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

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August 2013

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*We are grateful for comments by Kris Jacobs, Rachel Pownall, Clemens Sialm, and seminar participants at the Federal Reserve Board, 2012 Lone Star Finance Symposium, 2013 FMA Asian Annual Meetings, 2013 University of Oregon Finance Conference on Institutional Investors, U of Delaware, Temple U, American U, and U of Houston. The views presented in this paper are solely those of the authors and do not necessarily represent those of the Federal Reserve Board or its staff. All errors are the sole responsibility of the authors.

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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, the sensitivity of fund flows to investor risk preferences varies significantly across funds with different levels of active share, different return skewness or different market risk hedging properties, and across retirement and retail funds.

JEL: G11, G23
Keywords: active management, mutual funds, tail-sensitive preferences, probability weighting function

Introduction

Despite the 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 issue has attracted considerable interest in the mutual fund literature. While some studies attempt to rationalize the underperformance of active funds by modeling state-dependent managerial efforts or skills, in this paper we directly explore the equally important side of investor demand for active funds and investigate whether it is related to certain distributional features of mutual fund returns. Our paper identifies new components in the demand for active management which stem from investor preferences for tail risks. While we do not attempt to address the broader issue concerning the size of the active fund industry, our findings contribute to the understanding of investor demand for actively managed mutual funds.

These has been growing investor attention to distributional features of fund returns beyond mean fund performance. For example, Morningstar now publishes individual funds' upside and downside capture ratios to accommodate investor demand for information on conditional fund performance.[2] We therefore begin by comparing the bootstrapped distributions of monthly returns of actively managed mutual funds and passive benchmarks. We find substantial differences in distributions using as passive benchmarks either the market index or passively managed funds within the same investment category. Compared to passive benchmarks, active growth funds exhibit stronger upside-seeking properties in that their returns tend to be more volatile, less negatively skewed and have higher conditional means for the upper quantiles, especially during market expansions. On the other hand, the comparison of active value funds with their passive benchmarks reveals that the returns of active value funds exhibit stronger downside hedging properties: they are less volatile and have higher conditional means for the lower quantiles, especially during market bust periods. We also examine whether actively managed funds have significant loadings on option-based factors designed to capture funds' hedging and upside-seeking ability. To do this, we augment the standard Carhart (1997) four-factor model with returns of at-the-money (ATM) straddles and ATM call

[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] According to Morningstar, upside/downside capture ratio shows whether a given fund has outperformed–gained more or lost less than–a broad market benchmark during periods of market strength and weakness, and if so, by how much.

options on S&P 500 index. Our results indicate that, unlike their passive counterparts, actively managed large-growth funds tend to have significantly positive loadings on returns of ATM calls, while actively managed large-value funds have significantly positive loadings on straddle returns.

It is important to point out that these differences in return distributions cannot be explained by lower diversification of actively managed funds compared to passive funds, nor can they be attributed to different types of securities held by active versus passive funds. We show that actively managed funds and their corresponding index funds tend to hold stocks with very similar characteristics shown to predict expected returns including size, book-to-market ratio, and momentum. And simple under-diversification cannot generate the smaller left tail of the return distribution for active value funds, nor it can lead to time-varying skewness in growth funds which becomes more positive during market expansions. Therefore, various dynamic active management strategies are likely to be responsible for the observed differences in fund return distributions.

Given the observed differences in the return distributions of active funds from their passive benchmarks, we hypothesize that active funds may appeal to investors who are sensitive to upside potential and downside risk. To provide a theoretical foundation to our empirical tests, we model risk preferences using a rank-dependent expected utility (RDEU, Quiggin, 1983 and Yaari, 1987) with an inverse-S probability weighting function which combines preferences for the upside potential with the aversion to downside risk.[3] While seemingly contradictory, as the oxymoron in the paper's title, such a behavior is widely supported by extensive experimental evidence and has been applied in the literature on portfolio diversification (see, for example, Shefrin and Statman, 2000 and Mitton and Vorkink, 2007). Using simulated distributions of monthly returns for active and passive funds in growth and value categories, we analyze comparative statics of the optimal portfolios of RDEU investors. Our simulation results show that active growth funds are more attractive when investor risk preferences place more emphasis on the upper tail of the return distribution while active value funds may be more attractive to those investors who are more concerned with protecting against the downside risk. Therefore, our model generates empirical predictions about how the demand for actively managed funds versus their passive counterparts should respond to changes in investor

[3]Technically, 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 Tversky (1992).

preferences.

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 versus upside-seeking, following Polkovnichenko and Zhao (2013). We construct two sets of proxies at the 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. Throughout the paper we mainly rely on Prelec model proxies for investor risk attitudes due to their clear economic interpretations from the structural preference model, although we also use slopes of the pricing kernel for robustness checks. In the Prelec probability weighting function one parameter (α) controls the extent of over- or under-weighting of the tails while the other one (β) allows for the shifting of overweighting either towards the right or left side of the return distribution. 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 the 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 expect that our option-based risk preference estimates are representative of the risk attitudes of the average mutual fund investor.[4]

We show that the parameters of the probability weighting function estimated from the pricing kernel implied in index options have significant explanatory power for monthly fund flows into actively managed funds, similar in economic significance compared to that of past fund performance. Specifically, we find that flows into actively managed growth funds significantly increase with investor sensitivity to upper tail events. At the same time, flows into value funds significantly increase with investor aversion to lower tail events. These findings are consistent with our theoretical predictions and suggest that active growth funds appeal to investors with strong risk-taking preferences while active value funds are attractive to investors seeking downside risk protection.[5]

We also investigate if our main results relating fund flows to tail-sensitive preferences are robust

[4]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).

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

to the control of investor sentiment. 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 the demands for both downside protection and upside seeking and 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, our findings remain robust after controlling for the NBER recession indicator and the Baker and Wurgler (2006, 2007) sentiment measure in our flow regressions.

To further establish the link between investor preferences and the observed pattern of fund flows, we present several cross-sectional analyses which strengthen our main findings. We first group funds based upon the extent of their active management, as proxied by the active share measure (Cremers and Petajisto, 2009). More active funds can be more appealing to investors seeking upside potential or downside protection and we should expect to see more pronounced effects of risk preferences on their flows. This is indeed what we find: flow sensitivities to investor risk preferences become significantly stronger for funds with higher active share. We then directly compare flow patterns across funds with different return distribution characteristics. To examine cross-sectional variations in the effect of upside seeking preferences on flows, we group funds based on the skewness of their recent returns. We find that for growth funds with higher performance skewness, flows are more sensitive to Prelec α that captures the upside potential preference. We also examine funds' hedging function by sorting funds based on their return correlations with the market returns. Funds that have lower return correlations with the market are expected to provide better downside protection for investors. We indeed find stronger sensitivity of flows to Prelec β among value funds with lower return correlations with market index but do not find such a difference for growth funds.

As an alternative to cross-sectional analyses based on fund features, we analyze flows in retirement and retail funds which have clienteles with potentially distinct risk attitudes. Our results indicate that flows into retirement funds in the value category exhibit a significantly weaker sensitivity to the preference for upside potential yet a much stronger sensitivity to the preference for downside protection, relative to non-retirement retail funds with the same investment style. 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). Also interestingly, flows into non-retirement retail growth funds demonstrate significantly larger exposures to Prelec α.

Our paper is related to the recent literature studying flows into actively managed funds. Glode (2011) presents a model where mutual fund managers decide on efforts according to the price of risk, leading to time-varying fund performance. Savov (2012) models active funds as providing hedging to investors with substantial non-traded income exposure and therefore charging investors a premium beyond their alpha. Further, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2012) develop a model of strategic effort allocation by fund managers.[6] Our work complements this literature by focusing on investor decisions rather than managerial skills and conditional fund performance. 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 distinct because it has implications on investor preferences for both upside-seeking and downside protection with different testable implications for growth versus value funds. Our empirical analysis is thus able to demonstrate the simultaneous impact of investor risk aversion and upside-seeking preference on the demand for active funds. Furthermore, we conduct several unique cross-sectional analyses using fund or investor characteristics to help establish the causal effect of investor risk attitudes on the demand for active mutual funds. Our paper thus provides a new perspective on what active funds may offer to investors beyond their mean performance.

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 presents a model of tail-sensitive preferences and discusses its empirical predictions on the demand for active growth versus value funds. Section 4 provides empirical analyses on the relation between fund flows and investor risk preferences. Section 5 conducts cross-sectional analyses of this relation. Section 6 discusses the results of robustness analyses. Finally, Section 7 concludes the paper.

1 Data

Our empirical analyses mainly utilize two types of data: the S&P 500 index option prices and mutual fund flows and returns both at the individual fund level and at the investment category

[6]Empirical studies in this literature include, for example, Gruber (1996), Moskowitz (2000), Kosowski (2006), Lynch, Wachter and Boudry (2007), Sun, Wang, and Zheng (2009), and Fama and French (2010) among others.

level.

We obtain data on S&P 500 index options (symbol SPX) from OptionMetrics for the period from February 1996 to December 2008. This period is also going to be our main sample period throughout the paper since most of our analyses involve risk preference measures derived from option prices and returns. 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 S&P 500 index futures. We select the monthly quotes of options that are closest to 28 days from each month's expiration date and employ bid and ask prices. We also obtain the term structure of default-free interest rates from OptionMetrics. Following the procedure in Aït-Sahalia and Lo (1998) and other empirical studies on index options, we remove options that are not liquid and infer the option implied underlying price to avoid non-synchronous recording between the options market and the index price. More details on our sample of option 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 the physical measure.[7]

For analyses involving mutual fund flows and returns, we extract data from Morningstar and CRSP survivorship bias free mutual fund database for the same period of 1996 to 2008. 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.[8] In addition, we only examine large-cap growth and large-cap value funds in our analyses as blend funds tend to resemble both growth funds and value funds, making it difficult to identify the exact performance features that influence individual investment decisions. For analyses concerning 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 individual fund-level data, we extract our sample funds from CRSP. To avoid outliers, we only keep funds with TNA exceeding $5 million. We then merge the CRSP data with the Morningstar

[7]The index return series has an earlier start date of January 1990 since we need to obtain the rolling estimates of the physical distribution. In the comparative analysis not reported here, we apply fixed, rolling and recursive windows for estimating the physical distribution function and our results are not affected by any particular choice.

[8]However, in the robustness section we present main results using fund flows for small and medium-cap categories for completeness.

data to classify individual funds into the growth versus value investment categories. For funds that fail to be matched to Morningstar or have missing Morningstar investment categories, we identify their investment categories using the Lipper fund objective from CRSP.

In Table 1 we report summary statistics for our sample of actively managed funds. The median fund size as measured by TNA is relatively uniform across both large growth and large value 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 funds exhibit greater volatility relative to value funds. Lastly, all of our sample active funds have relatively high levels of active management, as suggested by their high mean and median active share (Cremers and Petajisto 2009) of over 70%, suggesting that more than 70% of their portfolio holdings differ from the benchmark index holdings.

For the return distributions of the passive benchmarks, we examine the monthly return series of both the market portfolio as proxied by the CRSP value-weighted index and those of Vanguard large-growth (VIGRX) and large-value (VIVAX) index funds. We choose the market portfolio as the passive benchmark because investing in the market portfolio is the simplest passive investment accessible to individual investors. Alternatively, we follow Fama and French (2010) to focus on Vanguard index funds as the passive benchmarks for several reasons. Vanguard index funds are bellwethers in the index fund industry in terms of both assets under management and performance. They also tend to have the longest return history for both investment categories. Therefore, they serve as investable passive alternatives for investors who want to choose between passive and active fund portfolios with similar investment styles. In contrast, many other passive funds start much later than do Vanguard funds and thus have much shorter time-series of return data.

To ensure that any differences in return moments between actively managed funds and Vanguard index funds with the same investment style do not merely come from different characteristics of their holdings, we compare the average size, book-to-market ratio, and return momentum of stocks held by the typical actively managed funds versus those of stocks held by Vanguard index funds, within the large-growth and large-value categories, respectively. Specifically, each quarter we group stocks held by funds into their respective size, book-to-market (BM) and momentum quintiles.[9] For each

[9]We thank Russ Wermers for providing stocks' size, book-to-market and momentum quintile ranks. See Daniel,

actively managed fund and the corresponding Vanguard index fund within the same investment category in each period, we then compute the value-weighted size, BM and momentum quintile ranks across all fund holdings. For example, a fund primarily holding large-cap, growth stocks with strong return momentum would have a size rank of 5, a BM rank of 1 and a momentum rank of 5. Lastly, we compute the average size, BM and momentum ranks across all actively managed funds, separately for the growth and value categories, and compare these holding characteristics of active funds with those of the corresponding Vanguard index fund.

As expected, Table 2 indicates that all of our sample large-cap funds have relatively high size ranks, with growth funds having significantly lower BM ranks and higher momentum ranks compared to value funds. More importantly for our purpose, our sample actively managed funds and their corresponding Vanguard index funds tend to hold stocks with very similar characteristics in all three key dimensions that are related to expected returns. Therefore, any differences in return moments between our sample active funds and their Vanguard index fund benchmarks are more likely to be attributed to managerial skills, as opposed to differences in their holdings. Alternatively, we also consider using the hypothetical portfolios formed on lagged reported fund holdings of individual funds' as their passive benchmarks. However, since these tracking portfolios, by construction, adjust their composition quarterly as new fund holdings are disclosed, they are equivalent to actively managed funds whose holdings would largely embed the stock-picking skill of the active funds they track (except for any managerial skill that might drive the active fund's intra-quarter trades). They are thus expected to have very similar time-series return distributions relative to their actively managed counterparts.[10] Furthermore such tracking portfolios are not feasible, low cost alternatives to active funds for average individual investors. Therefore, throughout the paper, we use Vanguard funds as the representative passive funds to facilitate the comparison of performance between passive and active funds within the same investment category.

Grinblatt, Titman and Wermers (1997) and Wermers (2004) for details on the stock ranking procedure. The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

[10] Our investigation into the return distribution of this alternative benchmark verifies this prediction. Moreover, several recent papers show that copy-cat funds that invest in such tracking portfolios perform similarly to the original active funds, suggesting that they largely embed the stock-selection skills of the funds they mimic (see, for example, Frank *et. al.*, 2004 and Verbeek and Wang, 2010).

2 Return Distributions of Actively Managed Funds

2.1 Moments of the Return Distributions

Do actively managed funds offer different upside and downside features from passively managed ones? We address this question by comparing the distributional characteristics of these two types of funds. When examining the returns of the representative active fund, we do not use the average return across all active funds because holding a portfolio of all active funds amounts to holding the market portfolio. Instead, we randomly pick one active fund each period from the value and growth categories, respectively, to generate a path of monthly returns over our sample period and compute moments estimates for each path. We choose each period to be one, six or twelve months and find similar results. The confidence interval of these estimates can be computed over many bootstrapped paths. We generate 40,000 paths for our reported moments estimates and their p-values and find this sample size adequate for necessary precision. Furthermore, we account for differences in fund size by using individual funds' prior-month total net assets as the weight in the random draw of the current month's return. Note that the number of active funds grows considerably over our sample period with the growth rate varying across styles. The average return across a specific fund style would have a smoother path when the number of funds of the style is larger. Since we randomly draw one fund each period, our bootstrapping method is less susceptible to this issue. As to our choices of passively managed portfolios, we first use the CRSP value-weighted market returns as the passive benchmark, assuming implicitly that passive investors on average hold the market portfolio. To account for the possibility that investors may engage in passive investments with a particular investment style, we also employ returns of Vanguard index funds for individual investment categories as the passive benchmarks.

The specific sample moments computed from the bootstrapped paths of monthly returns include mean, volatility, skewness, and conditional means in both the worst and best 10 and 25 percentiles of return distributions.[11] For example, the expected return in the best 10 percentiles is computed as $E\left[R|R \geq q_{0.90}\right]$ where $q_{0.90}$ is the $90^{\text{-th}}$ percentile of the return distribution. Similarly, we compute $E\left[R|R \leq q_{0.10}\right]$, where $q_{0.10}$ is the $10^{\text{-th}}$ percentile, for the expected return in the worst 10 percentiles. These conditional means help highlight differences in the upside and downside of the

[11]We also compute conditional returns in the best and worst 3 and 5 percentiles and find similar results.

return distributions between active and passive funds. 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.

To utilize a return time series that's as long as possible, the sample period for moments estimation is from January 1993 to December 2008 as Vanguard large-cap growth and value index funds were introduced at the end of 1992. Given prior evidence that mutual fund performance varies with business cycles (see, e.g., Glode, 2011 and Kacperczyk, Van Nieuwerburgh and Veldkamp, 2012), we compare return distributions separately for boom and bust periods in addition to the whole sample.[12] To measure business cycles, 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 boom versus bust periods based upon the median cumulative six-month returns.

In Table 3, we compare return moments and conditional mean returns between large-cap active funds and the market portfolio.[13] As expected, active funds exhibit lower unconditional mean returns than the market after fees over the whole sample, and more so for active large-growth (LG) funds. However, active large-value (LV) funds tend to outperform the market during the bust period while active LG funds tend to do so during the boom period. Moreover, active LG and LV funds have a monthly (non annualized) return volatility of 5.40% and 4.02%, respectively, versus 4.38% for the market portfolio. Across business cycles, active LG funds are much more volatile than the market during the boom than during the bust and active LV funds are significantly less volatile than the market primarily during the bust. Considering the asymmetry of the return distribution, active LG funds are significantly less negatively skewed than the market across the whole sample period. Particularly, they have positive skewness during the boom. Therefore when we go beyond the unconditional mean returns, the results indicate that actively managed funds offer distinct features in seeking upside potential and protecting against market downturns.

Next we explicitly examine differences in tail distributions by focusing on the comparison in conditional mean returns across active funds and their passive benchmarks. The results show that

[12] 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.

[13] 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.

active LG funds have significantly higher returns in the upside. In the top 10- and 25-percentiles of return distributions, active LG funds offer an average monthly returns of 9.24% and 6.72%, respectively, as compared to 7.03% and 5.44% for the market portfolio. Both differences are statistically significant at the 1% level. In terms of economic significance, these differences translate into 26% and 15% annual return differentials in the top 10- and 25-percentiles. As for the downside, active LG funds have worse returns than the market. However, the magnitude of the underperformance is smaller than that of the outperformance for the upside. This asymmetry is mainly due to LG funds' outperformance during the boom: active LG funds have an annualized return that is 22% above the market in the top 25-percentiles and 8% below the market in the bottom 25-percentiles. Interestingly, the performance of active LV funds on the downside mirrors that of LG funds on the upside: the annualized return of LV funds is 12% above the market in the bottom 10 percentiles and is only 2% below the market in the top 10 percentiles. That is, across business cycles active LV funds outperform the market mostly during the bust.

In Table 4, we employ the Vanguard LG and LV index funds as our passive benchmarks. They are among the best performing passive funds and dominate the index fund industry in market share. By comparing a randomly picked active fund against one of the most successful index funds, we essentially set a higher hurdle for active funds to demonstrate their advantages over their passive benchmarks. This comparison in return moments between active funds and Vanguard index funds is therefore a more stringent test. Table 4 shows that the differences in return moments between active funds and Vanguard funds remain quite striking, although with smaller magnitudes. During the boom, active LG funds have an annualized return differential of 26% above the market return in the top 10 percentiles and 5.5% below the market in the bottom 10 percentiles, relative to the Vanguard LG fund. In addition, active LV funds have smaller volatility than the Vanguard LV fund during the bust and yet similar volatility during the boom.

Overall, we find that the distributional characteristics of active funds' returns are significantly different from those of passive benchmarks, both statistically and economically. They are likely manifestations of the presence of active portfolio management. Since mutual funds have very little use of derivatives, active management is required for the active LV fund's variance to be significantly lower than that of the market portfolio or a well diversified passive LV fund. Active management is also evidently present for active LG funds to have an asymmetric return distribution more skewed to the upside. Lastly, these differences in distributional characteristics vary over the business cycles. Active LG funds are more upside seeking than their passive benchmarks, especially during the market boom. Active LV funds focus more on risk reduction during the market bust. This finding echoes those in Glode (2011) and Kacperczyk, Van Nieuwerburgh and Veldkamp (2012) in that the performance of active funds exhibits state-dependency. Therefore, the distributional features of active funds are correlated with the market condition and thus the aggregate pricing kernel.

2.2 Active funds' exposures to option-based strategies

As an alternative to the comparison in return moments between active and passive funds, we next analyze the relation between the performance of actively managed funds and certain investment strategies that cater to investors with tail-sensitive preferences. The goal is to examine whether active funds display larger exposures to these strategies than passive funds. In addition, we will account for the effect of systematic risk factors by focusing on risk-adjusted fund returns.

We use SPX options to construct portfolios that capture either downside risk aversion or upside-seeking performance characteristics. 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. Therefore, we construct ATM straddles that take long positions in both ATM call and put options to capture the potential downside protection feature of fund performance. As to the proxy for the upside-seeking component of fund performance, we simply use returns of ATM call options. 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.

We first form value-weighted fund portfolios within each investment category with the weight being prior-month total net assets.[14] The time-series mean returns of these portfolios are representative of the mean returns earned by typical active funds with certain investment styles. For returns of passive funds in the growth and value categories, we again employ the monthly returns of Vanguard large-cap growth and value funds. To adjust for differences in fund characteristics and

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

risks, we fit fund returns into the Carhart (1997) four-factor model, but augment it with straddle returns, as well as ATM call returns.[15] These time-series regression analyses are conducted separately for individual investment categories since funds catering to different investor risk preferences are unlikely to have the same exposure to various option-like strategies that help capture their distinct return distributions. Both fund returns and factor returns are expressed in percentage. We report t-statistics computed with Newey-West (1987) robust standard errors to account for potential autocorrelation in average fund returns.

Table 5 indicates that returns of actively managed large-value funds have significantly positive loadings on straddle returns, while returns of actively managed large-growth funds have significantly positive loadings on ATM call returns. 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. These differences between active and passive funds in their loadings on option-based portfolio returns are both statistically and economically significant.[16] 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 without a large amount of investable funds. Passive funds, while cheaper, cannot offer close substitutes to these return characteristics of active funds. Our findings thus suggest that investors with tail-sensitive risk preferences may invest in active managed funds even though active funds do not outperform (or may even underperform) passive funds on average.

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

3.1 Utility Function with Probability Weights

Since Tables 3 and 4 suggest significant differences in return distributions across the active and passive fund universes, we conjecture that they should cater to investors with different tail-sensitive

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

[16]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.

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. 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.[17] 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 $G(P)$:

$$U = \int u(w) dG(P) = \int u(w) G'(P) dP = E\{u(w)Z(P)\}, \tag{1}$$

where $Z(P) \equiv G'(P) \geq 0$ denotes the probability weighting density. 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 $EZ \equiv \int dG(P) = 1$.

3.2 Inverse-S Probability Weighting Function

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 payoff distribution, i.e. for P near 0 and 1, relative to events in the middle of the distribution. This type of behavior 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):

$$G(P; \alpha, \beta) = \exp(-(-\beta \log(P))^{\alpha}) = \exp(-(-\log(P^{\beta}))^{\alpha}) \quad , \quad \alpha > 0 \; , \; \beta > 0 \tag{2}$$

[17] 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.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.

To understand the properties of this function, we first set $\beta = 1$ and consider the effects of α only. 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 agents may underweight tail events and instead be 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 G and its density Z in (2) in the top two panels of figure 1. 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 top right panel. When $\alpha > 1$ (not shown), the weighting function becomes S-shaped instead and under-weights the tails.

To understand the effects of β on risk preferences, note that the weighting function in (2) can be represented as a compound function $G(P; \alpha, \beta) = G(P^\beta; \alpha, 1)$. If we set $\alpha = 1$, then we obtain $G(P^\beta; 1, 1) = P^\beta$ which is 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 1 which present the probability weighting G and its density Z 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 attitudes 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. Thus two parameters allow the weighting function to independently control the relative strengths of downside risk aversion versus upside potential seeking.

We use the specification in (2) 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.

3.3 Certainty Equivalents of Active and Passive Funds

As discussed in section 2, we use bootstrapped time series to compute moments shown in table 3 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.[18] 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.[19] 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. We use parameter ranges that are consistent with both experimental estimates and with empirical results on probability weighting estimated from options.

Figure 2 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.

[18]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.

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

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.

3.4 Portfolio Choices

Comparative statics of the CEs inform us about changes in the "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 the returns correlation and other higher order cross-moments.

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 3 and 4 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 3 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 a 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 a lower α and this makes the 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 4 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 growth fund. When α is low, as the investor becomes more attracted to the upside of returns, the risky portion completely and 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 from 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.[20] As α becomes *lower*,

[20]Note that in the case of value funds this is not the case since active value fund has both lower mean *and* 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. This type of behavior is reminiscent of the portfolio "layers" result 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.[21] 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 4 also shows that holdings of the growth fund are increasing with respect to β. This is intuitive since for lower β 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 βs. In these cases the effect of β on the downside is not sufficient to counteract a strong upside-seeking preference from 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 the following 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.

When we conduct our empirical analysis, we interpret these results in the context of time-variation in aggregate preferences. We do not model this explicitly because a dynamic model with time-varying preferences is beyond the scope of the paper. However, we believe that our main conclusions would hold in such a model as well. If preference shocks are unpredictable, then the results from the dynamic model would be similar to a two-period solution. If time variations in

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variance than its passive benchmark. Thus, there is a traditional mean-variance tradeoff between active and passive value funds and the changes in demand are more gradual.

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

preferences were predictable by some state variable, it would result in the hedging portfolio demand. Depending on the assumptions about the predictable state variable, the hedging demand may add to or subtract from the static demand and amplify or smooth the effect from time-variations in preferences. But qualitatively, the effects from probability weighting function would remain similar to those we present in our current model.

4 Empirical Evidence from Fund Flows

4.1 Option-implied risk attitudes towards the upside and downside

Following Polkovnichenko and Zhao (2013), we extract the risk attitudes of the representative investor toward the upside potential and downside losses in returns of the aggregate wealth portfolio from returns of S&P 500 index options. This approach relies on the estimation of the empirical pricing kernel 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 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 the empirical pricing kernel.[22]

To estimate probability weighting functions 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 the 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 the utility function we use the CRRA (power) specification $u(R) = \frac{R^{1-\gamma}}{1-\gamma}$ and set it to the benchmark risk neutral case of $\gamma = 0$.[23] To approximate the empirical probability weighting function we use Prelec function from (2). We use monthly data for options

[22] For further technical details including assumptions and derivations, we refer readers to Polkovnichenko and Zhao (2013).

[23] 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, 2013). 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.

with 28-days to expiration in order to construct a time series of the estimated coefficients α and β.[24] Since α and β are correlated because they both reflect the attitude toward downside risk, we orthogonalize α against β in the time series regression so that the residual α mainly captures the risk attitude toward the upside.

Later in the paper we discuss robustness analyses using alternative measures of tail sensitivity constructed from the slopes of the pricing kernel for OTM options. However, the pricing kernel slopes are not developed from structural models of preferences and cannot be directly linked to portfolio choices we discussed earlier. As a result, the economic interpretation of these slopes relies on their correlation with the Prelec model parameters. Technically, the estimation of the slopes puts more weight on the less liquid OTM options, which makes the slopes noisier proxies of preferences as opposed to the probability weighting functions estimated from the entire range of the pricing kernel. Therefore, throughout the paper we rely on Prelec α and β as our main measures of investor risk preferences.

4.2 Fund flows and option-implied risk attitudes

To test the prediction we develop in section 3 concerning the relation between the portfolio demand for active funds and risk preferences, 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). As mentioned earlier, we focus on large-cap funds because we have the most reliable time series data for benchmark 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 is a large-cap portfolio.[25]

Since previous studies show that flows into different investor categories are related to investor preferences for different fund styles (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 investor sentiment for a particular fund style

[24] 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 (2013) for details.

[25] However, our results for medium and small-cap funds, as presented later in the robustness section of the paper, are qualitatively similar.

or equity funds in general. In addition, we include the average TNA weighted monthly returns of each investment category in excess of market returns in each of the previous three months as controls to account for flows resulting from the return chasing behavior of mutual fund investors. We also control for contemporaneous market returns in order to capture the effect of macroeconomic factors on mutual fund investments. We proxy for market returns using the returns of CRSP value-weighted market index. The coefficient estimates of these time-series regressions and their t-statistics are shown in Panel A of Table 6. Given the potential autocorrelation in fund flows, we report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors with 36 lags.

Panel A shows that flows into active funds are significantly positively correlated with past category returns and flows into passive funds with the same investment style. This is expected since flows into active funds should be influenced by their recent performance as well as investor sentiments for certain fund styles in general. More interestingly, Table 6 indicates that flows into large-growth funds have a significantly negative loading on Prelec α. Recall from our previous discussion that a lower value of α is associated with a greater preference for the upside potential. Thus, the result indicates that, other things being equal, a greater preference for the upside leads to larger flows into active growth funds. In terms of economic significance, a one standard deviation change in the Prelec α would lead to as large a change in flows into large-cap growth funds as does a one standard deviation change in one-month lagged category returns, the most significant determinant of fund flows in our regressions besides Prelec parameters. This finding on the impact of investor preference 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 option prices is stronger, fund flows are directed more towards active growth funds that can better cater to such an investor preference, relative to their passive benchmarks.

For large-value funds we find that the coefficient on β is significantly negative. 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. This result indicates that more money flows into active value funds when β is lower, which corresponds to higher demand for downside risk protection. This is again consistent with our earlier observation from the empirical return moments of value funds. Specifically, active value funds provide higher conditional returns on the downside and have less volatile returns than their passive benchmarks during market downturns. 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 flow regression analysis confirms that when investor preferences for downside risk protection increase, more money flows towards actively managed large-value funds.

In Panel B of Table 6 we present the results from an alternative specification where we use as the dependent variable monthly flow differences between active and passive funds with the same investment objective, 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 highly consistent with those presented in Panel A.[26]

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 addition, investors may prefer actively managed funds because active managers can engage in sentiment-timing (Yadav and Massa, 2012). One important distinction of our risk preference measures from investor sentiment, however, is that they separately identify downside protection and upside seeking preferences. When a sentiment index is high, it could be because investors are less concerned with downside risks, more excited regarding upside potential, or both. Our measures, on the other hand, can allow us to differentiate the demand for fund investments with large payoffs in specific parts of the performance distribution. Therefore, it is interesting to see if separating sentiment in the upper and lower tails is empirically relevant for fund flows over and above some single sentiment indexes.

Our first measure of investor sentiment is simply the NBER recession indicator since investor

[26]in unreported analyses, we also conduct all tests in Table 6 excluding data from 2008 (i.e., the crisis period). Our findings are qualitatively and quantitatively very similar. These results are available upon requests.

sentiment is usually closely related to the overall economic condition. Recessions are likely to be associated with low investor sentiment. During our sample period, the correlations between the NBER indicator and Prelec α and β are -0.125 and 0.075, respectively. Alternatively, we also 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.[27] We adopted both the original Baker and Wurgler sentiment index and the one that has been orthogonalized to several macroeconomic conditions and found similar effects. Over our sample period, the correlations between the Baker and Wurgler investor sentiment index and Prelec α and β are -0.24 and 0.23, respectively. Essentially, the more upside-seeking and the less risk averse investors are, the higher is the overall investor sentiment. The Baker and Wurgler measure of investor sentiment is expected to capture different aspects of investor sentiment than those related to the overall business cycles as its correlation with the NBER indicator is only 0.38.

In Table 7, we show estimates from the regressions of net flows into active funds (expressed as a percentage of NAV) on option-implied measures of investor risk attitude, controlling for monthly investor sentiment. 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. In contrast, the two investor sentiment measures appear to have an insignificant effect on flows into active funds.

5 Cross-Sectional Variations

5.1 The effect of fund activeness

Since active management allows funds to achieve greater upside potential or steer away from the downside risk compared to passive indexing, we expect that funds that are more active in their asset

[27]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.

management will exhibit a greater flow sensitivity to proxies of investor risk preferences, as they can better cater to investor preferences for the desired tail distributions. To measure the extent a fund engages in active management, we follow the existing literature to employ the active share measure developed by Cremers and Petajisto (2009). According to Cremers and Petajisto (2009) and Cremers, Ferreiar, Mados and Starks (2013), active share represents the share of portfolio holdings that differs from the benchmark index holdings. Therefore, it serves as an ideal measure for us to ex-ante identify funds that are expected to have distinctive return distributions relative to passive funds and thus may attract investors with the demand for upside potential or downside protection.

According to Cremers et al. (2013), U.S. actively managed funds have the lowest level of closet indexing among all countries. As a result, average U.S.equity funds in our sample have relatively high active share as shown in Table 1. To separate out funds with low levels of active management or even engage in closet indexing, each quarter and within each investment category we classify funds with active share ranked among the bottom one third into the low active share group and classify the rest into the high active share group. We then compare the sensitivity of fund flows to Prelec α and β between the two groups of funds. Since Cremers and Petajisto (2009) show that active share can help predict mean fund performance, instead of controlling for past category performance, we explicitly control for the lagged market-adjusted returns of the high versus low active share portfolios within each investment category, respectively, along with contemporaneous market returns. Similar to our baseline analyses in Table 6, we report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors with 36 lags.

The result of this analysis is presented in Table 8. Again, actively managed large growth funds have a significantly negative loading on Prelec α while actively managed large value funds have a significantly negative loading on Prelec β. More interestingly, these effects of investor preferences on flows into active funds are significantly more pronounced among funds with higher levels of active management. For example, for LG funds in the high active share portfolio, the coefficient on Prelec α is around -0.017. In contrast, LG funds with low active share have less than half as high a sensitivity to this measure of investors' upside-seeking preference. Similarly, large value funds with high active share exhibit a significantly stronger flow sensitivity to Prelec β. Therefore, the more actively managed a fund is, the more its flows are influenced by investors' risk preferences. These findings suggest that the investor demand for active funds is at least partially driven by active management that allows funds to generate certain distributional features in performance and thus cater to investor risk preferences.

5.2 Comparison across funds with different performance features

In the previous subsection, we take the first step to examining cross-sectional variations in funds' flow sensitivities to investor risk preferences by simply comparing funds with different levels of active management. To establish the causal effect of risk preferences on investor demand for funds with different performance features, we now directly link individual funds' distributional features in performance to their flow sensitivities to investor preferences for upside seeking versus downside protection. Specifically, in this subsection we examine variations in flow sensitivity to Prelec α and β across funds with different distributional characteristics in performance.

Given that funds' three-year performance has been a key performance metric serving as the focus of attention for fund rating companies as well as average fund investors, we classify funds based upon the performance features inferred from monthly returns in the past 36 months. First, we measure a fund's ability to achieve the upside gain by focusing on the skewness of monthly returns over the past 36 months. Funds with more positive return skewness in the recent past are likely to be those with greater ability to capture the upside gain in the equity market. Each quarter and within each investment category, we classify funds with return skewness ranked in the top one-third as high skewness funds and the rest as low skewness funds. We then compute TNA-weighted flows for each of the fund portfolios formed on return skewness as well as investment category and separately regress them on Prelec α and β. The results in Table 9 indicate that the skewness in recent performance does have a significant effect on investor demand for large-growth funds. Specifically, when a large-growth fund has demonstrated high return skewness in the most recent 36 months, its flows react much more strongly in response to an increase in investor preference for upside gain relative to a large-growth fund with low return skewness in the same performance measurement period. This finding suggests that the more a growth fund demonstrates the desired upside-seeking ability, the more its flows are influenced by changes in investor preference for the upside gain. Consistent with this interpretation, Table 9 shows that the loading on Prelec

β, which reflects the influence of investor preference for downside protection on fund flows, appears to be significantly more positive (i.e., less negative) for large-growth funds with high performance skewness. On the other hand, we do not observe similarly large contrasts in flow sensitivities to Prelec α and β between large-value funds with high versus low skewness, suggesting that return skewness, or the potential for upside gain, is less of a concern for investors going into value funds.

Next, we examine how a fund's hedge function affects fund flows. To group funds based upon their ability to provide downside protection, we compute individual funds' monthly return correlations with the market return over the past 36 months. We use CRSP value-weighted index returns to proxy for the market performance. The more negative is a fund's return correlation with the market return, the higher would be the fund's hedging utility. We consider funds with return correlations with the market ranked in the bottom one-third as high-hedging ability funds and separately estimate the flow sensitivity to investor risk preferences for the high versus low-hedging fund portfolios. As illustrated in Table 10, while active growth funds have insignificant or even significantly positive flow sensitivities to Prelec β, flows into active value funds are strongly sensitive to this measure of investor preference for downside protection. Moreover, this effect of downside protection preference is much more pronounced among value funds with low return correlations with the market portfolio. That is, for value funds, the more hedging utility a fund is able to provide to its investors, in terms of its performance correlation with the overall market performance, the more sensitive its flows would be to changes in investor preferences for downside protection.

Finally, in untabulated analyses, we control for lagged market adjusted returns of individual fund portfolios instead of those of their respective investment categories and find very similar results. Therefore, even after we account for differences in mean performance, the performance features of active funds concerning upside gain or downside protection still strongly influence investors' choices across different active funds.

5.3 Comparison across different investor clienteles

In the previous subsections, we have shown that flows into active funds behave consistently with predictions derived from our model of "tail-sensitive" preferences. It is conceivable that even among investors of active funds, the sensitivity of fund flows to option-implied risk attitude may vary 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 50,000 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 institutional investors. As a result, we focus on the comparison between two types of funds with distinct 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 among growth funds. On the other hand, flows into retirement funds with a value-oriented investment style should be more sensitive to Prelec β.

In Table 11, we repeat our baseline analysis for retirement and retail funds. Each month, we compute the value-weighted average flows into each of the two investor clienteles within individual investment categories. We then run time-series regressions of average monthly flows on Prelec α and β for individual investor groups within each investment category, controlling for lagged market-adjusted category returns, contemporaneous 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 earlier years), we mainly focus on monthly observations where there are at least 10 funds in an investor clientele. We report t-statistics computed with Newey-West (1987) robust standard errors with 36 lags to account for potential autocorrelation in fund flows.

The results in Table 11 indicate that retail funds with the large-growth investment objective have a significantly negative loading on Prelec α. In contrast, large-growth retirement funds have a significantly positive loading on Prelec α (i.e., a negative exposure to investor preference for upside potential). This difference is statistically significant at the 1% level according to the F-test. Similar differences are observed among large-value funds, where retirement funds again have significantly positive loadings on Prelec α. On the other hand, flows into retirement funds with the large-value 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 five times as large in magnitude for retirement funds as for retail funds within the large-value category, with the differences statistically significant at the 1% level according to the F-test. 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), flows into retirement funds exhibit a much weaker sensitivity to upside potential yet a 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 capture heterogeneity in investor preferences for tail events, the cross-sectional evidence in Table 11 validates our earlier finding that investor preferences for tail events are an important source of the demand for actively managed funds.

6 Robustness Analyses

6.1 Fund flows and alternative measures of tail-sensitivity

The Prelec measures of investor preference capture the shape of the empirical pricing kernel succinctly and provide helpful economic intuition in understanding its variation over time. For robustness of our findings, we also construct alternative measures directly from the shape of the pricing kernel. These measures do not have structural preference interpretations, but they may be correlated with both upside and downside preference parameters, which jointly determine the shape of the pricing kernel. We evaluate the shape of the pricing kernel at different levels of moneyness and characterize its slope with respect to the cumulative physical distribution function.

We construct the slopes of the pricing kernel 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:

$$\int_0^{P_0} m(P)dP = \int_0^{R_0} m(P)pdR = Q(R_0) \tag{3}$$

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. The slopes measure how much of the risk neutral probability mass is concentrated in the tails relative 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 the 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 protection versus upside potential preferences. Panel A of 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 (down)" 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 high at 0.84 because they both increase with the convexity of the pricing kernel. To better separate the upside seeking and downside aversion 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 Panel A, the correlation of the normalized upside slope with the downside slope drops to 0.15. Note, however, that this 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. Since a lower alpha implies greater upside-seeking sentiment in preferences, their negative correlation suggests that the normalized upside slope of the SDF is increasing with the upside-seeking sentiment. Similarly, the downside slope is increasing with the downside risk aversion.

The results of time-series regressions of fund flows on the pricing kernel slopes are shown in Panel B of Table 12. 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 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 down) 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 greater upside sentiment is associated with lower flows to active value funds. Overall, the results using the slopes of the pricing kernel are consistent with those using the Prelec weighting function. Our findings are therefore not sensitive to alternative measures of risk attitude.

6.2 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 the medium- and small-cap categories. We note that the number of observations used in the regressions is significantly shorter for some fund groups due to the shorter time-series of aggregate flows into passive funds as provided by Morningstar.

Table 13 shows the results from regressions of active fund flows on Prelec α (orthogonalized) and β. We find that both flows into medium and flows into small-cap growth funds have significantly negative loadings on Prelec α. On the other hand, for active medium and small-cap value funds, we find that flows are negatively related to Prelec β and again with similar economic and statistical significance relative to large-cap funds, as shown in Table 6. We conclude from these findings that the relation between flows into active funds and investor risk attitudes is largely consistent across small, medium, and large-cap funds.

7 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), given the distinct distributional features of active fund performance relative to their passive counterparts. We evaluate this hypothesis from several angles and find strong empirical and theoretical support. Specifically, we show that flows into active growth funds are strongly influenced by investors' preference for upside gain while flows into active value funds tend to respond more to investors' demand for downside protection. These findings are stronger among funds with greater levels of active management and exhibit stronger upside-seeking or downside hedging properties. Furthermore, we show that flows into retirement funds have a lower sensitivity to investor preference for upside potential but a higher sensitivity to the preference for downside protection, relative to non-retirement retail funds.

Since our study uncovers a new source of 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[28]. 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.[29][30] 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.[31] This procedure 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

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

[29] 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).

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

[31] 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.

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

$$\begin{aligned} m &= u'(R)Z(P) \;\; \text{and} & \text{(B.7)} \\ q &= \frac{m}{Em} \times p = \frac{R^{-\gamma}Z(P)p}{E\{R^{-\gamma}Z(P)\}}, & \text{(B.8)} \end{aligned}$$

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 function

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 only estimate combined SDF and cannot separately identify the marginal utility and the 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 (2013) investigate other popular specifications and show that this choice does not significantly affect 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.[32] 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 closely follows Rosenberg and Engel (2002).

To estimate the 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. (2).

[32] 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: **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 $\beta \leq 1$.

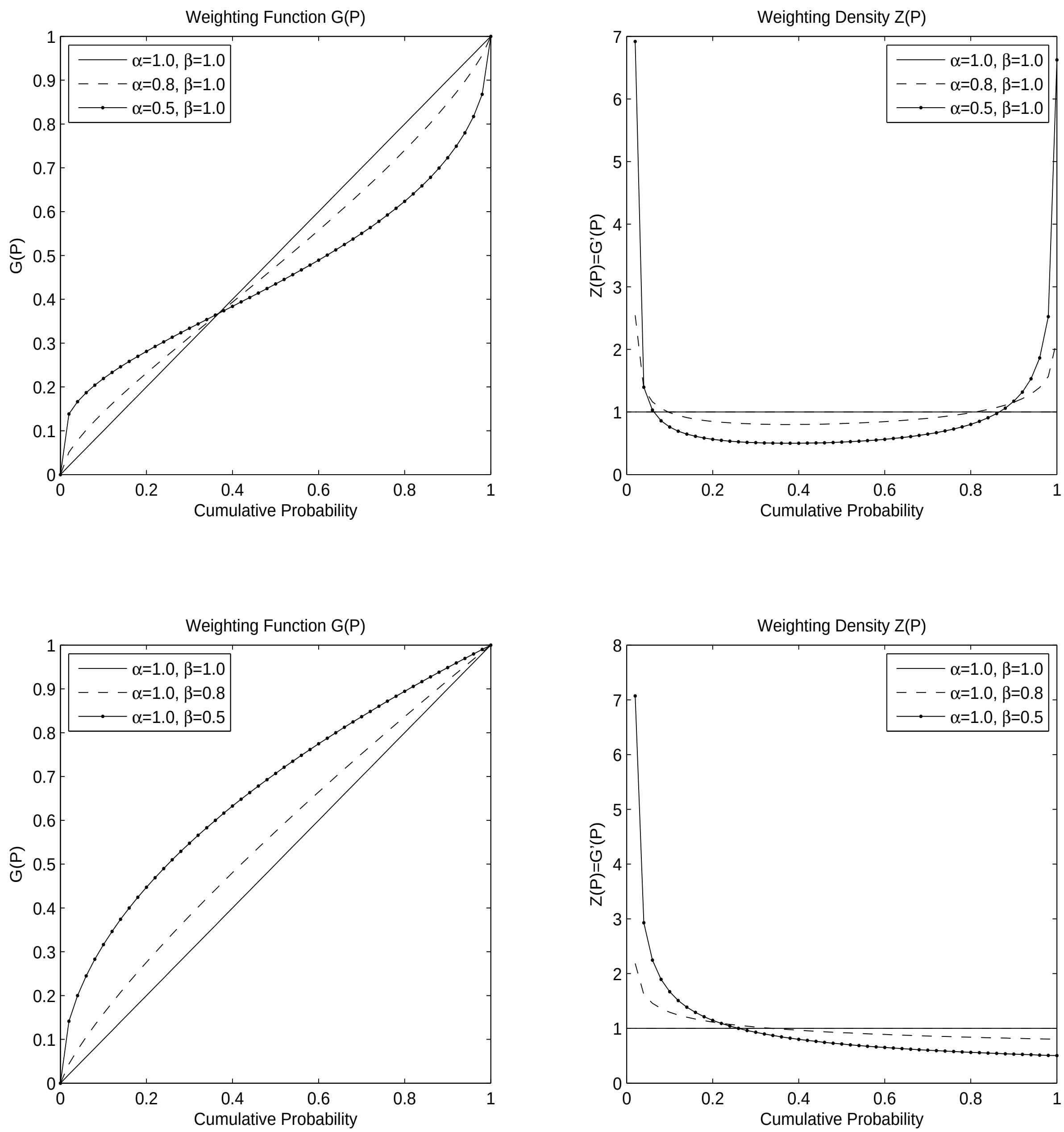

Figure 2: **Difference in certainty equivalent (CE) returns of active and passive funds.** We use simulated return series from the Pearson distribution system to construct three-year and five-year returns for passive and active funds with the growth and value investment objectives matching bootstrapped 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.

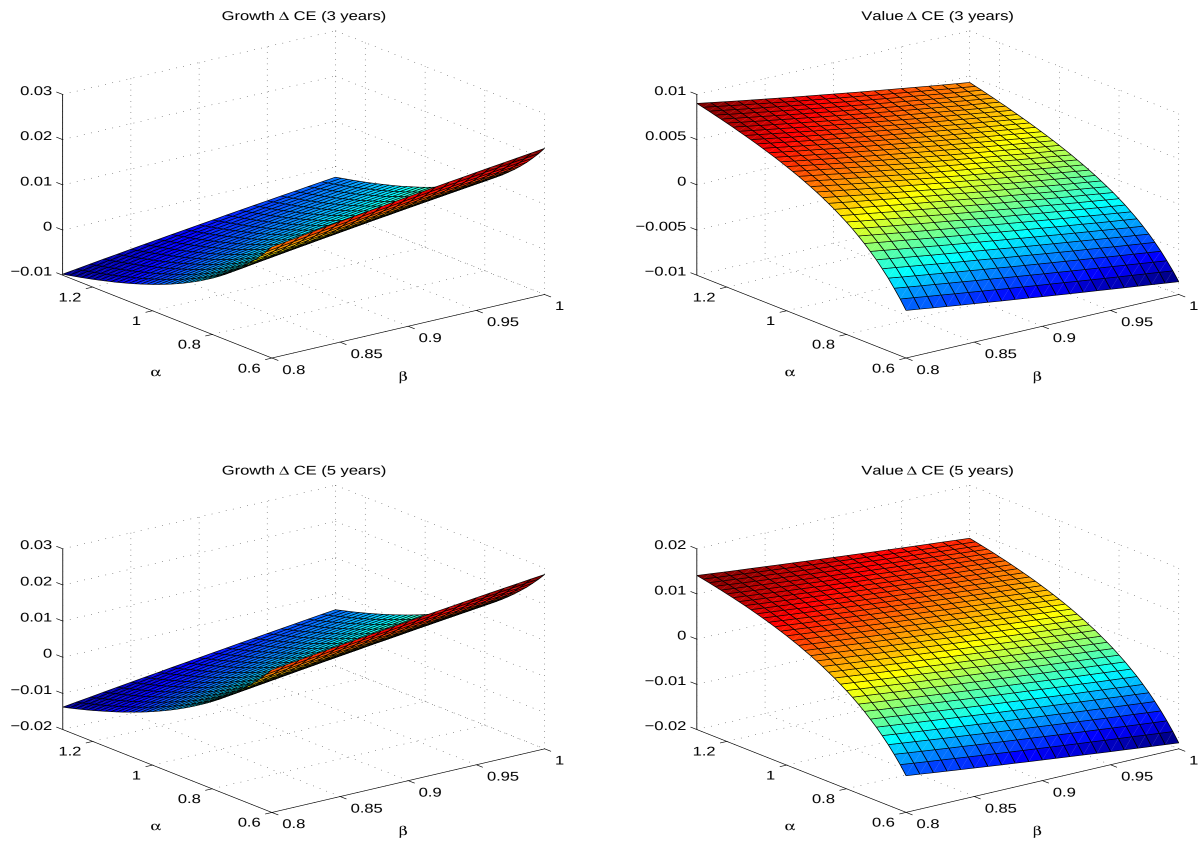

Figure 3: **Fraction of the portfolio allocated to the active value fund.** We use fund returns from 1996 to 2008, to generate long bootstrapped time series of monthly returns. Passive and active funds returns are sampled at the same time to preserve their correlations. Monthly returns are cumulated into three and five years holding periods. Portfolio assets include: a passive and active fund and a risk free asset with a constant return of two percent per annum. Utility is CRRA with power parameter $\gamma = 1$. The figures show $\theta_f(n)$, the fraction of risky assets allocated to the active fund where $n = \{3, 5\}$ is the holding period. The top two panels and bottom two panels show optimal portfolio fraction as a function of Prelec α and β, respectively.

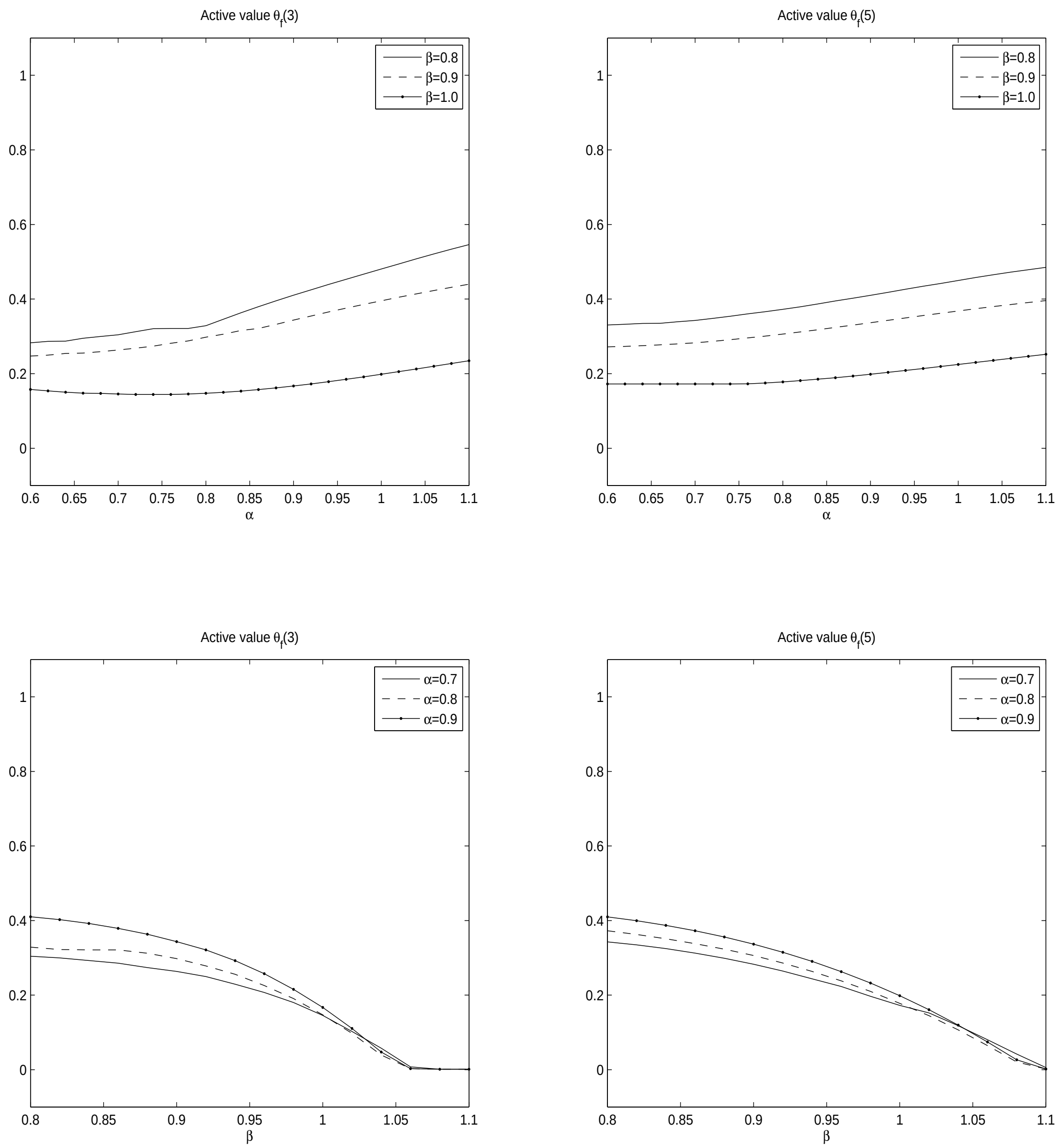

Figure 4: **Fraction of the portfolio allocated to the active growth fund.** We use fund returns from 1996 to 2007, to generate long bootstrapped time series of monthly returns. Passive and active funds returns are sampled at the same time to preserve correlation. Monthly returns are cumulated into three and five years holding periods. Portfolio assets include: a passive and active fund and a risk free asset with a constant return of two percent per annum. Utility is CRRA with power parameter $\gamma = 0.2$. The figures show $\theta_f(n)$, the fraction of risky assets allocated to the active fund and $n = \{3, 5\}$ is the holding period. The top two panels and bottom two panels show optimal portfolio fraction as a function of Prelec α and β, respectively.

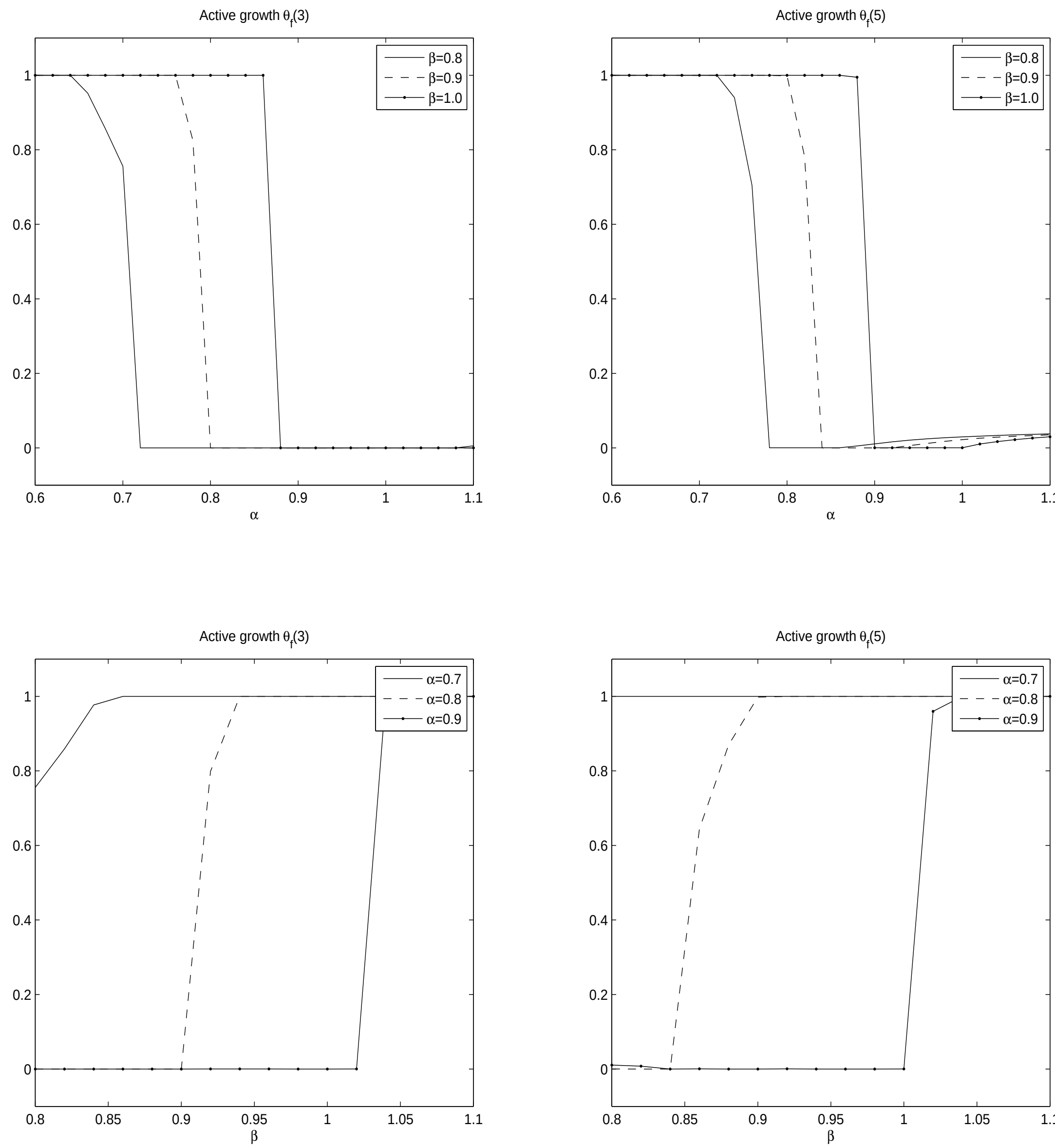

Table 1: **Summary statistics of individual fund level information for actively managed funds.** For each investment category, we report the mean, median, standard deviation and 25-th and 75-th percentiles of the following fund characteristics: TNA (in millions of US dollars), monthly returns (in percent), monthly flows (as a percentage of TNA), annual expense ratio (in percent), and Active Share (Cremers and Petajisto, 2009)

	TNA ($ mil.)	Return (%)	Flow (%TNA)	Expense (%)	Act. shr.
			LG		
Mean	1541	0.32	0.33	1.35	0.715
Std. Dev.	6231	6.22	5.21	0.50	0.155
P25	62	-2.61	-1.56	1.02	0.633
Median	240	0.70	-0.36	1.28	0.743
P75	918	3.90	1.24	1.64	0.830
			LV		
Mean	1467	0.53	0.50	1.24	0.740
Std. Dev.	4665	4.64	5.37	0.43	0.144
P25	78	-2.06	-1.41	0.95	0.652
Median	251	0.84	-0.17	1.20	0.773
P75	907	3.25	1.45	1.51	0.855

Table 2: **Comparison of holdings between active funds and passive benchmarks.** Each quarter, we group stocks held by funds into their respective size, book-to-market (BM) and momentum quintiles. For each actively managed fund and the corresponding Vanguard index fund within the same investment category in each period, we then compute the value-weighted size, BM and momentum quintile ranks across all fund holdings. Lastly, we compute the average size, BM and momentum ranks across all actively managed funds, separately for the growth and value categories, and compare these holding characteristics of actively funds with those of the corresponding Vanguard index funds.

		Size Rank	BM Rank	Mom Rank
LG	Vanguard	4.6233	2.1533	3.1537
	Active	4.6660	2.2974	3.3496
LV	Vanguard	4.4413	3.4119	2.7079
	Active	4.6620	3.1092	2.8161

Table 3: **Comparison of return moments of active funds and market index (Jan 1993 - Dec 2008).** We use monthly fund returns from 1993 to 2008 to generate 40,000 bootstrapped time series. Using bootstrapped distributions we compute estimates for time-series mean, volatility, skewness, and conditional expected returns in both the best and worst 10 and 25 percentiles of the distributions of monthly returns for individual actively managed funds and the market portfolio as proxied by CRSP value-weighted index. P-values of the statistical differences in moments between active and passive funds are reported at the bottom with italics indicating ten percent or higher significance levels.

	Mean	Std. dev.	Skewness	-10%	-25%	25%	10%
Market	0.0064	0.0438	-1.0210	-0.0846	-0.0517	0.0544	0.0703
Bust	-0.0077	0.0504	-0.7314	-0.1079	-0.0746	0.0496	0.0707
Boom	0.0204	0.0303	-0.3700	-0.0355	-0.022	0.0555	0.0682
LG	0.0054	0.0540	-0.5099	-0.1017	-0.0636	0.0672	0.0924
Bust	-0.0114	0.0591	-0.5378	-0.1264	-0.0894	0.0563	0.0819
Boom	0.0222	0.0422	0.4017	-0.0475	-0.029	0.0741	0.098
LV	0.0063	0.0402	-0.9268	-0.0743	-0.0454	0.0511	0.0686
Bust	-0.0050	0.0456	-0.8543	-0.0968	-0.0638	0.0455	0.0652
Boom	0.0176	0.0301	0.0104	-0.0345	-0.0209	0.0544	0.0694
	P value for one-sided test on the difference of return moments						
LG vs Mkt	0.235	*0.000*	*0.030*	*0.000*	*0.000*	*0.000*	*0.000*
Bust	*0.023*	*0.000*	0.198	*0.006*	*0.000*	*0.035*	*0.048*
Boom	0.180	*0.000*	*0.034*	*0.011*	*0.015*	*0.000*	*0.000*
LV vs Mkt	0.452	*0.008*	0.292	*0.008*	*0.002*	*0.031*	0.279
Bust	*0.026*	*0.018*	0.328	*0.051*	*0.002*	*0.059*	0.110
Boom	*0.010*	0.448	*0.079*	0.411	0.325	0.316	0.400

Table 4: **Comparison of return moments for active funds and Vanguard index funds (Jan 1993 - Dec 2008).** We use monthly fund returns from 1993 to 2008 to generate 40,000 bootstrapped time series. Using bootstrapped distributions we compute estimates for time-series mean, volatility, skewness, and conditional expected returns in both the best and worst 10 and 25 percentiles of the distributions of monthly returns for individual actively managed funds and passive funds as proxied by Vanguard large-growth and large-value index funds. P-values of the statistical differences in moments between active and passive funds are reported at the bottom with italics indicating ten percent or higher significance level.

	Mean	Std. dev.	Skewness	-10%	-25%	25%	10%
Vang. LG	0.0058	0.0466	-0.7264	-0.0900	-0.0553	0.0590	0.0780
Bust	-0.0087	0.0523	-0.4905	-0.1104	-0.0784	0.053	0.0765
Boom	0.0204	0.0346	-0.2435	-0.0429	-0.0247	0.0633	0.0765
Vang. LV	0.0068	0.0422	-0.8772	-0.0770	-0.0485	0.0537	0.0732
Bust	-0.0056	0.0484	-0.7069	-0.1002	-0.0683	0.0485	0.0712
Boom	0.0192	0.0305	-0.0004	-0.0327	-0.0210	0.0559	0.0711
LG	0.0054	0.0540	-0.5099	-0.1017	-0.0636	0.0672	0.0924
Bust	-0.0114	0.0591	-0.5378	-0.1264	-0.0894	0.0563	0.0819
Boom	0.0222	0.0422	0.4017	-0.0475	-0.0290	0.0741	0.098
LV	0.0063	0.0402	-0.9268	-0.0743	-0.0454	0.0511	0.0686
Bust	-0.0050	0.0456	-0.8543	-0.0968	-0.0638	0.0455	0.0652
Boom	0.0176	0.0301	0.0104	-0.0345	-0.0209	0.0544	0.0694
	P value for one-sided test on the difference of return moments						
LG vs Vang.	0.383	*0.000*	0.228	*0.012*	*0.001*	*0.003*	*0.005*
Bust	*0.075*	*0.003*	0.409	*0.017*	*0.006*	0.196	0.235
Boom	0.172	*0.002*	*0.070*	0.220	*0.093*	*0.009*	*0.004*
LV vs Vang.	0.273	*0.076*	0.453	0.242	*0.078*	*0.067*	*0.074*
Bust	0.330	*0.096*	0.289	0.277	*0.094*	0.118	*0.092*
Boom	*0.083*	0.397	0.495	0.345	0.488	0.264	0.320

Table 5: **Fund return exposures to option returns.** This table reports the regression estimates from Carhart (1997) four-factor model augmented with returns of option-based strategies. Each month we form value-weighted portfolios of active managed funds (by individual funds' TNAs) according to their investment categories. We use Vanguard large-growth and large-value index fund returns to proxy for returns of passively managed funds. For each fund portfolio, we estimate the time-series regressions of portfolio excess returns on the Carhart (1997) four factors and returns of portfolios constructed from the S&P 500 index options that proxy for downside hedging (ATM straddle) and upside seeking (ATM calls) function. 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. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors. The last two rows report F-test statistics for the differences in loadings on option-based strategy between active and passive funds with *** corresponding to 1% significance level.

	LG				LV			
	model 1		model 2		model 1		model 2	
	Active	Passive	Active	Passive	Active	Passive	Active	Passive
Straddle	0.0014	0.0685	0.0089	0.0627	0.2220	-0.0086	0.2163	-0.0141
	0.02	1.29	0.13	1.17	2.88	-0.10	2.78	-0.16
ATM Call			0.1325	-0.1009			-0.1006	-0.0951
			1.98	-1.57			-1.20	-0.84
Adj. R^2	0.9731	0.9715	0.9735	0.9718	0.9209	0.9419	0.9210	0.9419
N	155	155	155	155	155	155	155	155
F-test straddle	0.52		0.33		2.99***		2.97***	
F-test call			5.87***				0.00	

Table 6: **Flows into active funds as a function of option-implied risk attitude.** Panel A of the table reports the result from regressing aggregate monthly flows into actively managed funds on Prelec α and β, controlling for flows into passive funds of the same investment category, lagged category market-adjusted returns in each of the past three months, and contemporaneous market returns as proxied by monthly CRSP value-weighted index returns. Prelec α is orthogonalized against β. In Panel B, we replace the dependent variable with the 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). Time-series regressions are performed separately for individual investment categories. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors with 36 lags.

Panel A	LG		LV	
Const.	0.0889	-0.1530	0.0807	3.7413
	1.00	-0.22	0.46	4.04
Prelec Alpha		-0.7116		0.899
		-2.31		1.39
Prelec Beta		0.2933		-4.0271
		0.36		-3.74
Cat. ret (t-1)	0.0231	0.0248	0.0314	0.0335
	5.96	5.77	3.65	3.45
Cat. ret (t-2)	0.0098	0.0098	0.0109	0.0064
	2.86	2.89	1.34	1.01
Cat. ret (t-3)	0.0121	0.0139	0.0144	0.012
	2.71	3.64	1.70	2.07
Mkt	0.0041	0.0028	0.005	0.0079
	0.53	0.30	0.51	1.21
Passive Flows	7.4867	6.0324	5.5175	4.4667
	6.55	6.83	2.02	1.29
Adj. R^2	0.3522	0.3858	0.0781	0.1901
N	155	155	155	155
Panel B	LG		LV	
Const.	0.1798	-0.1432	0.1863	3.6334
	1.45	-0.19	1.09	3.85
Prelec Alpha*		-1.1216		1.0451
		-2.92		2.07
Prelec Beta		0.3623		-3.819
		0.40		-3.40
Cat. ret (t-1)	0.0261	0.0278	0.034	0.0346
	5.49	5.49	3.97	3.65
Cat. ret (t-2)	0.0137	0.0123	0.0127	0.0078
	3.52	3.68	1.87	1.62
Cat. ret(t-3)	0.0149	0.0167	0.0159	0.0126
	2.86	4.08	2.13	2.30
Mkt	0.0116	0.0069	0.0046	0.0081
	1.24	0.66	0.47	1.23
Adj. R^2	0.1406	0.2616	0.0579	0.1784
N	155	155	155	155

Table 7: **Flows into active funds as a function of option-implied risk attitude controlling for investor sentiment.** This table reports the result from regressing the aggregate 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 the NBER recession indicator or Baker and Wurgler (2006, 007) investor sentiment index. 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 with 36 months lags.

	LG			LV		
	(1)	(2)	(3)	(1)	(2)	(3)
Const.	-0.2213	-0.1739	-0.1737	3.8041	4.0716	4.0744
	-0.26	-0.36	-0.28	3.50	3.49	3.43
Prelec Alpha*	-0.7990	-0.7236	-0.7738	0.8964	0.9955	0.9906
	-2.38	-2.47	-2.51	1.54	1.43	1.67
Prelec Beta	0.4099	0.3205	0.3492	-4.1253	-4.4541	-4.4624
	0.40	0.54	0.47	-3.32	-3.14	-3.18
NBER rec.	-0.2375		-0.2486	0.1265		0.0349
	-0.21		0.47	1.77		1.47
BW sentiment		-0.0105	0.0255		0.1523	0.1456
		-1.85	-1.68		0.30	0.09
Cat. ret (t-1)	0.0216	0.0247	0.0217	0.0355	0.0346	0.0351
	5.43	4.84	4.92	3.38	2.38	2.35
Cat. ret (t-2)	0.0073	0.0097	0.0074	0.0078	0.0065	0.0069
	2.76	1.98	2.05	1.02	0.79	0.70
Cat. ret (t-3)	0.0121	0.0138	0.0123	0.0130	0.0125	0.0127
	3.58	3.24	3.24	2.15	1.66	1.65
Mkt	0.0043	0.0029	0.0043	0.0073	0.0078	0.0076
	0.30	0.44	0.43	1.23	0.90	0.97
Passive Flows	5.5495	5.9844	5.6437	4.8836	4.9365	5.0309
	6.52	6.11	6.04	1.57	1.97	2.11
Adj. R^2	0.3980	0.3817	0.3944	0.1872	0.1972	0.1918
N	155	155	155	155	155	155

Table 8: **The effects of option-implied risk attitudes across funds with different levels of active share (Cremers and Petajisto, 2009).** Each quarter and within each investment category, we group funds into the high versus low active share fund portfolios. Funds with active share in the bottom tercile are considered as low active share funds. For each active share fund portfolio within each investment category, we regress the monthly flows into actively managed funds on Prelec α and β, controlling for flows into passive funds of the same category, lagged market-adjusted returns of the portfolio in each of the past three months, and contemporaneous market returns as proxied by monthly CRSP value-weighted index returns. Prelec α is orthogonalized against β. For brevity, we only report coefficients and t-statistics for Prelec α and β and the p-values for tests of their differences across funds with different levels of active share. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors with 36 lags.

	Low Active Share	High Active Share	F-test p-value
		LG	
Alpha	-0.0075	-0.0172	0.01
	-1.74	-3.57	
Beta	0.0150	0.0095	0.62
	1.58	0.74	
Adj. R^2	0.3068	0.3911	
N	155	155	
		LV	
Alpha	-0.0048	0.0128	0.01
	-1.14	3.88	
Beta	-0.0302	-0.0495	0.03
	-3.76	-4.84	
Adj. R2	0.2821	0.3765	
N	155	155	

Table 9: **The effects of option-implied risk attitude across funds with different return skewness.** Each quarter and within each investment category, we group funds into the high versus low return skewness portfolios based upon the skewness of their monthly returns in the past 36 months. Funds with return skewness in the top tercile are considered as high skewness funds. For each return skewness fund portfolio within each investment category, we report the result from regressing the monthly flows into actively managed funds on Prelec α and β, controlling for flows into passive funds of the same category, lagged category market-adjusted returns in each of the past three months, and contemporaneous market returns as proxied by monthly CRSP value-weighted index returns. Prelec α is orthogonalized against β. For brevity, we only report coefficients and t-statistics for Prelec α and β and the p-values for tests of their differences across funds with different return skewness. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors with 36 lags.

	Low Skewness	High Skewness	F-test p-value
		LG	
Alpha	-0.0111	-0.0202	0.00
	-4.25	-4.69	
Beta	0.0044	0.0247	0.05
	0.42	1.89	
Adj. R^2	0.3793	0.4516	
N	155	155	
		LV	
Alpha	0.0058	0.0005	0.08
	2.11	0.08	
Beta	-0.0400	-0.0429	0.77
	-5.20	-3.29	
Adj. R^2	0.3705	0.1483	
N	155	155	

Table 10: **The effects of option-implied risk attitude across funds with different levels of return correlations with market returns.** Each quarter and within each investment category, we group funds into the high versus low hedging ability portfolios based upon the correlation of their monthly returns with market returns in the past 36 months. Funds with market correlations ranked in the bottom tercile are consider as high hedging ability funds. For each hedging ability fund portfolio within each investment category, we report the result from regressing the monthly flows into actively managed funds on Prelec α and β, controlling for flows into passive funds of the same category, lagged category market-adjusted returns in each of the past three months, and contemporaneous market returns as proxied by monthly CRSP value-weighted index returns. Prelec α is orthogonalized against β. For brevity, we only report coefficients and t-statistics for Prelec α and β and the p-values for tests of their differences across funds with different levels of market hedging function. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors with 36 lags.

	Low Corr.	High Corr.	F-test p-value
		LG	
Alpha	-0.0117	-0.0139	0.48
	-1.93	-5.90	
Beta	0.0246	0.0030	0.03
	1.98	0.31	
Adj. R^2	0.3943	0.4419	
N	155	155	
		LV	
Alpha	0.0192	-0.0012	0.01
	4.06	-0.45	
Beta	-0.0712	-0.0272	0.01
	-4.45	-2.87	
Adj. R^2	0.3691	0.3367	
N	155	155	

Table 11: **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 investment categories. Reported t-statistics are computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors with 36 lags. At the bottom of the table, we report P-values from F-tests for the differences in the coefficients of Prelec α and β between non-retirement retail funds and retirement funds.

	Retirement	Retail	F-test p-value
		LG	
Alpha	0.0289	-0.0186	0.01
	5.14	-4.22	
Beta	-0.0282	0.0185	0.08
	-0.69	1.45	
Adj R^2	0.1393	0.4767	
N	155	155	
		LV	
Alpha	0.0565	0.0025	0.01
	5.59	0.68	
Beta	-0.1869	-0.0397	0.01
	-2.00	-4.07	
Adj R^2	0.2641	0.2475	
N	155	155	

Table 12: **The effects of pricing kernel slopes as alternative measures of investor risk attitude.** In panel A, we report correlation coefficients between the 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 6. SDF (up norm.) is the upside slope normalized by the downside slope in order to separate their common variations. 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. It is normalized by the SDF (down) as discussed in Section 6. In panel B, we report 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 flows into passive funds of the same investment category, lagged category market-adjusted returns in each of the past three months, and contemporaneous market returns as proxied by monthly CRSP value-weighted index returns. We report t-statistics computed using the Newey and West (1987) autocorrelation and heteroskedasticity consistent standard errors with 36 lags.

Panel A: Correlation coefficient between SDF slopes and Prelec function parameter estimates.

	SDF (down)	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

Panel B: Flows into active funds as a function of pricing kernel slopes.

	LG				LV			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Const.	-0.8131	-0.8186	-0.9109	-0.8727	1.3121	1.4719	1.2834	1.4471
	-1.75	-1.82	-1.91	-1.91	1.02	1.14	1.06	1.22
SDF up*	0.8691	0.8788	1.0640	0.9979	-2.3985	-2.7995	-2.4670	-2.7984
	2.10	2.16	2.42	2.48	-2.18	-2.27	-2.01	-2.31
SDF down	0.1822	0.1813	0.1624	0.1685	0.6527	0.7422	0.6953	0.7538
	0.69	0.68	0.60	0.61	1.94	2.42	2.51	2.67
BW sentiment		-0.0036		0.0279		0.1839		0.1697
		-0.06		0.44		1.96		1.79
NBER rec.			-0.2365	-0.2468			0.1762	0.0768
			-1.61	-1.51			0.40	0.19
Cat. ret (t-1)	0.0243	0.0242	0.0211	0.0212	0.0301	0.0309	0.0328	0.0320
	5.95	5.61	4.56	4.69	2.55	2.42	1.98	1.92
Cat. ret (t-2)	0.0096	0.0096	0.0073	0.0074	0.0048	0.0046	0.0066	0.0054
	2.48	2.48	1.88	1.93	0.63	0.61	0.60	0.50
Cat. ret (t-3)	0.0126	0.0125	0.0108	0.0110	0.0107	0.0110	0.0120	0.0115
	3.16	3.08	2.82	2.81	1.61	1.67	1.40	1.38
Mkt	0.0026	0.0026	0.0040	0.0040	0.0095	0.0098	0.0088	0.0094
	0.27	0.27	0.39	0.39	1.54	1.66	1.16	1.30
Passive Flows	6.4634	6.4467	5.9872	6.0944	3.0283	3.2817	3.5230	3.4779
	7.17	6.42	6.14	5.73	0.69	0.79	1.00	1.00
Adj. R^2	0.3726	0.3683	0.3842	0.3805	0.1786	0.1905	0.1780	0.1858
N	155	155	155	155	155	155	155	155

Table 13: **Flows into 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 flows into passive funds of the same investment category, lagged category market-adjusted returns in each of the past three months, and contemporaneous market returns as proxied by monthly CRSP value-weighted index returns. 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 with 36 months lags.

	Med. G	Med. V	Sml. G	Sml. V
Const.	5.6265	8.8542	2.6429	3.7395
	3.50	3.13	1.79	3.87
Prelec Alpha*	-1.0586	1.4259	-1.3497	-0.4911
	-2.51	0.54	-2.40	-0.62
Prelec Beta	-6.0489	-8.5783	-2.6697	-3.7464
	-3.59	-2.18	-1.61	-3.50
Cat. ret (t-1)	0.0469	0.07	0.0409	0.0522
	3.36	1.92	9.44	2.57
Cat. ret (t-2)	0.0181	0.0359	0.0187	0.0126
	2.56	1.94	1.96	1.28
Cat. ret (t-3)	0.0247	0.0185	0.0117	0.0166
	4.75	0.53	1.95	2.08
Mkt	-0.0179	-0.0328	-0.021	0.0072
	-1.60	-0.70	-2.70	0.84
Passive flow	8.0918	-1.7768	4.013	0.8125
	5.06	-0.87	2.21	2.89
Adj. R^2	0.2823	0.0615	0.1590	0.1408
N	83	81	127	155