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

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Abstract

Despite their mediocre mean performance, actively managed mutual funds have distinct return distributions from their passive benchmarks in that their performance serves to reduce the downside risk and capture the upside potential. Based upon the idea that such return distributions may be attractive to investors who overweight tail events, we show that preferences for upside potential and downside protection estimated from the empirical pricing kernel have significant explanatory power for active fund flows. Moreover, the sensitivity of fund flows to investor risk preferences varies significantly across funds with different levels of active management, different return skewness or different hedging properties, and across retirement and retail funds.

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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 investments in actively managed funds despite their poor unconditional performance by modeling state-dependent managerial efforts or skills, in this paper we directly explore the equally important side of investor demand for active funds. Our paper identifies new components in the demand for active management which stem from investor preferences for upside potential or downside risk protection. While we do not attempt to address the broader issue concerning the size of the active management industry, our findings contribute to the understanding of various sources of investor demand for actively managed mutual funds.

There 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 our understanding of the performance differences between active and passive funds by comparing the bootstrapped distributions of monthly returns of actively managed mutual funds and their passive counterparts. We find substantial differences in return distributions of actively managed funds vis-a-vis 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. The active management component of their performance, as measured by their excess returns over the passive benchmarks, has positive covariance with market returns, especially during market expansions. Excess returns properties also suggest that active large-growth (LG) funds are more positively skewed than Vanguard LG funds during market booms. On the other hand, the returns of active value funds exhibit stronger downside hedging properties: they are less volatile and their excess returns over the passive benchmarks have

[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.

negative covariance with market returns, especially during periods of market declines. And analysis of excess returns suggests that skewness of active large-value (LV) funds exceeds that of Vanguard LV benchmark during market downturns.

It is important to point out that these differences in return distributions cannot be explained solely by different types of securities held by active versus passive funds, nor can they be attributed to potential lower diversification of actively managed funds compared to passive funds. We show that actively managed funds and their corresponding passively managed counterparts tend to hold stocks with very similar return-predictive characteristics including size, book-to-market ratio, and momentum. In addition, returns of hypothetical portfolios with the same level of diversification as active funds but constructed with stocks randomly drawn from those held by passive funds do not exhibit the same distributional features as those of active fund returns.

Given the observed distributional differences in the performance of active versus passive funds, we hypothesize that active funds may appeal to investors who jointly have a preference for upside potential and an aversion to downside risk.[3] While seemingly contradictory, as the oxymoron in the paper's title, such behavior is widely supported by experimental evidence.[4] Several theoretical models of portfolio choice demonstrate that investors with tail-overweighting risk preferences may prefer portfolio return distributions with limited downside risk and high upside potential.[5] Changes in investors' risk attitudes would naturally generate flows in and out of asset classes. Thus, we investigate if investor preferences are related to the demand for different types of active funds in a way consistent with the distributional properties of the funds' performance.

To construct measures of investor preference for upside potential and aversion to downside risk we use risk-neutral distributions of returns constructed from index option prices and physical distributions constructed from the underlying index returns. Specifically, the basic no-arbitrage restrictions imply the existence of the risk-neutral distribution of returns that is connected to

[3]In line with much of the traditional financial economics, we do not need to assume that investors are sophisticated enough to understand the properties of active funds' returns. Rather, investors may act on their sentiment and rebalance portfolios "as if" it was a result of risk preferences towards certain attractive distribution properties of active funds.

[4]See, for example, surveys by Camerer and Ho (1994), Camerer (1995), and Starmer (2000).

[5]For example, Shefrin and Statman (2000) show that such investors would construct optimal portfolios with downside protection containing upside lottery-like security. Polkovnichenko (2005) and Mitton and Vorkink (2007) find that investors with tail-overweighting preferences, while being risk averse overall, may invest in less- diversified assets to increase the upside potential of portfolio returns.

the underlying physical distribution through a pricing kernel. The pricing kernel (PK) contains information about investor risk attitude and we use it to construct empirical measures of risk preferences in different parts of the returns distribution.[6]

For our empirical investigations linking the demand for actively managed funds to investors' risk preferences, we define PK slopes on the left and right sides of the market returns distribution. Intuitively, these slopes correspond to the ratio of risk-neutral to physical cdf on the left side and the ratio of the risk-neutral to physical de-cumulative probabilities on the right side. That is, they measure investor preferences for risk in different parts of the return distribution. Higher values of the left slope correspond to stronger aversion to downside risk while higher values for the right slope indicate a stronger upside potential seeking preference.

We use empirical proxies for upside seeking and downside risk protection estimated from S&P index options prices. Estimating the empirical pricing kernel and investor preferences from the option market has been a commonly applied approach (see, for example, Jackwerth 2000, Ait-Sahalia and Lo 2000). The no-arbitrage link 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 stock market capitalization, we expect that our index option-based risk preference estimates are representative of the risk attitude of the average mutual fund investor.[7]

Using flows into U.S. open-end mutual funds during the period of 1996 to 2008, we show that our estimates of the pricing kernel slopes have significant explanatory power for monthly fund flows into actively managed funds. The economic magnitude of this effect is comparable to that of past fund performance. Specifically, we find that flows into actively managed growth funds significantly increase with investor preference for upside events. At the same time, flows into value

[6]Our present analysis does not require assumptions on the shape of the pricing kernel or utility of investors. In standard neoclassical models PK is a non-increasing function of wealth or consumption while some other models imply a U-shaped PK. Recent empirical literature on option pricing suggests that PK may exhibit a U-shaped relation with index returns (Jackwerth 2000, Rosenberg and Engle 2002, Bakshi, Madan and Panayotov 2010). On the theoretical side, there are several preference models capable of accommodating this type of PK, for example, a rank-dependent utility model of Quiggin (1983) and Yaari (1987) and cumulative prospect theory of Kahneman and Tversky (1991).

[7]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 the "Corporate Equities" table at www.federalreserve.gov/releases/z1/20100311). Since mutual funds conduct more active trading compared to some other types of institutional investors such as pension funds and insurance companies, their share of the total equity market trading volume is also expected to be significant.

funds significantly increase with investor aversion to downside events. These findings 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.[8]

We also investigate if our main results are robust to the control of market-wide investor sentiment. While investor sentiment may lead to a strong demand for either 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 individual demands 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 pricing kernel slopes in our framework. Nonetheless, our findings of the effect of investor risk preferences on fund flows remain robust after controlling for the NBER recession indicator, the Baker and Wurgler (2006, 2007) sentiment measure, and the market volatility index (VIX).

To further establish the link between investor preferences and the observed pattern of fund flows, we present several cross-sectional analyses which help illustrate the role of preferences for upside potential and downside protection. We first group funds based upon the extent of their active management, as proxied by the Active Share measure (Cremers and Petajisto, 2009). Since more active funds should be more appealing to investors seeking upside potential or downside protection given that they are more likely to exhibit those distributional differences in performance between active and passive funds, we should expect to see more pronounced effects of investor risk preferences on their flows. This is indeed what we find: flows into active large-growth funds are significantly more sensitive to investors' upside-seeking preferences and flows into large-value funds are significantly more sensitive to investors' downside aversion among funds with higher Active Share. We then directly compare the flow sensitivities to risk preferences 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 the upside PK slope that captures the upside-seeking preference. Regarding funds' hedging function, we sort funds based on their return correlations with the market returns. Funds that have lower return

[8]As noted earlier, these two types of behaviors are not mutually exclusive under certain utility functions and our results do not imply investor segmentation in the mutual fund market.

correlations with the market are expected to provide better downside protection for investors. We indeed find stronger sensitivity of flows to the downside PK slope among value funds with lower return correlations with the market index but do not find such a difference among growth funds.

As an alternative to these cross-sectional analyses based on fund features, we analyze flows into retirement versus 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 the downside slope 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 the upside-seeking preference.

Our paper is related to 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 exposures and therefore charging investors a premium beyond their alpha. Further, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2013a) develop a model of strategic effort allocation by fund managers based upon the relative payoffs of their performance under different economic conditions. In these studies, active funds are attractive to investors because fund managers generate abnormal returns that covary positively with a component of the pricing kernel. Pastor and Stambaugh (2012) propose a model without time-varying managerial skill but with decreasing returns to scale. The large size of the active fund industry can be rational if investors believe that active funds face decreasing returns to scale and their learning about the degree of returns to scale in active management is slow.[9]

Our study complements this literature by focusing on investor preferences rather than managerial skills or conditional fund performance. We demonstrate the existence of the link between time-varying investor risk preferences and flows into actively managed funds, which validates the

[9]Empirical studies in this literature include, for example, Gruber (1996), Moskowitz (2000), Kosowski (2006), Lynch, Wachter and Boudry (2007), Sun, Wang, and Zheng (2013), and Fama and French (2010) among others.

assumption in Frazzini and Lamont (2008) in their study of the relation between fund flows and stock returns.[10] Our approach is also distinct because we separately consider investor preferences for upside-seeking and downside protection and analyze their implications for flows into growth versus value funds. Furthermore, we conduct several unique cross-sectional analyses using fund or investor characteristics to help establish the link between investor risk attitudes and the demand for actively managed mutual funds. Our paper thus identifies investor risk preference as an important determinant of the demand for active management and 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 framework for evaluating preferences from option prices using risk-neutral and physical probability distributions. 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 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

[10] Frazzini and Lamont (2008) assume that investor preferences for specific stock types are reflected in active funds flows and show that flows negatively predict future returns. Besides validating their assumption about linkages of flows and investor sentiment, our results also suggest that active management plays a distinct role in generating returns features beyond those determined by the characteristics of stocks held by active funds and that investors may be attracted to these features. We also show that flows are not solely determined by returns-chasing behavior and reflect changes in investor risk preferences.

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 options data and the related filtering procedures are provided in Appendix A. We also obtain S&P 500 index returns for estimating the probability distribution function under the physical measure.[11]

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. We normalize flows into active and those into passive funds by the sum of their TNAs in our analyses. 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.[12] 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 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 exist considerable cross-sectional variations in fund size both within and across

[11]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.

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

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%.

We use the market portfolio as one of the passive benchmarks 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 when we construct the excess returns of the active funds over the benchmarks. 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.

2 Return Distributions of Actively Managed Funds

2.1 The distribution of active fund returns

Do actively managed funds offer different upside and downside performance 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 assume that each month, a representative active fund investor randomly picks one active fund, and holds the fund for a period of time. This strategy generates a path of monthly fund returns over our sample period which we use to estimate the return moments of active funds. This simulation is conducted for the value and growth fund categories separately. For robustness, we alternately choose the holding period to be one, six or twelve months and find similar results. The confidence interval of our moments estimates can be computed over bootstrapped paths. We generate 40,000 paths for computing our reported moments estimates and their p-values and find this bootstrap size adequate for necessary precision.[13] 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 (although equal-weighted results are similar to those reported). Note that over our sample period the number of active funds grows considerably with the growth rate varying across fund investment 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 in 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.[14] 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^{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^{th} percentile for the expected return in the worst 10 percentiles. We also compute the autocorrelations of the monthly return series (not reported) and find the serial correlation rather weak, having little effect on our sample moments calculation.

To utilize a return time series that starts as early 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, 2013b), we compare return distributions separately for boom and bust periods in addition to the whole sample period. 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 2, we compare return moments and conditional mean returns between large-cap active

[13]Funds have varied starting and ending dates and gaps in reporting monthly returns, which makes simple average of moments across funds problematic.

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

funds and the market portfolio. Not surprisingly, 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 periods while active LG funds tend to do so during the boom periods. Interestingly, active LG and LV funds have a monthly (non annualized) return volatility of 5.40% and 4.02%, respectively, as compared to 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 are associated with distinct performance features in terms of seeking upside potential and protecting against market downturns.

Next we explicitly examine differences in upper and lower sides of the distributions by focusing on the comparison in conditional mean returns across active funds and market index benchmark. The results show that 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 performance than the market portfolio. However, the magnitude of this underperformance on the downside is smaller than that of their outperformance on 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 outperformance of active LV funds relative to the market portfolio 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 bust periods.

2.2 Comparing return distributions between active funds and their hypothetical benchmark portfolios

While investing in the market index might be the simplest way of passive investment, in practice investors often engage in passive investment with certain styles. We therefore employ Vanguard index funds with the same investment styles as the underlying active funds as alternative passive benchmarks. To ensure that any potential differences in returns between actively managed funds and Vanguard index funds with the same investment style do not merely come from differences in the types of stocks they each hold or the extent of their portfolio diversification, we take the following steps before we compare the return distributions of active funds versus Vanguard index funds with the same investment styles.

First, we compare characteristics of stocks held by typical actively managed funds versus those 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.[15] For each actively managed fund and its corresponding Vanguard index fund within the same investment category in each period, we analyze the distribution of the size, BM and momentum quintile ranks across all of the funds holdings. For example, a fund primarily holding large-cap, growth stocks with strong return momentum would have an average size rank of 5, a BM rank of 1 and a momentum rank of 5. Not only that we compute the average size, BM and momentum quintile ranks for each fund, we also examine the median, standard deviation, 25^{th} and 75^{th} percentiles of each of these quintile ranks across all stocks held by the fund to account for potential differences in the dispersion of stock types within individual active versus passive fund portfolios.[16] Lastly, we average these summary statistics on size, BM and momentum quintiles ranks across all actively managed funds, separately for the growth and value categories, and compare these holding characteristics of active funds with those of their corresponding Vanguard index funds

As expected, Table 3 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 com-

[15]We thank Russ Wermers for providing stocks' size, book-to-market and momentum quintile ranks. See Daniel, Grinblatt, Titman and Wermers (1997) and Wermers (2004) for details on the stock ranking procedure. The DGTW benchmarks are available via www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

[16]We obtain similar inferences whether we compute equal-weighted or holdings-weighted average size, BM and momentum quintile ranks for each fund.

pared to value funds. More importantly for our purposes, 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. Not only that active funds and Vanguard index funds in the same investment category tend to hold stocks with similar average size, BM and momentum ranks, the distributions of these stock characteristics are also similar across active funds and their Vanguard index benchmarks. 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 the types of stocks they hold. Throughout the paper, we thus use Vanguard funds as the representative passive funds to facilitate the comparison of performance between passive and active funds within the same investment category.

Second, we control for potential differences in portfolio diversification between active and passive funds by constructing hypothetical passive portfolios which have the same level of diversification as active funds. Every quarter, for each actively managed fund, we replace each of its holdings with a randomly drawn stock from the fund's corresponding Vanguard benchmark fund.[17] We then use the active fund's portfolio weights to compute hypothetical portfolio's returns for each month in the quarter. These hypothetical portfolios hold the same types of stocks as Vanguard index funds but have similar level of diversification as active funds. We apply the same bootstrap procedure we used in the previous section to this simulated sample of passive benchmarks and analyze the differences in return distributions between active and passive funds that are more likely to be attributed to active management.[18]

In Table 4, we compare return moments and conditional means between active managed funds and their corresponding hypothetical benchmark portfolios following exactly the same methodology as Table 2. The results indicate that, even after we control for differences in portfolio diversification,

[17]We draw stocks with replacement because many active funds hold a larger number of stocks than Vanguard index funds of the same category. Thus, the diversification level of a simulated portfolio on average is the same or little lower than that of the original active fund due to possibile repeated draws.

[18]Alternatively, we also formed hypothetical portfolios using lagged reported active fund holdings, i.e. without random replacement of stocks. However, such benchmarks largely embed the stock-picking skill of the active funds they track (at the quarterly frequency). Our investigation into the return distributions of these alternative benchmarks confirms they have very similar time-series return distributions relative to their actively managed counterparts, consistent with several recent papers showing that copy-cat funds that invest in such tracking portfolios perform similarly to the original active funds (Frank *et. al.*, 2004, and Verbeek and Wang, 2010). Also, such tracking portfolios are not feasible low-cost alternatives to active funds for average individual investors. For these reasons, we use the random replacement procedure to construct passive benchmarks.

we reach the same conclusions as those from Table 2. That is, returns of active LG funds are more volatile than those of their hypothetical benchmark portfolios, primarily during the boom. On the other hand, returns of active LV funds are significantly less volatile than those of their hypothetical benchmark portfolios, primarily during the bust. In addition, active LG funds have significantly higher returns on the upside while active LV funds have significantly higher returns on the downside, relative to their passive benchmarks.

2.3 Analysis of excess returns of active over passive funds

As an alternative way to illustrate distributional differences in the returns of active versus passive funds, in Table 5, we compute moments for long-short excess returns of active funds relative to the corresponding Vanguard index fund returns within the same investment category, defined as $R_e = R_{active} - R_{passive}$. These excess returns capture the active management component of the returns of active funds, beyond return features attributed to fund investment styles. We first examine the covariance of these excess returns with the market returns, that is, their market "beta" ($\beta(R_e)$). The result in Table 5 indicates that LG funds' excess returns positively covary with the market while LV funds' excess returns negatively covary with the market. Specifically, LG funds' excess returns have a market beta of 0.10 and LV funds' excess returns have a market beta of -0.08, both of which are significantly different from zero. Furthermore, the covariance of active funds' excess returns with the market returns is more positive during the boom for LG funds and more negative during the bust for LV funds. These findings are consistent with the notion that active LG funds primarily provide investors with upside potential and active LV funds primarily help hedge downside risk. These properties are also confirmed by the skewness of active funds' excess returns. Specifically, the second column of Table 5 suggests that both LG and LV active funds add positive skewness to returns relative to their Vanguard counterparts.[19] More interestingly, active LG funds are more positively skewed than Vanguard LG index funds during the boom while active LV funds are more positively skewed than Vanguard index LV funds during the bust.

Finally, we try to distinguish the "factor exposure" from "stock selection" components of active

[19]The table shows results for tests of differences because this condition determines if skewness is incrementally higher for active fund. It can be shown algebraically that the sufficient condition for $skew(R_{active}) - skew(R_{passive}) > 0$ is that $\beta(R_e) > 0$ (as for active LG funds), $skew(R_{passive}) < 0$ and $skew(R_e) - skew(R_{passive}) > 0$. Additionally, in cases where $\beta(R_e) < 0$ (as for active LV funds), based upon our numerical estimates of $Var(R_{active})$, $Var(R_{passive})$ and $\beta(R_e)$, we also have that $skew(R_e) - skew(R_{passive}) > 0$ is sufficient for $skew(R_{active}) - skew(R_{passive}) > 0$.

management by analyzing the return variance of R_e. We first regress the excess returns, R_e, onto the returns of passive Vanguard benchmarks and obtain the factor loading $\beta_{passive}$ and residuals ε. The variance ratio $\frac{var(R_{active})}{var(R_{passive})}$can be decomposed as the following:

$$\frac{var(R_{active})}{var(R_{passive})} - 1 = \underbrace{\left[\left(1+\beta_{passive}\right)^2 - 1\right]}_{\triangleq VR_1} + \underbrace{\frac{var(\varepsilon)}{var(R_{passive})}}_{\triangleq VR_2}.$$

The first part of the decomposition, VR_1, can be positive or negative while the second part, VR_2, should always be non-negative. Any differences in variance between active fund returns and those of their Vanguard benchmarks that come from ”factor exposure” versus ”stock selection” can then be attributed to VR_1 and VR_2, respectively. We find that VR_1 is negligible and VR_2 is quite large for LG funds, making the variance of active fund returns about 30% larger than Vanguard fund returns over our sample period. This difference increases to 47% during the boom. On the other hand, VR_1 is significantly negative for active LV funds at around -20% over the whole sample period, and VR_2 is around 10%. Together, they make the variance of active LV fund returns 10% smaller than of Vanguard LV fund returns. Interestingly, VR_2 for LV also goes up from 9.5% during the bust to 17% during the boom, making the variance difference between active and passive LV funds mainly significant during the bust. These results from variance decomposition suggest that active LG funds achieve upside potential mainly through ”stock selection” while active LV funds offer greater downside hedging mainly by adjusting factor exposures, with less ”stock selection” in general. Additionally, both LG and LV funds offer better ”stock selection” during the boom period. These findings are consistent with Kacperczyk, Van Nieuwerburgh and Veldkamp (2013b) that managers' stock selection skill tends to be more pronounced during the market boom, while market timing skill dominates in the downturn.

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 active LV funds' 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.

Our findings echo those in Glode (2011) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2013a) in that the performance of active funds exhibits state-dependency. Our paper's main objective, however, is to illustrate how investors' preferences for these distributional features of active fund performance might affect the demand for actively managed funds. In line with much of traditional financial economics, we do not assume that investors are sophisticated enough to understand the properties of active funds' return distributions.[20] Rather, investors may act on their sentiment and rebalance their portfolios "*as if*" it was a result of risk preferences towards certain attractive distribution properties of active funds. In subsequent sections we examine fund flows to address this question.

3 Pricing kernel and risk preferences

Variation in investors' risk attitudes generates flows in and out of asset classes. Using measures of investor preferences for upside potential or downside risk protection, we can empirically examine whether investors' risk preferences affect the demand for actively managed funds in a way that is consistent with the distributional properties of active fund performance.[21]

One of the widely used methods for gauging risk attitudes of investors relies on the estimation of risk-neutral probability density from option prices. All neoclassical asset pricing theories admit the existence of the pricing operator (pricing kernel) m_t such that a return on a security R satisfies the following pricing equation:

$$E_t^P\{m_{t+1}R_{t+1}\} = 1, \tag{1}$$

where the expectation is taken over P, a joint conditional distribution at time t of returns and other state variables guiding m_t. The existence of this relationship is typically justified on the grounds of the basic no-arbitrage principle while the equilibrium-based derivations tie m_t to the marginal utilities of the agents in the economy. The latter interpretation imposes a restriction on m_t to be a

[20]For example, even basic mean-variance analysis or life-cycle portfolio selection problems involve fairly complicated concepts for an average investor. Yet the investor actions are widely studied empirically *as if* they result from a complex decision making process relying on information few investors can actually obtain and analyze.

[21]We are agnostic about whether the time-variation in preferences we observe is a result of shifts in investor composition or direct variation in individual investor utilities.

monotone non-increasing function of investor wealth or consumption, assuming risk preferences are described by a neoclassical expected utility.

A number of papers in the literature on option pricing present significant evidence that the pricing kernel may be non-monotone (see for example Jackwerth 2000, Ait-Sahalia and Lo 2000, Rosenberg and Engle 2002, Bakshi, Madan and Panayotov 2010) and in particular that it could be U-shaped. Bakshi, Madan and Panayotov (2010) show that the non-monotonicity of the pricing kernel is also consistent with negative expected returns on OTM calls. Polkovnichenko and Zhao (2013) show that non-monotonic pricing kernel is consistent with preferences for the upside potential in the return distribution. Our present analysis does not require assumptions on the shape of the pricing kernel as we use it to directly measure risk preferences in different parts of the distribution without imposing any constraints.

In our empirical analysis we do not consider any specific model of preferences. Instead we pursue a more general approach which relies only on the concept of risk neutral distribution Q:

$$1 = E_t^P\{m_{t+1}R_{t+1}\} = E_t^Q\{R_{t+1}\}E_t^P\{m_{t+1}\} \tag{2}$$

where Q is obtained from P through a change of measure and m_t is thus interpreted as a Radon-Nikodym derivative of Q with respect to P after a normalization.[22] The basic idea is that risk neutral distribution Q is different from P in a way that reflects investor risk preferences. For example, for a strictly risk averse investor Q assigns relatively higher probabilities than P to those events which investors are averse to, i.e. events where consumption or wealth is low and the marginal utility is high. When the pricing kernel is U-shaped, the risk-neutral probability also assigns relatively higher mass to the events where investors seek the upside potential. Thus, the differences between P and Q allow us to empirically measure the intensity of downside risk aversion and upside seeking preferences.[23]

To construct Q and P, we follow the estimation procedures developed originally in Ait-Sahalia and Duarte (2006) and Rosenberg and Engle (2002) and adopted for the estimation of the pricing kernel slopes in Polkovnichenko and Zhao (2013). In Appendix B we provide more detailed descriptions and further references. We measure the differences between P and Q at the monthly frequency

[22]We omit time subscripts for brevity, but both P and Q are allowed to be time-varying in empirical estimation.

[23]Our approach does not require specifying a particular utility which can support coexistence of such risk preferences. However several models accommodating this type of behavior are well developed in decision sciences, for examples see Quiggin (1993), Yaari (1987) and Kahneman and Tversky (1991).

by constructing the slope of the pricing kernel as follows. First, given the index return distribution function under the physical measure, $P(R)$, we define the slope as the ratio of the area under the pricing kernel with respect to probability P relative to the cumulative probability P. That is, for a given return R_0 and cumulative probability $P_0 = P(R_0)$, the area is $\int_0^{P_0} m(P)dP$ on the left, or $\int_{P_0}^1 m(P)dP$ on the right and the corresponding slopes are defined as follows:

$$Slope\ Down = \frac{\int_0^{P_0} m(P)dP}{P_0} \tag{3}$$

$$Slope\ Up = \frac{\int_{P_0}^1 m(P)dP}{1 - P_0} \tag{4}$$

where P_0 need not be the same for different slopes and the pricing kernel is scaled so that $\int_0^1 m(P)dP = 1$. These definitions have an intuitive interpretation. Specifically, note that we can write:

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

Thus, our definitions of the slopes correspond to the ratio of risk-neutral to physical cdf in the left side and the ratio of the risk-neutral and physical de-cumulative probabilities in the right side. The pricing kernel slopes measure how much of the risk neutral probability mass is concentrated in the respective areas relative to the underlying physical probability mass. Thus, the slopes reflect investor risk attitude in different parts of the return distribution. Higher values of the left slope correspond to stronger aversion to downside risk while higher values for the right slope indicate stronger upside-seeking.

We use data on options with 28 days to expiration to construct the slopes corresponding to moneyness of 0.99 for the left side to capture the attitude toward downside risk and 1.01 for the right side to capture the attitude toward upside potential.[24] 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 pricing kernel slopes across different months.

[24] We chose $\pm1\%$ moneyness for our slopes to maximize available options data due to higher liquidity of options closer to the ATM mark. But in unreported robustness exercises we also used 0.97 and 1.03 cutoffs for OTM slopes and obtained consistent results.

4 Empirical Evidence from Fund Flows

4.1 Fund flows and option-implied risk attitudes

To test the effect of upside-seeking and downside protection sentiments on the demand for active funds, we regress net flows into active funds on the contemporaneous option-implied slopes of the pricing kernel (*Slope Up* and *Slope Down*). As mentioned earlier, our baseline analyses focus on large-cap funds because we have the most reliable time series data for benchmark passive funds in this category. More importantly, large-cap funds may be more relevant for our purpose because the pricing kernel we extract from options is based on 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. We normalize flows into active funds and those into passive funds in each investment category by the sum of TNAs of these two types of funds in the 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 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. Warther (1995) shows that aggregate flows into equity mutual funds are correlated with both concurrent and lagged stock returns. We therefore also control for contemporaneous and three months lagged 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 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.

Table 6 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

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

flows into active funds should be influenced by their recent performance as well as investor sentiments for certain fund styles in general. More interestingly, the table indicates that flows into large-growth funds have a significantly positive loading on *Slope Up*. Thus, other things being equal, a greater preference for the upside potential leads to larger flows into active growth funds. In terms of economic significance, a one standard deviation increase in *Slope Up* would lead to an even larger increase in monthly flows into actively managed growth funds as compared to a one standard deviation increase in one-month lagged market-adjusted category returns, based upon the coefficient estimates in column 3 of Table 6.

This finding on the impact of investor preference is consistent with the properties of growth fund return moments presented earlier. Recall that active growth funds have higher conditional expected returns on the upside and higher volatility than their passive benchmarks, and that their excess returns over those of their passive benchmarks exhibit positive skewness which is more pronounced during market booms. 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 investor preference for the upside potential.

For large-value funds we find that the coefficient on *Slope Down* is significantly positive. This result indicates that more money flows into active value funds when investors are more concerned with the downside risk. This is again consistent with our earlier observation from the empirical return moments of value funds. Recall that active value funds provide higher conditional returns on the downside. In addition, during market downturns, they have less volatile returns than their passive benchmarks and their excess returns over passive benchmarks have a lower market beta. Again, the economic significance of the effect of *Slope Down* on flows into actively managed value funds is comparable to that of lagged market-adjusted category returns.[26]

4.2 Controlling for Investor Sentiment

The pricing kernel slopes we use may be related to 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.

[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.

In addition, investors may prefer actively managed funds because active managers can engage in sentiment-timing (Yadav and Massa, 2012). Moreover, it is not clear how the pricing kernel slopes might be related to the volatility index, VIX. VIX may also contain information on investor preferences because, like our measures, it is constructed based on information from index options.

One important distinction between our risk preference measures and investor sentiment or market-wide implied volatility measures, however, is that our slope measures separately identify downside protection and upside seeking preferences. When a sentiment index is high (or when VIX is low), 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 emphasis on payoffs in separate parts of the performance distribution. Therefore, it is interesting to see if separately identifying preferences in the upper and lower sides is empirically relevant for explaining fund flows over and above some single sentiment or volatility indexes.

Our first measure of investor sentiment is simply the NBER recession indicator since investor sentiment is usually closely related to the overall economic condition. Recessions are likely to be associated with low investor sentiment. 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 adopt both the original Baker and Wurgler sentiment index and the one that is orthogonalized to several macroeconomic conditions and find similar effects. 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. As yet another alternative, we use the volatility index (VIX) as an indicator of investor sentiment.

In Table 7, we show estimates from the regressions of net flows into active funds on option-implied measures of investor risk attitudes, controlling for various measures of investor sentiment. The result in this table indicates that after controlling for investor sentiment, we still find a significantly positive loading of fund flows on *Slope Up* for growth funds and a significantly positive loading on *Slope Down* for value funds. That is, when investors have a greater preference for upside potential,

[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.

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, various market-wide sentiment measures do not appear to have any significant 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 downside risk compared to passive indexing, we expect that funds that are more active in their asset management will exhibit a greater flow sensitivity to proxies of investor risk preferences, as they can better cater to investor preferences for the desired performance 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 when their demand for upside potential or downside protection increases.

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 *Slope Up* and *Slope Down* 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 fund portfolios within each investment category, respectively, along with contemporaneous and lagged market returns. Similar to our baseline analyses, 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 positive loading on *Slope Up* while actively managed large value funds have a significantly positive loading on *Slope Down*. More interestingly, these effects of investor preferences on flows into active funds are much more pronounced among funds with higher levels of active management. For example, for large growth funds in the high Active Share portfolio, the coefficient on *Slope Up* is around 0.045. In contrast, the coefficient on this proxy for investors' upside-seeking preference is only 0.027 for large growth funds with low Active Share. Similarly, large value funds with high Active Share exhibit a significantly stronger flow sensitivity to *Slope Down*. 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 the sensitivity of fund flows to investor risk references across funds with different levels of active management. To establish the direct effect of risk preferences on investor demand for funds with different performance features, we now 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 the flow sensitivities to *Slope Up* and *Slope Down* across funds with different performance skewness and hedging properties.

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 *Slope Up* and *Slope Down*.

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, as proxied by *Slope Up*, relative to a large-growth fund with low return skewness in the same period. This finding suggests that the more a growth fund demonstrates the desired upside-seeking ability, the more its flows are influenced by investor preference for the upside gain. On the other hand, we do not observe similarly large contrasts in flow sensitivities to *Slope Up* 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 investing with value funds.

Next, we examine how a fund's hedging 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 flow sensitivities to *Slope Down*, flows into active value funds are highly 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, as measured by its performance correlation with the overall market performance, the more sensitive its flows would be to investor preferences for downside protection.

Finally, in untabulated analyses, we control for lagged market adjusted returns of individual fund portfolios formed on distributional features of fund performance instead of those of their respective investment categories and find very similar results. Therefore, even after we account for potential 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 variation in investor 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 *Slope Up* 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 *Slope Down*.

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 *Slope Up* and *Slope Down* for individual investor groups within each investment category, controlling for lagged market-adjusted category returns, contemporaneous and lagged 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 positive loading on *Slope Up*. In a stark contrast, flows into large-growth retirement funds have a significantly negative loading on *Slope Up* (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 a significantly negative loading on *Slope Up*. On the other hand, flows into retirement funds with the large-value style are highly sensitive to *Slope Down*, suggesting that investors in these funds are more concerned with reducing downside risk. Particularly, this sensitivity to downside risk aversion is more than four times as large in magnitude for retirement funds as for retail funds within the large-value category, with the difference 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 investment options available to plan participants as demonstrated in Sialm, Starks and Zhang (2013).

In summary, using investor clienteles to capture heterogeneity in investor preferences for upside potential and downside protection, the cross-sectional evidence in Table 11 validates our earlier finding that investor preferences for upside potential and downside hedging are an important source of the demand for actively managed funds.

6 Robustness Analyses

6.1 Alternative control variables

To check the robustness of the effect of investor preferences on fund flows, in Table 12 we consider several alternative specifications to account for the potential confounding effects of several factors on fund flows. First, we include the 24-month moving average of lagged fund flows in the large growth or large value category as an additional control to account for the potential slow-moving time trend in flows into equity funds. Second, although we have controlled for flows into passive funds in the same investment category to account for the influence of investor preference for particular investment styles on flows into growth versus value funds, in model 2 of Table 12, we further control for aggregate flows into all equity mutual funds (across all investment categories) during the same period to account for investor sentiment for equity in general (Ben-Rephael, Kandel, and Wohl, 2011). In model 3 we consider specifications where both of these alternative controls are included at the same time. And finally, in model 4, we replace passive flows with flows into Vanguard index funds in the same investment category.

The results in Table 12 suggest that none of these alternative controls change our findings in any material way. That is, we continue to find that flows into large growth funds increase with *Slope Up* while flows into LV funds increase with *Slope Down*. The economic and statistical significance of these results are also similar to those based upon our baseline specification.

6.2 Results for medium-cap and small-cap funds

Our analyses on the relationship between flows into active funds and pricing kernel slopes 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 *Slope Up* and *Slope Down*. We find that both flows into medium and flows into small-cap growth funds have significantly positive loadings on *Slope Up*. On the other hand, for active medium and small-cap value funds, we find that flows are positively related to *Slope Down*, although for the medium value funds the coefficient is not statistically significant perhaps due to the relatively short sample period available for their passive benchmark. Overall though, we find 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

Overweighting of tail events have been identified as a salient feature of individual risk preferences 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, 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 support. Specifically, we show that flows into active growth funds are significantly related to investors' preference for upside gain while flows into active value funds tend to be more related to investors' demand for downside protection. These findings are stronger among funds with greater levels of active management, 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. We leave these questions for future research.

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. 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 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

[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.

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 risk neutral and physical probability distributions

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 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, we closely follow Rosenberg and Engle (2002).

[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).

References

Aït-Sahalia, Y., J. Duarte, 2003. Nonparametric Option Pricing under Shape Restrictions. Journal of Econometrics 116, 9–47.

Aït-Sahalia, Y., A. Lo, 2000. Nonparametric Risk Management and Implied Risk Aversion. Journal of Econometrics 94, 9–51.

Ameriks, J., S. P. Zeldes, 2001. Portfolio Choice in Retirement Accounts: An Analysis of Longitudinal Data from TIAA-CREF. working paper, Columbia University.

Bakshi, G., N. Kapadia, D. Madan, 2003. Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options. The Review of Financial Studies 16(1), 101–43.

Bakshi, G., D. Madan, 2000. Spanning and Derivative-Security Valuation. Journal of Financial Economics 55(2), 205–38.

Bakshi, G., D. Madan, G. Panayotov, 2010. Returns of Claims on the Upside and the Viability of U-Shaped Pricing Kernels. Journal of Financial Economics 97, 130–154.

Benartzi, S., R. H. Thaler, 2007. Heuristics and Biases in Retirement Savings Behavior. Journal of Economic Perspectives 21(3), 81–104.

Camerer, C. F., 1995. Individual Decision Making. in *Handbook of Experimental Economics*, ed. by J. H. Kagel, and A. E. Roth. Princeton University Press Princeton, NJ pp. 587–703.

Camerer, C. F., T. Ho, 1994. Violations of the Betweenness Axiom and Nonlinearity in Probability. Journal of Risk and Uncertainty 8(2), 167–196.

Chen, Q., I. Goldstein, W. Jiang, 2010. Payoff Complementarities and Financial Fragility: Evidence from Mutual Fund Outflows. Journal of Financial Economics 97(2), 239–62.

Cremers, M., M. A. Ferreira, P. P. Matos, L. T. Starks, 2013. The Mutual Fund Industry Worldwide: Explicit and Closet Indexing, Fees, and Performance. working paper, University of Notre Dame.

Cremers, M., A. Petajisto, 2009. How active is your fund manager? A new measure that predicts performance. The Review of Financial Studies 22, 3329–3365.

Fama, E. F., K. R. French, 2010. Luck versus Skill in the Cross Section of Mutual Fund Returns. Journal of Finance 65(5), 1915–47.

Fleming, J., B. Ostdiek, R. E. Whaley, 1996. Trading Costs and the Relative Rates of Price Discovery in Stock, Futures, and Option Markets. Journal of Futures Markets 16(4), 353–87.

Frank, M. M., J. M. Poterba, D. A. Shackelford, J. B. Shoven, 2004. Copycat funds: Information disclosure regulation and the returns to active management in the mutual fund industry. Journal of Law and Economics 47, 515–541.

Frazzini, A., O. A. Lamont, 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. Journal of Financial Economics 88, 299–322.

Glode, V., 2011. Why Mutual Funds Underperform?. Journal of Financial Economics 99(3), 546–559.

Gruber, M. J., 1996. Another Puzzle: The Growth in Actively Managed Mutual Funds. Journal of Finance 51, 783–810.

Jackwerth, J. C., 2000. Recovering Risk Aversion from Option Prices and Realized Returns. The Review of Financial Studies 13, 433–51.

Kacperczyk, M., S. V. Nieuwerburgh, L. Veldkamp, 2013a. Rational Attention Allocation over the Business Cycle. Working paper, New York University.

——— , 2013b. Time-Varying Fund Manager Skill. Journal of Finance forthcoming.

Kosowski, R., 2006. Do Mutual Funds Perform When It Matters Most to Investors? US Mutual Fund Performance and Risk in Recessions and Expansions.. Working paper, INSEAD.

Lynch, A., J. Wachter, W. Boudry, 2007. Does Mutual Fund Performance Vary over the Business Cycle?. working paper, NYU.

Madrian, B. C., D. F. Shea, 2001. The Power of Suggestion: Inertia in 401(K) Participation and Savings Behavior. The Quarterly Journal of Economics 116(4), 1149–87.

Moskowitz, T. J., 2000. Mutual Fund Performance: An Empirical Decomposition Into Stock- Picking Talent, Style, Transaction Costs, and Expenses: Discussion. Journal of Finance 55, 1695–1703.

Nelson, D. B., 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. Econometrica 59(2), 347–70.

Pastor, L., R. F. Stambaugh, 2012. On the Size of the Active Management Industry. Journal of Political Economy 120, 740–781.

Polkovnichenko, V., F. Zhao, 2013. Probability Weighting Functions Implied in Options Prices. Journal of Financial Economics 107(3), 580–609.

Quiggin, J., 1993. Generalized Expected Utility Theory: The Rank-Dependent Model. Kluwer Academic Pulishers, Norwell, MA 02061 USA.

Rosenberg, J. V., R. F. Engle, 2002. Empirical Pricing Kernels. Journal of Financial Economics 133, 341–72.

Savov, A., 2012. The Price of Skill: Performance Evaluation by Households. Journal of Finance forthcoming.

Sialm, C., L. Starks, H. Zhang, 2012. Defined Contribution Pension Plans: Sticky or Discerning Money?. working paper, UT Austin.

Sirri, E. R., P. Tufano, 1998. Costly Search and Mutual Fund Flows. Journal of Finance 53(5), 1589–622.

Starmer, C., 2000. Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk. Journal of Economic Literature 38, 332–382.

Sun, Z., A. Wang, L. Zheng, 2013. Only When the Tide Goes Out: Downside Returns and Hedge Fund Performance. Working paper, UC Irvine.

Verbeek, M., Y. Wang, 2010. Better than the Original? The Relative Success of Copycat Funds. Working paper, Rotterdam School of Management, Erasmus University.

Wermers, R., 2000. Mutual Fund Performance: An Empirical Decomposition Into Stock-Picking Talent, Style, Transactions Costs, and Expenses. Journal of Finance 55(4), 1655–95.

——— , 2004. Is Money Really 'Smart'? New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence. working paper, University of Maryland.

Wu, G., R. Gonzalez, 1996. Curvature of the Probability Weighting Function. Management Science 42, 1676–1690.

Yadav, V. N., M. Massa, 2012. Do Mutual Funds Play Sentiment?. working paper INSEAD.

Table 1: **Summary statistics of individual fund level information for actively managed funds during the period of 1996 to 2008.** 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 rat.(%)	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 return moments of active funds and market index.** We use fund returns from 1993 to 2008 to generate 40,000 bootstrapped time series of monthly returns. 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 of individual actively managed funds and the market portfolio as proxied by CRSP value-weighted index returns. P-values of the statistical differences in return moments between active and passive funds are reported with italics indicating ten percent or higher significance levels.

	Mean	Std. dev.	Skewness	-10%	-25%	25%	10%
LG	0.0054	0.0540	-0.5099	-0.1017	-0.0636	0.0672	0.0924
Market	0.0064	0.0438	-1.0210	-0.0846	-0.0517	0.0544	0.0703
P value	0.235	*0.000*	*0.030*	*0.000*	*0.000*	*0.000*	*0.000*
LG Bust	-0.0114	0.0591	-0.5378	-0.1264	-0.0894	0.0563	0.0819
Mkt Bust	-0.0077	0.0504	-0.7314	-0.1079	-0.0746	0.0496	0.0707
P value	*0.023*	*0.000*	0.198	*0.006*	*0.000*	*0.035*	*0.048*
LG Boom	0.0222	0.0422	0.4017	-0.0475	-0.0290	0.0741	0.0980
Mkt Boom	0.0204	0.0303	-0.3700	-0.0355	-0.0220	0.0555	0.0682
P value	0.180	*0.000*	*0.034*	*0.011*	*0.015*	*0.000*	*0.000*
LV	0.0063	0.0402	-0.9268	-0.0743	-0.0454	0.0511	0.0686
Market	0.0064	0.0438	-1.0210	-0.0846	-0.0517	0.0544	0.0703
P value	0.452	*0.008*	0.292	*0.008*	*0.002*	*0.031*	0.279
LV Bust	-0.0050	0.0456	-0.8543	-0.0968	-0.0638	0.0455	0.0652
Mkt Bust	-0.0077	0.0504	-0.7314	-0.1079	-0.0746	0.0496	0.0707
P value	*0.026*	*0.018*	0.328	*0.051*	*0.002*	*0.059*	0.110
LV Boom	0.0176	0.0301	0.0104	-0.0345	-0.0209	0.0544	0.0694
Mkt Boom	0.0204	0.0303	-0.37	-0.0355	-0.022	0.0555	0.0682
P value	*0.010*	0.448	*0.079*	0.411	0.325	0.316	0.400

Table 3: **Comparison of fund 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 examine the mean, median, standard deviation, 25th (Q1) and 75th (Q3) percentiles of each of these quintile ranks across all stocks held by the fund. We then 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 their corresponding Vanguard index funds.

	LG Active	LG Vanguard	LV Active	LV Vanguard
Size				
Median	4.9072	4.6154	4.9229	4.6731
Mean	4.6660	4.6233	4.6620	4.4413
Std. dev.	0.5517	0.5346	0.5629	0.6617
Q1	4.5441	4.5577	4.5323	4.0000
Q3	4.9875	5.0000	4.9867	5.0000
Book-to-Market				
Median	2.0179	1.7692	3.1414	3.6346
Mean	2.2974	2.1533	3.1092	3.4119
Std. dev.	1.2782	1.2305	1.3364	1.3228
Q1	1.0894	1.0000	2.0419	2.2500
Q3	3.1901	2.9423	4.2000	4.8269
Momentum				
Median	3.5416	3.2885	2.7657	2.6250
Mean	3.3496	3.1537	2.8161	2.7079
Std. dev.	1.3565	1.4544	1.3326	1.3829
Q1	2.2835	1.9231	1.6818	1.3654
Q3	4.5363	4.5000	3.9085	3.9615

Table 4: **Comparison of return moments between active funds and simulated passive funds.** We generate 40,000 bootstrapped time series of monthly returns for active funds and for simulated passive funds during the period of 1993 to 2008. To generate simulated passive funds, we start from quarterly reported holdings of each active fund and replace each of its stock holding with a random drawn stock (with replacement) from holdings of the Vanguard index fund with the same investment style. Using bootstrapped return distributions, we compute estimates of 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. P-values of the statistical differences in return moments between the original active funds and their corresponding simulated passive funds are reported with italics indicating ten percent or higher significance levels.

	Mean	Std. dev.	Skewness	-10%	-25%	25%	10%
LG	0.0067	0.0570	-0.5188	-0.1064	-0.0668	0.0736	0.1001
LG Sim.	0.0059	0.0522	-0.9638	-0.1023	-0.0624	0.0639	0.0833
P Value	0.338	*0.056*	*0.053*	0.333	0.166	*0.015*	*0.013*
LG Bust	-0.0108	0.0635	-0.4120	-0.1324	-0.0941	0.0630	0.0931
LG Sim Bust	-0.0085	0.0619	-0.6068	-0.1328	-0.0893	0.0631	0.0883
P Value	0.178	0.383	0.184	0.480	0.256	0.481	0.344
LG Boom	0.0239	0.0430	0.2073	-0.048	-0.0289	0.0783	0.1019
LG Sim. Boom	0.0205	0.0342	-0.2603	-0.043	-0.0241	0.0617	0.076
P Value	*0.075*	*0.002*	*0.035*	0.233	0.127	*0.001*	*0.001*
LV	0.0073	0.0436	-0.7731	-0.0784	-0.0488	0.0570	0.0762
LV Sim	0.0083	0.0497	-0.9387	-0.0890	-0.0539	0.0633	0.0888
P Value	0.219	*0.002*	0.235	*0.024*	*0.047*	*0.012*	*0.005*
LV Bust	-0.0051	0.0485	-0.7966	-0.1022	-0.0676	0.0484	0.0693
LV Sim Bust	-0.0038	0.0565	-0.9315	-0.1170	-0.0741	0.0571	0.0830
P Value	0.262	*0.006*	0.292	*0.040*	*0.079*	*0.029*	*0.043*
LV Boom	0.0200	0.0342	0.0941	-0.0379	-0.0228	0.0623	0.0795
LV Sim Boom	0.0204	0.0376	0.2036	-0.0446	-0.0257	0.0668	0.0896
P Value	0.383	*0.057*	0.306	0.102	0.190	*0.079*	*0.043*

Table 5: **Properties of excess returns over the benchmark.** We use fund returns from 1993 to 2008 to generate 40,000 bootstrapped time series of monthly returns. Using bootstrapped return distributions we compute skewness of excess returns of active funds relative to their corresponding Vanguard benchmark funds (i.e., $R_e = R_{active} - R_{passive}$), the beta of the excess returns with respect to the market portfolio $\beta(R_e)$, and decompose the variance of the excess returns into components due to factor loading versus stock selection. P-values at the bottom for tests of, respectively by column, significance of $\beta(R_e)$, the differences between R_e and $R_{passive}$ skewness, significance of the factor variance component and significance of differences of boom/bust selection variance component from their unconditional values, with italics indicating ten percent or higher significance levels

	$\beta(R_e)$	R_e Skewness	Var. Factor	Var. Selection
LG	0.0984	0.4697	0.0473	0.2680
P Value	*0.018*	*0.038*	0.333	–
LG Bust	0.0842	-0.0958	0.0520	0.191
P Value	*0.082*	0.222	0.378	*0.073*
LG Boom	0.1105	0.8586	-0.0549	0.5208
P Value	*0.073*	*0.093*	0.343	*0.070*
LV	-0.0808	0.1598	-0.2183	0.1068
P Value	*0.017*	*0.021*	*0.002*	–
LV Bust	-0.0854	0.1219	-0.2241	0.0952
P Value	*0.055*	*0.059*	*0.010*	*0.241*
LV Boom	-0.0578	-0.0250	-0.1894	0.1724
P Value	*0.098*	0.425	*0.029*	*0.048*

Table 6: **Flows into active funds as a function of option-implied risk attitude.** This table reports the result from regressing aggregate monthly flows into actively managed funds on slopes of the pricing kernel (*Slope Up* and *Slope Down*), controlling for flows into passive funds of the same investment category, lagged market-adjusted category returns in each of the past three months, and value-weighted index returns and their lagged values in each of the past three months. 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 months lags.

	LG			LV		
Constant	-0.0156	-0.0083	-0.0112	-0.0133	-0.0056	-0.0038
	-1.94	-0.71	-1.03	-1.33	-0.51	-0.38
Slope Up	0.0178	0.0138	0.0198	-0.0197	-0.0224	-0.0226
	2.10	1.77	2.44	-1.47	-1.49	-1.51
Slope Down	0.0001	-0.0036	-0.0059	0.0297	0.0251	0.0237
	0.04	-0.78	-1.46	8.56	3.63	3.76
cat(t-1)	0.0488	0.0191	0.0262	0.1024	0.1568	0.1617
	4.26	1.38	1.83	4.37	6.47	6.72
cat(t-2)	0.0441	0.0384	0.0405	0.0641	0.0904	0.0931
	2.35	2.39	1.74	2.73	3.05	3.48
cat(t-3)	0.0622	0.0258	0.0237	0.0803	0.0985	0.0976
	2.68	0.84	0.78	2.34	2.33	2.29
passive	3.5673	5.5693	2.9826	5.5586	3.3059	2.2802
	3.86	7.25	3.45	3.10	1.82	1.32
mkt(t)	0.0361		0.0361	0.0253		0.0248
	3.65		3.62	1.52		1.75
mkt(t-1)		0.0324	0.0282		0.0524	0.0506
		5.13	7.42		7.99	5.44
mkt(t-2)		0.0077	0.0131		0.0168	0.0201
		1.14	2.45		1.78	2.61
mkt(t-3)		0.0268	0.0279		0.0169	0.0169
		2.96	2.99		1.39	1.42
Adj. R2	0.3843	0.4093	0.4712	0.3075	0.3626	0.3803
N	155	155	155	155	155	155

Table 7: **Flows into active funds as a function of option-implied risk attitudes controlling for market-wide sentiment.** This table reports the result from regressing the aggregate monthly flows into actively managed funds on slopes of the pricing kernel (*Slope Up* and *Slope Down*), the Baker-Wurgler investor sentiment measure, the NBER recession indicator, and the VIX volatility index. We also control for average flows into passive funds of the same investment category, lagged market-adjusted category returns in each of the past three months, and value-weighted index returns and their lagged values in each of the past three months. 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)	(4)	(1)	(2)	(3)	(4)
Const.	-0.012	-0.0109	-0.0108	-0.0107	-0.0035	-0.004	-0.0057	-0.0062
	-1.09	-1.02	-0.96	-0.95	-0.37	-0.40	-0.58	-0.67
Slope Up	0.0209	0.019	0.0194	0.0188	-0.0233	-0.0208	-0.0199	-0.0175
	2.49	2.64	2.09	2.32	-1.51	-1.39	-1.38	-1.33
Slope Down	-0.0059	-0.0056	-0.0061	-0.0058	0.0238	0.0228	0.0246	0.0232
	-1.43	-1.36	-1.60	-1.42	3.69	3.92	3.76	4.23
NBER rec.	-0.0012			0.0005	0.0017			-0.0015
	-0.92			0.73	0.74			-1.24
BW sentiment		0.0003		-0.0015		-0.0009		0.0026
		0.55		-0.92		-0.89		0.83
VIX(t)			0.0012	0.0022			-0.0063	-0.0077
			0.19	0.39			-1.21	-1.18
mkt(t)	0.0348	0.0361	0.0371	0.0364	0.0272	0.0236	0.0208	0.0218
	3.26	3.60	3.53	3.19	2.30	1.55	1.37	1.46
mkt(t-1)	0.0258	0.0283	0.0288	0.0268	0.0542	0.0506	0.0468	0.0517
	4.81	7.37	5.48	4.07	4.32	6.05	5.28	4.36
mkt(t-2)	0.0111	0.0131	0.0136	0.0117	0.0235	0.0209	0.0173	0.0235
	1.94	2.43	1.97	1.54	3.87	2.81	2.08	3.59
mkt(t-3)	0.0265	0.0281	0.0284	0.0274	0.019	0.0173	0.0149	0.0186
	2.61	3.05	2.87	2.61	1.79	1.41	1.17	1.57
cat(t-1)	0.0265	0.0272	0.0258	0.0276	0.1633	0.1653	0.1592	0.1668
	1.91	1.99	1.87	2.17	6.72	6.81	6.83	7.13
cat(t-2)	0.0394	0.0427	0.0409	0.0438	0.0953	0.1008	0.092	0.1075
	1.78	1.75	1.85	2.01	3.75	3.34	3.40	4.14
cat(t-3)	0.0229	0.0249	0.0233	0.0243	0.0983	0.105	0.096	0.1085
	0.74	0.80	0.75	0.76	2.26	2.37	2.21	2.60
passive	2.8677	3.0723	2.92	2.8852	2.4933	2.1036	1.9046	1.8726
	3.20	3.71	3.81	3.76	1.48	1.26	1.02	1.02
Adj. R2	0.4713	0.4683	0.4676	0.4663	0.3803	0.3803	0.3774	0.3828
N	155	155	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 slopes of the pricing kernel (*Slope Up* and *Slope Down*), controlling for flows into passive funds of the same category, lagged market-adjusted category returns in each of the past three months, and value-weighted index returns and their lagged values in each of the past three months. For brevity, we report only the coefficients and t-statistics for the slopes and p-values for F-tests of the difference in coefficients across funds with different Active Share. 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.

	Low Active Share	High Active Share	F-test p-value
		LG	
Slope Up	0.0273	0.0455	0.047
	4.05	4.56	
Slope Down	-0.0103	-0.0028	0.314
	-2.62	-0.33	
Adj. R^2	0.3820	0.4121	
N	152	152	
		LV	
Slope Up	0.0129	-0.0317	0.000
	1.36	-3.33	
Slope Down	0.021	0.0306	0.085
	3.47	3.46	
Adj. R2	0.3469	0.3981	
N	152	152	

Table 9: **The effects of option-implied risk attitudes 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 their skewness of their monthly returns in the past 36 months. Funds with skewness in the top tercile are consider 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 slopes of the pricing kernel (*Slope Up* and *Slope Down*), controlling for flows into passive funds of the same category, lagged market-adjusted category returns in each of the past three months, and value-weighted index returns and their lagged values in each of the past three months. For brevity, we report only the coefficients and t-statistics for the slopes and p-values for tests of the difference in coefficients across funds with different skewness. 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.

	Low Skewness	High Skewness	F-test p-value
		LG	
Slope Up	0.0320	0.0503	0.032
	4.38	4.57	
Slope Down	-0.0016	-0.0126	0.132
	-0.40	-1.17	
Adj. R^2	0.4233	0.4397	
N	152	152	
		LV	
Slope Up	-0.0136	-0.0017	0.139
	-1.94	-0.09	
Slope Down	0.0247	0.03072	0.541
	3.31	3.80	
Adj. R^2	0.4358	0.1593	
N	152	152	

Table 10: **The effects of option-implied risk attitudes across funds with different levels of correlations with market return.** 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 correlation 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 slopes of the pricing kernel (*Slope Up* and *Slope Down*), controlling for flows into passive funds of the same category, lagged market-adjusted category returns in each of the past three months, and value-weighted index returns and their lagged values in each of the past three months. For brevity, we report only the coefficients and t-statistics for the slopes and p-values for tests of the difference in coefficients across funds with different market hedging properties. 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.

	Low Corr. Mkt	High Corr. Mkt	F-test p-value
		LG	
Slope Up	0.0307	0.039	0.320
	1.96	6.45	
Slope Down	-0.0141	-0.0006	0.060
	-1.51	-0.17	
Adj. R^2	0.3832	0.5055	
N	152	152	
		LV	
Slope Up	-0.0476	0.0043	0.000
	-3.65	0.64	
Slope Down	0.0449	0.0179	0.001
	3.94	2.61	
Adj. R^2	0.3803	0.4232	
N	152	152	

Table 11: **The effects of option-implied risk attitudes across investor clienteles.** This table compares the impact of SPX index option implied slopes of the pricing kernel (*Slope Up* and *Slope Down*) on active flows into non-retirement retail versus retirement funds, controlling for flows into passive funds of the same category, lagged market-adjusted category returns in each of the past three months, and value-weighted index returns and their lagged values in each of the past three months. For brevity, we report only the coefficients and t-statistics for the slopes and p-values for tests of the difference in coefficients across funds with different market hedging properties. 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.

	Retirement	Retail	F-test p-value
		LG	
Slope Up	-0.0638	0.0474	0.000
	-4.71	5.25	
Slope Down	0.0024	-0.0090	0.558
	0.08	-1.53	
Adj R^2	0.1025	0.5715	
N	152	152	
		LV	
Slope Up	-0.1333	-0.0056	0.000
	-6.18	-0.550	
Slope Down	0.1200	0.0259	0.000
	1.85	3.67	
Adj R^2	0.2288	0.3820	
N	152	152	

Table 12: **Flows to active funds as a function of option-implied risk attitudes with additional controls.** This table reports the result from regressing the aggregate monthly flows into actively managed funds on slopes of the pricing kernel (*Slope Up* and *Slope Down*). In addition to previously used control variables we consider the following alternative specifications: (1) add 24-months moving average of active flows for an investment category, (2) add lagged aggregate flows, (3) jointly control for lagged category flows and lagged aggregate flows, (4) replace passive flows with flows into Vanguard index funds with the same investment category. 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)	(4)	(1)	(2)	(3)	(4)
Const.	-0.0161	0.0021	-0.0022	-0.0025	-0.0062	0.0129	0.0161	0.0161
	-2.46	0.40	-0.47	-0.47	-0.44	1.36	0.93	1.21
Slope Up	0.0157	0.0111	0.0103	0.0123	-0.0196	-0.0343	-0.0345	-0.0343
	3.88	2.03	3.80	2.80	-1.58	-2.27	-2.36	-2.91
Slope Down	0.001	-0.0124	-0.0079	-0.0091	0.0222	0.0166	0.0129	0.0128
	0.33	-5.93	-3.32	-3.70	3.13	3.27	2.20	2.28
mkt(t)	0.0316	0.004	0.0085	0.0137	0.0102	-0.0122	-0.0226	-0.0221
	2.95	0.61	1.37	2.03	0.62	-1.02	-1.51	-1.31
mkt(t-1)	0.0273	0.0001	0.0059	0.0044	0.0484	0.0199	0.0167	0.0173
	5.68	0.03	1.90	1.46	4.58	3.62	3.07	2.97
mkt(t-2)	0.0079	0.0017	0.0016	0.0028	0.0118	0.005	-0.0017	-0.0012
	1.37	0.38	0.31	0.45	2.13	0.85	-0.41	-0.24
mkt(t-3)	0.018	0.0068	0.0062	0.0065	0.006	-0.0035	-0.0086	-0.0082
	2.16	1.15	0.95	0.99	0.64	-0.39	-0.79	-0.71
cat(t-1)	0.0227	0.0736	0.0571	0.0626	0.1787	0.1244	0.1373	0.1386
	1.66	5.04	4.43	5.42	8.80	5.81	6.75	6.83
cat(t-2)	0.0527	0.0621	0.0567	0.0636	0.1014	0.0734	0.0843	0.0849
	4.00	5.78	5.36	6.67	5.07	2.41	3.43	3.48
cat(t-3)	0.0541	0.0631	0.0709	0.072	0.0913	0.0772	0.0812	0.0818
	3.82	3.42	3.64	3.54	3.23	2.07	2.72	2.78
MA(24)	0.4486		0.6933	0.6989	0.4476		0.8312	0.8439
	3.86		8.79	10.18	2.38		4.50	3.75
Agg. Flow		0.8175	2.2027	0.0122		0.8353	0.498	-0.0099
		11.46	2.73	1.11		7.28	0.19	-0.27
Passive or	3.3051	1.3562	0.2351	0.2274	0.6311	1.1621	0.4763	0.4854
Vanguard	4.00	1.60	2.07	2.31	0.30	0.48	3.03	3.22
Adj. R2	0.66	0.7523	0.7897	0.7804	0.4601	0.5441	0.5708	0.5709
N	131	155	131	131	131	155	131	131

Table 13: **Flow into Medium and Small Active Funds as a Function of Option-Implied Risk Attitudes.** This table reports the coefficient estimates from regressing the average monthly flows into actively managed medium-cap and small-cap funds on slopes of the pricing kernel (*Slope Up* and *Slope Down*), controlling for flows into passive funds of the same investment category, lagged market-adjusted category returns in each of the past three months, and value-weighted index returns and their lagged values in each of the past three months. 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.	-0.044	-0.0639	-0.0391	-0.0534
	-2.10	-1.20	-2.46	-4.62
Slope Up	0.0294	0.0627	0.0248	0.0272
	1.92	0.77	2.22	1.76
Slope Down	0.0159	0.0145	0.0164	0.0275
	1.72	0.57	1.43	4.28
cat(t-1)	0.0856	0.7475	0.1073	0.1559
	1.57	3.06	7.96	5.19
cat(t-2)	0.0185	0.5434	0.109	0.1767
	0.31	4.59	7.44	6.48
cat(t-3)	0.0161	0.7088	0.0801	0.0851
	0.36	4.49	3.66	3.34
passive	0.6249	-1.1497	1.2665	0.7244
	0.40	-0.49	1.49	3.22
mkt(t)	0.0742	0.0689	0.0747	0.0363
	7.15	2.74	6.83	1.93
mkt(t-1)	0.0384	0.1458	-0.0008	0.0742
	4.34	1.54	-0.05	2.68
mkt(t-2)	0.0192	0.0943	-0.0174	-0.001
	2.80	2.46	-0.82	-0.06
mkt(t-3)	0.0365	0.026	-0.0159	-0.0062
	3.75	0.97	-0.76	-0.41
Adj. R2	0.3492	0.4338	0.2961	0.3953
N	83	81	127	155