Cautious Risk-Takers: Investor Preferences and Demand for Active Management*

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Abstract

Actively managed mutual funds have distinct return distributions from their passive benchmarks and our theoretical analysis using tail-sensitive risk preferences suggests that active value and growth funds may serve to reduce downside risk and capture upside potential, respectively. Furthermore, tail-sensitivity measures estimated from the empirical pricing kernel have significant explanatory power for active fund flows, even after controlling for business cycles and market-wide sentiment. Finally, active funds, unlike their passive counterparts, have exposures to option strategies hedging downside risk or capturing upside potential.

JEL: G11, G23

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Introduction

Despite poor performance of actively managed mutual funds relative to their passively managed counterparts, assets under active management continue to significantly outweigh those of index funds.[1] This puzzling phenomenon has spurred considerable interest in the mutual fund literature. Several recent papers develop models of state-dependent fund manager effort or skill that allude to the active management puzzle (see, for example, Kacperczyk, Van Nieuwerburgh and Veldkamp, 2012, and Glode, 2011). A central feature of this line of research is that active managers can generate conditional returns that are attractive to fund investors.[2] While the focus of these existing studies has been on fund manager actions and fund performance, in this paper we approach the issue from the equally important side of investor demand. We take funds returns as given and use them as inputs to individual investors' portfolio decisions to identify features of investor risk preferences which could generate the demand for active funds.

Using bootstrapped fund return distributions, we show that actively managed mutual funds are distinct from their passive counterparts, particularly in the tails of their return distributions. We conjecture that due to such differences, active funds may appeal to investors who are sensitive to downside risk or upside potential. Such features of individual preferences are widely supported in experimental studies and have been applied in the literature on portfolio diversification (see, for example, Shefrin and Statman, 2000 and Mitton and Vorkink, 2007). We use a structural model of a rank-dependent utility function which allows overweighting of tail events to generate testable implications about the demand for active funds. We then examine how active fund flows respond to changes in risk preferences inferred from the empirical pricing kernel and find strong support

[1]For example, Fama and French (2010) estimate that during the period from 1984 to 2006, active equity mutual funds underperformed benchmark portfolios by approximately 1% annually, roughly the average cost of investing in mutual funds.

[2]Specifically, in Kacperczyk, Van Nieuwerburgh and Veldkamp (2012) time-varying managerial skill emerges from constrained information processing capacity, while in Glode (2011) fund managers have a disutility from applying effort. Both of these mechanisms imply that managers endogenously generate higher abnormal returns when state prices are higher. Active funds could therefore be attractive to investors because their conditional performance (alpha) positively covaries with a component of investors' pricing kernel even though the unconditional alpha is negative.

for our predictions. While prior studies often examine the relation between fund performance and the pricing kernel, we directly link investor demand for active funds with the pricing kernel. Furthermore, as our framework is able to disentangle investor risk preferences towards the upper and lower tails, we show that these two channels of investor demand have different effects on flows into value and growth funds.

Using a sample of US domestic mutual funds during the period from 1996 to 2008, we first compare the distribution of monthly returns between actively and passively managed funds within the same investment category. We compare several conditional and unconditional moments: standard deviation, skewness, kurtosis, and conditional means in the upper and lower tails. Based upon bootstrapped moments for each type of funds, we show that the return distributions of active and passive funds are quite different. Active growth funds tend to be more volatile while active value funds tend to be less volatile than their passive alternatives.[3] In addition, active growth funds are less negatively skewed and have higher conditional means for the upper quantiles than passive growth funds. Active value funds, on the other hand, have lower standard deviations and higher conditional means for the lower quantiles. Active funds also tend to have higher kurtosis (higher probability of tail events). We therefore hypothesize that investors may be attracted to active funds given their distinctive return distributions, particularly in the upper and lower tails.

To explore this channel of demand for active funds, we use a model of preferences to examine whether investors may find active mutual funds attractive when their risk preferences are sensitive to downside risk or upside potential. Specifically, we model risk preferences using a rank-dependent expected utility (RDEU, Quiggin, 1983 and Yaari, 1987) with probability weighting function. This weighting function allows us to model investor preference for the upside potential jointly with the aversion to downside risk.[4] While seemingly contradictory, as the oxymoron in the paper's title, such

[3]For example, during the period of 1996 to 2007, active large-growth funds have a monthly standard deviation of returns of 5.3% versus 4.7% for passive large-growth funds, while active large-value funds have a monthly standard deviation of returns of 3.9% as compared to 4.2% for their passive counterparts. These differences are statistically significant at 5% level.

[4]This is possible because risk attitude in RDEU is not tied to the curvature of the utility function. The probability weighting function captures the risk attitude toward event probabilities separately from the standard risk aversion toward wealth or consumption. A similar mechanism is used in the Cumulative Prospect Theory of Kahneman and

behavior is widely supported by extensive experimental evidence in decision science literature. We hypothesize that upside potential seeking and downside risk aversion are important determinants of the demand for active management.

Through simulation exercises we demonstrate that the observed differences in return distributions between active and passive funds are quantitatively significant to an RDEU investor. In our simulation exercises we use a two-parameter version of the Prelec (1998) probability weighting function that allows us to model a wide variety of risk attitudes towards tail events. One parameter (α) controls the extent of over- or under-weighting of the tails while the other (β) allows us to tilt the tail overweighting either towards the right or left side of the distribution. We simulate distributions of monthly returns for active and passive funds in growth and value categories and compute differences in certainty equivalents (CE) of these distributions for a range of Prelec function parameters. We also consider the portfolio problem of an investor who has a choice between active and passive funds with a joint return distribution bootstrapped from the data. We solve numerically for optimal portfolios and examine the comparative statics of the demand for active management with respect to parameters of the probability weighting function.

The results from both the comparative statics of the CEs and the optimal portfolios show that active growth funds may be more attractive to investors with probability weighting functions that place more emphasis on the upper tail of the return distribution due to active growth funds' greater upside potential. On the other hand, active value funds may be more attractive to investors who are more concerned with protecting against the downside risk. The model generates empirical predictions about how the demand for actively managed funds versus their passive counterparts should respond to changes in investor preferences. We then test these predictions using mutual fund flows.

In our empirical tests, we estimate the probability weighting function from the S&P 500 index options and construct proxies for individual components of the pricing kernel responsible for downside risk aversion and for upside potential seeking, following Polkovnichenko and Zhao (2012).

Tversky (1992).

We construct two sets of proxies with monthly frequency: α and β from the Prelec (1998) two-parameter probability weighting function, and the left-tail and right-tail slopes of the pricing kernel estimated non-parametrically. Estimating the empirical pricing kernel and investor preferences from the option market has been a commonly applied approach (see, for example, Jackwerth, 2000 and Ait-Sahalia and Lo, 2000). The no-arbitrage assumption between stock and option markets ensures that the empirical pricing kernel reflects risk preferences of stock investors even if not all of them trade index options. In addition, since investments by U.S. open-end equity mutual funds account for a significant part of the stock market capitalization, we would expect that our option-based risk preference estimates are representative of the risk attitudes of the average mutual fund investor.[5]

We show that the parameters of the probability weighting function estimated from pricing kernel implied in index options have significant explanatory power for monthly fund flows into actively managed funds after controlling for flows into passive funds within the same investment category and overall category and market performance. Specifically, we find that flows into actively managed growth funds significantly increase as investor sensitivity to upper tail events raises. At the same time, flows into value funds increase with investor aversion to lower tail events. These findings are consistent with our theoretical predictions and suggest that active growth funds are attractive to investors with strong risk-taking preferences while active value funds are attractive to investors seeking downside risk protection.[6]

We also investigate if our main results relating fund flows to tail-sensitive preferences are robust to the control of investor sentiment. On one hand, prior studies have documented certain links between investor sentiment and fund flows (see, e.g., Ben-Rephael, Kandel and Wohm, 2011 and Yadav and Massa, 2012). On the other hand, while investor sentiment may lead to a strong demand for either the downside protection or upside potential at a particular point in time, our framework allows for the coexistence of demands for both downside protection and upside seeking.

[5]For example, according to the Federal reserve data, U.S. open-end mutual fund equity holdings at the end of 2009 account for more than 25% of the total capitalization of equity markets (see "Corporate Equities" table at www.federalreserve.gov/releases/z1/20100311).

[6]As noted previously, these two types of behavior are not mutually exclusive under this utility function and our results do not necessarily imply investor segmentation in the mutual fund market.

In addition, when a sentiment index is high it could be because investors are less concerned with the downside risk, more excited about the upside potential, or both. Our measures of tail preferences, however, can differentiate the demand for investments with payoffs in specific parts of the distribution. Therefore, it is not clear whether investor sentiment can indeed serve as a substitute for tail preferences. Nonetheless, we control for the Baker and Wurgler (2006, 2007) sentiment measure in our flow regressions. We find that the market-wide sentiment measure is not strongly related to flows into active funds except for the blend fund category. However, in all specifications our measures of tail sensitivity maintain their significant economic and statistical relationships with flows into active funds.

In an attempt to cross-validate the link between investor preferences and the observed pattern of fund flows, we examine the investment behavior of different investor clienteles with potentially distinct risk attitudes in order to see whether differences in their demands can be explained by our measures of tail-sensitivity. Our results indicate that flows into retirement funds exhibit significantly weaker sensitivity to the preference for upside potential yet much stronger sensitivity to the preference for downside protection, relative to non-retirement retail funds with similar investment styles. The significant sensitivity of retirement fund flows to Prelec β is thus in stark contrast to prior evidence of inertia among retirement investors in changing asset allocations (see, e.g., Ameriks and Zeldes, 2001; Madrian and Shea, 2001; Benartzi and Thaler, 2007). On the other hand, flows into non-retirement retail funds often demonstrate significant exposures to either Prelec α or Prelec β depending on their styles.

Finally, we examine whether actively managed funds indeed have returns which can help reduce downside risk or capture upside potential. We augment the standard Carhart (1997) four-factor model with returns of straddle and ATM or OTM call options and test whether actively managed funds are more likely to load on these option-based factors compared to passive funds. As expected, our results indicate that actively managed large-growth funds tend to have significantly positive loadings on returns of ATM or OTM calls, while actively managed large-value or large-blend funds have significantly positive loadings on straddle returns. In contrast, their passively managed counterparts have insignificant loadings on these option-based factors.

Our paper is closely related to several recent theoretical and empirical studies addressing the coexistence of poor unconditional performance of actively managed funds relative to their passive benchmarks and persistent investor demand for active management.[7] Particularly, Glode (2011) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2012) explore the idea that fund managers cater to fund investor risk preferences.[8] Glode (2011) presents a model where negative unconditional expected fund performance and the demand for active management simultaneously arise in equilibrium because mutual fund managers decide on efforts and thus fund performance according to the price of risk. In a related study, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2012) show that fund managers allocate their attention strategically in response to the time varying rewards to active management. Essentially, in both of these studies, mutual fund managers generate active abnormal returns that covary positively with a component of the pricing kernel.

Our work is focused on investor decisions and complements these studies from both theoretical and empirical sides. We use a structural model of investor risk preferences to generate predictions about how the demand for actively managed funds should be affected by changes in preferences. Our framework is also distinct because it has implications for both upside potential-seeking and downside protection demand with different testable implications for growth versus value funds. Finally, our empirical analysis demonstrates the simultaneous impact of investor risk aversion and upside-seeking preference on demand for active funds while the emphasis in the existing literature has been on the performance of active funds relative to passive funds conditional on market cycles.[9]

[7] Empirical studies in this literature include, for example, Gruber (1996), Moskowitz (2000), Kosowski (2006), Lynch, Wachter and Boudry (2007), and Fama and French (2010) among others.

[8] Other recent theoretical studies include, for example, Pastor and Stambaugh (2010), and Savov (2012). In Savov (2012) active managers also perform a valuable service to investors but it emerges from superior information processing skill of professional managers. The mechanism in his model is not mutually exclusive to the ones used in Glode (2011) or Kacperczyk, *et al.* (2012). The model in Pastor and Stambaugh (2012) captures the idea that managers have skill but active management has a decreasing returns to scale. While investors can learn the manager's skill from noisy returns, this process is slow and the size of active fund industry is persistent.

[9] See also Moskowitz (2000), Kosowski (2006), and Sun, Wang, and Zheng (2009) for empirical evidence on the outperformance of active funds in down markets.

Lastly, we note that the upside-seeking feature of investor preferences is related to non-monotonicity in the pricing kernel, a well documented empirical property in the option pricing literature (see, for example, Jackwerth, 2000; Ait-Sahalia and Lo, 2000; Bakshi, Madan and Panayotov, 2010). The empirical pricing kernel implies that payoffs with high upside potential are valuable to some investors.[10] Consistent with this interpretation, our paper appears to be the first to show that investor demand for active growth funds is related to the upside seeking preference in the pricing kernel.

The rest of the paper is organized as follows. In Section 1, we describe our data and discuss summary statistics of our sample funds. Section 2 compares the return distributions of active versus passive funds. Section 3 provides an introduction to the utility function with probability weighting. Section 4 explains the demand for active funds from investors with tail-sensitive risk preferences through both simulation exercises and empirical analyses on fund flows and fund returns. Finally, Section 5 concludes the paper.

1 Data

Our empirical analyses mainly utilize two types of data: the S&P 500 index option prices and fund flows and returns for active and passive funds for individual investment styles.

We obtain data on S&P 500 index options (symbol SPX) from OptionMetrics for the period from February 1996 to December 2008. The market for SPX options is one of the most active index option markets in the world. These options are European, have no wild card features, and can be hedged using the active market for the S&P 500 index futures. We select the monthly quotes of options that are closest to 28 days from each month's expiration date. The average of the bid and ask prices is taken as the option price. We also obtain the term structure of default-free interest rates from OptionMetrics. Following the procures in Aït-Sahalia and Lo (1998) and others, we remove options that are not liquid and infer the option implied underlying price to avoid

[10]Bakshi, Madan and Panayotov (2010) also show that this implies, consistent with empirical facts, negative expected return on the out-of-the-money call options.

nonsynchronous recording between the two markets. More details on our sample of options data and the related filtering procedures are provided in Appendix A. We also obtain S&P 500 index returns for estimating the inverse probability distribution function under physical measure. The index returns series has an earlier start date of January 1990 since we need to obtain the rolling estimates of the physical distribution.[11]

For analyses involving aggregate-level and individual fund-level mutual fund flows and returns, we extract the data from Morningstar for the same period of 1996 to 2008. We include funds in the following Morningstar investment categories: large blend (LB), large growth (LG), large value (LV), medium blend (MB), medium growth (MG), medium value (MV), small blend (SB), small growth (SG), and small value (SV). Since our main analyses concern mutual fund investments at the aggregate level, we directly employ aggregate monthly flows into active and passive funds by investment categories as provided in Morningstar. For analyses involving information aggregated from the individual fund-level data, we only keep funds with TNA exceeding $10 million. To have a benchmark for the return distribution of index funds, we focus on funds managed by Vanguard since Vanguard funds are bellwether in the index fund industry and tend to have more complete return history across all investment categories. In contrast, many other passive funds began much later than did Vanguard funds and thus have much shorter time-series of return data. Therefore, following Fama and French (2010) we use Vanguard funds as the representative of all passive funds to facilitate the comparison of performance between passive and active funds.

In Table 1 we report summary statistics for aggregate monthly fund flows and TNAs as obtained directly from Morningstar. Active funds have considerably larger dollar flows and TNAs than passive funds in most investment categories. Figure 1 further demonstrates the time series of dollar fund flows for active and passive funds. As expected, flows into active funds are generally significantly larger and more volatile than those into passive funds.

In Table 2 we report summary statistics for individual fund-level information about actively

[11]In the comparative analysis not reported here, we apply fixed, rolling and recursive window for estimating the physical distribution function and our results are not affected by this particular choice.

managed funds. The median fund size as measured by TNA is relatively uniform across all categories, but there exists considerable cross-sectional variations in fund size both within and across categories. Particularly, the mean fund size and fund flows are markedly larger than the median values, suggesting that some funds rake in significantly more money than the average fund. The returns of growth-oriented funds also generally exhibit greater volatility relative to funds in other investment categories. Since large-cap funds dominate small-cap and medium-cap funds in terms of both the number of funds and money flows, our analyses to follow will mainly focus on large-cap funds where we have the most complete time-series of aggregate flow and return data in all investment styles to analyze the behavior of aggregate investments in actively managed funds. However, in the robustness section we present main results using fund flows for small and medium-cap categories for completeness.

2 Return Distributions of Actively Managed Funds

Do actively managed funds have different return distributions from index funds? We address this question by comparing sample moments of active fund returns with index fund returns for each fund investment style. The number of active funds grows considerably over our sample period with the growth rate varies across styles. To compute the moments from a return distribution that is stationary and representative of each style, we use the bootstrap method to generate paths of monthly return series for each style. We account for differences in fund size in our sampling by using the total net assets of the prior month as the weight in the random draw of the current month's return. We generate 250,000 paths of monthly return series for each investment style and compute the sample moments and confidence intervals of these moments. For index funds we compute the sample moments of the returns series for Vanguard funds in each investment category. Since the recent financial crisis in 2008 could have altered the return distribution of mutual funds beyond what mutual fund investors have normally expected of them, especially for large-value funds due to their heavy holdings of the financial sector, we examine differences in sample moments between active and passive funds with and without data in 2008.

The specific sample moments computed from the generated paths of monthly return series include mean, volatility, skewness, and kurtosis, as well as the conditional mean in both the worst and best 5-, 10-, and 25-percentile of return distributions. For example, the expected return in the best 10-percentile is computed as $E[R|R \geq q_{0.90}]$ where $q_{0.90}$ is 90% quantile of the return R distribution. On the other hand, we compute $E[R|R \leq q_{0.10}]$, where $q_{0.10}$ is 10% quantile, for the expected return in the worst 10-percentile. These conditional means help highlight differences in characteristics between the upside versus downside of the return distributions. We also compute the autocorrelations of the monthly return series (not reported) and find the serial correlation rather weak and having little effect on our sample moments calculation.

We report return moments and conditional mean returns in Tables 3 and 4, respectively, for large active and passive funds.[12] Panels A and B report the results excluding and including 2008 data, respectively. As expected, Panel A of Table 3 indicates that active funds exhibit lower unconditional mean returns than their passive benchmark regardless of the investment style. However, when we compare sample moments beyond the mean, the results indicate that active growth funds offer better upside potential than their passive counterparts, while active value funds offer greater downside protection. In terms of magnitudes, active large-growth (LG) funds have a monthly (non annualized) return volatility of 5.26% versus 4.69% for passive benchmarks. Active large-value (LV) funds have a return volatility of 3.90% versus 4.24% for passive benchmarks. These differences are both statistically and economically significant. They are manifestation of differences in performance distributions between active and passive management.

Since mutual funds have very little use of derivatives, active management is thus needed for a fund portfolio's variance to be significantly lower than that of a passive portfolio with similar holdings. The same is true for a portfolio to have an improved upside yet a limited downside

[12] In unreported analyses, we find that actively and passive managed medium and small-cap funds exhibit similarly different patterns in conditional returns and in moments. The comparison, however, is often based upon shorter time-series of return data as monthly return data of medium and small-cap passively managed funds in certain investment styles are not always available from the beginning of our sample period.

relative to a passive benchmark. Active LG funds have significantly higher kurtosis and yet less negative skewness than their passive counterparts. In panel B, we include year 2008 in our sampling. Our finding on growth funds remains robust with similar statistical significance. However, the difference in standard deviation between active and passive value funds, although qualitatively similar, becomes statistically insignificant.

In Table 4, we explicitly examine differences in tail distributions by focusing on conditional mean returns of active versus passive funds. The results indeed show that active LG funds have significantly higher returns in the upside. In the top 5- and 10-percentile of return distributions, active LG funds offer an average monthly returns of 11.2% and 9.4%, respectively, as compared to 8.7% and 8.1% for passive LG funds. Both differences are statistically significant. In terms of economic significance, these differences translate into 30% and 15.6% annual return differentials between active and passive LG funds in the top 5- and 10-percentiles. As for the downside, although active LG funds appear to have slightly lower returns than passive funds, the difference is statistically insignificant and much smaller in magnitude than the upside difference.

In contrast to LG funds, the pattern in conditional mean for active LV funds is reversed with smaller losses than passive LV funds in the worst case scenarios: 9.6% and 8.4% in annual return differences in the worst 5 and 10 percentiles, respectively. Active LV funds also show smaller gains on the upside, -4% and -7% differences in annual return in the top 5- and 10-percentiles, than the passive benchmark. In addition, active LB funds tend to do better on both sides than their passive benchmarks, although the differences are not statistically significant. Lastly, we report the result including 2008 in Panel B. Again, active LV funds tend to have lower conditional means on both the up and down sides, although the difference becomes insignificant for the down side. This reduced performance advantage of active value funds when including 2008 is possibly driven by value funds' large exposures to financial stocks, which performed exceptionally poorly during the 2008 financial crisis.

Given prior evidence that mutual fund performance varies with business cycles, we next compare return distributions separately for boom and bust periods in our sample period.[13] Each month we compute the average market return in a six-month window that ends with the current month and then divide the whole sample period into high/low market return periods using the average six-month returns. The results for conditional means for the sample 1996-2007 are shown in Table 5.[14] Interestingly, the advantage of active LG funds over passive benchmarks is more pronounced during the high market return periods while the advantage of LV funds becomes more evident during the low market return periods. Specifically in terms of annual return differential, active LG funds outperform passive benchmarks by 18% (high return periods) and 10.8% (low return periods) in the best 10-percentile and under-perform by 4.4% (high return periods) and 16% (low return periods) in the worst 10-percentile. On the other hand, active LV funds outperform passive LV funds by 3% (high return periods) and 11.5% (low return periods) in the worst 10-percentile and under perform by 7.2% (high return periods) and 4.8% (low return periods) in the best 10-percentile. These findings echo those in Glode (2011) and Kacperczyk, Van Nieuwerburgh and Veldkamp (2012) in that the distribution of active fund performance exhibits state-dependency. Therefore, the distribution of active fund performance is correlated with the market condition and thus the pricing kernel of the aggregate investor.

3 Demand for Active Funds from Investors with Tail-Sensitive Risk Preferences

3.1 Basics of a Utility Function with Probability Weights

Since Table 3 suggests significant differences in return moments across the active and passive universes, we conjecture that they should cater to investors with different tail-sensitive preferences. Before we conduct simulation and empirical analyses on the effect of investor preferences on fund flows, we briefly introduce the rank-dependent expected utility (RDEU) and refer the reader to Quiggin (1993) for details. The RDEU is defined over outcomes ranked from the worst to the best.

[13] See, for example, Glode (2011) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2012) for theoretical studies, and Gruber (1996), Moskowitz (2000), Kosowski (2006), Lynch, Wachter and Boudry (2007) for empirical studies.

[14] The results including 2008 are similar and are omitted for brevity.

Here it is natural to rank outcomes by investor wealth w and we assume w to be a random variable with c.d.f. $P(w)$ and density $p(w) = P'(w)$. A *probability weighting function* $G(P)$ is a continuous, non-decreasing function $G(\cdot) : [0,1] \to [0,1]$, s.t. $G(0) = 0$ and $G(1) = 1$. For convenience, we also assume that $G(\cdot)$ is differentiable. The purpose of G is to transform original probabilities into decision weights that are used to compute the weighted average utility value. From this standpoint the RDEU is similar to EU, but instead of expectations taken with respect to P as is standard under EU, the utility is determined by expectation under $G(P)$:

$$U = \int u(w)dG(P) \tag{1}$$

If we define the probability weighting density as $Z(P) \equiv G'(P) \geq 0$, we can rewrite the utility function as the following:

$$U(w) = \int u(w)G'(P)dP = E\{u(w)Z(P)\} \tag{2}$$

Note that outcomes with $Z > (<)1$ are weighted more (less) than their objective probabilities. As a special case with $G(P) = P$ $(Z = 1)$, the RDEU nests the standard EU. Also note that since the decision weights integrate to 1, we have $EZ \equiv \int dG(P) = 1$.

We note here that while the weighting function is a transformation of the original probability measure P into $G(P)$, the decision maker is assumed to know the underlying distribution P. Intuitively, the probability weighting function is a modeling mechanism for *risk attitude* toward the probabilities of ranked events. It transforms events' probabilities into decision weights in a way that is conceptually similar to the utility function mapping wealth or consumption into utility values. In this sense, probability weights address the criticism put forth by Allais (1988) that risk aversion should be independent of the curvature of the utility in the absence of risk.[15]

Experimental studies (e.g. Camerer and Ho (1994), Wu and Gonzales (1996), Tversky and Kahneman (1992)) find that individuals tend to overweight events in the tails of the distribution, i.e. for P near 0 and 1, relative to events in the middle of the distribution. This type of behavior

[15] See also a related discussion in Quiggin (1993, section 5.6, p. 68). Also, unlike subjective beliefs, probability weights depend on the actions of the agent through the cumulative distribution of ranked outcomes.

may be characterized by the inverse-S shaped probability weighting function G with a corresponding U-shaped density Z. One weighting function frequently used in the literature follows Prelec (1998):

$$G(P) = \exp(-(-\log(P))^{\alpha}) \quad , \quad \alpha > 0 \tag{3}$$

Experimental studies typically find $\alpha \in [0.5, 1]$ corresponding to the inverse-S shaped overweighting probabilities in the tails. However, some studies surveyed by Camerer and Ho (1994) also find that $\alpha > 1$, implying that occasionally investors may underweight tail events and instead are more concerned with outcomes in the middle of the distribution. Ultimately the shape of tail preferences is an empirical object, much like the risk aversion and discount factor. Prelec's function admits both types of behavior and this flexibility allows us to empirically identify the prevailing risk attitude implied in index options. Lower α corresponds to stronger overweighting in the tails relative to the middle of the distribution. We show the effects of α on the weighting function in (3) in the top two panels of figure 2. When $\alpha = 1$ we have the case of EU: the weighting function is a diagonal 45-degree line and its derivative is a constant 1. As alpha becomes lower the inverse-S shape becomes more pronounced and the overweighting of the tails is stronger as can be seen from the right top panel. When $\alpha > 1$ (not shown), the weighting function becomes S-shaped instead and under-weights the tails.

While convenient for experimental work due to its one-parameter structure, one of the shortcomings of this weighting function is that it does not allow independent variation in the strengths of the overweighting in the left and right tails of the distribution. Prelec also proposed a two-parameter extension of this function that can accommodate different attitudes toward events in the left versus right tails:

$$G(P) = \exp(-(-\beta \log(P))^{\alpha}) = \exp(-(-\log(P^{\beta}))^{\alpha}) \quad , \quad \alpha > 0 \ , \ \beta > 0 \tag{4}$$

As seen from the above formula, this weighting function can also be represented as a compound function using the one-parameter Prelec specification from (3) as $G(P^{\beta})$. Note that P^{β} is itself a valid weighting function and is either globally concave ($\beta < 1$) or convex ($\beta > 1$). The former implies risk aversion (overweighting of the left tail) while the latter implies upside seeking (overweighting in the right tail). The effects of β on the weighting function are shown in the two lower panels of figure 2 which present the cases for $\beta < 1$. As β becomes lower the weighting becomes more concave and the left tail is more over-weighted, which can be seen on the lower right panel. For $\beta > 1$ (not shown), the weighting is convex and acts in reverse to over-weight the right tail. Thus, the coefficient β in the compound representation can independently reinforce or weaken the effect of risk attitude in the tails which is determined by α. Lower β corresponds to a uniform increase in risk aversion, while lower α leads to stronger risk aversion on the left and simultaneously stronger risk seeking on the right. The two-parameter extension allows the weighting function to independently control the relative strengths of downside risk aversion and upside potential seeking.

We use the specification in (4) in conjunction with simulated distributions of active and passive fund returns to develop empirical predictions from the model of tail-sensitive preferences. Specifically, we are interested in comparative statics of the demand for actively managed funds with respect to the two structural parameters of the probability weighting function, α and β. We consider two types of experiments. One involves the analysis of certainty equivalent differences between active and passive funds and the other one is based on the optimal portfolio allocation between the two types of funds.

3.2 Certainty Equivalents of Active and Passive Funds

As discussed in section 2, we use 250,000 bootstrapped time series to compute moments shown in table 3 (Panel A) for active and passive funds within each investment category. We use these moments as inputs to create a very large simulation from the Pearson system of distributions which is a statistical parametric family of distributions designed to match a given first four moments. For the computation of certainty equivalents we equalize mean monthly returns for all categories to 6% annualized rate, which allows us to compare simulated funds based on the higher order moments only.[16] We simulate 900,000 monthly returns for each type of fund and construct non-overlapping returns for three and five years from these series.

To compute certainty equivalents we set $u(w) = w$ and normalize initial wealth to 1. By using a risk-neutral u we can make a clean comparison of the effects of the weighting function on the preference for the return distributions of passive versus active funds.[17] We then compute the utility value for a given set of Prelec weighting function parameters α and β which, given our choice of u, corresponds to the certainty equivalent return (CE) for a given distribution. We report differences between CEs ($\Delta CE = CE_{\text{active}} - CE_{\text{passive}}$) within each investment category for a range of Prelec parameter values.

Figure 3 shows the results for two fund styles and two holding periods. We observe that the preference for active growth funds is decreasing in α and increasing in β. This is consistent with active growth funds providing higher return volatility and higher upside potential as evidenced in the relatively higher skewness of their return distribution, as compared to their passive counterparts. Investors with lower α and higher β have a tendency to overweight upper tail outcomes and would thus find active growth funds relatively more attractive. The preference for value funds is increasing in α and decreasing in β. Higher α means that the investor is concerned with earning good returns in the middle of the return distribution while lower β implies a greater concern with downside risk. Such an investor is therefore more conservative regarding tail behaviors in general and the downside risk in particular. Since the active value fund in the simulation has a higher skewness and lower volatility compared to the passive benchmark, investors with higher α and lower β would find it more attractive. These patterns are similar whether we consider three-year or five-year return distributions.

[16] In the portfolio choice problem we use the original bootstrapped time series which preserves mean return differences due to fees and return correlations between active and passive funds.

[17] Additionally, by allowing $\beta < 1$ in simulations we effectively introduce global risk aversion similar to that in the standard concave utility function.

3.3 Portfolio Choice

Comparative statics of the CEs inform us about the changes in "distance" (in terms of utility) between active and passive funds. They are indicative of the direction of preferences for one type of distribution versus another. We now more directly evaluate changes in optimal portfolio allocation with respect to preference parameters. Ideally, this requires a simulation which preserves the complex structure of cross-moments between passive and active funds. Since this is hard to achieve with a random-number generator, we therefore use the original bootstrapped data where we sample passive and active funds at the same time to preserve correlation and other higher cross-moments structures.

We consider a portfolio problem where an investor has a choice of three assets: a risk-free asset, a passive fund, and an active fund of the same investment category. We deliberately choose this simple asset set in order to focus on the changes of optimal portfolio holdings in active vs. passive funds in response to changes in probability weighting parameters. Since it is outside the scope of our paper to explain how an investor would narrow down the choice of particular assets or fund styles, we thus employ the simplest setting to focus on the choice between active versus passive fund investments.

We restrict portfolio shares to be between zero and one to preclude short selling of funds and the risk-free asset and set the risk free rate to two percent per annum. We assume power utility function $u(w) = w^{1-\gamma}/(1-\gamma)$ and normalize the initial wealth to 1. We set the power parameter to $\gamma = 1$ for value funds and $\gamma = 0.2$ for growth funds in order to stay within constraints and better illustrate the variation in optimal portfolio allocations with probability function parameters. Using bootstrapped distributions of funds in each category we compute the optimal portfolio weights for two holding periods ($n \in \{3, 5\}$ years) $\theta^*(n) = [\theta_1^*, \theta_2^*, \theta_3^*]$ for risk-free asset, passive fund and active fund respectively. We then compute the fraction of the portfolio's risky assets invested in active fund: $\theta_f(n) = \frac{\theta_2^*}{\theta_2^*+\theta_3^*}$. Figures 4 and 5 present our results for value and growth styles, respectively. Each figure has four panels with the columns corresponding to the two holding periods and the rows showing the variation of $\theta_f(n)$ as a function of either Prelec α or β.

Figure 4 shows the results for value funds. As a function of α, the allocation to active value fund is increasing for certain values of β or is close to flat. That is, as investors become less upside-seeking they allocate slightly higher fraction to the active value fund. This muted response to α can be understood through probability weighting changes on both ends of the distribution. As α moves *lower*, the inverse-S shape becomes more pronounced and the upside-seeking preference becomes stronger. But the active value fund has a lower variance and a lower upside in general compared to the passive value fund. This contributes to a *lower* demand for the active value fund. However, at the same time the downside portion of the inverse-S is also stronger with lower α and this makes active value fund more attractive. As a result we get a "mixed" response of portfolio share to changes in α. On the other hand, we find a much more pronounced and decreasing response of portfolio allocation to the active fund with respect to β, which is quite consistent for a wide range of α values. Here, the effect is unambiguous since *lower* β only implies more over-weighting of the left tail and hence higher demand for downside protection provided by the active value fund.

In Figure 5 we show the results for growth funds. As a function of α, the allocation to active growth fund is decreasing. When α is high, there is no demand for the active fund. When α is low, as the investor becomes more attracted to the upside of returns, the risky portion completely and rather abruptly changes to the active fund. The best way to understand this pattern is to note that the active growth fund is strictly inferior to the passive growth fund on the basis of traditional mean-variance metric. That is, the active growth fund has higher variance *and* lower average return than the passive growth fund. There is also virtually no diversification benefit to holding the active fund in conjunction with the passive fund. Thus, an investor with risk preferences "sufficiently close" to mean-variance will completely disregard the active growth fund. As α becomes *lower*, the investor becomes more and more risk-seeking and at some point switches completely to the active fund, going for the option which maximizes upside potential when the risk-seeking preference becomes sufficiently strong. Again, the abrupt nature of the switch is explained by virtually nonexistent diversification benefit of jointly holding active and passive funds.[18] This type of behavior is reminiscent of the portfolio "layers" result first discussed by Shefrin and Statman (2000). They show that under complete markets investors with probability weighting functions similar to the one we use here will choose to hold a safe layer of protection in portfolio and then add to that a maximally undiversified asset.[19] A similar force operates here as the investor becomes sufficiently risk-seeking, the active fund is the only risky asset that the investor is willing to hold.

Figure 5 shows that holdings of the growth fund are increasing with respect to β. This is intuitive since for lower beta the investor is more concerned with downside protection and prefers the lower volatility of the passive fund. However, for sufficiently low α, the investor always prefers the active fund and its share is flat at 1 for a wide range of β's. In these cases the effect of β on the downside is not sufficient to counteract a strong upside-seeking preference as a result of a lower α.

The results from our analyses of portfolio demand and from certainty equivalent differences point to a consistent pattern regarding how the demand for active value and growth funds vis-a-vis their passive alternatives should respond to changes in market participants' attitudes towards downside risk and upside potential. We conclude this section by summarizing these empirical predictions from the model of tail-sensitive preferences:

Result 1: For *growth funds*, the demand for active funds (relative to passive ones) is *decreasing* in α and is *increasing* in β.

Result 2: For *value funds*, the demand for active funds (relative to passive ones) is *increasing* in α and is *decreasing* in β.

To investigate whether these predictions are borne out in the data, in the next section we will consider how active fund flows are affected by changes in investor preference towards downside risk and upside potential. Specifically, we construct direct empirical estimates of Prelec parameters as well as proxies for tail-sensitive preferences which do not rely on parametric assumptions and relate

[18] Note that in the case of value funds this is not the case since active value fund has both lower mean *and* lower variance than its passive benchmark. Thus, there is a traditional diversification tradeoff between active and passive value and the changes in demand are more gradual.

[19] Specifically, investors choose to hold a portfolio of constant payoffs in all states and a state contingent claim which maximizes the upside potential.

both sets of measures to the behavior of fund flows.

4 Empirical Evidence from Fund Flows

4.1 Option-implied risk attitudes towards the upside and the downside

Following Polkovnichenko and Zhao (2012), we extract the risk attitudes of the representative investor toward upside potential and downside losses in returns on the aggregate wealth portfolio from returns of S&P 500 index options. This approach relies on the estimation of the empirical pricing kernels and the implied probability weighting functions, a transformation of the original actual probability measure P into $G(P)$ reflecting the nonlinear weights assigned to different parts of the return distribution. We present the results from the parametric-based method with assumptions concerning the pricing kernel in this section and the results from non-parametric method in the robustness Section 5. Employing these two alternative estimation methods helps us check the robustness of our estimation. We now briefly describe how we construct the measures of tail-sensitivity from option returns. Appendix B provides a summary of theoretical framework and empirical methods used to obtain probability weighting functions from empirical pricing kernel.[20]

In the parametric approach we use the pricing kernel for RDEU given as:

$$m(R) = u'(R)Z(R)$$

where R is the market index return. Under the standard assumptions about marginal utility and probability weighting function this SDF is positive everywhere and is arbitrage-free. Using the option-implied price density allows us to estimate the pricing kernel m nonparametrically which can then be approximated using a given parametric specification for u leaving the Z estimate as nonparametric "residual". For utility we use the CRRA (power) specification $u(R) = \frac{R^{1-\gamma}}{1-\gamma}$ and set it to the benchmark risk neutral case $\gamma = 0$.[21] To approximate the empirical probability weighting

[20] For further technical details, assumptions, and derivations, we refer readers to Polkovnichenko and Zhao (2012).

[21] Using logarithmic or $\gamma = 2$ does not have any significant effect on Prelec α and only affects the average level of β (see Polkovnichenko and Zhao 2012). For our purposes here, we are more interested in the time-series variation of these parameters rather than their levels. We prefer the risk-neutral case for u because in that case $u'(R) = 1$ and the behavior of the pricing kernel in the tails is captured parsimoniously only through the weighting function.

function we use two-parameter Prelec function from (4). We use monthly data for options with 28-days to expiration in order to construct a time series of the estimated coefficients α and β.[22] Since α and β are correlated because they both reflect the attitude toward downside risk, we orthogonalize α against β in a time series regression so that our residual measure of α captures the risk attitude toward the upside. The resulting series are shown in Figure 6.

4.2 Fund flows and option-implied risk attitudes

As we show in section 2, growth funds tend to provide greater upside potential while value funds offer greater downside protection. To test the prediction we developed in section 3 with respect to portfolio demand for active funds, we regress net flows into active funds (expressed as a percentage of TNA) on the option-implied measures of investor risk attitude (β and orthogonalized α). Since previous studies show that flows into different investor categories are related to investor sentiments in different fund sectors (Sirri and Tufano, 1998), we separately conduct this analysis for individual investment categories and control for flows to passive funds within the same category. Controlling for flows into passive funds of the same investment objective can help capture flow variations that are attributable to factors affecting investment sentiment for a particular investment style or equity funds in general. In addition, we include average TNA weighted monthly returns of each investment category in the previous month as an explanatory variable to account for flows resulting from the return chasing behavior of mutual fund investors. We also control for total market returns in the past six months in order to account for the effect of macroeconomic factors on mutual fund investments. In addition, this control will help alleviate the concern that any observed effect of investor risk preference might be driven by the business cycle if risk preferences vary across business cycles.

As mentioned earlier, we focus on large-cap funds because we have the most reliable time series data for passive funds in this group. More importantly, large-cap funds may be more relevant because the probability weights we extract from options are based on the S&P 500 index, which itself

[22] Our conclusions are robust to the choice of expiration time. Other expiration dates of 45 or 56 days result in qualitatively similar estimates for the weighting function parameters. See Polkovnichenko and Zhao (2012) for details.

is a large-cap portfolio. However, our results for medium and small-cap categories, as presented later in the robustness section of the paper, are qualitatively similar. Similar to the bootstrapped moments analysis, we also present this regression separately for the full sample of 1996-2008 (Panel A) and for the sample excluding 2008 (panel B).[23] The time-series coefficient estimates and their t-statistics are shown in Table 6. Given the autocorrelation in fund flows, we report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors.

Table 6 (Panel A) shows that flows into active funds are significantly positively correlated with category returns, market returns and flows into passive funds, particularly for large-growth and large-blend funds. This is expected since flows into active funds should be influenced by factors driving investments in the equity market in general. More interestingly, Table 6 indicates that the coefficient on α for large growth funds is negative and statistically significant. Recall from our previous discussion that α is a measure of upside potential and a *lower* value of α is associated with a *greater* preference for the upside. Thus, the result indicates that, other things being equal, a greater preference for the upside leads to *larger* flows into active growth funds. This finding is consistent with the properties of fund return moments presented earlier. Active growth funds have higher conditional expected returns on the upside and higher volatility than their passive benchmarks, which would be attractive to investors with preferences for upside potential as shown in our simulation exercise. The result from the flow regression shows that when the demand for upside seeking implied in index options is stronger, fund flows are directed more towards active growth funds that can better cater to such investor preferences, relative to their passive benchmarks.

For large-value funds we find that the coefficient on β is negative and statistically significant. Since α is orthogonalized with respect to β in our specification, β is used to capture downside risk aversion with the *lower* value corresponding to greater risk aversion. Thus, the result indicates that more money flows into active value funds when β is lower and the investor demand for downside

[23]Since our results of all subsequent analyses are very similar whether we exclude data from 2008 or not, we only report the results from the full sample.

risk protection is higher. This is again consistent with our earlier observation from the empirical moments of value fund returns. Specifically, active value funds provide higher conditional returns on the downside and have less negative skewness than their passive benchmarks. From simulation exercises we show that these distributional features would make active value funds more attractive to investors whose risk attitudes imply a lower value of β. Indeed, the result from the regression analysis confirms that when investor preferences for downside risk protection increase, more money flows towards actively managed large-value funds. Panel B of Table 6 confirms the robustness of all main results in the full sample to the exclusion of 2008, which is marked by the abnormally poor performance of value funds during the financial crisis.

In Table 7 we present the results from an alternative specification where we use as the dependent variable monthly flow differences between active and passive funds, standardized by the sum of the total net assets for active and passive funds during the preceding month. The results under this alternative specification are consistent with those previously discussed from Table 6. The coefficient on α for growth funds is significantly negative, indicating that a stronger preference for the upside tends to increase the difference between active and passive flows. Likewise, the coefficient on β is significant negative for value funds, showing that as concerns with the downside risk become greater, more money flows into the active value funds net of flows to passive value funds.[24]

4.3 Controlling for Investor Sentiment

The proxies we use to capture preferences for tail events may be related to the existing measures of investor sentiment because they are constructed from market-wide indicators. Ben-Rephael, Kandel, and Wohl (2011) show that aggregate net exchanges between equity and bond funds can be a proxy for investor sentiment. In the same spirit, it is plausible that the relative flows into active versus passive funds may also be related to investor sentiment. For example, actively managed funds may outperform passively managed funds because active managers can engage in sentiment-timing

[24]in unreported analyses, we also conduct all tests in Table 7 excluding data from 2008 (i.e., the crisis period). Our findings are qualitatively and quantitatively very similar. These results are available upon requests.

(Yadav and Massa, 2012). If investor preferences for tail events are related to investor sentiment, then our earlier findings may merely reflect the impact of investor sentiment on flows into active funds as well as those into equity funds as a whole.

On the other hand, one important distinction of our measures of tail-sensitivity from any single investor sentiment index is that while investor sentiment may capture stronger investor demand for either downside protection or upside potential at a particular point in time, our framework allows for the coexistence of demands for both downside protection and upside seeking. Furthermore, we employ different investor preference proxies reflect separate movements in state prices for upside potential and downside risk. When a sentiment index is high, it could be because investors are less concerned with downside risks, more excited regarding upside potential, or both. Since a single sentiment index does not distinguish between these cases, it therefore cannot differentiate the demand for investments with payoffs in specific parts of the distribution. In contrast, our measures contain more detailed information on investor risk attitudes and can explain the co-existence of investor demand for both upside potential and downside protection. Nevertheless, in this subsection we conduct a robustness analysis for the effect of investor preferences on monthly flows into actively managed funds while controlling for investor sentiment.

We adopt the monthly investor sentiment measure in Baker and Wurgler (2006, 2007). This measure is a composite sentiment index based on the first principal component of a number of proxies for sentiment as suggested in the prior literature.[25] To ensure that we are not merely controlling for systematic risks, we adopt the sentiment index that has been orthogonalized to several macroeconomic conditions. Over our sample period, the correlations between the investor sentiment index and Prelec α and β are -0.20 and 0.27, respectively. Essentially, the more profit seeking and the less risk averse investors are, the higher the overall investor sentiment.

In Table 9, we show estimates from the regression of net flows into active funds (expressed as a percentage of NAV) on option-implied measures of investor risk attitude, controlling for monthly

[25] Specifically, Baker and Wurgler (2006) consider the following proxies for sentiment: the close-end fund discount, turnover, number of IPOs, average first-day returns, equity share in total equity and debt issues, and dividend premiums.

investor sentiment. Similar to Table 6, we again control for category returns, total market returns and flows into passive funds, and separately conduct analyses for individual investment categories among large-cap funds. The result in this table indicates that after controlling for investor sentiment, we still find a significantly negative loading on Prelec α for growth funds and a significantly negative loading on Prelec β for value funds. That is, when investors have a greater preference for upside potential, we observe greater flows into actively managed growth funds. On the other hand, when investors have a stronger downside risk aversion, we observe greater flows into actively managed value funds. As in Table 6, we again find that flows into blend funds load negatively on Prelec β, suggesting that investors seeking downside protection are more likely to put money into large cap blend funds. In addition, although investor sentiment does not have significant explanatory power for flows into active growth and value funds, it has a significantly positive effect on flows into active blend funds.

4.4 The comparison across different investor clienteles within the same investment category

In the previous subsection, we have shown that flows into active funds behave consistently with predictions derived from "tail-sensitive" preferences. It is conceivable that even among investors of active funds, the sensitivity of fund flows to option-implied risk attitude varies across different investor clienteles when there exists significant heterogeneity in their preferences. For example, investors investing in actively managed mutual funds as part of their retirement plans may be more concerned with reducing downside risk as opposed to seeking extreme upside payoffs. On the other hand, retail investors holding mutual funds through traditional mutual fund accounts may have a stronger upside seeking preference given their shorter-term investment objectives. Therefore, in this section we compare the effects of investor risk attitudes on flows into active funds across different investor clienteles.

First, we identify mutual fund investor clienteles using information from Morningstar concerning investor types. Following Chen, Goldstein, and Jiang (2010), we consider a fund share as in the retirement class if it is indicated so by the Morningstar retirement fund indicator or its name carries words such as "Retirement" or "Pension" (or their various abbreviations), or contains a suffix of R, K, or J. For the remaining funds, we further separate them into institutional versus retail funds. Funds or fund shares with a Morningstar institutional fund indicator equal to "yes" or require a minimum initial investment of 100,000 USD or more are considered institutional funds. Note that since individual investors may also invest in institutional shares through their employer-sponsored defined contribution plans, it is unclear whether flows into some institutional shares may reflect more of the investment behaviors of individual investors or those of institutional investors. As a result, we focus on the comparison between two fund clienteles: retirement funds and non-retirement retail funds. We expect that flows into non-retirement retail funds should exhibit greater sensitivities to Prelec α relative to flows into retirement funds, especially in growth oriented investment categories. On the other hand, flows into retirement funds should be more sensitive to Prelec β.

In Table 10, we repeat the analysis in Table 6 for retirement and retail funds separately.[26] Each month, we compute the flows of individual funds as the percentage change in total net assets during the month, adjusted for investment returns (assuming flows occur at the end of each month). We then compute the average flows into each of the two investor clienteles for each Morningstar investment category. Finally, we run time-series regressions of average monthly flows on Prelec α and β for individual investor groups within each Morningstar investment category, controlling for category returns, market returns and passive flows in the same category. Since certain investment categories have too few funds that can be clearly classified into individual investor clienteles (especially in the earlier years), we mainly focus on monthly observations where there are at least 10 funds in an investor clientele. In addition, to facilitate the comparison of flow sensitivities to risk attitudes across different investment clienteles, we standardize average flows into individual clienteles within each investor category so that they all have the same mean (zero) and standard deviation (one). We report t-statistics computed with Newey-West (1987) robust standard errors to account for

[26]For brevity we report results only for large cap funds. For other Morningstar investment categories, our results are qualitatively similar, although not uniformly significant due to the smaller number of funds within these fund categories.

potential autocorrelation in fund flows.

Results in the table indicate that retail funds with the large-growth investment objective have significantly negative loadings on Prelec α. In contrast, large-growth retirement funds have a much smaller loading on this proxy for investor preferences for upside potential. This difference is statistically significant at the 5% level according to the F-test. Similar but smaller differences are observed among large-value and large-blend funds, where retirement funds have statistically insignificant loadings on Prelec α. On the other hand, flows into retirement funds with the large-value or large-blend style are highly sensitive to Prelec β, suggesting that investors in these funds are more concerned with reducing downside risk. Particularly, this sensitivity to the downside risk aversion is at least twice as large in magnitude for retirement funds as for retail funds within the large-value or large-blend category, with the differences statistically significant at the 1% level according to F-tests. Therefore, despite prior evidence of inertia among retirement investors in changing asset allocations (see, e.g., Ameriks and Zeldes, 2001; Madrian and Shea, 2001; and Benartzi and Thaler, 2007), on average flows into retirement funds exhibit much weaker sensitivity to upside potential yet much stronger sensitivity to downside risk aversion, relative to non-retirement retail funds. These flow patterns could potentially reflect the active role played by the sponsors of retirement plans in adjusting the investment options available to plan participants as demonstrated in Sialm, Starks and Zhang (2012).

In summary, using investor clienteles to proxy for heterogeneity in investor preferences for tail events, the cross-sectional evidence in Table 10 validates our earlier finding that investor preferences for tail events can help explain flows into actively managed funds.

4.5 Active funds' exposures to option-based strategies

Our findings so far suggest that investors sensitive to tail events may prefer actively managed value funds because they can help reduce downside risk. At the same time, these investors may also prefer actively managed growth fund because they can help them better achieve upside potential. We next analyze the performance of individual fund categories to see whether returns of active funds indeed exhibit characteristics that better cater to investors with tail-sensitive preferences than passively managed funds do.

We use SPX options to construct portfolios that capture either downside risk aversion or upside-seeking performance characteristics. For the risk aversion feature, we construct ATM straddles that take long positions in both ATM call and put options. Since index straddles deliver a positive payoff if the underlying index is more volatile than expected, holding a straddle essentially insures against large losses of the underlying portfolio. As to the proxy for upside-seeking, we simply use returns of ATM or OTM call. Following Agarwal and Naik (2004), at the beginning of each month we select options that expire in the following month and compute returns from the beginning of the current month to the beginning of the next month. Option returns are normalized by their sample standard deviations.

In Table 11, we examine the time-series monthly returns of active versus passive fund portfolios. The individual fund portfolios for large-growth, large-value and large-blend investment categories are formed as value-weighted portfolios with the weight being prior-month total net assets.[27] Both fund returns and factor returns are expressed in percentage. To adjust for differences in fund characteristics and risks, we fit fund returns into the Carhart (1997) four-factor model, but augment it with straddle returns, as well as ATM or OTM call returns.[28] These time-series regression analyses are conducted separately for individual investment categories since funds catering to different investor preferences are unlikely to have the same exposure to various option-like strategies. We report t-statistics computed with Newey-West (1987) robust standard errors to account for potential autocorrelation in aggregate fund returns.

For actively managed funds, we find that returns of both large-value and large-blend funds have statistically significant loadings on straddle returns, while returns of large-growth funds have significant loadings on ATM or OTM call returns. These loadings are also economically significant

[27]Since we focus on large-cap funds, the correlation between equal-weighted and value-weighted fund portfolio returns is about 0.98.

[28]The Carhart (1997) four-factor model includes four factors: market return, Fama-French SMB and HML factors, and the momentum factor.

and often exceed 10 percent.[29] Consistent with earlier observations on return moments, passively managed funds do not exhibit significant loadings on any of the option-based factors, regardless of their investment categories. Thus, for investors seeking downside risk protection or aspiring for upside potential in portfolio returns, active funds represent an attractive investment option. Under active management, they can deliver returns that have exposures to option-based strategies which are difficult and/or costly to implement for an average fund investor with a small amount of investable funds. Passive funds, while cheaper, cannot offer close substitutes to these return characteristics of active funds.

5 Robustness Analyses

5.1 Fund flows and non-parametric measures of tail-sensitivity

To have a model-free measure of the shape of the weighting function, we construct alternative measures of the slope of the pricing kernel. We evaluate the shape of the kernel at different levels of moneyness and characterize its slope with respect to the cumulative physical distribution function. We construct the slopes as follows. Given the return distribution function under the physical measure, $P(R)$, we define the slope via the area under the pricing kernel with respect to probability P. That is, for a given return R_0 and cumulative probability $P_0 = P(R_0)$, the area is $\int_0^{P_0} m(P)dP$ and the (left) slope is defined as $\frac{\int_0^{P_0} m(P)dP}{P_0}$. The right slope is defined similarly as $\frac{\int_{P_0}^1 m(P)dP}{1-P_0}$. The pricing kernel is scaled so that $\int_0^1 m(P)dP = 1$. These definitions have an intuitive interpretation. Note that we can write:

$$\int_0^{P_0} m(P)dP = \int_0^{R_0} m(P)pdR = Q(R_0) \tag{5}$$

Thus, our definitions of the slopes correspond to the ratio of risk-neutral to physical cdf in the left tail and the ratio of the risk-neutral and physical de-cumulative probabilities in the right tail.[30] The slopes measure how much risk neutral probability mass is concentrated in the tails relative

[29] Since option strategy returns are normalized by their standard deviations, the coefficients on option-based factors show the change in fund portfolio returns in response to one standard deviation move in option strategy returns.

[30] Note that these slopes can also be interpreted using the probability weighting function G corresponding to the constant marginal utility. In general the pricing kernel is given by $m = u'(R)Z(P_R)$. If we set $u' = 1$ then $m = Z$

to the underlying physical probability. A value above 1 corresponds to overweighting and below 1 corresponds to underweighting; a value above 1 for the right tail measure indicates a U-shaped pricing kernel over some ranges of moneyness.

We construct the slopes corresponding to moneyness of 0.97 for the left tail to capture the attitude toward downside risk and 1.03 for the right tail to capture the attitude toward upside potential. We use points on a moneyness scale rather than on cumulative probability because physical and risk neutral distributions are time-varying, while constant moneyness allows us to compare slopes across different months.

We also perform a normalization of the upside slope in order to better separate proxies for downside risk versus upside potential. Table 12 shows correlations between various measures of risk attitude. The left tail measure constructed from the 3% out-of-the-money threshold to the left and labeled as "SDF (dwn)" measures downside risk aversion while the right side measure constructed from 3% OTM to the right and labeled "SDF (up)" measures upside-seeking preference. The correlation between these raw slopes is relatively high (0.84) because they both increase with the convexity of the pricing kernel. To better separate these two proxies, we use the upside slope normalized by the downside slope (labeled "SDF (up norm.)") in the regressions . This normalization corrects for the common variation in the slopes. As seen from Table 12, the correlation of the normalized upside slope with the downside slope drops to 0.15. Note, however, that normalization has a very small effect on the correlation of the upside slope with (orthogonalized) α: the correlation is -0.84 for the raw upside SDF slope and -0.83 for the normalized upside SDF slope. Recall that lower α implies greater upside-seeking sentiment in preferences and therefore the normalized upside slope of the SDF captures this sentiment well. On the other hand, the downside slope is correlated with Prelec β and captures the downside risk aversion. In Figure 7, we show the time series of the

and we obtain:

$$\int_0^{P_0} m(P)dP = \int_0^{P_0} Z(P)dP \equiv G(P_0)$$

Therefore, our pricing kernel slopes coincide with the slopes of G defined as $G(P_0)/P_0$ on the left and $(1-G(P_0))/(1-P_0)$ on the right side of the distribution.

SDF slopes constructed from 28-days options.

The results of flow regressions using the non-parametric measures of risk attitude are shown in Table 13. We first consider the results for large-growth funds. The coefficient on the (normalized) upside measure (SDF up) is significantly positive, consistent with our earlier result using the parametric specification of Prelec's function. When the upside sentiment is high, flows to actively managed large-growth funds are larger. On the other hand, we find a positive coefficient on the left tail measure (SDF dwn) for value funds. This suggests that when option prices imply more overweighting of the left tail, more fund flows will be directed toward active value funds. Interestingly, for value funds we also see a significant negative coefficient on the upside slope suggesting that high upside sentiment is associated with lower flows to active value funds. Overall, the results in Table 13 are consistent with those using the parametric specification of the weighting function. Our findings are therefore not sensitive to alternative measures of risk attitudes.

5.2 Results for medium-cap and small-cap funds

Our analyses on the relationship between flows into active funds and tail-sensitivity measures so far focus on large-cap funds. For completeness, we now present the results of our baseline analysis for middle- and small-cap categories. We note that for some investment categories the data availability of Morningstar aggregate flows into passive benchmarks considerably restricts the length of our time-series of category flows.

Table 14 shows the result from regressions of fund flows on Prelec α (orthogonalized) and β. We find that medium and small-cap growth fund flows are negatively related to Prelec α. The magnitudes of the coefficients are similar to those estimated for large-cap funds, although statistically the result for small-cap category is somewhat weaker. On the other hand, for active medium and small-cap value funds, we find that flows are negatively related to Prelec β. Once again, the coefficients have similar magnitudes relative to large-cap funds in Table 6, although the coefficient of Prelec β is not statistically significant for medium-cap value funds. The latter finding is perhaps due to considerably shorter time-series of data for this category. Lastly, similar to the finding for large-cap category, flows into medium and small-cap blend funds are significantly negatively related to Prelec β, indicating that greater downside risk aversion tends to increase flows into these funds. We conclude from these results that the relation between flows into active funds and investor risk attitude is largely consistent across small, medium and large-cap funds.

6 Conclusion

Preferences for tail events have been identified as a salient feature of individual risk attitudes in numerous independent studies in decision sciences. We propose that the demand for actively managed funds may be associated with investor preferences for return distributions tilted toward either upside potential or downside risk protection (i.e., tail-sensitive preferences). We evaluate this hypothesis from several angles and find strong empirical and theoretical support.

Since our study uncovers a new mechanism behind investor demand for actively managed funds, it suggests that fund managers may better structure their active portfolios to cater to different investor clienteles. Our results also have implications for the performance evaluation of active funds. If investors pay attention to the tail behavior of fund returns, then traditional performance evaluation may be expanded to reflect that.

Appendix A Description of the options data and filtering procedures

To exclude illiquid options, we discard the in-the-money options, options with zero trading volume or open interest, and the options with quotes less than 3/8. We also exclude options that allow for arbitrage across strikes[31]. The average number of options is approximately 34 each month. There are more OTM puts than OTM calls, averaging about 16 puts that are at least 3% OTM versus about 7 calls that are at least 3% OTM each month for the 28-day options. The average Black-Scholes implied volatilities exhibit the "smirk" shape as documented in the option pricing literature. The average trading volumes for the OTM options suggest they are quite liquid compared with the near-the-money options.

Next, we apply the procedure from Aït-Sahalia and Lo (1998) to address the problem of non-synchronous prices between the option and underlying index and the unobserved dividend process in the data.[32][33] Specifically, on each day t the forward price $F_t(T)$ of maturity T and the spot price S_t are linked via the no-arbitrage condition:

$$F_t(T) = S_t e^{\left(r_{t,T} - \delta_{t,T}\right)(T-t)}, \tag{A.1}$$

where $r_{t,T}$ is the risk free rate and $\delta_{t,T}$ is the dividend yield from t to T. This forward price can be inferred from option prices through put-call parity. That is, the call price $C(t)$ and put price $J(t)$ of the same maturity T and strike price X satisfy:

$$C\left(S_t, X, T-t, r_{t,T}, \delta_{t,T}\right) - J\left(S_t, X, T-t, r_{t,T}, \delta_{t,T}\right) = e^{-r_{t,T}(T-t)}\left[F_t(T) - X\right]. \tag{A.2}$$

This relation is independent of any specific option pricing model. Using near-the-money call and put option prices, we can derive the implied forward price of the underlying index.[34] This procedure

[31]Specifically, we exclude options that violate the monotonicity constraint across strikes but keep options that violate the convexity constraint which is more frequent.

[32]The underlying index prices are usually recorded at a different time from the option prices within the day, inducing nontrivial pricing biases as suggested in Fleming, Ostdiek, and Whaley (1996).

[33]We do not use the dividend yields provided in OptionMetrics because they are not observable ex ante.

[34]We use near the money options since they are more liquid. In addition, prior studies have shown that the put-call parity holds well for them.

removes the problem of matching option prices and the underlying spot price by their recording times. Next, we compute the in-the-money call prices from the out-of-the-money puts using the put-call parity and implied forward price. This is necessary when we later estimate the risk-neutral density by taking derivatives of the call price with respect to the strike. The index returns in our setting are the ratios of the forward prices, $F_T(T)/F_t(T) = S_T/F_t(T)$, rather than the spot prices S_T/S_t. For stochastic dividend processes, returns on the forward prices are better proxies for returns on the total wealth process by not excluding dividends.

Appendix B Estimating Probability Weighting Function from Empirical Pricing Kernel

B.1 SDF with probability weighting function

To derive the SDF we use a static model with utility function in Eq. (1) over terminal wealth w. Assume that markets are complete, the consumer has initial wealth w_0, and he has access to $N+1$ traded securities. Let θ^k be portfolio share of investment in security k as and R^k be its return. The portfolio constraint implies $\theta^0 = 1 - \sum_{k=1}^{N} \theta^k$ and the terminal wealth is given by

$$w = w_0 \left(\sum_{k=0}^{N} R^k \theta^k \right). \tag{B.3}$$

Using results from Ai (2005) on differentiability of RDEU with respect to continuously distributed random variables, the first order optimality condition with respect to θ^k is given by

$$E\{u'(w)Z(P)(R^k - R^0)\} = 0 \;\; k = 1, ..., N. \tag{B.4}$$

We can write this equation in a standard stochastic discount factor form as

$$m = u'(w)Z(P). \tag{B.5}$$

We then can write the risk-neutral probability density function (PDF) q as

$$q = \frac{m}{Em} \times p = \frac{u'(w)Z(P)p}{E\{u'(w)Z(P)\}}. \tag{B.6}$$

If we denote $R \equiv \frac{w}{w_0}$ gross return on total investor wealth and specialize to power utility $u(w) = \frac{w^{1-\gamma}}{1-\gamma}$, after normalizing initial wealth to one, we can rewrite the SDF and the price density as

$$m = u'(R)Z(P) \text{ and} \tag{B.7}$$

$$q = \frac{m}{Em} \times p = \frac{R^{-\gamma}Z(P)p}{E\{R^{-\gamma}Z(P)\}}, \tag{B.8}$$

where P and p now denote the CDF and PDF of R. This SDF is positive everywhere and is arbitrage-free.

B.2 Estimation of probability weighting functions

To directly estimate the function G we use the following approach. Given the physical distribution function $P(\cdot)$ and its density $p(\cdot)$ and the risk-neutral distribution $Q(\cdot)$ and its density $q(\cdot)$ over the returns R, we proceed as follows. For a specific P_0 with corresponding return R_0 such that $P(R_0) = P_0$, we have

$$\begin{aligned} G(P_0) = G(P^{-1}(R_0)) = \int_0^{P_0} Z(P)dP \\ = \int_0^{R_0} Z(P(R))p(R)dR = c\int_0^{R_0} \frac{q(R)}{u'(R)}dR \\ = c\left[\frac{Q(R_0)}{u'(R_0)} + \int_0^{R_0} Q(R)\frac{u''(R)}{u'(R)^2}dR\right], \end{aligned} \tag{B.9}$$

where $u'(\cdot)$ is the marginal utility and the normalizing constant $c = \left(\int_0^\infty \frac{q(R)}{u'(R)}dR\right)^{-1}$. If the utility function is linear, we have $G(R_0) = Q(R_0)$, where the probability weighting amounts to the change of measure.

We can estimate only combined SDF and cannot separately identify the marginal utility and probability weighting density. Therefore, we only assume the utility to be non-convex. In this paper we use $u(w) = w$. However, Polkovnichenko and Zhao (2012) investigate other popular specifications and show that this choice does not affect significantly the estimates of Prelec α and mainly affects the level of Prelec β.

To estimate risk-neutral density q, we apply the constrained local polynomial method with the guidance of the semi-nonparametric method. Specifically, we have three steps in our procedure.

First, the risk-neutral moments are estimated based on the spanning result from Bakshi and Madan (2000) and Bakshi, Kapadia, and Madan (2003). Second, we use the Gram-Charlier series expansion (GCSE) to estimate semi-nonparametric risk-neutral density from the moments estimates. Finally, we estimate the density using the constrained local polynomial method in which the smoothing parameter, the bandwidth, is chosen by minimizing the simulated mean squared errors (MSEs) using the bootstrapped samples generated from the semi-nonparametric estimates. There are two advantages in this procedure. First, the semi-nonparametric estimates provide a robust benchmark for choosing the bandwidth via simulation.[35] Second, the semi-nonparametric estimates themselves can be used as a robust check for conclusions based on the nonparametric estimates.

We also need to estimate the distribution function under the physical measure to compute the probability weighting function. Consistent with the time-varying estimates of the risk-neutral distribution, we allow the physical distribution to vary month by month. Because we estimate the distribution from time series of the daily S&P 500 index returns, we rely on simulation to generate estimates for returns over the horizons of our interest. We also want to employ the most widely used models for the data generating process of daily returns as it resembles most closely the aggregate view of market participants. To this end, we use the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model of Nelson (1991). Furthermore, we use the filtered innovation terms from the EGARCH model for simulation to avoid making distributional assumptions on them. Overall, our procedure follows closely Rosenberg and Engel (2002).

To estimate Prelec function parameters we approximate the nonparametric estimators by fitting the two-parameter Prelec function. In this paper we use pricing kernels estimated each month from options with 28 days to maturity. Assuming $u(w) = w$, we construct nonparametric estimators of the weighting function and then approximate them with the best-fit Prelec function $G(P) = G(P^{\beta}; \alpha)$ from Eq. (4).

[35]The reason that simulation is necessary for the choice of the bandwidth is that we are dealing with small samples and finite sample bias and variance are not available especially for the constrained local polynomial method proposed in Aït-Sahalia and Duarte (2003).

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Figure 1: **Aggregate monthly fund flows.** We report aggregate monthly fund flows for active and passive funds during each year from 1996 to 2008.

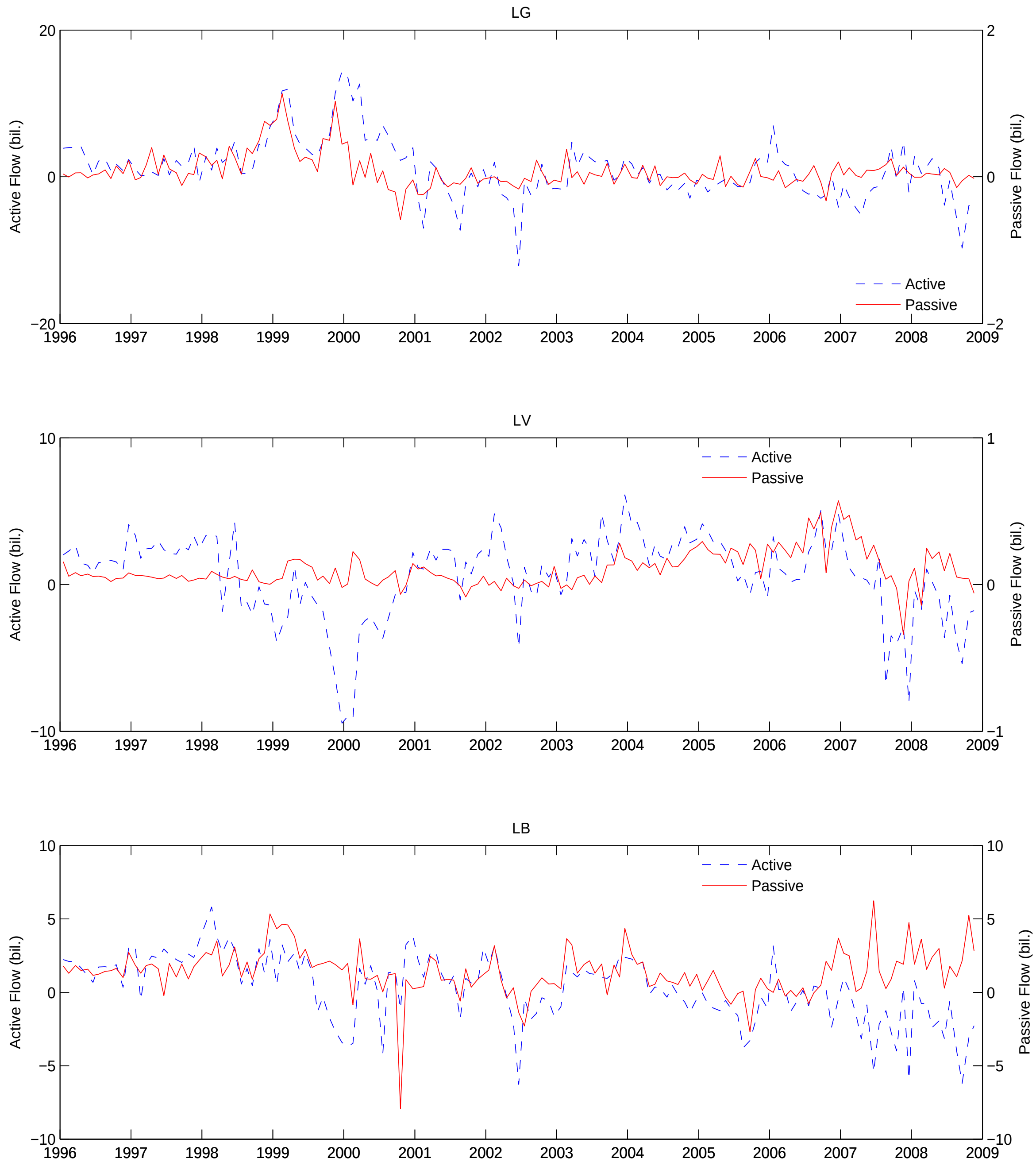

Figure 2: **Prelec probability weighting functions and corresponding density functions.** Top panels show the Prelec probability weighting functions and corresponding density functions for inverse-S shape with $\beta = 1$ and several values of $\alpha \leq 1$. Bottom panels show the Prelec probability weighting and corresponding density functions for concave shape with $\alpha = 1$ and several values of $\beta \leq 1$.

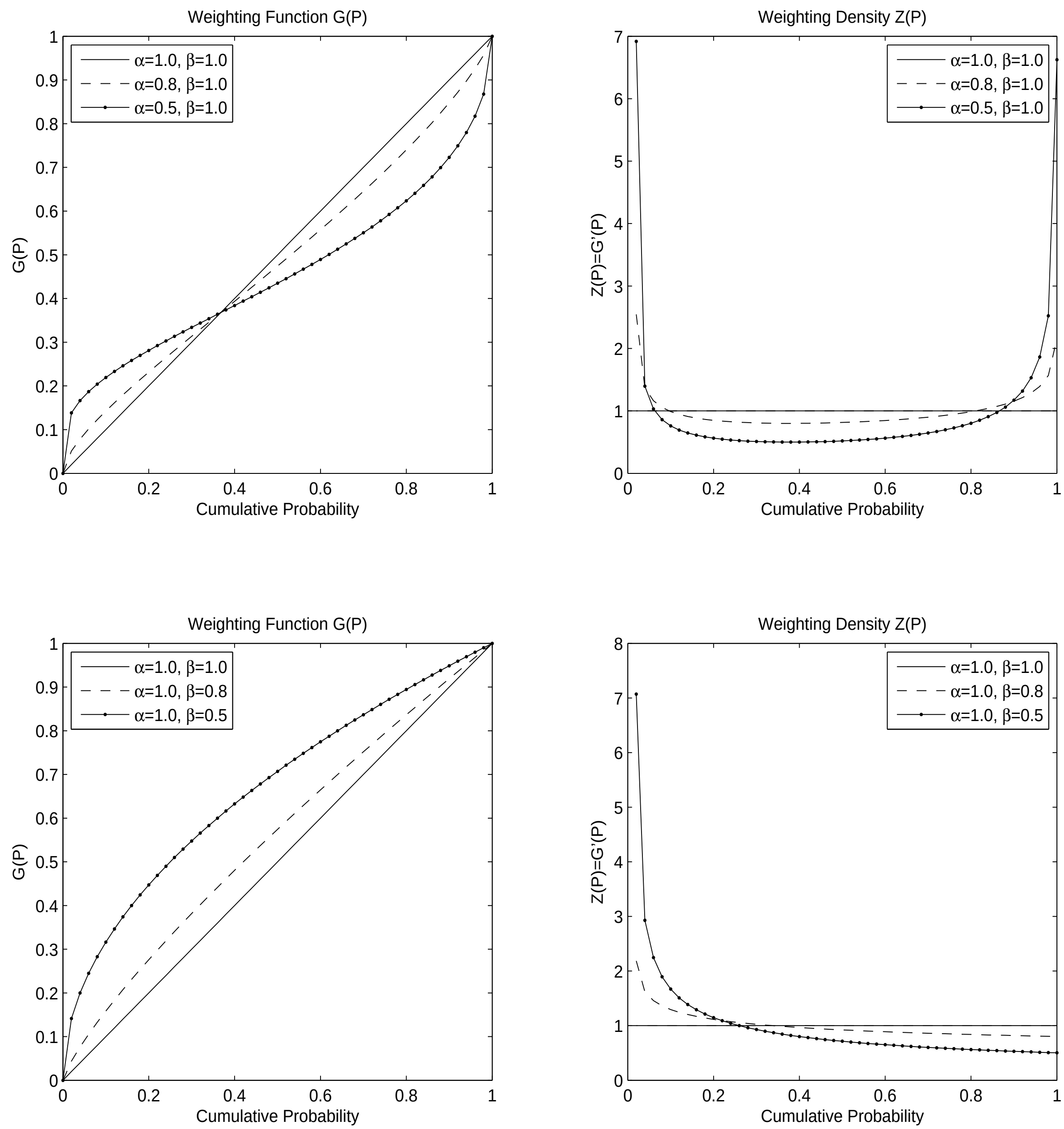

Figure 3: **Difference in certainty equivalent (CE) returns of active and passive funds.** We use simulated return series from the Pearson distribution system to construct three-year and five-year returns for passive and active funds with the growth and value investment objectives matching bootstrapped moments. Using simulated returns we compute differences between CEs for active and passive funds in each investment category. The figure reports CE differences for a range of weighting function parameters.

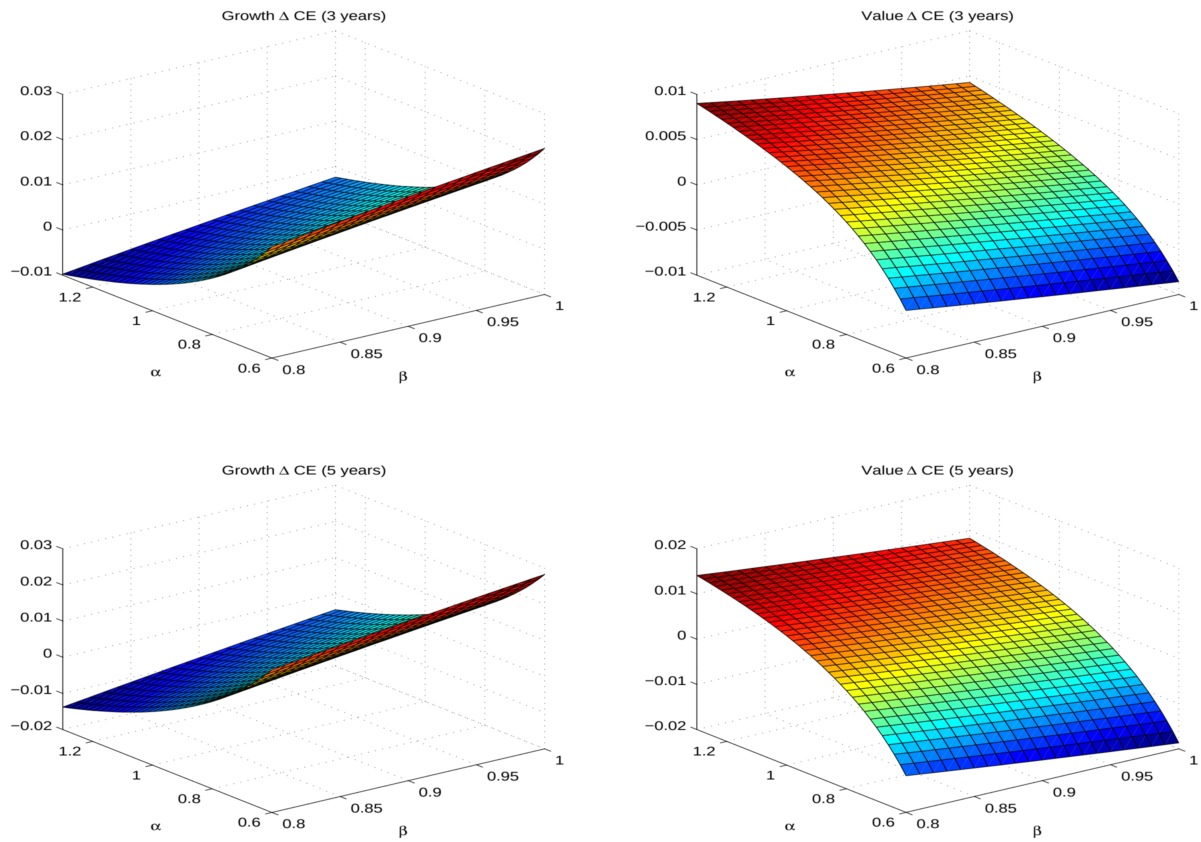

Figure 4: **Fraction of portfolio allocated to the active value fund.** We use fund returns from 1996 to 2007, to generate long bootstrapped time series of monthly returns. Passive and active funds returns are sampled at the same time to preserve correlation. Monthly returns are cumulated into three and five years holding periods. Portfolio assets include: passive and active fund and a risk free asset with a constant return of two percent per annum. The figures show $\theta_f(n)$, the fraction of risky assets allocated to the active fund and $n = \{3, 5\}$ is the holding period. Top two panels show optimal portfolio fraction as a function of Prelec α, and the bottom two panels as a function of Prelec β. Utility is CRRA with power parameter $\gamma = 1$.

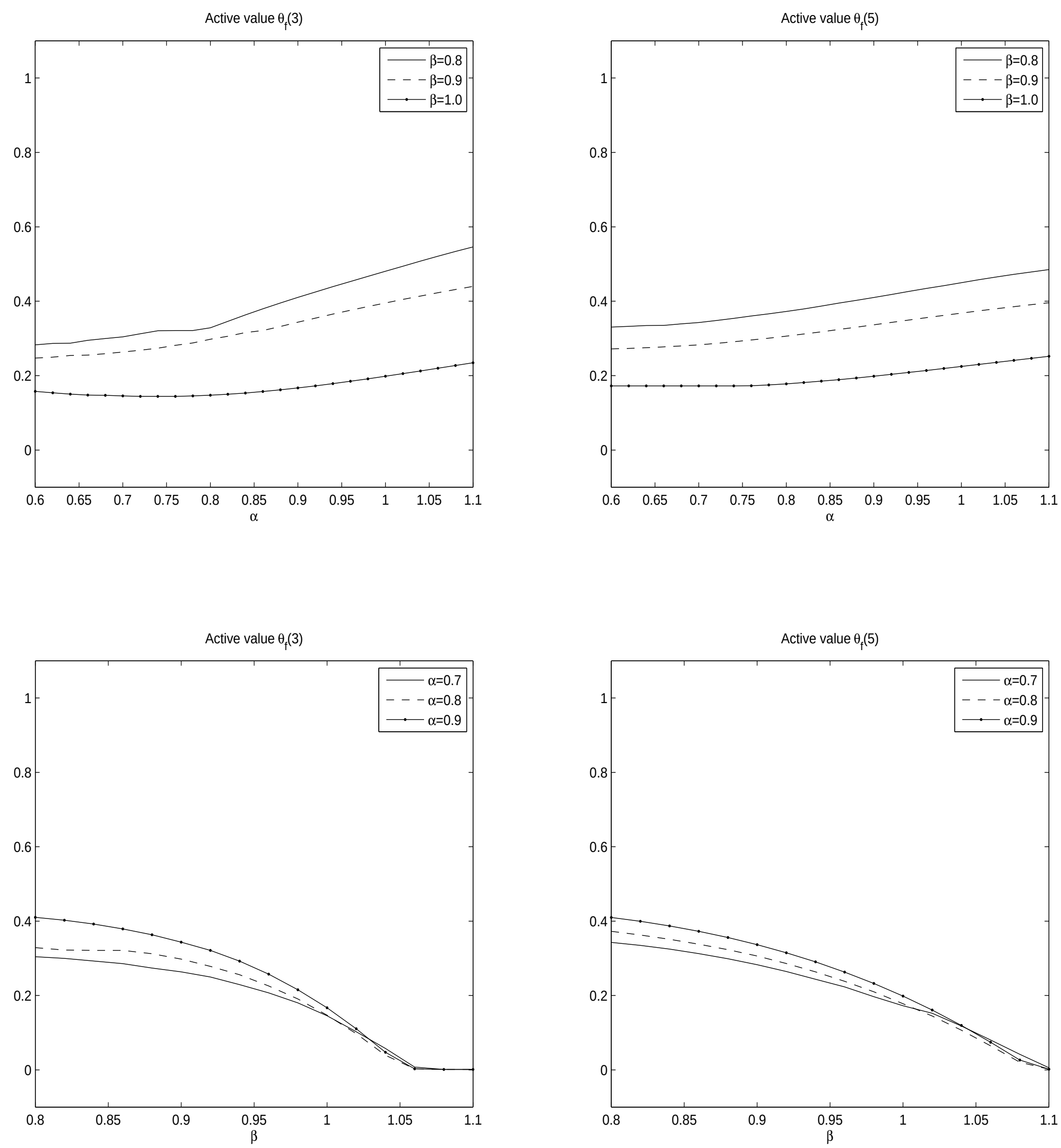

Figure 5: **Fraction of portfolio allocated to the active growth fund.** We use fund returns from 1996 to 2007, to generate long bootstrapped time series of monthly returns. Passive and active funds returns are sampled at the same time to preserve correlation. Monthly returns are cumulated into three and five years holding periods. Portfolio assets include: passive and active fund and a risk free asset with a constant return of two percent per annum. The figures show $\theta_f(n)$, the fraction of risky assets allocated to the active fund and $n = \{3, 5\}$ is the holding period. Top two panels show optimal portfolio fraction as a function of Prelec α, and the bottom two panels as a function of Prelec β. Utility is CRRA with power parameter $\gamma = 0.2$.

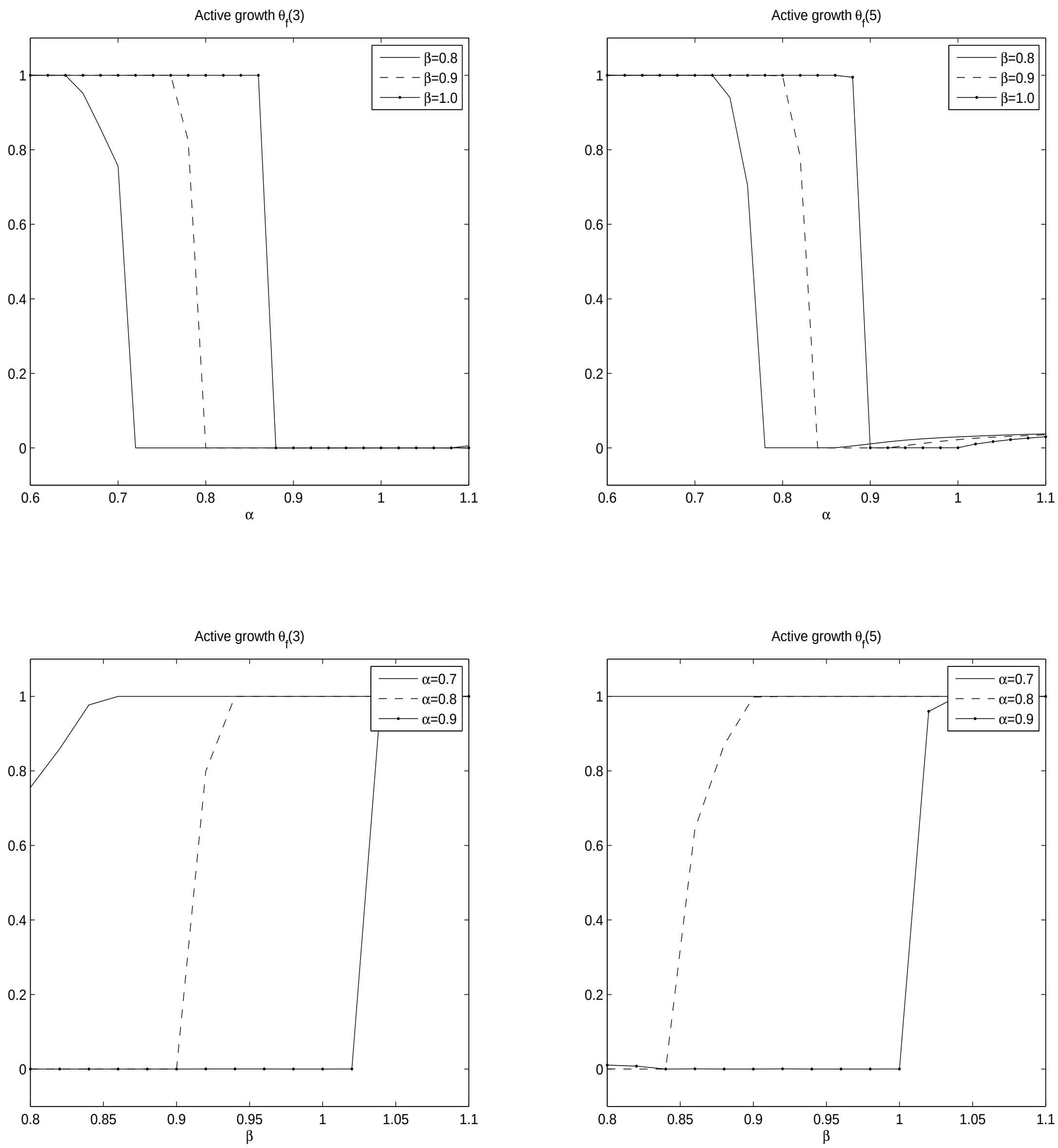

Figure 6: **Coefficient values for the two-parameter Prelec function.** We estimate the Prelec parameters α and β by minimizing the distance between the Prelec function implied values and the nonparametric estimates of the probability weighting functions obtained from the 28-day options. This figure shows the estimated α and β, and the Prelec α that is orthogonalized to β (a residual from a time series regression) during the sample period from January 1996 to December 2008. The CRRA parameter is set to $\gamma = 1$. The nonparametric estimates are obtained from the constrained local linear estimator with bandwidth chosen based on the simulated samples of the OTM option prices. We use the A-type and C-type GCSE semi-nonparametric estimates for this simulation.

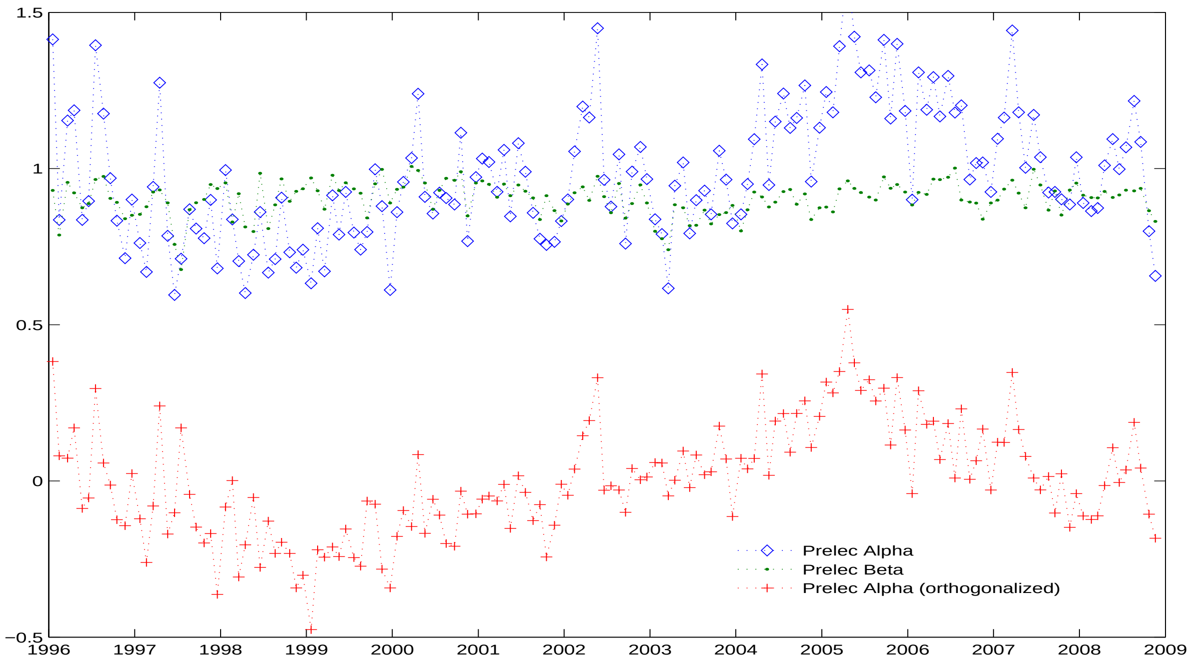

Figure 7: **Slopes of the pricing kernel.** We plot the slopes of the pricing kernel m obtained from 28-day options on the S&P500 index for ±3% out-of-the-money thresholds, that is, a moneyness of 0.97 and 1.03. The sample period is from January 1996 to December 2008. We use returns corresponding to a moneyness of 0.97 for the left slope and returns corresponding to a moneyness of 1.03 for the right slope. The upside slope is normalized by the downside slope as discussed in Section 5.

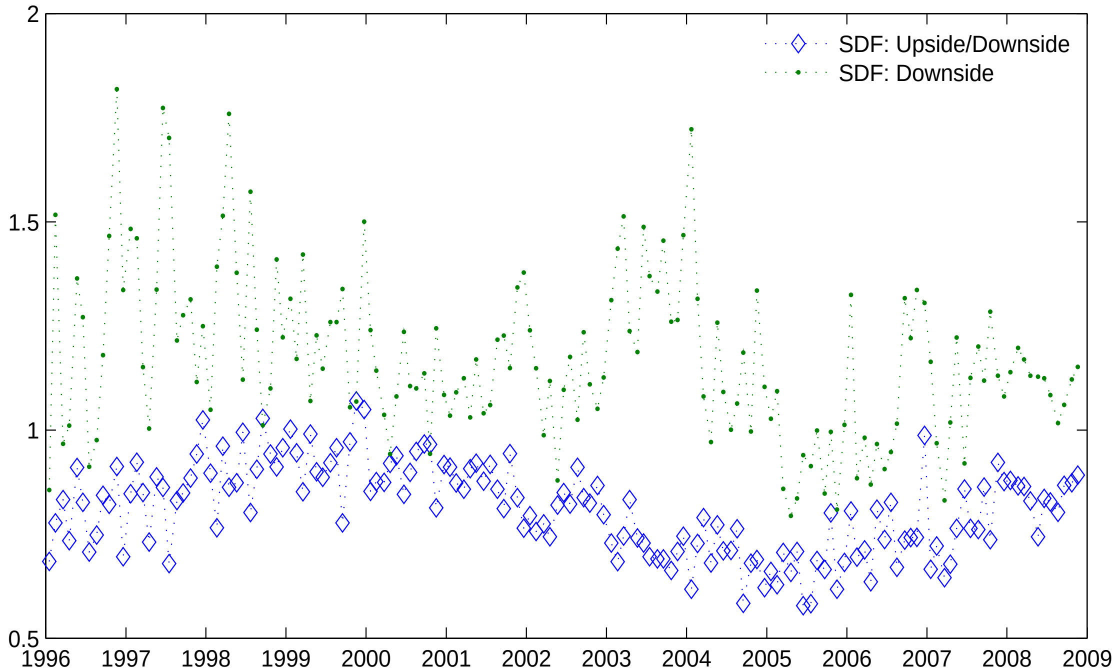

Table 1: **Summary statistics of aggregate fund flows and total net assets.** This table reports the average monthly aggregate dollar net flows (in billions of US dollars) and percentage net flows relative to total net asset values along with aggregate TNAs (in billions of US dollars) for actively and passively managed funds during the period from 1996 to 2008.

	Large			Medium			Small		
	Blend	Growth	Value	Blend	Growth	Value	Blend	Growth	Value
					Active				
Flow ($, bill.)	0.0504	0.5875	0.3487	0.1242	0.3277	0.2453	0.2336	0.1533	0.1085
Flow (% of TNA)	0.1194	0.1076	0.1326	0.3792	0.3664	0.6163	0.7994	0.4177	0.6878
TNA ($, bill.)	434.8	639.7	407.6	58.5	115.4	48.3	55.0	58.3	37.8
					Passive				
Flow ($, bill.)	1.3462	0.0752	0.0957	0.2053	0.0109	0.0208	0.0901	0.0272	0.0391
Flow (% of TNA)	0.7672	1.7617	1.2377	1.1714	63.0840	28.1160	0.8502	2.7115	0.8653
TNA ($, bill.)	243.4	12.4	9.8	18.9	0.1	0.3	16.2	1.2	7.3

Table 2: **Summary statistics of individual fund level information for actively managed funds.** This table reports summary statistics for TNA (in millions of US dollars), monthly returns (in percent) and monthly flows (in percent of TNA) for individual active funds. The table shows the mean, median, standard deviation and 25-th and 75-th percentiles for each investment category.

	Large			Medium			Small		
	Blend	Growth	Value	Blend	Growth	Value	Blend	Growth	Value
TNA ($ mil.)									
Mean	664	953	803	424	394	349	258	216	220
Median	100	122	102	83	94	78	87	73	73
Std.	2819	4054	3323	1642	1031	956	499	515	469
P25	37	38	36	29	31	29	32	30	30
P75	366	469	401	280	317	256	263	199	212
Return (%)									
Mean	0.41	0.39	0.45	0.60	0.54	0.62	0.65	0.54	0.70
Median	0.39	0.37	0.45	0.58	0.50	0.64	0.63	0.52	0.69
Std.	1.51	2.05	1.38	2.37	2.38	1.78	1.97	2.48	1.72
P25	-0.40	-0.77	-0.33	-0.71	-0.90	-0.40	-0.52	-1.00	-0.29
P75	1.21	1.52	1.24	1.91	1.99	1.67	1.79	2.06	1.68
Flow (%)									
Mean	2.64	2.39	2.20	2.27	2.36	3.40	3.02	2.16	2.74
Median	0.12	-0.01	0.07	0.06	-0.04	0.54	0.24	0.06	0.39
Std.	29.21	23.95	18.44	16.24	21.41	20.68	23.70	18.71	17.00
P25	-1.21	-1.29	-1.26	-1.46	-1.53	-1.25	-1.40	-1.63	-1.55
P75	2.35	2.23	2.25	2.47	2.39	3.51	2.62	2.63	3.41

Table 3: **Return moments for active and passive funds.** We use fund returns from 1996 to 2007 or 1996 to 2008 to generate 250,000 bootstrapped time series. Using bootstrapped distributions we compute the confidence intervals and the averages for time-series mean, volatility, skewness and kurtosis of monthly returns of individual actively and passively managed funds. Statistical significance of the difference in moments between active and passive funds at 5% and 10% significance levels are indicated by ** and *, respectively.

	Panel A: 1996-2007			
	Mean (%)	St. Dev. (%)	Skewness	Kurtosis
LG Active	0.77	5.26**	-0.41	4.92**
LG Passive	0.82	4.69	-0.46	3.06
LV Active	0.82	3.90**	-0.55	4.89
LV Passive	0.86	4.24	-0.62	4.44
LB Active	0.78	4.12	-0.55	4.38
LB Passive	0.83	4.22	-0.54	3.63
	Panel B: 1996-2008			
	Mean (%)	St. Dev. (%)	Skewness	Kurtosis
LG Active	0.40	5.55**	-0.55	4.83*
LG Passive	0.47	5.01	-0.66	3.59
LV Active	0.48	4.29	-0.90	5.66
LV Passive	0.53	4.51	-0.78	4.69
LB Active	0.42	4.51	-0.87	5.22
LB Passive	0.49	4.52	-0.74	4.14

Table 4: **Conditional means for active and passive funds.** We use fund returns from 1996 to 2007 or 1996 to 2008 to generate 250,000 bootstrapped time series. Using bootstrapped distributions we compute the confidence intervals and conditional expected returns in both the best and worst 5-th, 10-th and 25-th percentiles of return distributions. Statistical significance of the difference in moments between active and passive funds at 5% and 10% significance levels are indicated by ** and *, respectively.

Panel A: 1996-2007						
		Lowest			Highest	
	5%	10%	25%	25%	10%	5%
LG Active	-11.98	-9.44	-5.85	6.92	9.41*	11.15**
LG Passive	-10.39	-8.48	-5.35	6.55	8.14	8.69
LV Active	-8.81	-6.60*	-4.10**	5.42**	7.28	8.39
LV Passive	-9.59	-7.30	-4.58	5.86	7.86	8.73
LB Active	-9.31	-7.20	-4.46	5.69	7.46	8.50
LB Passive	-9.33	-7.56	-4.63	5.92	7.45	8.33
Panel B: 1996-2008						
		Lowest			Highest	
	5%	10%	25%	25%	10%	5%
LG Active	-13.36	-10.53	-6.71	6.76	9.11*	10.82**
LG Passive	-11.73	-9.52	-6.17	6.39	7.98	8.59
LV Active	-10.78	-8.03	-4.99	5.29**	7.08*	8.18
LV Passive	-10.95	-8.28	-5.32	5.69	7.65	8.60
LB Active	-11.18	-8.60	-5.37	5.56	7.26	8.33
LB Passive	-10.57	-8.58	-5.43	5.78	7.27	8.24

Table 5: **Conditional means for active and passive funds under different market conditions.** We use fund returns from 1996 to 2007, to generate 250,000 bootstrapped time series. Using bootstrapped distributions we compute the confidence intervals and conditional expected returns in both the best and worst 5-th, 10-th and 25-th percentiles of the return distributions. To condition on low and high market returns, the sample is divided based on 6-months lagged market return, including the current month. Statistical significance of the difference in moments between active and passive funds at 5% and 10% significance levels are indicated by ** and *, respectively.

	Low market return					
		Lowest			Highest	
	5%	10%	25%	25%	10%	5%
LG Active	-13.14	-10.41	-6.80	7.13	9.23	10.85
LG Passive	-10.94	-9.05	-6.03	6.67	8.33	9.12
LV Active	-9.39	-7.01*	-4.45**	5.80*	7.58	9.03
LV Passive	-10.60	-7.97	-5.31	6.43	7.99	8.89
LB Active	-9.73	-7.85	-5.02	6.04	7.75	8.99
LB Passive	-9.37	-8.17	-5.21	6.25	7.96	8.90
	High market return					
		Lowest			Highest	
	5%	10%	25%	25%	10%	5%
LG Active	-9.96	-7.57	-4.82	6.55	9.11	11.14**
LG Passive	-9.16	-7.20	-4.45	6.17	7.64	7.91
LV Active	-7.76	-5.79	-3.66	4.94	6.70	7.72
LV Passive	-7.98	-6.04	-3.80	5.26	7.31	8.57
LB Active	-7.91	-5.96	-3.83	5.24	6.87	7.86
LB Passive	-7.86	-6.05	-3.86	5.52	6.73	7.50

Table 6: **Flows into active funds as a function of option-implied risk attitude.** This table reports the result from regressing average monthly flows into actively managed funds on Prelec α and β, controlling for average flows into passive funds of the same investment category, lagged category returns, and market returns as proxied by average monthly CRSP value-weighted index returns during the prior six months. Prelec α is orthogonalized against β. Time-series regressions are performed separately for individual Morningstar investment categories. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors.

Panel A: 1996-2008						
	Large Growth		Large Value		Large Blend	
	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
Const.	-0.5393	-0.86	3.4555	2.66	0.8128	2.07
Prelec Alpha	-0.6802	-2.05	1.106	1.61	-0.012	-0.04
Prelec Beta	0.6329	0.87	-3.7282	-2.45	-1.0005	-2.25
Market Ret.	0.0929	4.92	0.0347	0.57	0.0458	1.95
Category Ret.	0.0314	5.28	0.0514	5.02	0.0186	2.78
Passive Flow	4.9518	5.55	2.6403	1.00	0.75	3.74
Adj. R-sq	0.4364		0.2151		0.4498	
N (obs.)	155		155		155	
Panel B: 1996-2007						
	Large Growth		Large Value		Large Blend	
	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
Const.	-0.5970	-0.96	3.2442	2.42	0.7660	1.71
Prelec Alpha	-0.6575	-1.93	1.1936	1.65	0.0193	0.07
Prelec Beta	0.7046	0.97	-3.4534	-2.19	-0.9250	-1.86
Market Ret.	0.0927	4.58	0.0290	0.43	0.0219	0.97
Category Ret.	0.0282	4.30	0.0526	3.64	0.0087	2.16
Passive Flow	4.9530	5.55	1.9532	0.73	0.8643	4.75
Adj. R-sq	0.4045		0.1893		0.4640	
N (obs.)	143		143		143	

Table 7: **Flows differences between active versus passive funds as a function of option-implied risk attitude.** This table reports the result from regressing the average monthly flow differences between actively and passively managed funds (as a percentage of the sum of TNA for both types of funds in the previous month) on Prelec α and β, controlling for lagged category returns, and market returns as proxied by the average monthly CRSP value-weighted index returns during the prior six months. Prelec α is orthogonalized against β. Time-series regressions are performed separately for individual Morningstar investment categories. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors.

	Large Growth		Large Value		Large Blend	
	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
Const.	-0.5887	-0.86	3.3922	2.63	0.6233	1.31
Prelec Alpha	-0.9922	-2.70	1.1797	1.84	0.1145	0.53
Prelec Beta	0.7320	0.93	-3.6225	-2.41	-0.8528	-1.58
Market Ret.	0.1142	4.92	0.0411	0.68	0.0334	1.25
Category Ret.	0.0346	6.07	0.0526	5.75	0.0168	2.18
Adj. R-sq	0.3530		0.2101		0.0849	
N (obs.)	155		155		155	

Table 8: **Flows to active funds as a function of option-implied risk attitude controlling for business cycles.** This table reports the result from regressing the average monthly flows into actively managed funds on Prelec α and β, controlling for the average flows into passive funds of the same investment category, lagged category returns, and NBER recession indicator. Prelec α is orthogonalized against β. Time-series regressions are performed separately for individual Morningstar investment categories. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors.

	Large Growth		Large Value		Large Blend	
	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
Const.	-0.3821	-0.80	3.6322	2.95	0.8047	1.77
Prelec Alpha	-0.7196	-2.13	1.0575	1.43	-0.0183	-0.07
Prelec Beta	0.5701	0.94	-3.9506	-2.61	-0.9529	-1.92
Recession	-0.2882	-2.04	0.1148	0.31	-0.1584	-1.09
Category Ret.	0.0277	3.22	0.0554	3.49	0.0158	2.75
Passive Flow	0.3882		0.2119		0.4325	
Adj. R-sq	0.4364		0.2151		0.4498	
N (obs.)	155		155		155	

Table 9: **Effect of option-implied risk attitude controlling for market sentiment.** This table reports the result from regressing the average monthly flows into actively managed funds on Prelec α and β, controlling for the Baker-Wurgler (2006, 2007) market sentiment index, average flows into passive funds of the same category, lagged category returns, and market returns as proxied by the average monthly CRSP value-weighted index returns during the prior six months. Prelec α is orthogonalized against β. Time-series regressions are performed separately for individual Morningstar investment categories. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors.

	Large Growth		Large Value		Large Blend	
	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
Const.	-0.5016	-0.83	3.7851	2.59	1.2375	3.95
Prelec Alpha	-0.6607	-2.08	1.2145	1.77	0.1729	0.68
Prelec Beta	0.5843	0.84	-4.1481	-2.45	-1.5549	-4.49
Market Ret.	0.094	4.39	0.048	0.89	0.0625	3.78
B-W Sentiment	0.0174	0.30	0.1491	1.35	0.2109	5.40
Category Ret.	0.0317	5.49	0.052	4.86	0.0217	3.92
Passive Flow	5.0224	5.32	2.7915	1.07	0.7933	4.78
Adj. R-sq	0.4328		0.2212		0.5204	
N (obs.)	155		155		155	

Table 10: **The effects of option-implied risk attitudes across investor clienteles.** This table compares the impact of SPX index option implied measures of Prelec α and β on active flows into non-retirement retail versus retirement funds. Time-series regressions are performed separately for each investor clientele within individual Morningstar investment categories. Reported t-statistics are computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors. At the bottom of the table we report F-test statistics along with their corresponding P-values for the difference in the coefficients of Prelec α and β between non-retirement retail funds and retirement funds.

	Large Growth		Large Value		Large Blend	
	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
Retail						
Const.	-0.6083	-0.76	3.5785	3.52	0.4792	0.44
Prelec Alpha	-2.6534	-8.85	-0.7362	-1.78	-1.2908	-3.92
Prelec Beta	0.5025	0.56	-4.0191	-3.48	-0.6642	-0.55
Category Ret.	0.0289	2.59	0.0528	3.31	0.0410	2.72
Market Ret.	0.1904	6.02	0.0380	0.69	0.1386	3.30
Passive Flow	0.2743	4.05	0.3710	3.61	0.4398	4.08
Adj. R-sq	0.5592		0.2524		0.5012	
N (obs.)	155		155		155	
Retirement						
Const.	0.7006	0.45	8.0641	5.43	9.5951	5.16
Prelec Alpha	-1.7802	-4.70	0.8096	1.23	0.2382	0.35
Prelec Beta	-0.8180	-0.48	-8.9465	-5.52	-10.7036	-5.03
Lag. Cat. Ret.	0.0131	0.81	0.0503	1.72	0.0358	1.33
Market Ret.	0.0443	0.61	-0.1398	-1.28	-0.0596	-0.52
Passive flow	0.1327	1.41	0.2167	0.83	-0.1097	-0.53
Adj. R-sq	0.1330		0.1997		0.2430	
N (obs.)	155		90		94	
Coefficient Differences Tests (Retirement vs Retail)						
	F-stat.	p-value	F-stat.	p-value	F-stat.	p-value
Prelec Alpha	5.59	0.02	1.99	0.16	0.55	0.46
Prelec Beta	1.21	0.27	9.80	0.00	20.05	0.00

Table 11: **Fund return exposures to option returns.** This table reports the regression estimates from Carhart (1997) four-factor model augmented with option strategy returns. Each month we form value-weighted portfolios (by individual funds' TNAs) according to their Morningstar investment categories. For each fund portfolio, we estimate the time-series regressions of portfolio returns on the Carhart (1997) four factors and returns of portfolios constructed from the S&P 500 index options that proxy for investor preferences for downside hedging (ATM straddle) and upside-seeking (ATM or OTM calls). Fund returns and factor returns are expressed in percentage. The returns of option strategies are normalized to have mean of zero and standard deviation of one. For brevity, we only report the regression coefficient estimates for option related variables along with their t-statistics. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors.

	Active			Passive		
Category	Straddle	OTM Call	ATM Call	Straddle	OTM Call	ATMCall
Large Growth	0.0102			-0.0734		
(t-stat.)	0.17			-0.76		
Large Value	0.1686			0.1463		
(t-stat.)	2.09			1.44		
Large Blend	0.0988			0.0620		
(t-stat.)	2.34			1.27		
Large Growth	-0.0131	0.1182		-0.0645	-0.0452	
(t-stat.)	-0.22	1.82		-0.62	-0.39	
Large Value	0.1948	-0.1328		0.1657	-0.0981	
(t-stat.)	2.09	-1.35		1.46	-0.94	
Large Blend	0.1084	-0.0487		0.0807	-0.0946	
(t-stat.)	2.29	-0.95		1.46	-1.55	
Large Growth	0.0172		0.1222	-0.0755		-0.0361
(t-stat.)	0.30		2.04	-0.78		-0.30
Large Value	0.1604		-0.1446	0.1404		-0.1042
(t-stat.)	2.02		-1.57	1.39		-1.08
Large Blend	0.0956		-0.0562	0.0564		-0.0987
(t-stat.)	2.30		-1.14	1.14		-1.67

Table 12: **Correlation Coefficients between SDF Slopes and Prelec Function Parameter Estimates.** We report the correlation coefficients between the model-free SDF slopes and the estimated Prelec function parameters. Prelec α is orthogonalized to β. SDF (up) and SDF (down) correspond to the SDF slopes for the upside potential and the downside risk as defined in Section 5. SDF (up norm.) is the upside slope normalized by the downside slope in order to separate their common variations.

	SDF (dwn)	α (Orthog.)	β
SDF (down)	1.00	-0.50	-0.76
SDF (up)	0.84	-0.84	-0.37
SDF (up norm.)	0.15	-0.83	0.31

Table 13: **Flows into Active Funds as a Function of Model-Free Measures of Risk Attitude.** This table reports the coefficient estimates from regressing the average monthly flows into actively managed funds on risk-attitude measures implied in the S&P 500 index options, controlling for average flows into passive funds of the same investment category, lagged category return, and market returns as proxied by average monthly CRSP value-weighted index returns during the past 6 months. SDF (down) represents the ratio of RN probability to physical probability computed from the left tail, 3% OTM Put and below, and is a proxy for downside risk aversion. SDF (up norm.) is the ratio of RN probability to physical probability computed from the right tail, from 3% OTM and above, normalized by the SDF (down), and is a proxy for preferences for upside potential. The upward side slope is normalized by the downside slope as discussed in Section 5. Time-series regressions are performed separately for individual Morningstar investment categories. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors.

	Large Growth		Large Value		Large Blend	
	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
Const.	-0.8110	-1.80	1.5693	1.34	-0.2499	-0.64
SDF (up norm.)	1.0453	2.44	-2.5265	-1.91	-0.0882	-0.22
SDF(down)	-0.0097	-0.04	0.5107	1.73	0.1986	1.44
Market Ret.	0.0958	4.33	0.0195	0.29	0.0423	1.82
Category Ret.	0.0319	5.72	0.0471	4.30	0.0172	2.70
Passive Flow	5.2739	5.40	1.8013	0.54	0.7516	4.02
Adj. R-sq	0.4277		0.1975		0.4411	
N (obs.)	155		155		155	

Table 14: **Flow to Medium and Small Active Funds as a Function of Option-Implied Risk Attitude.** This table reports the coefficient estimates from regressing the average monthly flows into actively managed medium-cap and small-cap funds on Prelec α and β, controlling for average flows into passive funds of the same category, lagged category return, and market returns as proxied by the average monthly CRSP value-weighted index returns during the prior six months. Prelec α is orthogonalized against β. Time-series regressions are performed separately for individual Morningstar investment categories. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors.

	Medium Growth		Medium Value		Medium Blend	
	Coefficient	t-stat.	Coefficient	t-stat.	Coefficient	t-stat.
Const.	4.0044	2.64	6.7572	1.82	4.0106	4.17
Prelec Alpha	-1.0630	-2.66	1.3219	0.74	1.0255	1.14
Prelec Beta	-4.3290	-2.72	-6.3686	-1.36	-4.1750	-3.55
Market Ret.	0.1093	2.70	0.0652	0.33	-0.0549	-0.53
Category Ret.	0.0501	3.39	0.1359	2.60	0.0670	4.93
Passive flow	4.7876	2.58	-2.3450	-1.23	0.4975	1.19
Adj. R-sq	0.2767		0.1242		0.1748	
N (obs.)	83		81		155	
	Small Growth		Small Value		Small Blend	
Const.	1.9534	1.08	3.6568	4.50	2.9931	3.12
Prelec Alpha*	-1.0551	-1.66	-0.3092	-0.36	0.3446	0.51
Prelec Beta	-1.9813	-0.97	-3.6327	-3.79	-3.0017	-2.96
Market Ret.	0.0102	0.18	-0.1132	-0.86	-0.021	-0.27
Category Ret.	0.0425	5.09	0.0874	4.27	0.0524	7.01
Passive flow	3.8730	1.82	0.8529	2.26	1.8114	3.70
Adj. R-sq	0.1355		0.2120		0.3241	
N (obs.)	127		155		155	