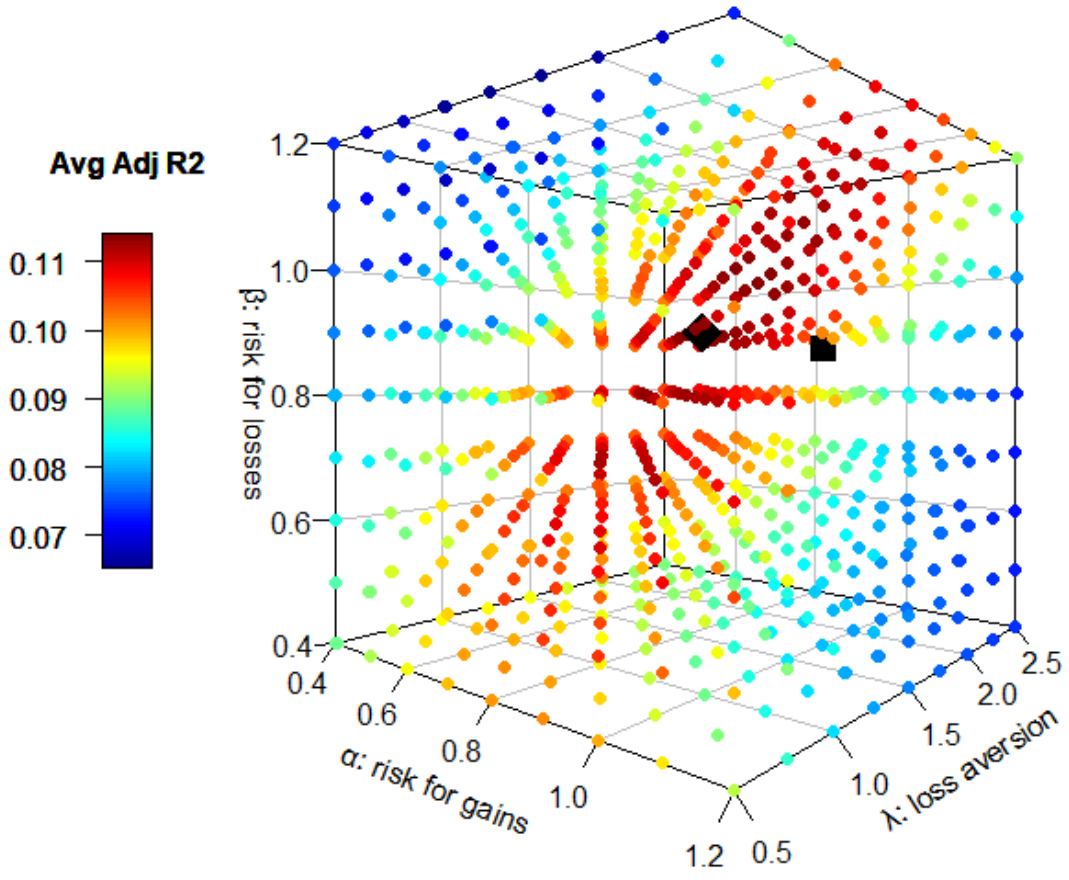

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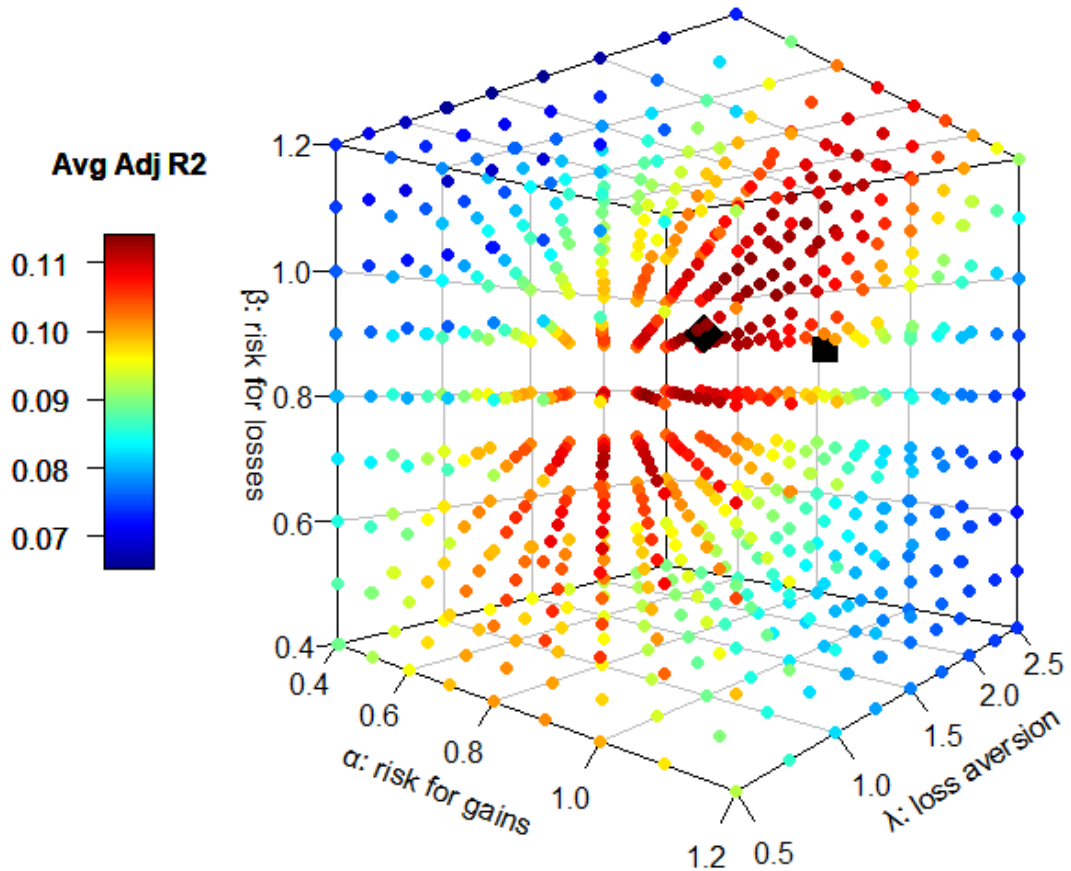
Explanatory Power of Expected Utility of Returns under RDP



Max explanatory power ($Adj.R^2 = 11.4\%$) for $\lambda = 1.45,\ \alpha = 0.85,\ \beta = 0.90$

λ is close to recent experimental and field/market studies, but lower than Kahneman & Tvesky (1992) ($\lambda = 2.25$) $\Rightarrow$ consistent with Barberis et al. (2016)

Adding Probability-Weighting

- Under cumulative prospect theory, in addition to RDP, agents can overweight extreme outcomes through probability-weighting
  That is, agents use probability weights (π_j) of the form:

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

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

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

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- Parameters equal to unity (γ, δ=1) imply no probability-weighting

Probability Weighting & Mutual Fund Flows

	Only RDP
RDP lambda	1.45
RDP alpha	0.85
RDP beta	0.90
PW gamma	**1.00**
PW delta	**1.00**
Coefficient	1.274
Avg Adj R^2	0.114

Probability Weighting & Mutual Fund Flows

	Only RDP	PW and RDP
RDP lambda	1.45	1.50
RDP alpha	0.85	0.80
RDP beta	0.90	0.90
PW gamma	**1.00**	0.90
PW delta	**1.00**	0.90
Coefficient	1.274	1.279
Avg Adj R^2	0.114	0.115

- We repeat our analysis, for the 5 parameters $(\lambda, \alpha, \beta, \gamma, \delta)$ with wider increments and narrower ranges of plausible parameter values

Probability Weighting & Mutual Fund Flows

	Only RDP	PW and RDP	PW given RDP	Only PW
RDP lambda	1.45	1.50	**1.45**	**1.00**
RDP alpha	0.85	0.80	**0.85**	**1.00**
RDP beta	0.90	0.90	**0.90**	**1.00**
PW gamma	**1.00**	0.90	0.95	1.00
PW delta	**1.00**	0.90	0.95	0.95
Coefficient	1.274	1.279	1.275	1.245
Avg Adj R^2	0.114	0.115	0.115	0.109

- We repeat our analysis, for the 5 parameters $(\lambda, \alpha, \beta, \gamma, \delta)$ with wider increments and narrower ranges of plausible parameter values
- We do not find evidence supporting that mutual fund investors over-weight extreme outcomes, as in Barberis et. al (2016)

  But we work with mutual funds $\Rightarrow$ extreme outcomes are scarce

Probability Weighting & Mutual Fund Flows

	Only RDP	PW and RDP	PW given RDP	Only PW	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

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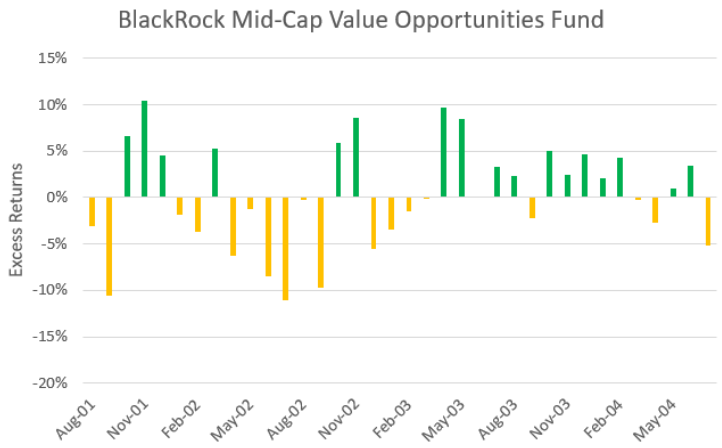
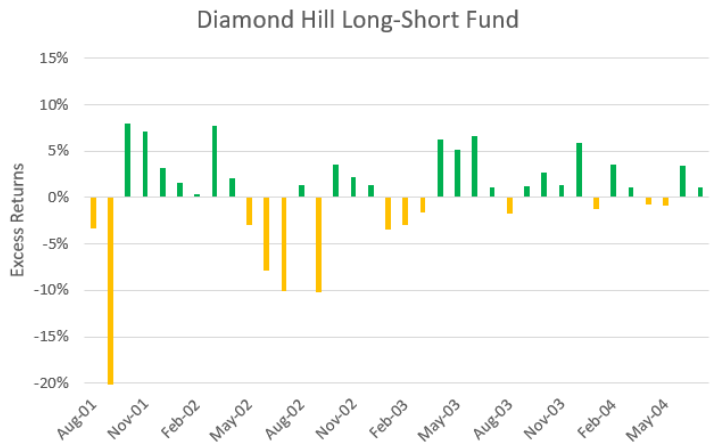
  But we work with mutual funds $\Rightarrow$ extreme outcomes are scarce
- Applying the Kahneman & Tvesky (1992) parameters to mutual fund data $\Rightarrow$ explanatory power drops by 24%

Framework Comparison - Example: BlackRock vs Diamond Hill

These two funds have exactly the same mean return (0.3%) and standard deviation (5.7%)



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



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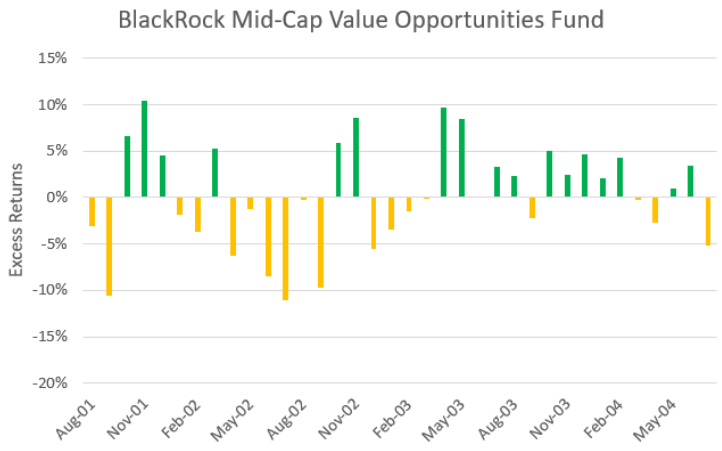
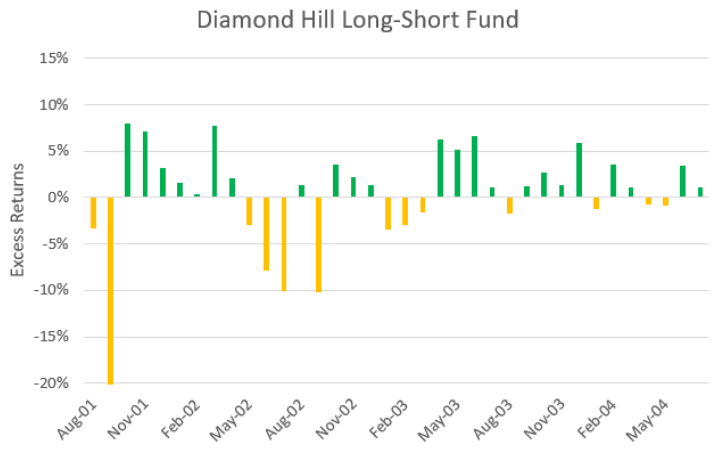


$EU(r)_{GRA} = 0\%$, $EU(r)_{RDP} = -0.4\%$



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

- Thus, they are indistinguishable under the GRA framework
  But for an investor with RDP, Diamond Hill is superior

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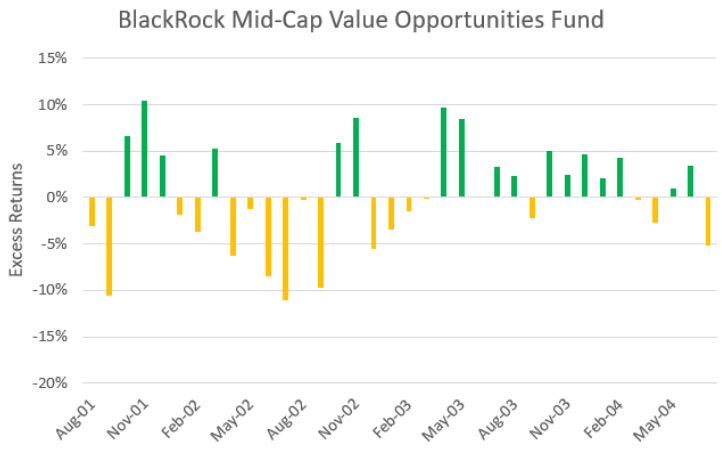

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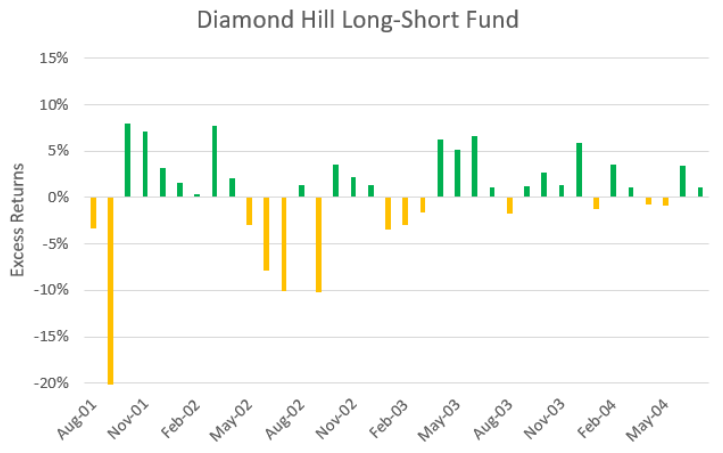


$EU(r)_{GRA} = 0\%$, $EU(r)_{RDP} = 0\%$

- Thus, they are indistinguishable under the GRA framework
  But for an investor with RDP, Diamond Hill is superior
- We test whether Diamond Hill receives significantly more flows than BlackRock $\Rightarrow$ Support for RDP

Comparison of GRA & RDP in Explaining Mutual Fund Flows

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

	(1)	(2)	(3)
Exret	1.236***		
	(21.12)		
GRA		1.256***	
		(20.95)	
RDP			1.274***
			(20.99)
RDP-GRA			
Fund Controls	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes
Avg Adj R^2	0.108	0.112	0.114
Observations	460,923	460,923	460,923

Comparison of GRA & RDP in Explaining Mutual Fund Flows

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

	(1)	(2)	(3)	(4)	(5)
Exret	1.236***				0.102
	(21.12)				(0.40)
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					
Fund Controls	Yes	Yes	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes	Yes	Yes
Avg Adj R^2	0.108	0.112	0.114	0.116	0.120
Observations	460,923	460,923	460,923	460,923	460,923

- The RDP coefficient subsumes competing variables and remains significant

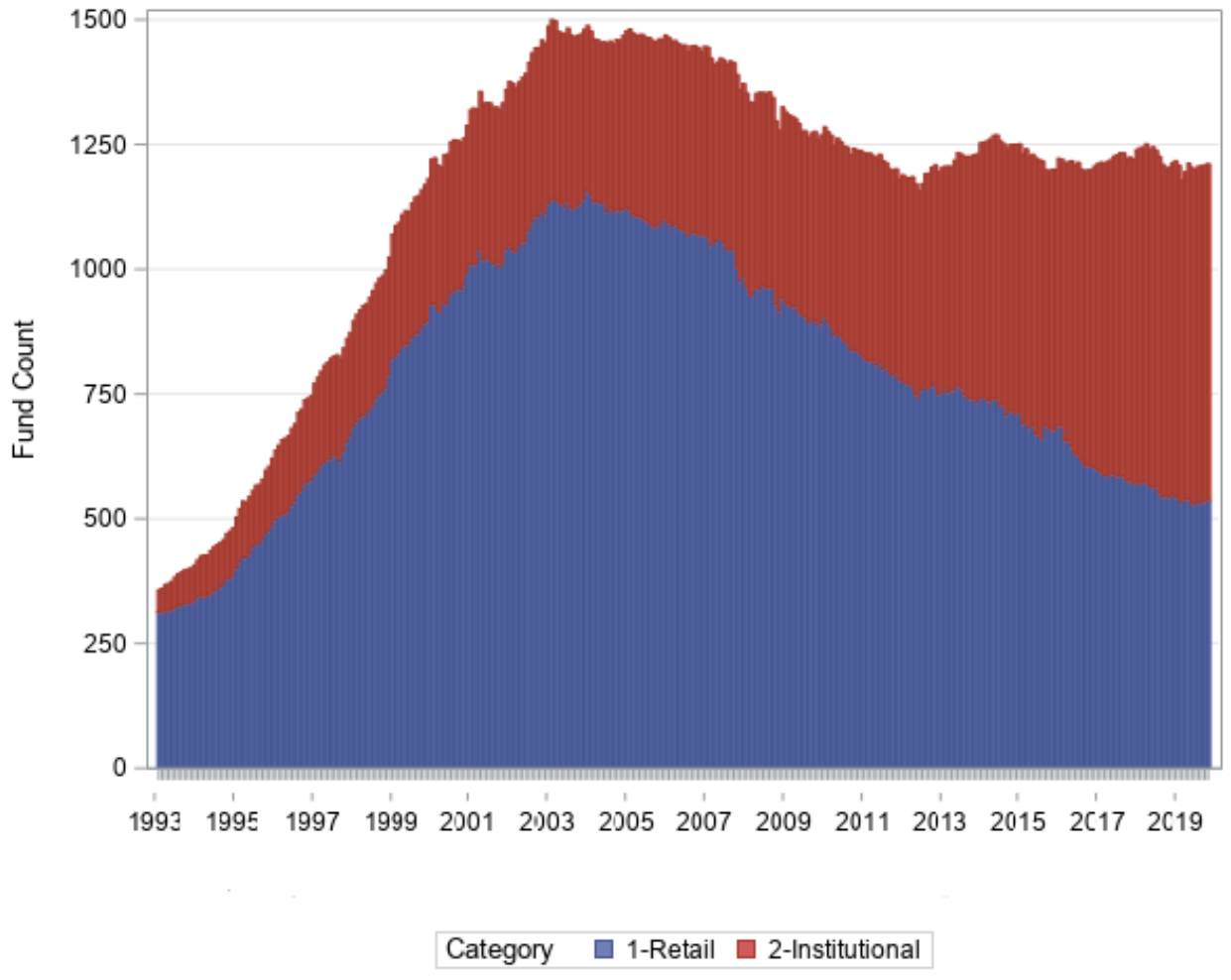
Comparison of GRA & RDP in Explaining Mutual Fund Flows

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

	(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)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
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

- The RDP coefficient subsumes competing variables and remains significant
- Economically significant differences $\Rightarrow$ Diamond Hill would receive 1% more than Black Rock next month

Retail vs Institutional Funds over Time



The number and portion of institutional funds increase significantly in the second half of our sample period

Retail & Institutional Funds

Panel A: FM Regressions on Return and Risk

	Retail Funds		Institutional Funds	
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)

Panel C: FM Regressions on Expected Utility of Returns

	Retail Funds			Institutional Funds		
	$\theta = 1.65$ $\lambda = 1.45, \alpha = 0.85, \beta = 0.90$			$\theta = 1.60$ $\lambda = 1.60, \alpha = 0.90, \beta = 1.00$		
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

Retail & Institutional Funds

Panel A: FM Regressions on Return and Risk

	Retail Funds		Institutional Funds	
Return	1.362***	1.373***	1.108***	1.131***
	(14.42)	(14.64)	(14.30)	(15.32)
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Panel C: FM Regressions on Expected Utility of Returns

	Retail Funds			Institutional Funds		
	$\theta = 1.65$			$\theta = 1.60$		
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Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund Obj FE	Yes	Yes	Yes	Yes	Yes	Yes
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Retail & Institutional Funds

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	Retail Funds			Institutional Funds		
	$\theta = 1.65$			$\theta = 1.60$		
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Observation	254,471	254,471	254,471	118,535	118,535	118,535

Sub-period Analysis

Panel A: FM Regressions on Return and Risk

	Dec93-Nov05		Dec05-Nov20	
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)

Panel C: FM Regressions on Expected Utility of Returns

	Dec93-Nov05			Dec05-Nov20		
	$\theta = 1.65$			$\theta = 1.70$		
	$\lambda = 1.65, \alpha = 0.75, \beta = 0.90$			$\lambda = 1.35, \alpha = 0.95, \beta = 0.95$		
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

Sub-period Analysis

Panel A: FM Regressions on Return and Risk

	Dec93-Nov05		Dec05-Nov20	
Return	1.640***	1.660***	1.173***	1.182***
	(13.06)	(13.90)	(23.69)	(25.09)
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Panel C: FM Regressions on Expected Utility of Returns

	Dec93-Nov05			Dec05-Nov20		
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Observations	158,283	158,283	158,283	302,640	302,640	302,640

Sub-period Analysis

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Panel C: FM Regressions on Expected Utility of Returns

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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

Sub-period Analysis

Panel A: FM Regressions on Return and Risk

	Dec93-Nov05		Dec05-Nov20	
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Panel C: FM Regressions on Expected Utility of Returns

	Dec93-Nov05			Dec05-Nov20		
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	(15.10)		(0.05)	(23.09)		(1.56)
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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

Robustness Tests

		Estimation	Reference Point		Performance Horizon		Flow
	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
Coefficients of Expected Utility of Returns and Average Adjusted R-squared							
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
FM Regressions on Expected Utility of Returns under GRA and RDP together							
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)

Robustness Tests

		Estimation	Reference Point		Performance Horizon		Flow
	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
Coefficients of Expected Utility of Returns and Average Adjusted R-squared							
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	(6.41)	(5.35)	(6.06)	(3.67)	(5.63)	(4.93)	(2.44)

Robustness Tests

		Estimation	Reference Point		Performance Horizon		Flow
	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
Coefficients of Expected Utility of Returns and Average Adjusted R-squared							
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RDP beta	0.90	0.88	0.90	0.95	0.90	0.95	0.95
Coefficients of Expected Utility of Returns and Average Adjusted R-squared							
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
FM Regressions on Expected Utility of Returns under GRA and RDP together							
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)

Comparison with Asset Pricing Models

	(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)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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

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- Other studies on the topic compare prospect theory to widely-used asset pricing models $\Rightarrow$ comparing apples to oranges
- Even GRA can outperform CAPM, FF3 & FF4 (less restrictive)
- RDP coefficient subsumes everything $\Rightarrow$ **Key: The parameter values**

Conclusion

1. We infer information about mutual fund investors' preferences using the well-documented flow-performance relationship
    - We find evidence in support of loss aversion and differential attitudes toward risk over gains and over losses
    - We do not find evidence that mutual fund investors overweight extreme outcomes (probability-weighting)

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2. We show that adopting parameter values from experimental settings significantly reduces the explanatory power of RDP on mutual fund flows

3. For parameter values that best explain fund flows, RDP outperforms the GRA framework in all tests
    - These results are stronger for retail funds and for the earlier sub-period of our sample