Mutual Fund Risk-Shifting and Management Contracts[☆]

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Abstract

We study risk-shifting linked to the performance contracts of portfolio managers. Our theory predicts that mutual fund managers with asymmetric performance contracts and mid-year performance close to their announced benchmark increase their portfolio risk in the second part of the year. As predicted by our theory, performance deviation from the benchmark decreases risk-shifting only for managers with performance contracts. Managers without performance contracts do not shift risk. Deviation from the benchmark dominates the incentives from the flow-performance relation, suggesting that risk-shifting is motivated more by management contracts than by a tournament to capture flows.

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1. Introduction

This paper is an empirical examination of mid-year risk-shifting by mutual fund managers who are motivated by typical contracts with investment advisors. Previous studies have used the relationship between the advisors and the shareholders to examine risk-shifting. Brown, Harlow, and Starks (1996) first found evidence that mutual fund managers increase the volatility of their portfolio in the second half of the year when they underperform in the first half. Brown, Harlow, and Starks (1996) motivate the incentive to shift risk by using the conclusions reached by Chevalier and Ellison (1997) and Sirri and Tufano (1998) that a disproportionately large amount of money flows into top-performing funds compared to the flow out of poorly performing funds. Brown, Harlow, and Starks (1996) argue that this asymmetry creates a tournament in which the winner is compensated by fees earned on the assets acquired. Managers of poorly performing funds can increase their chances of winning the tournament by increasing their portfolio volatility. If they perform well, they win more than they stand to lose if they perform poorly.

However, Spiegel and Zhang (2013) argue that asymmetry in the flow-performance relation is a statistical artifact that is linear when properly estimated. Furthermore, investors in mutual funds and the board of directors collectively delegate the task of portfolio management to an investment advisor who, in turn, hires a portfolio manager. It is the advisor who collects the fees and pays the manager. In a recent paper, Ma, Tang, and Gómez (2016) find that more than 98% of portfolio managers have a contract with variable compensation; for more than 79%, the variable compensation is based on the mutual fund's performance relative to a specified benchmark. Moreover, these contracts are asymmetric: that is, the manager is not penalized if the fund underperforms the benchmark. This means that most portfolio managers will receive higher compensation from taking more risk if the fund outperforms the benchmark. With the portfolio manager making day-to-day portfolio decisions, this asymmetric contract should be as important a determinant of risk-shifting as the response of flows to performance.

This paper is about the contract between the investment advisors and the portfolio managers. Studies of risk-shifting motivated by mutual funds tournament focus on the contract between the advisors and the shareholders. Unlike the portfolio managers' contract, the advisors' contract with the shareholders is regulated (see Section 205 (a) (1) of the Investment Advisers Act of 1940), is specified as a percentage of fund's assets under management (AUM), and is symmetric if there is a performance bonus (i.e., Deli (2002) and Golec and Starks (2004)). If the shareholder pays more for good performance, they will also receive a lower fee for poor performance. This is called a "fulcrum" fee by the regulators. In sharp contrast, the contract with the portfolio managers has asymmetric, option-like payoff in which value of the fund at the end of the year is the underlying asset of the option and the stochastic benchmark is the strike price. Using the model of an exchange option in Margrabe (1978), we show theoretically that the distance of the asset's return from the benchmark's return is the key variable in determining the vega of the manager's contract, that is, the derivative of the option's price with respect to the volatility of the portfolio. The vega reaches its maximum value when the distance is the smallest, that is, when the mutual fund's return is closest to the benchmark's return. This is the point at which volatility is most valuable to the manager. With this result, we hypothesize that risk-shifting by the portfolio manager is inversely related to the distance of the portfolio's return from the benchmark's return. This paper is the first to examine the contract between the manager and the advisor as an exchange option and derive the implications of that contract for mid-year risk-shifting. This paper is also the first to hypothesize an inverse relation between risk-shifting and the distance of the portfolio's return from its benchmark.

However, the impact of vega will likely be less important as the risk of being fired increases. Khorana (1996) and Chevalier and Ellison (1997) show that management turnover is empirically related to poor performance. Carpenter (2000) uses a dynamic investment allocation model and shows that portfolio volatility will converge to infinity as a managed portfolio approaches bankruptcy. In such instances of extreme poor performance, the need to preserve a job dominates the vega of the option contract. Chen and Pennacchi (2009), who carefully model the manager's contract relative to a benchmark, also arrive at a similar conclusion. However, their model assumes that the manager competes in a tournament for flows. Finally, Khorana (2001) finds evidence that managers engage in risk-shifting before being replaced. Based on these papers, we hypothesize that there is a positive relation between risk-shifting and extremely poor performance.

To test these hypotheses, we collect a sample of 3,265 US equity mutual funds and match them with their announced benchmarks. We use the daily fund and benchmark returns to estimate the extent of risk-shifting. We find that a simple bivariate plot of the ratio of the standard deviation of daily excess returns in the second half of the year to that of the first half plotted against the distance between the first half of the year's fund return and the benchmark's return shows a striking inverted U-shaped pattern around zero. When the distance is smallest, the ratio is highest. This pattern does not hold for a random benchmark. Moreover, when the negative performance is more than 2.5 standard deviations below the benchmark, the ratio is extremely large. This suggests that career concerns outweigh the vega of the contract and supports the Carpenter (2000) model. Given that the outliers are clearly important in this relation, we estimate a quantile regression model that is robust to outliers. Our baseline results show that distance from the benchmark is significantly and inversely related to the ratio of the standard deviations, controlling for a list of variables used in previous studies.[1] Importantly, the flow of assets is not significant in this regression. This baseline regression holds even when we use the alternative holdings-based measure of Kempf, Ruenzi, and Thiele (2009) to estimate intended risk-shifting. It also holds if we define the evaluation period as a two-year window, the performance period as 1.5 years, and the risk-shifting period as 0.5 years.

Our identification strategy for capturing the role of benchmarks in risk-shifting decisions is to categorize funds into three sub-groups: funds with a clear compensation benchmark, funds with an unclear compensation benchmark, and funds without a compensation benchmark. To execute this strategy we hand-collect portfolio manager compensation data from the Statement Additional Information (SAI). The above sub-groups display strikingly different risk-shifting behaviors. Funds with a clear compensation benchmark shift their portfolio risk the most, while no such evidence is found among the funds that do not have performance-based compensation. These results are exactly aligned with our prediction that risk-shifting is driven by management contracts. Furthermore, relative to purely advised funds, sub-advised funds shift risk considerably more when they hire multiple investment subadvisors to manage their assets. To shed light on other perspectives of contracting environments, we introduce additional measures. First, manager's ownership in the fund significantly reduces the risk-shifting; second, the larger the Active Share of a fund (i.e., Cremers and

[1]The more convex the compensation, the higher the incentive to risk-shift. Unfortunately, the Securities and Exchange Commission (SEC) does not require disclosure of the extent of the compensation. Ma, Tang, and Gómez (2016) state that "Based on the 1,087 funds that release some information about the ratio of bonus to salary we find that the bonus can be as large as three times the base salary."

Petajisto (2009)) the more the risk-shifting; and third, the tenure of the manager mitigates the risk-shifting emanating from poor performance in the previous year. Importantly, the introduction of these measures does not change the impact of our key variable, *distance*.

To better examine the importance of the flow-performance relation, we examine two measures. First, we show that the distance measure is significant and incentive driven by flows is not significant when we control for the difference between the return of the fund and the median return of funds within the same style, a variable that determines the mid-year winner or loser in the tournament literature. Second, we use the semiparametric model of Chevalier and Ellison (1997) to estimate the shape of the flow-performance relation and derive a measure of implicit incentives. We find that it is not significant in a model that includes our measure of the option vega.

These results suggest that portfolio managers are shifting the volatility of the fund to maximize the value of their compensation. Kempf, Ruenzi, and Thiele (2009) show that risk-shifting behavior changes over time, based on the level of employment risk in the economy. However, this is not the case for risk-shifting based on management contracts. We show that if any one year of the sample period, 2000-2013, is dropped from the estimation, the distance measure is still significant. It is also significant if we break the time series into four sub-periods and if we perform a bootstrap analysis by randomly selecting 27,141 observations (the number of observations of the baseline regression) from the sample with replacement and estimate the baseline regression 500 times. In robustness checks, we show that the baseline regression results are not based on funds with a zero or positive benchmark adjusted return, or a negative benchmark adjusted return, or on the definition of distance, or on the definition of "mid-year." July works as well as June. We show that risk-shifting is not concentrated in a few styles. If we drop the November and December returns, the distance measure continues to be significant, suggesting that it is not driven by the window dressing found by Lakonishok et al. (1991), and Sias and Starks (1997). Finally, we show that the distance measure is not affected by intra-year changes in daily return correlation as in Busse (2001), nor by the tendency for mean reversion in fund volatility suggested by Schwarz (2012).

Our paper makes several contributions to the literature. To the best of our knowledge, we are the first paper to study risk-shifting based on compensation contracts of portfolio managers. The existing evidence of mid-year risk-shifting is best characterized as mixed. The initial evidence of Brown, Harlow, and Starks (1996) was challenged by a series of papers. Busse (2001), Kempf, Ruenzi, and Thiele (2009), Elton et al. (2010), and Schwarz (2012) use a variety of measures of risk-shifting and empirical techniques to provide contrary evidence. Each of these papers is motivated by the assumption that the flow-performance relation is convex. This economic foundation is challenged by Spiegel and Zhang (2013), who find that the flow-performance relation is linear when properly estimated. Our paper shows that a focus on individual managers and their contracts is more productive than relying on a potentially unstable flow-performance relation in explaining the risk-shifting behavior of mutual fund managers. Furthermore, we use the methodology of Huang, Sialm, and Zhang (2011) and show that risk-shifting based on management contracts with portfolio managers costs investors about \$26 billion per year on average.

Our second contribution is to demonstrate that the region of fund return in which the risk-shifting incentive is most dominant is in the neighborhood of the announced benchmark's return, except in cases of extreme negative returns. This is not the region found by other studies, including Chen and Pennacchi (2009), who carefully model the manager's contract and argue that the incentive to risk-shift monotonically decreases with a fund's relative performance. While we agree with their conclusion that "Measuring risk appropriately as tracking error, rather than total return volatility, appears to make a big difference for tests of tournament behavior," we do not find that the incentives are monotonic. As discussed above, when we plot the ratio of the tracking error volatility from the second half of the year to that from the first half of the year against the fund's excess return, we see a striking inverse U-shaped risk-shifting pattern emerge around zero. In the plot, consistent with our theoretical predictions, it is precisely those managers whose mid-period performance is close to the benchmark's performance who increase their portfolio volatility the most. However, we do find support for the Chen and Pennacchi (2009) model in the case of extreme negative returns. In these extreme cases, the incentive to keep a job outweighs the incentive to maximize the option vega of the employment contract.

Our third contribution is to highlight the importance of the prespecified benchmark for tests of agency issues. With the exception of Sensoy (2009), who uses nine benchmarks, and Cremers and Petajisto (2009), who use nineteen benchmarks,, studies have not used self-designated benchmarks. Our results do not hold for a randomly selected benchmark. We show that when a benchmark is randomly assigned the distance measure is insignificant. The inverse U-shaped relation holds only for the self-designated benchmark.

Finally, our results are consistent with the broader literature on risk-shifting in the delegated portfolio management industry. Hodder and Jackwerth (2007) and Aragon and Nanda (2012) examine the dominant risk-shifting region for hedge fund managers. The point of convexity, in the case of hedge funds, is around the deterministic high-water mark, which is known at the beginning of the year. However, in the case of mutual funds, the benchmark return is stochastic and unknown until the time of performance evaluation. Modeling the managerial compensation like an exchange option helps in clarifying what the precise risk-shifting region should be.

2. Hypothesis

The hypothesis of Brown, Harlow, and Starks (1996), and of Chevalier and Ellison (1997), is that managers who have mid-year (six-month) performance below the median return of all managers have an incentive to increase their portfolio risk significantly in comparison to mid-year winners. Both studies find evidence of risk-shifting. However, subsequent literature challenges this evidence. Busse (2001) argues that when daily, instead of monthly, returns are used, and when the auto-correlations in these returns are considered, tournament effects disappear. Schwarz (2012) argues that a bias toward risk-shifting is created when funds are sorted into winners and losers based on their mid-year performance. Kempf, Ruenzi, and Thiele (2009) argue that overall market conditions affect the direction and extent of managerial risk-taking behavior. Managers are interested in increasing their compensation, but they also have career concerns that could cause risk-shifting to work in the opposite direction. More precisely, Kempf, Ruenzi, and Thiele (2009) find that poorly performing managers decrease their portfolio risk if market conditions in the first half of the year are not ideal, since such conditions proxy for periods of higher job insecurity. Similarly, poorly performing funds increase risk during strong market conditions, when compensation concerns are likely to be more important. The authors find no evidence of risk-shifting in the aggregate. In a related context, Basak, Pavlova, and Shapiro (2007) investigate a fund manager's risk-shifting incentives by considering a multitude of convex flow-performance relations. However, they do not use the manager's self-designated benchmark: they use the S&P 500. Since the incentive in their model is determined by an assumed flow-performance relation, the risk-shifting range over which the manager gambles is quite different from that of our model. Basak, Pavlova, and Shapiro (2007), however, conclude that their findings are "in line with

Busse (2001), who argues that underperforming managers do not seem to manipulate their portfolio standard deviations towards year end."[2]

Our hypothesis is that management contracts can be modeled as an exchange option in which the long position has the option to exchange one risky asset for another. The payoff of this option is similar to the payoff of most portfolio managers, who earn a bonus when the fund's return is greater than the benchmark's return. Ma, Tang, and Gómez (2016) document that "unlike the advisor contract, which is mostly based on funds' AUM, the majority of compensation contracts for individual portfolio managers include a bonus directly linked to investment performance." They also document that the performance-based fee is asymmetric: outperformance relative to the designated benchmark is rewarded, but underperformance is not penalized. Thus, in effect, the manager has the option of exchanging the return of the benchmark for the return of the portfolio. On expiration, the manager's bonus is equal to $Max(0, P_T - B_T)$, where P_T and B_T are the portfolio's and benchmark's returns over the evaluation period, T. Using the model of Margrabe (1978) to price this option, we show in AppendixA that the value of this option increases with volatility and that the vega takes a maximum value when the distance $P_T - B_T$ is smallest. Our hypothesis is that the above distance is negatively related to the relative risk of the portfolio in the second half of the year.

Our hypothesis assumes that the portfolio manager is evaluated on an annual calendar basis and that the risk of a portfolio cannot be shifted over a very short period of time. Our focus on the calendar year is based on the findings of Ma, Tang, and Gómez (2016), who report that most funds report multiple evaluation windows, ranging from one quarter to ten years, with a median minimum evaluation period of one year. Although the median manager has a three-year horizon, from our extensive reading of the compensation contracts, we can confirm that these contracts also have a significant part of the bonus based on an annual

[2] Hu et al. (2011) present a theoretical model that simultaneously considers the career concerns of managers and their implicit incentives arising from the flow-performance relation to shift risk. Their paper proposes a U-shaped relation between mid-year fund performance and subsequent changes in portfolio risk, such that the most poorly performing and the best-performing funds will increase their portfolio risk in the second half of the year, while funds closer to the median of the relative performance distribution will decrease their risk. The predictions of Hu et al. (2011) are considerably different from ours because (a) they assume the portfolio managers to be risk-neutral and (b) they do not consider the explicit incentives of asymmetric contracts.

evaluation. Our assumption that a portfolio manager cannot affect a year's performance by shifting weights for a very short time period is based on the transaction costs and common practices in the mutual fund industry. Several studies on institutional trading demonstrate that short horizons (horizons of less than nine months) are not dominant in trading and are not profitable.[3] Furthermore, if risk is shifted over the last quarter of a year, it may not have a significant effect on the year's performance.

We consider two alternative interpretations of our results. First, we consider whether management contracts, which we denote as explicit incentives, are different than flow-driven incentives, which we term implicit incentives. Our paper argues that a fund's performance relative to its self-designated benchmark, rather than an implicit reward through increased fund flow, induces the manager to change portfolio risk. Our key measure is the distance of the first six-month return from the benchmark. A critical question is whether our new measure is different from the conventional measure (i.e., Brown, Harlow, and Starks (1996)), which supposedly reflects flow-driven incentive. Second, Schwarz (2012) argues that the mean reversion in aggregate volatility mechanically gives rise to a tournament effect. Are our results an artifact of such sorting bias?

The most crucial step in identifying the causal channel is to characterize the sample of funds by contract type. In Section 3, we document how we characterize the funds into one of three categories: funds that have clearly a defined performance benchmark, funds that have performance benchmarks but these benchmarks are fuzzily defined, and funds that do not have performance-based compensation. If the alternative hypothesis is true and our measure is only capturing the relative performance among funds (implicit incentives), then the importance of the incentive variable should be uniform across the three different contract types — clear, fuzzy, and no benchmarks. Importantly, any alternate story that is unrelated to the compensation choice should hold regardless of the contract type. This is also true for a sorting bias-based explanation. Additionally, to ameliorate the above concerns, we a) perform a horse race between our measure of explicit incentives and multiple other proxies of implicit incentives, b) conduct a falsification test by randomizing the benchmark of the fund, c) use portfolio holdings data to compute the intended risk-shifting by the manager, and d)

[3]For more information, see Chakrabarty, Moulton, and Trzcinka (2015) and Pastor, Stambaugh, and Taylor (2015).

replicate the methodology prescribed by Schwarz (2012, Sec 3.1) to address the sorting bias issue. In our empirical analysis, several other tests also speak to these alternative stories.

3. Data and summary statistics

We use data from four sources. First, we select domestic equity funds from Morningstar, which provides survivorship-bias free data on mutual fund names, their categories, and their self-designated benchmarks. From this sample of funds, we focus on domestic U.S. equity mutual funds. The benchmark reported is the self-designated index reported in the fund's primary prospectus. In 1999, the SEC mandated that funds report their passive benchmarks along with the fund's returns. This ruling constrains the beginning of our sample, which we follow from January 2000 through December 2013.[4]

The Center for Research in Security Prices (CRSP) Mutual Fund database is our second source of data. We merge the Morningstar database with the CRSP Mutual Fund database, which includes fund characteristics, net asset values (NAVs), and returns for each share class. The matching is done using the CUSIP number, the ticker, or both. We use a name-matching algorithm for the remaining unmatched observations. We remove index funds from the sample by removing funds that have "index," "indx," or "idx" in their names. A share class should have at least 200 daily return observations in the year to be included in the sample for any given year.

Although all the above information is provided at the share class level, the underlying portfolio for the different share classes within a fund is the same. Therefore, to aggregate data at the fund level, we use the MFLINKS data provided by Wharton Research Data Services (WRDS).[5] A fund's return series, expense ratio, and turnover ratio are the weighted averages of the same variables of its different share classes. The weights are based on the total net

[4] To circumvent this restriction, Cremers and Petajisto (2009) compute the Active Share of a fund with respect to nineteen indices and assign the index with the lowest Active Share as the fund's benchmark. This approach is not suitable to us since the only benchmark relevant to a fund manager's compensation is the self-designated prospectus benchmark. Sensoy (2009) documents that some funds pick a benchmark which does not reflect their true investment style. Despite this misleading assignment, only the prospectus benchmark matters to fund managers since performance-based bonuses are determined relative to self-declared benchmarks.

[5] Despite the use of the MFLINKS file, some share classes are still not mapped to any identifier. Therefore, for these remaining observations, we use the CRSP portfolio number to aggregate the different share classes.

assets (TNA) of each share class at the beginning of the period. To construct the intended relative risk of each fund, we use holdings data from the Thomson Reuters Mutual Fund Holdings database, which is our third source of data.

Lastly, we retrieve the SAI of each fund in our sample between 2005 to 2010 from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database. In 2005, the SEC introduced a new rule that requires mutual funds to disclose the compensation structure of the fund managers in the SAI.[6] We then hand-collect the data on the compensation structure of mutual fund managers to categorize individual funds according to whether their compensation contracts have clear, unclear, or no benchmarks. More precisely, we record whether the incentive bonus exists; if the bonus exists, whether it is tied to the fund's investment performance; and, if the bonus is tied to the investment performance, whether the benchmark is clearly mentioned. We also record the relevant evaluation horizon if the investment performance-based bonus exists. In addition, by reading the SAI, we are able to find out the compensation structure of subadvisors if fund management is outsourced. Similarly, we record the compensation structure of the subadvisor(s) and the number of subadvisors hired for fund management, if there are multiple subadvisors. In AppendixB, we provide a detailed description and a frequency distribution of the observations in each category (i.e., clear, fuzzy, or no benchmarks).

Our sample has 3,265 unique funds and 27,141 fund-year observations for which complete data regarding fund returns, fund characteristics, and benchmark returns are available.[7] The median fund in the sample is ten years old and charges about 1.2 percent of the AUM as its expense ratio. A total of 57 different benchmarks are used. Table 1 reports the summary statistics regarding the current sample.

[Insert Table 1 about here]

The data on the benchmark returns used by the different funds are collected from a variety of sources. Most benchmark returns are obtained from the websites of the respective

[6]For a detailed description of disclosure regarding portfolio managers of registered management investment companies, see the SEC rule from https://www.sec.gov/rules/final/33-8458.htm.

[7]In comparison, Brown, Harlow, and Starks (1996) analyzed 334 growth funds; Kempf, Ruenzi, and Thiele (2009) examined 1,710 equity funds. Our need for holdings data and a self-designated benchmark reduces our sample relative to Chen and Pennacchi (2009), who examine 6,178 funds.

companies.[8] These are further substantiated with information provided by IHS Global Insight. The benchmark returns are collected at a daily frequency. Note that the benchmark information for each fund is observed only at one point in time. Sensoy (2009) shows that benchmark revisions are extremely rare in practice. Table 2 presents the top 20 benchmarks and the number of funds that use each of these benchmarks. By far, the most popular benchmark is the S&P 500 Total Returns, with close to 35 percent of the sample using it. The top 20 benchmarks cover more than 97 percent of the sample of funds.

The data on peer benchmark returns are calculated using the Lipper objective code provided by the CRSP Mutual Fund database. Most equity funds use one of the Lipper equity fund indices as their peer benchmark. The Lipper equity fund indices are based on the 30 largest funds, by asset size, within the Lipper objective.[9] We replicate these returns by choosing the 30 largest funds in each objective and computing the value-weighed daily returns.

[Insert Table 2 about here]

4. Empirical analysis

4.1. Variable construction

As mentioned above, our hypothesis is that a portfolio manager is most concerned about the performance of the fund with respect to its benchmark. To test the risk-shifting behavior of managers, we construct two key variables. First, we compute the excess return of each fund over its respective benchmark. For each fund, we compute the difference between the compounded daily returns of the fund and its benchmark for the duration of the first six months. This calculation is done for each year in our sample, as follows:

$$\mathrm{exret_{j,t}} = (1 + r_{j,t,1}) * (1 + r_{j,t,2}).....(1 + r_{j,t,n}) - (1 + b_{j,t,1}) * (1 + b_{j,t,2}).....(1 + b_{j,t,n}), \quad (1)$$

[8] The following webpage is an example of data provided by Russell Indexes: http://www.russell.com/indexes/americas/indexes/daily-returns.page. Other sources, including Google Finance and Yahoo Finance, are also used for the benchmark data.

[9] Regarding the Lipper equity fund indices, you can visit http://online.wsj.com/mdc/public/page/2_3020-lipperindx.html.

where $r_{j,t,n}$ is the daily return for fund j in year t, $b_{j,t,n}$ is the return on the benchmark associated with fund j, and n is the number of days in the first six months for year t. For robustness, we also compute the above variable by considering the first seven months as the mid-year period. Our hypothesis is that risk-shifting incentives diminish as a fund's performance deviates farther from its benchmark. After computing *exret*, we measure the *distance* of the fund's return from its benchmark return as the square of *exret*, giving equal importance to returns above and below the benchmark.

The second important variable is the measure of the portfolio's volatility. Given the asymmetric payoff of portfolio managers, if managers want to beat the benchmark by increasing portfolio risk, they have to do so by increasing the risk of the portfolio more than that of the benchmark. Therefore, managers have to change the relative volatility of their portfolio or the volatility of the tracking error. To capture changes in portfolio volatility, we redefine the Brown, Harlow, and Starks (1996) Risk Adjustment Ratio (RAR) as follows:

$$\mathrm{RAR_{j,t}} = \frac{\sigma_2(r_{j,t} - b_{j,t})}{\sigma_1(r_{j,t} - b_{j,t})}, \tag{2}$$

where $\sigma_1(r_{j,t} - b_{j,t})$ and $\sigma_2(r_{j,t} - b_{j,t})$ are the standard deviations of the fund j's return over the benchmark return for the first and second six months of the year, respectively. These standard deviations are computed using daily returns and hence provide a much more reliable estimate of managers' actions regarding fund volatility. Table 1 provides information about the distribution of excess returns and the RAR. The median fund's first-half return is quite close to its benchmark, since it earns an excess return of 0.1%. In addition, the median RAR is close to one, suggesting that there is no difference in the relative volatility for the two periods. However, the standard deviations of 5.6% and 1.005 for excess returns and RAR, respectively, show that there is considerable variation among funds. It is worth noting that this is not the ratio of standard deviations first analyzed by Brown, Harlow, and Starks (1996), which Schwarz (2012) shows is subject to a "sorting bias" that produces risk-shifting. This is the ratio of tracking errors to the fund's self-selected benchmark. We show below that our findings on risk-shifting do not hold for a random benchmark.

Our second measure of risk-shifting is developed by Kempf, Ruenzi, and Thiele (2009) who argue that it measures the intended level of change in portfolio risk. We use the semi-annual holdings information in the Thomson Reuters Mutual Fund Holdings database and make appropriate adjustments for stock splits. We first compute the realized risk of the portfolio for the first half of the year, $\sigma_{j,t}^{(1)}$, using the daily stock returns, daily benchmark returns for 26 weeks, and the actual portfolio holdings in the first half of the year. This variable is the standard deviation of the difference between the portfolio return and the benchmark return. To compute the intended risk for the second period, $\sigma_{j,t}^{(2),int}$, we follow appendix B in Kempf, Ruenzi, and Thiele (2009) calculating daily hypothetical portfolio returns based on holdings information from the second half of the year and stock returns and benchmark returns from the first half of the year. This gives us a daily time series; $\sigma_{j,t}^{(2),int}$ is the standard deviation of this time series.[10] The central idea here is that the volatility of the stock in the first half of the year is used as the estimator of the expected stock volatility in the second half of the year. The final measure of change in intended risk is computed as the ratio of intended risk in the second half of the year and the realized risk in the first half of the year:

$$RAR_{i,t}^{holdings} = \frac{\sigma_{i,t}^{(2),int}}{\sigma_{i,t}^{(1)}}. \tag{3}$$

4.2. Preliminary results

To understand the univariate relation between mid-period performance and future changes in risk-taking, we plot the average RAR for the different partitions of the $exret$ distribution. Fig. 1 shows the relation for the pooled sample. Based on their mid-year excess returns relative to benchmarks ($exret$), funds are grouped into the following ranges: $exret <$ -2.5σ, -2.5σ $< exret <$ -1.75σ, -1.75σ $< exret <$ -1σ, -1σ $< exret <$ -0.25σ, -0.25σ $< exret <$ 0.25σ, 0.25σ $< exret <$ 1σ, 1σ $< exret <$ 1.75σ, 1.75σ $< exret <$ 2.5σ, 2.5σ $< exret$.[11] For each range we compute the average RAR. For example, the left-most point on the graph is 1.305, which is the average RAR for managers whose mid-year excess returns are more than 2.5 standard deviations below zero. The RAR of one represents the threshold for which there is no change in the risk between the two periods. Panel B of Table 1 summarizes the data used for generating this plot.

[10]Kempf, Ruenzi, and Thiele (2009) use weekly returns rather than daily returns. We believe daily returns provide a better measure of standard deviation and is more consistent with our measure of RAR, which is computed with daily returns.

[11]The graph is robust to our choice of range for the bins. It is not robust to using the alternative benchmark. The only benchmark that produces this graph is the self-designated benchmark.

[Insert Fig. 1 about here]

Fig. 1 clearly shows that risk-taking has a striking inverted U-shaped relation with the distance of return from the fund's self-designated benchmark. This is exactly what modeling the management contracts as an exchange option predicts and contrasts sharply with theories that predict a monotonic relation (Chen and Pennacchi (2009)), or a U-shaped relation (Hu et al. (2011)). The obvious exception occurs in the case of extreme negative returns, defined as excess returns more than two and half standard deviations below zero, which shows the highest relative risk ratio. This supports the models of Carpenter (2000), Chen and Pennacchi (2009), and Hu et al. (2011) for large, negative mid-year returns relative to a benchmark. It also supports the general arguments of Kempf, Ruenzi, and Thiele (2009), who posit that risk-shifting for compensation is traded off with employment risk. We acknowledge that Fig. 1 is not a formal test of the hypothesis since there are no controls, especially for the flows of the fund. We develop the model for our testing in the next section.

4.3. Multivariate results

The striking findings of Fig. 1 could be due to omitted variables, so we now estimate a multivariate model that considers the effects of other fund characteristics on risk-taking decisions. We begin by employing a pooled ordinary least square (OLS) to estimate the following model

$$\mathrm{RAR_{j,t}} = a_t + c_1\mathrm{distance_{j,t}} + c_2\mathrm{exret_{j,t}} + c_3\mathrm{controls_{j,t}} + e_{it}, \tag{4}$$

where *distance* is measured as the square of the excess return (*exret*) and captures how far the excess return lies from zero. The control variables *exp ratio*, *turn ratio*, *log size*, and *log age* are the expense ratio, the turnover ratio, the log of the total AUM, and the log of the number of years from the inception of the fund, respectively. These variables are all evaluated at the beginning of the calendar year. The variable *shareclass* is a dummy variable that takes on the value of one if the fund is a multiple share class fund and zero otherwise. Our hypothesis suggests a significant negative coefficient for the *distance* variable. This prediction contrasts with the predictions of the model of Hu et al. (2011), who propose a U-shaped relation between mid-year performance and subsequent risk-taking, which would result in a positive coefficient. It is also inconsistent with Chen and Pennacchi (2009), who argue that the relation is monotonic.

Recently, Kempf, Ruenzi, and Thiele (2009) argue that the incentives to shift risk are time-varying and, in each period, managerial risk-taking is contingent on the relative importance of employment risk and compensation incentives. It is reasonable to expect the risk-taking decision to change as a function of the state of the economy. To account for this variation, all the specifications include a time-fixed effect. It is well recognized that OLS estimates are sensitive to outliers.[12] Given this sensitivity, and our expectation regarding the preferences of managers in the left tail, we first winsorize the data at the top and bottom 1%. We will follow with an econometric approach that minimizes the effect of outliers.

[Insert Table 3 about here]

Table 3 presents the pooled OLS results with the winsorized data. The coefficient estimate in column (I) shows that excess return alone is not sufficient to explain the variation in managerial risk-taking. Columns (II) through (V) of Table 3 include the key variable of interest, *distance*, along with other control variables. Different definitions of risk-shifting are used in columns (IV) and (V). The results show a statistically significant negative relation between *distance* and risk-shifting, regardless of how we measure risk-shifting.[13] In column (III) we use the classic definition of Eq. (2), in column (IV) we use the difference in the numerator and denominator, and in column (V) we use the Kempf, Ruenzi, and Thiele (2009) holdings-based measure of risk-shifting.[14] The standard errors are clustered by time and by fund to correct for any correlation in the error terms. The consistently negative *distance* coefficient lends considerable support to our hypothesis of risk-shifting by mutual fund managers and to our hypothesis that risk-shifting is strongest in the region in which the fund's return is close to the benchmark's return.[15]

[12]For an examination of the sensitivity of OLS to outliers, see Cameron and Trivedi (2005), who suggest quantile regression, which we implement after Table 3.

[13]The coefficients associated with time-fixed effects (not shown) are all statistically significant, supporting the findings of Kempf, Ruenzi, and Thiele (2009).

[14]The sample size for the specification using the holdings-based measure of risk-shifting is slightly diminished on account of the availability of holdings data.

[15]In a hypothetical set up, if $X_1$and X_2 are independent normal random variables with means μ_1, μ_2, and variances σ_1^2 , σ_2^2 respectively, then the distribution of the difference, $X_1 - X_2$, is normal with mean $\mu_1 - \mu_2$ and variance $\sigma_1^2 + \sigma_2^2$. We regress an independent variable scaled by $1/\sqrt{(\sigma_1^2 + \sigma_2^2)}$ on our distance measure $(\mu_1 - \mu_2)^2$. If the benchmark and portfolio return are independent there will be no relation between these functions of the first and second moments.

Given our concern about outliers, especially seen in Fig. 1 where the most extreme values of *exret* produce the largest risk-shifting, we use quantile regression to estimate the model with non-winsorized data. Quantile regression is very robust to outliers and is especially useful for our model. In OLS, the estimates are for a conditional expectation function; in quantile regression, we estimate the parameters of the conditional median function in the following specification:

$$Q_{0.5}(\mathrm{RAR_{j,t}}|\mathrm{I_{t,}}) = a_t + c_1 \mathrm{distance_{j,t}} + c_2 \mathrm{exret_{j,t}} + \gamma \mathrm{Controls}, \tag{5}$$

where $Q_{0.5}(.|.)$ is the conditional median function and $I_{t,}$ is the information set available at time t. Since quantile regressions are robust to outliers, we use the original, "un-winsorized" sample of funds to estimate the model. Table 4 presents the results for the quantile regression at the median. The coefficients of the quantile regression have a similar interpretation to the OLS coefficients. They represent the marginal effect of the independent variable on the dependent variable, holding constant the effect of the other independent variables, except that they are relevant only for the quantile for which they are estimated. All specifications of Table 4 include time-fixed effects, using the method described by Koenker (2004) to estimate fixed effects in a quantile regression for panel data. The bootstrapped standard errors associated with the estimates are reported in the parentheses.

[Insert Table 4 about here]

Each of the first three columns of Table 4 uses a different measure of risk-shifting. The coefficient of *distance* is statistically significant and negative in all three specifications, suggesting that for the median manager, the portfolio risk in the second half of the year will decrease as the portfolio's return deviates from the benchmark's return. Eq. (A.8) in the AppendixA shows that the maximum vega occurs near the benchmark but slightly above it, depending on the volatility. This suggests that the coefficient on *exret* when included with distance is likely to be volatile.

Overall, the results in Table 4 support the exchange-option model of management compensation over competing theories, and showcase the region in which risk-shifting is most prolific. Salient features of management contracts are disclosed in the SAI. According to Ma, Tang, and Gómez (2016), one of the key features is that "the performance-based incentive is asymmetric: advisors reward managers for outperformance relative to the assigned benchmark, but do not penalize them for underperformance." Based on our extensive reading of the compensation contracts in the SAI and the above description in Ma, Tang, and Gómez (2016), we believe that there is reasonable ground to assume that managers have an asymmetric option-like contract with the benchmark being the strike price. Multiple kink points in the contract are a possibility. This would mean that managers have an incentive to shift risk elsewhere, other than at the benchmark. However, if this were true, it should mitigate us from finding any evidence of risk-shifting at the pre-specified benchmark. Despite this, we find evidence supporting our hypotheses.

If we compare the coefficients of Table 3, estimated with OLS, with the coefficients of Table 4, estimated with quantile regression, we can see the effects of optimizing the conditional median in quantile regression versus the conditional mean in OLS. The statistically significant marginal effects are smaller for every specification in Table 4 than in Table 3. Furthermore, more of the control variables are statistically significant in Table 4. Based on these results, we will use quantile regressions in all subsequent tables.

According to Ma, Tang, and Gómez (2016), fund manager compensation can be influenced by performance longer than a year. To address this issue, we divide the two-year horizon into an evaluation period and a response period by using a break point of 1.5 years. Managers are assumed to evaluate their performance at the 1.5-year point and to respond with their choices of portfolio risk in the response period. Column (IV) of Table 4 reports the results of the multi-year case. At the end of June of each year, we compute the historical 18-month benchmark adjusted return. Column (IV) uses this historical return as *exret* and the square of it as *distance*. Even for the multi year evaluation, we continue to find evidence of risk-shifting. The coefficient is statistically significant and is negative. However, it is one-third the size of the coefficient in column (I). The smaller coefficient supports the predictions of Hodder and Jackwerth (2007), Panageas and Westerfield (2009), and Aragon and Nanda (2012), who argue that a relatively long investment horizon discourages excessive risk-taking by fund managers.

The univariate result in Fig. 1 shows that the most poorly performing funds increase their portfolio risk the most. To formally test this, we perform a quantile regression at the 95th percentile instead of the median. Column (V) of Table 4 shows that among the extreme risk-shifters (95th percentile of RAR), the *distance* does not matter any more.

Instead, the most significant explanatory variable is the excess return (*exret*). The highly negative coefficient is consistent with our earlier evidence, and implies that the most intense risk-shifters increase their portfolio risk further in response to poor performance despite the already severe deviation from their performance benchmark. Note that this evidence is not consistent with any alternate mechanical relations discussed in Section 2.

Lastly, we repeat our earlier specification by using a peer benchmark return instead of the index benchmark return. We replicate the daily return of Lipper indices by choosing the 30 largest funds in each Lipper objective category provided by the CRSP Mutual Fund database. The associated results provided in Table 5 are qualitatively similar to those provided in Table 4. The above finding is consistent with our hypothesis regarding managerial behavior that evolves when managers are provided an incentive to beat their benchmark. The comparison of such a contract structure to an exchange option is applicable irrespective of which stochastic benchmark –index or peer– is used. Note that results in Table 5 are different from those in the literature that deal with flows-driven tournament (i.e., Brown, Harlow, and Starks (1996)). Unlike the conventional test of tournament in mutual funds, our model includes a squared term, *distance*, that captures the risk-shifting incentives driven purely from the management contracts.

[Insert Table 5 about here]

4.4. Contracting environment

4.4.1. Identification of contract

In order to establish the causal effect of managerial contract on mid-year risk-shifting, we adopt the identification strategy of segmenting the sample by contract types. The contract between an investment advisor and a portfolio manager is a private contract; hence, its parameters are not public knowledge. However, starting in 2005, the SEC has mandated funds to disclose some of the key features of the managerial compensation structure. One such information that funds report is whether the compensation is based on the fund's investment performance. Information on the portfolio manager's compensation is reported in the SAI. In order to capture the cross-sectional variation in compensation, we hand-collect the information on portfolio manager compensation structure for the period 2005-2010.

Of our original sample, we find compensation data for 11,555 fund-year observations. We assigned each of these observations to one of three categories. First is a group of funds which clearly state that portfolio manager compensation is not tied to fund performance. The second group includes funds whose managers are paid based on fund performance, but the details provided in the SAI are not very clear. Either no details are provided about how fund performance is evaluated to determine the compensation or, in case the SAI mentions that fund performance relative to a benchmark is used, it is not clear which precise benchmark is relevant. The final group consists of funds that clearly specify that the manager's compensation is based on performance relative to a specific peer or index benchmark. We label the first group above as "*no performance*," the second as "*performance unclear*," and the third as "*performance clear*." In AppendixB we provide a frequency distribution of the observations in each group. In our sample, about 24% of the funds do not have their compensation based on fund performance. This is close to the findings of Ma, Tang, and Gómez (2016), who report that about 21% of the managers do not have performance-based compensation. Detailed examples of these three cases can be found in AppendixC.

We run our main specification on each of the three sub-samples. Our prior beliefs are that we should find little to no evidence of risk-shifting in the "*no performance"* group and the most significant evidence of risk-shifting in the "*performance clear*" group. Columns (I), (II), and (III) of Table 6 provide the results from the sub-sample analysis. These results clearly support our hypothesis. For the "*no performance*" sample, the coefficient on the *distance* variable is -0.505, which is statistically indistinguishable from zero and, further, is significantly smaller than the coefficient of the distance variable from the "*performance clear*" sample. Further, in order to statistically test the differences between these groups, we run a pooled regression. We introduce an indicator variable, $I_{\{performance\}}$, that takes the value of one if the manager is in the "*performance unclear*" or "*performance clear*" group and zero otherwise.[16] In column (IV) of Table 6, we report the results from the pooled regression. The specification in column (IV) interacts the two variables, *distance* and $I_{\{performance\}}$, as this captures the incremental risk-shifting undertaken by managers with performance-based compensation. The coefficient on the above interaction term is negative and statistically significant, which is consistent with our hypothesis of risk-shifting driven by managerial

[16]For the funds in the "*performance unclear*" sample, the relevant benchmark used for performance evaluation is unclear. However, this is unclear only to the econometricians reading the SAI and not necessarily to the manager making the portfolio decisions.

contracts. Overall, the fact that we are able to categorize individual funds according to whether their compensation contracts have clear, fuzzy, or no benchmarks, and that the risk-shifting results line up exactly as we would expect suggests that our results are real.

[Insert Table 6 about here]

Importantly, segmenting the sample by contract types enables us to differentiate our hypothesis from other alternatives discussed in Section 2. First, our results clearly help us in distinguishing intentional risk-shifting from a simple story of reversion of tracking error to the mean (i.e., Schwarz (2012)) or any mechanical relation between tracking error and fund performance in the first half of the year. If any of these alternative stories is true, we should observe similar effects across funds with different contract types. Second, similarly, if our *distance* measure captures only flow-driven implicit incentives, then the importance of *distance* coefficient should, again, be uniform across contract types. However, our evidence runs contrary to either of these possibilities. Managers who have a clearly defined compensation benchmark risk-shift considerably more than those who have no performance bonus. Overall, our contract diversity results provide convincing evidence that sorting bias or other mechanical relations do not drive our main findings.

4.4.2. Risk-shifting and subadvising

Often, fund companies outsource the business of fund management to other investment management companies, who are known as *subadvisors*. Chen et al. (2013) examine how firm boundaries and contractual externalities affect under-performance of outsourced mutual funds relative to internally managed funds. Using the firm boundaries argument, Chen et al. (2013) reason that outsourced funds are expected to face high-powered incentives. The steeper incentive means that managers are more susceptible to the consequences of their actions and, therefore, poorer performance is more likely to yield replacement of the fund manager or closures of funds. Alternatively, it is the compensation structure provided by the subadvising firm to its portfolio manager(s) that should matter more for portfolio risk decisions. In this section, we empirically test which one of these two effects dominates.

While collecting the managerial compensation data (see Section 4.4.1), we also identify whether funds are subadvised and whether there is more than one subadvisor.[17] In Table 7, we examine the cross-sectional differences in risk-shifting between the two fund types: advised and subadvised. Columns (I) and (II) of Table 7 provide the results of our main specification applied separately to the two sub-samples. For the subadvised funds, the coefficient on the *distance* variable is -1.774, which is statistically significant and considerably larger than the coefficient of the *distance* variable for the advised funds. In order to statistically test the differences between these groups, we run a pooled regression. We introduce an indicator variable, $I_{\{subadvisor\}}$, that takes the value of one if fund uses an investment subadvisor and zero otherwise. Column (III) of Table 7 reports the results from the pooled regression. The interaction between *distance* and $I_{\{subadvisor\}}$ captures the incremental risk-shifting undertaken by the subadvised funds. The coefficient on the above interaction term is statistically insignificant, which indicates that there is no discernible difference in risk-shifting behaviors between these two groups.

[Insert Table 7 about here]

Having multiple subadvisors makes it more challenging to monitor subadvisors' operation, and the advisor is less likely to detect shirking by any particular subadvisor. To investigate this possibility, we introduce two new indicator variables. $I_{\{single\, subadvisor\}}$ takes the value of one if a fund uses a single investment subadvisor and zero otherwise. $I_{\{multiple\, subadvisors\}}$ takes the value of one if a fund uses more than one investment subadvisors and zero otherwise. We report the results from the pooled regression in column (IV) of Table 7. The coefficient on the interaction term between *distance* and $I_{\{multiple\, subadvisors\}}$ is statistically significant at the ten-percent level with the correct sign, which indicates that there is a discernible difference in risk-shifting behaviors when multiple subadvisors are hired.

These results suggest that a mutual fund company's internal culture may play a role in mitigating the agency cost of risk-shifting, since managers who are contractors rather than full-time employees are more likely to risk-shift. While we cannot observe every dimension of the internal environment where information is collected and implemented, there are three quantitative dimensions we can measure–the ownership of managers in the fund they manage,

[17] Note that SAI also covers subadvisors' compensation structure and details how many subadvisors are used by the fund.

the degree to which the fund is active, and the tenure of the manager. The next section shows the effect of these variables.

4.4.3. Managerial ownership, Active Share, and tenure

The focus of our model is on the benchmark-driven incentives in managerial compensation, but, as suggested above, this is unlikely to capture all the factors that determine risk-shifting. Fund managers are part of fund complexes, often referred to as families, that have different cultures and compensation schemes. For example, the AQR fund group does not pay performance compensation based on a benchmark, but the benchmark is critically important to management.[18] Furthermore, for some fund groups, performance has dimensions in addition to return and risk. Starks and Białkowski (2016) examine 117 funds with socially responsible objectives and find that the flows are less sensitive to performance and more persistent than conventional funds. They find these attributes increase after corporate environmental disasters and accounting scandals, suggesting that investors are concerned about more factors than risk and return.

Capturing the full cross-sectional variation of contracts and contracting environments is clearly difficult given the non-quantitative nature of this variation, but three variables may capture some of this variation. First, managers often own shares in their own fund. This ownership is intended to align the incentives of the manager with the shareholders, and should reduce the risk-shifting incentives of the fund manager. The SEC required disclosure of ownership starting in 2005. The disclosure is in six categories ($0-$10,000; $10,000-$50,000; $50,000-$100,000; $100,000-$500,000; $500,000-$1M; above $1 million) and is for all portfolio managers of a fund. We obtained this data from Morningstar and created two variables: the maximum ownership in the fund and a dummy variable representing the total ownership in the fund (high, medium, low). We have this variable from 2007 until the end of our sample in 2013. Second, funds vary widely in how active managers are relative to their benchmarks, often reflecting how aggressive the organization is about active management. We use Active Share, a variable advocated by Cremers and Petajisto (2009), to capture one aspect of active

[18]See the Harvard Case #9-211-025 "AQR's Momentum Funds" for a description of how AQR built a benchmark which was marketed through Standard & Poor's. The benchmark was used to sell AQR's momentum funds. Yet the Form N-1A filed on January 29, 2015 states that the compensation of portfolio managers who are not principals is based on a fixed salary and a discretionary bonus. The bonus is "not based on any specific fund's or strategy's performance but is affected by the overall performance of the firm."

management.[19] Third, manager tenure is likely to influence a manager's decision to risk-shift. A manager with a long, successful tenure is less likely to risk-shift after a poor performance than a manager with a short, less successful tenure. We have manager tenure data from 2005 until 2011.

[Insert Table 8 about here]

Table 8 reports the baseline model in Table 4 with manager ownership, Active Share, and manager tenure. All three variables are significant with the hypothesized sign. Management ownership is significantly negative, Active Share is significantly positive, and management tenure interacted with the most recent lagged excess return for the year is significantly positive. The coefficient on distance is significantly negative and larger than our baseline result in every regression. While the contracting environment certainly matters, the baseline findings of risk-shifting due to compensation relative to a benchmark do not change.

It is worth noting that ownership and Active Share significantly reduce the sample size. Using ownership cuts two-thirds of the sample. In unreported results, we assumed that all years before 2007 have exactly the same ownership as 2007. This doubles the number of observations. The results from this backfilling exercise are not materially different from those reported in Table 8.

4.5. Flow incentive vs. contract incentive

Brown, Harlow, and Starks (1996) argue that the convex flow-performance relation (i.e., Ippolito (1992) and Sirri and Tufano (1998)) leads to a tournament setting in which managers who are below the median in the half-yearly relative performance distribution have an incentive to increase portfolio risk, while those above the median have an incentive to decrease portfolio risk. Thus, the flow-performance relation implicitly creates an incentive to change portfolio risk. In this section, we define this incentive as flow incentive and contrast it with the contract incentive by testing the relative importance of this flow incentive on managerial risk-shifting.

[19]We thank Veronica Pool for graciously sharing the ownership data and thank Martijn Cremers for the updated Active Share data.

To account for the risk-shifting motive arising from a tournament, we introduce two new independent variables. First, BHS is defined as the return of the fund less the cross-sectional median return of the funds in the same style category. For those managers who are positioned as losers (i.e., having performed worse than average in an evaluation period), the incentive will be to increase the relative portfolio risk, since they can benefit by improving their performance by year-end.

Second, a nonlinear relation between fund flow and performance was first estimated by Chevalier and Ellison (1997) and Sirri and Tufano (1998), but the functional form of this nonlinearity is largely unknown. Recently, Spiegel and Zhang (2013) assert that the flow-performance relation is in fact linear and historically understood to be convex solely on account of the misspecification in the econometric model used. To avoid imposing any strong restrictions on the unknown flow-performance relation while computing implicit risk-shifting incentives, we use a partially linear semiparametric model to estimate the shape of the flow-performance relation. Although a piecewise regression model (i.e., Sirri and Tufano (1998), Huang, Wei, and Yan (2007), and Sialm, Starks, and Zhang (2015)) can be estimated, a very flexible semiparametric model is used to let the data describe the shape of flow-performance sensitivity nonparametrically while allowing for other parameters to be estimated linearly. From this nonrestrictive estimation process, we extract information about expected flows, which captures implicit flow-driven incentives. To us, the shape of the flow-performance relation is an empirical fact. We are less concerned about the economic reasons behind the shape but more interested in the incentives this shape creates to shift risk. This method of using a semiparametric technique to estimate the relation between fund performance and future flows is similar to that used by Chevalier and Ellison (1997) and Chen, Goldstein, and Jiang (2010).

More specifically, we fit the following model:

$$\begin{aligned}\text{Flows}_{j,t+1} = f(r_{j,t} - b_{j,t}) + c_1(r_{j,t-1} - b_{j,t-1}) + c_2(r_{j,t+1} - b_{j,t+1}) + c_3\text{log}(\text{assets}_{\text{j,t}}) \\ +c_4\text{IndustryGrowth}_{\text{t+1}} + c_5\text{log}(\text{age}_{\text{j,t}}) + e_{j,t}, \qquad (6)\end{aligned}$$

where $Flows_{j,t+1}$ is the growth in the total net assets (TNA) of the fund from the end of year t to the end of year $t+1$ and is given as follows:

$$\frac{\mathrm{TNA_{j,t+1}} - \mathrm{TNA_{j,t}}(1 + r_{j,t+1})}{\mathrm{TNA_{j,t}}}. \tag{7}$$

The relevant performance measure in the model is the return of the fund in excess of its benchmark, $r_{j,t} - b_{j,t}$. We also include benchmark-adjusted returns of year $t+1$ and year $t-1$ as explanatory variables. Additional controls include the natural logarithm of the ratio of the TNA of the fund to the cross-sectional mean TNA ($log(assets_{j,t})$), the growth in total AUM by the mutual fund industry ($IndustryGrowth_{t+1}$), and the natural logarithm of the age of the fund. The unknown function relating flow to performance is $f(\,)$.

Following Chevalier and Ellison (1997), we estimate the above model in two steps. First, we estimate the vector of coefficients, c. To get consistent estimates of the parametrically specified coefficients, we use the method described by Robinson (1988). We perform kernel regressions of both $Flows_{j,t+1}$ and the parametrically specified variables ($X_{j,t}$) on $r_{j,t} - b_{j,t}$ to get estimates of conditional expectation.[20] We then run an OLS regression of residual $Flows_{j,t+1}$ on the residual control variables. Second, having computed parameter vector c, we estimate the nonlinear flow-performance relation by performing a kernel regression of $Flows_{j,t+1} - \hat{c}X_{j,t}$ on $r_{j,t} - b_{j,t}$. For these kernel regressions, we use an Epanechnikov kernel and the optimal bandwidth computed using the cross-validation method. We plot the nonparametrically estimated relation between benchmark-adjusted fund returns and subsequent year percentage flows. Fig. 2 shows only a moderate level of convexity in the flow-performance relation.

Finally, we construct a measure to assess the incentives for risk-shifting. Following Chevalier and Ellison (1997), we note that the expected growth in flows for year $t+1$ conditional on the return of the fund at June for year t is given by :

$$E[\mathrm{Flows_{j,t+1}}] = E[f(r_{j,t}^{excess,\,June} + \tilde{u}) + cX_{j,t}], \tag{8}$$

where $r_{j,t}^{excess,\,June}$ is the benchmark-adjusted excess return of fund j in June of year t and $\tilde{u}$ is a random variable with mean zero and standard deviation σ that represents the benchmark-adjusted excess return of fund j for the period July to December of year t. Now, consider

[20]We winsorize the flows distribution at the top and bottom 1% to mitigate the impact of extremely young funds and of funds close to the bankruptcy boundary on flow-performance relation.

another random variable, $\tilde{v}$, which is identical to $\tilde{u}$ except that it has a standard deviation of $\sigma + \Delta\sigma$. Now, the expected change in the growth rate of flows by increasing the return volatility is given by :

$$\text{FlowsIncentive}(\sigma, \Delta\sigma) = E[f(r_{j,t}^{excess,\,June} + \tilde{v}) - E[f(r_{j,t}^{excess,\,June} + \tilde{u})]]. \tag{9}$$

We use Eq.(9) and the fit of $\tilde{f}()$ to estimate a manager's incentive. The distributions of $\tilde{u}$ and $\tilde{v}$ are taken to be truncated normals. The standard deviation of $\tilde{u}$, σ, is set to the sample standard deviation of half-yearly returns and $\Delta\sigma$ is set to 0.5σ. For every fund and for every period, we perform 5,000 iterations and use the Monte Carlo method to compute the expectation numerically.

[Insert Fig. 2 about here]

Table 9 presents the quantile regression results when we add both the BHS variable and the $FlowsIncentive$ variable to the baseline regression of Table 4. Each regression is estimated with time-fixed effects. The evidence rejects the flow-performance relation as a significant determinant of risk-shifting. In Column (II) of Table 9, the coefficient of BHS has a positive sign (contrary to expectations). In column (IV) of Table 9, $FlowsIncentive$ is insignificant, in spite of the effort to replicate the Chevalier and Ellison (1997) measure. In both columns, the distance measure continues to be negative, statistically significant, and with a coefficient that is close to that in Table 4. We conclude that using the explicit incentives arising from the asymmetric management contracts provides a much stronger determinant of risk-shifting than the implicit incentives of the flow-performance relations.

[Insert Table 9 about here]

4.6. Economic loss from risk-shifting

Our main finding of compensation-driven risk-shifting behavior has substantial implication for mutual fund investors. In this section, we attempt to quantify the economic consequences of risk-shifting. We use the methodology of Huang, Sialm, and Zhang (2011) who show that mutual fund managers can shift risk by changing the asset composition (i.e., equity holdings vs. cash holdings), by changing the exposure to either systematic or idiosyncratic risk, and by deviating from the benchmarks. Importantly, they show that, on average, funds that risk-shift have a significantly lower ex-post performance. This inferior performance is pronounced mainly among funds that increase the tracking error volatility relative to their benchmarks or idiosyncratic risk exposure, whereas both the asset composition change and the increase in systematic risk yield only mild reduction in subsequent performance. When using the tracking error volatility-based risk-shifting measure, Huang, Sialm, and Zhang (2011, Section 5.3) report that the top quintile of risk-shifting funds earn an abnormal Carhart alpha of -41 to -45 basis points per month. In our estimation, the economic loss is the dollar value of this negative abnormal performance. In each year, we rank all funds by their RAR measure and then compute the total AUM of the top quintile. We then multiply the above Carhart alpha, estimated by Huang, Sialm, and Zhang (2011), by the TNA of the top quintile of risk-shifting funds. This approach is similar to the value-added measure advanced by Berk and van Binsbergen (2015). Table 10 reports the estimates of economic loss using this back-of-the-envelope procedure. Our calculation shows that risk-shifting has a material effect on investors' wealth. The average year shows a loss of $25.99 billion, which varies from $11.63 billion in 2003 to $48.81 billion in 2011. Thus, our results are not only important to investors but are also relevant to policy makers.

[Insert Table 10 about here]

4.7. Falsification test using benchmark randomization

Portfolio managers have little explicit incentive to respond to other benchmarks, which suggests that performance benchmarks other than a fund's self-designated benchmark should create no significant differences in mid-year risk-shifting. To examine this implication, we try a falsification test by randomly assigning one of the 57 different benchmarks in the sample to each fund. We repeat the random benchmark assignment 500 times. At each iteration, we run a pooled OLS and a quantile regression on the randomized sample. All the control variables in Table 3 and in Table 4 are used in this analysis. We record the coefficient estimate of the *distance* variable from the 500 iterations. If a manager is indifferent to the benchmark in the portfolio risk decision, we should expect to observe the same relation between distance and RAR as in Table 3 and Table 4, after randomizing the benchmark. In Table 11, we provide the 5th and 95th percentiles of the distribution of point estimates from quantile regressions and pooled OLS separately. The confidence intervals of the quantile regression estimator and that of the pooled OLS estimator, in Table 11, do not contain the original point estimates of -1.007 (see Table 4) and -2.396 (see Table 3), respectively. In fact, the original point estimates of -1.007 and -2.396 are more than ten standard deviations away from the confidence interval. This test demonstrates that the self-designated benchmark does make a difference, and that our main result does not hold for randomly selected benchmarks, suggesting that it is not produced by a "sorting bias" (i.e., Schwarz (2012)) or any mechanical relation. Portfolio managers clearly respond more to their benchmark than to a randomly selected benchmark.

[Insert Table 11 about here]

4.8. Temporal stability analysis

Chen and Pennacchi (2009) find that evidence of tournament behavior varies over time. Further, Kempf, Ruenzi, and Thiele (2009) argue that a manager's incentives to change risk are contingent on the macroeconomic conditions and, therefore, are time-varying. When market conditions are good, compensation concerns are likely to drive strong risk-taking behavior; in contrast, when market conditions are bad, career concerns are likely to prevail and therefore curb excessive risk-taking. In this section, we address these concerns by examining the stability of our results over time.

To determine if any particular year is driving our results, we estimate a quantile regression by eliminating one year at a time from our sample. Panel A of Table 12 presents estimates of the risk-shifting coefficient for the sample with each year excluded. The coefficient has some variation, but is always negative and statistically significant for the sample no matter which year we exclude.

It is plausible that a subset of years is driving our results. To determine if any subset of observations is influential, we perform a bootstrap analysis. For each iteration in our bootstrap, we randomly pick 27,141 fund-year observations, which is the original size of our sample, and estimate the baseline model. Since each draw is done with replacement, there is considerable randomness associated with each generated sample. If there are one or two influential years in the sample, they will be overrepresented in some iterations and underrepresented in others. The variation in the generated samples should lead to a large variance in the estimator and affect the statistical significance of the coefficient. Panel B of Table 12 shows the mean and standard deviation of the estimator for the coefficient of *distance* from 500 iterations. The standard error of 0.142 is similar to the standard error of

0.116 reported in column (I) of Table 4. This suggests that no single year or subset of years is driving our results.

Finally, we conduct a sub-period analysis by dividing our sample into four sub-periods and estimating the baseline model. The results are shown in Panel C of Table 12. We find that the coefficient on *distance* is negative and significant in each of the four sub-periods. This coefficient is significant and negative, even during the period of economic downturn between 2007-2010 when unemployment risk was high. Managers change their portfolio risk depending on performance relative to its self-designated benchmark even when the returns on the benchmark are negative and a relatively high percentage of managers lost their jobs.[21]

[Insert Table 12 about here]

Taken as a whole, the evidence in Table 12 is consistent with managers risk-shifting as a fund's return gets closer to the benchmark regardless of the chance of being fired. The findings of Kempf, Ruenzi, and Thiele (2009), and of Chen and Pennacchi (2009), suggest that the risk-shifting by outliers (returns less benchmark returns lower than 2.5σ) are time-varying, but we find that management contract-driven risk-shifting is not.

4.9. Robustness

In this section, we explore the robustness of our previous results. In Table 13, we examine different measures of the vega of the management contract and the role of investment style. First, we investigate whether the risk-shifting effects originate from only one-half of the excess return distribution. To test whether this is the case, we divide our sample into two parts: funds with a zero or positive benchmark adjusted return (hereafter referred to as Sub-Sample1) and funds with a negative benchmark adjusted return (hereafter referred to as Sub-Sample2). In Sub-Sample1, a high excess return means that the fund return is above its benchmark return. However, in Sub-Sample2, a high excess return means that the fund return is closer to its benchmark return. Therefore, based on our hypothesis, we expect a strong negative relation between excess return and RAR in Sub-Sample1. Similarly, we expect a strong positive relation between excess return and RAR in Sub-Sample2. Columns

[21]According to Kostovetsky and Warner (2015), 2007 to 2009 had a higher number of managers fired (1,232) than any other three years of their sample period.

(I) and (II) in Panel A of Table 13 provide the estimates from a median quantile regression for Sub-Sample1 and Sub-Sample2, respectively.[22] Consistent with our expectations, we find a negative marginal effect of excess return on RAR in specification (I) and a strong positive effect in specification (II). These results confirm that risk-shifting is undertaken by managers on both sides of the excess return distribution. In addition, the different signs of the coefficient– negative in column (I) and positive in column (II), further confirm that our results are not driven by any mechanical relation.

Second, we show that our main result is robust to an alternative definition of the key variable *distance*. Our hypothesis is that a manager's incentive to take on additional risk in the second half of the year is a function of how far the first-half portfolio return is from the first-half return of the benchmark portfolio. To make our point, we drop the variable *distance* from our specification and, instead, use the new variable $|Exret|$, defined as the absolute value of the difference between the fund return and the benchmark return ($|r_{j,t} - b_{j,t}|$). The statistically significant negative coefficient associated with $|Exret|$ in column (III) is consistent with our expectation. It shows that it is the vega of the management contract that is driving the result and not the particular definition of *distance*.

Third, a cutoff point of June is arbitrary but widely used in the literature (for example, Brown, Harlow, and Starks (1996); Busse (2001); Kempf, Ruenzi, and Thiele (2009); and Schwarz (2012)) to make the point that a manager's choice of risk is conditional on prior performance. In the third robustness test, we change the mid-year point from June to July. Evidence from column (IV) suggests that changing the mid-year point does not affect the key results. We continue to find evidence supporting risk-shifting among fund managers and for our priors regarding the region in which it is strongest.

Fourth, we also test whether risk-shifting behavior is exhibited only by a specific style of funds or if this behavior is pervasive across different fund styles. To test this, we sort our sample into different sub-samples based on the objective code provided by the CRSP. We divide the sample into cap-based funds, growth funds, income funds, and funds that focus on both growth and income. The category "Cap-Based" includes large-, mid-, small-, and micro-cap funds. Panel B of Table 13 presents the results from a quantile regression

[22]Note, we do not include *distance* as an explanatory variable here because, for Sub-Sample1 and Sub-Sample2, the variable $Exret$ uniquely captures the distance of the fund return from the benchmark.

for each group. We estimate the full model shown in our baseline results with RAR as the dependent variable, but, for brevity, we only report the coefficient of *distance*. The strong negative coefficients across the different categories suggest that the risk-shifting behavior is not concentrated within a few styles but, instead, is prevalent across broad investment objectives.

[Insert Table 13 about here]

In Table 14, we examine three alternative explanations advanced in the literature to explain the Brown, Harlow, and Starks (1996) finding. First, mutual fund managers often change their portfolios in an attempt to mislead investors about their skills, by disclosing large positions in winner stocks and small positions in loser stocks, as shown by Lakonishok et al. (1991), and Sias and Starks (1997). This practice, referred to as "window dressing," is more pronounced for underperforming funds and may lead managers to decrease their holdings in high-risk securities to make their portfolios appear less risky as they get closer to the fiscal year-end.[23] In addition, Gibson, Safieddine, and Titman (2000) report that to minimize the taxable distribution, funds tend to trade more as they approach the end of the year. Such activities could distort our measure of risk-shifting. Since these incentives drive managerial actions toward the end of the year, we drop the return data in November and December to compute RAR. The results from this revised approach, presented in column (I) of Table 14, continue to support our hypothesis.

Second, Busse (2001) argues that intra-year changes in daily return autocorrelations can cause unintended changes to a mutual fund's intra-year risk. To address this bias, we follow Busse (2001) and model the fund's returns as a moving average (MA(1)) process. We estimate the moving average process for each of the two halves of the year in the following manner:

$$r_{j1,t} = \mu_{j1} + \varepsilon_{j1,t} + \theta_{j1}\varepsilon_{j1,t-1} \tag{10}$$

$$r_{j2,t} = \mu_{j2} + \varepsilon_{j2,t} + \theta_{j2}\varepsilon_{j2,t-1},$$

[23] See Musto (1997) and Musto (1999) for more information about window dressing in mutual funds.

where $r_{j1,t}$ and $r_{j2,t}$ represent the return of fund j on date t in the first and second halves of the year, respectively. We estimate the above process for every fund and for each year in our sample. We then compute the risk-shifting measure as follows:

$$\text{RAR}_{\text{MA}} = \frac{\sigma(\varepsilon_{j2,t} - b_{j,t})}{\sigma(\varepsilon_{j1,t} - b_{j,t})}. \tag{11}$$

Column (II) of Table 14 presents the results when RAR_{MA} is used as the measure of risk-shifting. The coefficient of the *distance* variable continues to be negative and statistically significant.

A third alternative hypothesis was advanced by Schwarz (2012), who points to the mean reversion in fund volatility. For instance, in periods following low measured risk, we might expect higher risk due to mean reversion, or the other way round. Our contract diversity results across the three different contract types— clear, fuzzy, and no benchmarks — in Section 4.4.1 clearly help us distinguish intentional risk-shifting from a story of reversion of tracking error to the mean. We follow two additional steps described in Schwarz (2012) to provide further robustness. First, we include the first half's return volatility in our regression specification and re-estimate the model to capture the effects of this reversion. The negative coefficient on the first half's return volatility in column (III) of Table 14 does support the idea of reversion. However, the presence of mean reversion does not completely explain the increased amount of risk-taking on the part of fund managers.

[Insert Table 14 about here]

In addition to the above tests, we follow the procedure described by Schwarz (2012, Sec 3.1) to address the potential bias in the relative risk change measure. We begin by using the information in portfolio holdings of the first half of the calendar year and establish a baseline. We then compare the risk characteristics of portfolio changes against the portfolios' average risk levels. The expectation is that managers whose performance is close to their benchmark would systematically sell low-risk securities and buy high-risk securities relative to their portfolio's average.

For each year, we calculate the changes in stock holdings for every security j in every fund i for each year y. The change is computed as

$$WgtChg_{jiy} = \frac{(DecShares_{jiy} - JuneShares_{jiy}) * DecPrice_{jy}}{DecAssets_{iy}}, \tag{12}$$

where DecAssets is the total dollar value of the December equity holdings. Then, using daily returns from the first six months of the year, we calculate the standard deviation and total return of each security. We then equally weight the security return and standard deviation to find the weighted average standard deviation and return for each fund based on its June holdings. This method ignores the correlations between the stock returns. Next, we calculate the Adjusted Standard Deviation (AS) and Adjusted Return (AR) of each stock in the portfolio by subtracting the June portfolio's average standard deviation and return from each security's standard deviation and return. Finally, we run the specification below to test our hypothesis:

$$\begin{aligned} WgtChg_{jiy} = \beta_0 + Distance_{iy}(\sigma_{jy} - \bar{\sigma}_{iy})\beta_1 + (\sigma_{jy} - \bar{\sigma}_{iy})\beta_2 \\ +Distance_{iy}\beta_3 + Distance_{iy}(r_{jy} - \bar{r}_{iy})\beta_4 \\ +(r_{jy} - \bar{r}_{iy})\beta_5 + Flows_{jy}\beta_6. \end{aligned} \tag{13}$$

If managers change their portfolio risk in response to their contracts, then we should expect to find a negative coefficient on β_1. As the portfolio return deviates from the benchmark return (or higher *distance*), managers should decrease the portfolio weights in high-risk securities. Table 15 presents the OLS and quantile regression results from the above specification. OLS coefficients are computed using Fama and MacBeth (1973), and standard errors are computed using the Newey-West method with three lags. We also winsorize the data at the top 1% and 99% to ensure that the extreme risk-shifters don't influence our results. We find the results in Table 15 consistent with our priors and that funds that are farther from their benchmarks decrease their weights in high standard deviation stocks. Overall, Table 15 provides additional support to our earlier results and helps us in ruling out mean-reversion in volatility as being the main driver of our results.

[Insert Table 15 about here]

5. Final remarks

Previous studies of risk-shifting have relied on the incentives from the flow-performance relation. We argue that the motives for risk-shifting should include the explicit incentives within the compensation contract provided by the investment advisor to the portfolio manager. Two features of this contract are critical. First, it designates a benchmark portfolio, and second, the payoffs are asymmetric, with the manager receiving a higher compensation if the fund's return is higher than the benchmark. We find that these features are critical in determining commonly used measures of risk-shifting. The closer to the benchmark, the more risk-shifting we find, with the exception of risk-shifting associated with very low returns relative to the benchmark. For these managers, the probability of being fired outweighs the incentives in the contract. Our evidence is consistent across time and across robustness tests used by other studies, many of which find that risk-shifting based on flow-performance relation is either volatile over time or does not survive robustness tests.

These results strongly support our hypothesis that portfolio managers who are compensated by performance-based contracts shift the volatility of the fund to maximize the value of their compensation. Using the most econometrically sophisticated estimate of the flow-performance relation in the literature, we find no evidence that managers are risk-shifting in response to a tournament for flows. However, risk-shifting based on management contracts is not mutually exclusive with risk-shifting from tournaments. Nevertheless, given our results, any study of tournaments needs to recognize the role of management contracts.

Table 1: Summary of the data

This table provides the summary statistics for our sample of funds from January 2000 to December 2013. The RAR is defined as the ratio of the standard deviation of the fund's excess return in the second half to the standard deviation of the fund's excess return in the first half. The intended change in portfolio risk, $RAR_{i,t}^{holdings} = \frac{\sigma_{i,t}^{(2),int}}{\sigma_{i,t}^{(1)}}$, is the ratio of the standard deviation of tracking errors of the intended portfolio in the second half of the year to the realized standard deviation of tracking errors for the first period. $RAR_{i,t}^{holdings}$ is computed using the mutual fund's holdings information. See eq (3) for more details.

	Mean	**Median**	**Standard Deviation**
Number of funds	3265		
Number of fund-year observations	27141		
Number of benchmarks	57		
Turnover ratio (%)	92.05	66	121
Expense ratio (%)	1.27	1.20	0.95
Age (in years)	13.33	10	12.78
Total Net Assets (TNA) (millions)	1226	198.1	4930.90
Semi-annual return in excess of benchmark (in %)	0.4	0.1	5.6
Risk Adjustment Ratio (RAR)	1.104	0.976	1.005
Holdings based Risk Adjustment Ratio ($RAR^{holdings}$)	1.054	1.016	0.322

Table 2: Summary of benchmarks

Our sample consists of 3,265 unique funds for which benchmark data are available. The table below displays the top 20 benchmarks that are used in the mutual fund industry. The second column shows the relative frequency with which each of the benchmarks is used. The third column is the percentage of the overall population that uses the specific benchmark. The final column is a cumulative sum of the percentages.

Benchmark	**# of Funds**	**% of Funds**	**Cumulative %**
S&P 500 TR USD	1138	34.85	34.85
Russell 1000 Growth TR USD	317	9.71	44.56
Russell 1000 Value TR USD	274	8.39	52.96
Russell 2000 TR USD	263	8.06	61.01
Russell 2000 Growth TR USD	191	5.85	66.86
Russell 2000 Value TR USD	164	5.02	71.88
Russell Mid Cap Growth TR USD	157	4.81	76.69
Russell 3000 TR USD	92	2.82	79.51
Russell Mid Cap Value TR USD	89	2.73	82.24
Russell 1000 TR USD	83	2.54	84.78
Russell Mid Cap TR USD	74	2.27	87.04
S&P MidCap 400 TR	57	1.75	88.79
Russell 3000 Growth TR USD	55	1.68	90.47
Russell 2500 TR USD	53	1.62	92.1
Russell 2500 Growth TR USD	48	1.47	93.57
Russell 3000 Value TR USD	45	1.38	94.95
Russell 2500 Value TR USD	29	0.89	95.83
S&P 500 PR	20	0.61	96.45
Russell Micro Cap TR USD	14	0.43	96.88
S&P SmallCap 600 TR USD	11	0.34	97.21

Table 3: Relation between fund performance and subsequent risk taking

This table shows the relation between the fund's performance in the first-half of the year and the extent of subsequent risk taking. In columns (I), (II) and (III), the dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). In specification (IV), the dependent variable is the difference between the standard deviation of tracking error of the second half of the year and that of the first part of the year ($\sigma_2(r_{j,t} - b_{j,t}) - \sigma_1(r_{j,t} - b_{j,t})$). In column (V) the dependent variable is the intended change in portfolio risk computed using holdings of the fund. The intended change in portfolio risk, $RAR_{i,t}^{holdings} = \frac{\sigma_{i,t}^{(2),int}}{\sigma_{i,t}^{(1)}}$, is the ratio of the standard deviation of tracking errors of the intended portfolio in the second half of the year to the realized standard deviation of tracking errors for the first period. See eq (3) for more details. The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; and *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. The estimates from a pooled OLS are reported below. All the specifications have time-fixed effects. The standard errors are clustered by fund and by time and are reported in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I) $RAR_{i,t}$	(II) $RAR_{i,t}$	(III) $RAR_{i,t}$	(IV) Difference	(V) $RAR_{i,t}^{holdings}$
Exret	-0.001	0.060	0.054	0.001	-0.256***
	(0.114)	(0.102)	(0.108)	(0.001)	(0.124)
Distance		-2.477 **	-2.396**	-0.027**	-1.736***
		(1.155)	(1.075)	(0.011)	(0.486)
Exp ratio			-1.429	0.001	-1.960*
			(1.648)	(0.012)	(1.103)
Turn ratio			-0.003	-0.001	0.020**
			(0.009)	(0.001)	(0.010)
Shareclass			-0.008	-0.001	0.008
			(0.009)	(0.001)	(0.014)
Log size			-0.006	-0.001**	-0.002
			(0.002)	(0.001)	0.001
Log age			0.004	0.001	-0.006
			(0.005)	(0.001)	(0.005)
Flows			0.010	-0.001	-0.001
			(0.008)	(0.001)	(0.001)
Observations	27,141	27,141	27,141	27,141	13,542
Adj R^2	0.57	0.59	0.59	0.55	0.03

Table 4: Quantile regression: relation between fund performance and risk taking

This table shows the relation between the fund's first-half performance and the extent of subsequent risk taking. A quantile regression is estimated where the conditional median function, $Q_{0.5}(.|.)$, is specified as

$$Q_{0.5}(dependent_{j,t}|I_{t,}) = a_t + c_1 * distance_{j,t} + c_2 * exret_{j,t} + \gamma * Controls.$$

In column (I), the dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year $(\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})})$. In column (II), the dependent variable is the difference between the tracking error of the second half of the year and that of the first part of the year $(\sigma_2(r_{j,t}-b_{j,t})-\sigma_1(r_{j,t}-b_{j,t}))$. In column (III) the dependent variable is the intended change in portfolio risk computed using holdings of the fund. The intended change in portfolio risk, $RAR^{holdings}_{i,t} = \frac{\sigma^{(2),int}_{i,t}}{\sigma^{(1)}_{i,t}}$, is the ratio of the standard deviation of tracking errors of the intended portfolio in the second half of the year to the realized standard deviation of tracking errors for the first period. See eq (3) for more details. In column (IV), we divide the two-year horizon into an evaluation period and a response period by using a break point of 1.5 years to investigate the case of multiyear evaluation period. In column (V) we estimate the same specification as in column (I). However, in column (V) we estimate a quatile regression at the 95^{th} percentile of the RAR distribution. The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; and *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. All the specifications have time-fixed effects and the bootstrapped standard errors are provided in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I) $RAR_{i,t}$	(II) Difference	(III) $RAR^{holdings}_{i,t}$	(IV) Multi-year	(V) 95^{th}percentile
Distance	-1.007***	-0.020***	-1.187***	-0.381***	-0.120
	(0.116)	(0.003)	(0.290)	(0.067)	(0.449)
Exret	-0.091***	0.001	-0.117***	0.023	-0.407***
	(0.025)	(0.001)	(0.034)	(0.021)	(0.118)
Exp ratio	0.311**	0.002	-1.429***	0.470**	-0.078
	(0.144)	(0.001)	(0.362)	(0.181)	(0.655)
Turn ratio	-0.002	0.001	0.002	-0.003*	0.026***
	(0.001)	(0.001)	(0.004)	(0.002)	(0.006)
Shareclass	-0.007***	0.001***	0.014	-0.010***	0.013
	(0.002)	(0.001)	(0.003)	(0.004)	(0.010)
Log size	-0.003***	0.001***	-0.001	-0.003***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Log age	0.004	0.001	-0.002	0.003	0.002
	(0.002)	(0.001)	(0.001)	(0.003)	(0.007)
Flows	0.001	0.001	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	27,141	27,141	13,542	23,724	27141
$Pseudo\, R^2$	0.38	0.32	0.02	0.38	0.56

Table 5: Quantile regression: relation between fund performance and risk taking (peer benchmark)

This table shows the relation between the fund's first-half performance and the extent of subsequent risk taking. A quantile regression is estimated where the conditional median function, $Q_{0.5}(.|.)$, is specified as

$$Q_{0.5}(dependent_{j,t}|I_{t,}) = a_t + c_1 * distance_{j,t} + c_2 * exret_{j,t} + \gamma * Controls.$$

In columns (I)-(III), the dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). $b_{j,t}$ here is the lipper benchmark associated with fund j. In column (IV), the dependent variable is the difference between the tracking error of the second half of the year and that of the first part of the year ($\sigma_2(r_{j,t} - b_{j,t}) - \sigma_1(r_{j,t} - b_{j,t})$). The variable *Exret* is the fund's first-half return in excess of its own peer benchmark; *Distance* is the square of the fund's return in excess of its peer benchmark and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; and *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. All the specifications have time-fixed effects and the bootstrapped standard errors are provided in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I) $RAR_{i,t}$	(II) $RAR_{i,t}$	(III) $RAR_{i,t}$	(IV) Difference
Distance		-1.758***	-1.800***	-0.018***
		(0.206)	(0.224)	(0.002)
Exret	0.195***	0.253***	0.257***	0.001***
	(0.033)	(0.029)	(0.033)	(0.001)
Exp ratio			0.358**	0.004***
			(0.146)	(0.001)
Turn ratio			-0.001	0.001
			(0.002)	(0.001)
Shareclass			0.003	-0.001
			(0.003)	(0.001)
Log size			-0.002*	-0.001
			(0.00)	(0.001)
Log age			0.004**	0.001***
			(0.002)	(0.001)
Flows			-0.001	0.001
			(0.001)	0.001
Observations	27,141	27,141	27,141	27,141
$Pseudo\, R^2$	0.38	0.38	0.38	0.31

Table 6: Contract diversity

A quantile regression is estimated here. The dependent variable, $RAR_{i,t}$, is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. The sample in column (I) are funds in which manager's pay is not based on fund performance. The results in column (II) are for the sample of funds that have some performance-based compensation; however, the details are not clear. The results in column (III) are for the sample of funds that clearly specify the benchmark, either peer or index, based on which manager is compensated. Column (IV) uses the entire hand-collected sample. $I_{\{performance\}}$ is an indicator variable to represent whether the manager's salary has a component that rewards her based on the performance of the fund. $I_{\{performance\}}$ turns on irrespective of whether the benchmark is clear. All the specifications have time-fixed effects and the bootstrapped standard errors are provided in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I)	(II)	(III)	(IV)
$Dependent\,Variable$	$RAR_{i,t}$	$RAR_{i,t}$	$RAR_{i,t}$	$RAR_{i,t}$
	(Not performance based)	(Performance based - unclear)	(Performance based - clear)	(All funds)
$Distance$	-0.505	-1.325**	-1.644***	-0.909***
	(0.377)	(0.677)	(0.336)	(0.132)
$Distance * I_{\{performance\}}$				-0.577**
				(0.279)
$I_{\{performance\}}$				-0.002
				(0.004)
$Exret$	0.012	0.104	0.199**	-0.019
	(0.081)	(0.105)	(0.083)	(0.035)
$Exret * I_{\{performance\}}$				0.250***
				(0.070)
$Exp\ ratio$	0.474	0.837	3.130***	1.112*
	(0.374)	(0.761)	(0.975)	(0.623)
$Turn\ ratio$	0.002	-0.006	0.002	0.001
	(0.002)	(0.007)	(0.003)	(0.002)
$Shareclass$	-0.003	-0.008	-0.013***	-0.008**
	(0.007)	(0.013)	(0.004)	(0.004)
$Log\,size$	0.003	0.001	0.001	0.001
	(0.003)	(0.003)	(0.001)	(0.001)
$Log\,age$	-0.006	0.006	0.004	0.002
	(0.004)	(0.007)	(0.004)	(0.003)
$Flows$	0.001	0.001	0.002*	0.001
	(0.001)	(0.004)	(0.001)	(0.001)
Observations	2846	2554	6155	11555
$Pseudo\,R^2$	0.45	0.48	0.48	0.47

Table 7: Subadvising and risk-shifting

A quantile regression is estimated here. The dependent variable, $RAR_{i,t}$, is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. The sample used in column (I) only includes funds that are not subadvised. The results in column (II) are for the sample of funds that are subadvised. Columns (III) and (IV) use the entire hand-collected sample of funds . $I_{\{subadvised\}}$ is an indicator variable to represent whether the fund is subadvised. $I_{\{one\,subadvisor\}}$ is an indicator variable that turns on when the fund has exactly one subadvisor. $I_{\{multiple\,subadvisors\}}$ is an indicator variable that turns on when the fund has more than one subadvisor. All the specifications have time-fixed effects and the bootstrapped standard errors are provided in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I)	(II)	(III)	(IV)
Dependent Variable	$RAR_{i,t}$ (Not subadvised)	$RAR_{i,t}$ (Subadvised)	$RAR_{i,t}$ (Full Sample)	$RAR_{i,t}$ (Full Sample)
Distance	-0.980***	-1.774***	-1.067***	-1.108***
	(0.226)	(0.346)	(0.358)	(0.342)
$Distance * I_{\{subadvised\}}$			-0.340	
			(0.634)	
$Distance * I_{\{one\,subadvisor\}}$				-0.437
				(0.568)
$Distance * I_{\{multiple\,subadvisors\}}$				-0.939*
				(0.486)
Exret	0.145***	0.134***	0.109**	0.118**
	(0.021)	(0.05)	(0.047)	(0.053)
Exp ratio	0.672***	2.771***	1.039***	0.955***
	(0.156)	(0.556)	(0.319)	(0.304)
Turn ratio	0.002	-0.006**	0.001	0.001
	(0.002)	(0.003)	(0.001)	(0.001)
Shareclass	-0.003	-0.026***	-0.006*	-0.008*
	(0.005)	(0.010)	(0.004)	(0.004)
Log size	0.001	0.001	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Log age	0.006	0.002	0.001	0.002
	(0.005)	(0.005)	(0.004)	(0.004)
Flows	-0.001***	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)

$I_{\{subadvised\}}$			-0.005	
			(0.006)	
$I_{\{one\,subadvisor\}}$				-0.007
				(0.008)
$I_{\{multiple\,subadvisors\}}$				-0.004
				(0.005)
$Exret * I_{\{subadvised\}}$			0.071**	
			(0.036)	
$Exret * I_{\{one\,subadvisor\}}$				0.100
				(0.086)
$Exret * I_{\{multiple\,subadvisors\}}$				-0.006
				(0.062)
Observations	7566	3979	11555	11555
$Pseudo\,R^2$	0.49	0.44	0.47	0.47

Table 8: Managerial ownership, Active Share, and tenure

A quantile regression is estimated where the conditional median function, $Q_{0.5}(.|.)$, is specified as

$$Q_{0.5}(dependent_{j,t}|I_{t,}) = a_t + c_1 * distance_{j,t} + c_2 * exret_{j,t} + \gamma * Controls.$$

$RAR_{i,t}$ is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). $RAR_{i,t}^{holdings}$ is the intended change in portfolio risk computed using holdings of the fund. $RAR_{i,t}^{holdings}$ is the ratio of the standard deviation of tracking errors of the intended portfolio in the second half of the year to the realized standard deviation of tracking errors for the first period. See eq (3) for more details. The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year; *Max ownership* is the maximum of the dollar amount (in millions) invested by all the managers; *High ownership dummy* is a dummy variable that takes the value one if *Max ownership* is greater than one million; *Medium ownership dummy* is a dummy variable that takes the value one if *Max ownership* is greater than zero but is less than one million ; *LagExret* is the previous year's return of the fund in excess of its own self-designated benchmark; *Tenure* is the demeaned value of the log of the number of years of service of the manager in the fund; and $LagExret * Tenure$ is the interaction between *LagExret* and *Tenure*. All the specifications have time-fixed effects and the bootstrapped standard errors are provided in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I)	(II)	(III)	(IV)	(V)	(VI)
Dependent Variable	$RAR_{i,t}$	$RAR_{i,t}$	$RAR_{i,t}^{holdings}$	$RAR_{i,t}$	$RAR_{i,t}$	$RAR_{i,t}$
Distance	-1.412***	-1.356***	-1.960***	-1.237***	-1.239***	-1.578***
	(0.196)	(0.203)	(0.506)	(0.119)	(0.117)	(0.310)
Exret	0.149***	0.128***	-0.233***	0.070**	0.097***	0.280***
	(0.051)	(0.050)	(0.058)	(0.037)	(0.029)	(0.043)
Exp ratio	0.766	0.721	-2.140***	0.398	0.285	0.933**
	(0.816)	(0.933)	(0.626)	(0.396)	(0.186)	(0.447)
Turn ratio	-0.004*	-0.005**	0.001	-0.003	-0.003	-0.001
	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)	(0.002)
Shareclass	-0.020***	-0.020***	0.019***	-0.004	-0.010***	-0.009***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
Log size	-0.003*	-0.003*	-0.001	-0.003**	-0.003***	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Log age	0.002	0.002	0.003	0.005	0.003	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.005)
Flows	0.001	0.001	0.001**	-0.007***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Max ownership	-0.016***					
	(0.004)					

$High\,ownership\,dummy$		-0.012**	-0.020**			
		(0.005)	(0.010)			
$Medium\,ownership\,dummy$		-0.006*	-0.007			
		(0.003)	(0.005)			
$activeshare$				0.046***		
				(0.008)		
$LagExret$					-0.066***	-0.163***
					(0.018)	(0.030)
$Tenure$						-0.001
						(0.001)
$LagExret * Tenure$						0.100***
						(0.032)
Observations	9225	9225	4589	15834	25514	10346

Table 9: Flow incentive vs. contract incentive

This table shows the relation between the fund's first-half performance and the extent of subsequent risk taking. The dependent variable is the ratio of the standard deviation of the tracking error from the second half of the year to that from the first part of the year ($\frac{\sigma_2(r_{j,t}-b_{j,t})}{\sigma_1(r_{j,t}-b_{j,t})}$). The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; and *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. BHS is the return of the fund, adjusted by the cross-sectional median return of the funds in the same style segment. $FlowsIncentive$ is a semiparametrically estimated measure of manager's incentive to risk-shift on account of convex flow-performance relation. Eq. (6) and Eq. (9) provide further details regarding the computation of $FlowsIncentive$. All the specifications have time-fixed effects and the bootstrapped standard errors are provided in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I)	(II)	(III)	(IV)
Distance		-0.912***		-1.002***
		(0.156)		(0.116)
Exret		-0.386***	0.049*	0.089***
		(0.124)	(0.026)	(0.029)
BHS	0.248***	0.603***		
	(0.061)	(0.148)		
$FlowsIncentive$			0.135	-0.357
			(0.836)	(0.809)
Exp ratio	0.307	0.420	0.207	0.311*
	(0.197)	(0.261)	(0.243)	(0.164)
Turn ratio	-0.004*	-0.003	-0.002*	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)
Shareclass	-0.005	-0.007	-0.006***	-0.008***
	(0.005)	(0.005)	(0.002)	(0.002)
Log size	-0.003***	-0.003**	-0.003***	-0.003***
	(0.001)	0.001	(0.001)	(0.001)
Log age	0.004	0.003	0.004*	0.004*
	(0.003)	(0.003)	(0.002)	(0.002)
Flows	-0.001	0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	26,390	26,390	27,141	27,141
$Pseudo\,R^2$	0.37	0.38	0.37	0.38

Table 10: Economic loss from risk-shifting.

This table summarizes the annual economic loss estimates from Risk-Shifting. Section 5.3 of Huang, Sialm, and Zhang (2011) estimates that when the tracking error volatility based risk-shifting measure is employed, the top quintile of risk-shifting funds earn an abnormal Carhart alpha of -41 to -45 basis points per month. In our estimation, the economic loss is the dollar value of this negative abnormal performance. In each year, we rank all funds by their RAR measure and then compute the total assets under management of the top quintile. We then multiply the Carhart alpha of -45 basis points, estimated by Huang, Sialm, and Zhang (2011), by the TNA of the top quintile of risk-shifting funds.

Year	Total # of Funds	Total AUM ($ billions)	# of Funds in Top 20% Risk Shifter	AUM of Top 20% Risk Shifter ($ billions)	Economic loss from Risk-Shifting ($ billions)
2000	1701	2,377.5	340	515.8	(27.85)
2001	1873	2,345.9	374	416.1	(22.47)
2002	1980	2,095.8	396	547.1	(29.54)
2003	2065	1,648.8	413	215.4	(11.63)
2004	2105	2,201.9	421	339.3	(18.32)
2005	2103	2,492.6	420	512.2	(27.66)
2006	2207	2,670.7	441	418.9	(22.62)
2007	2228	3,026.0	445	613.0	(33.10)
2008	2194	3,126.3	439	669.1	(36.13)
2009	2072	1,813.6	414	269.1	(14.53)
2010	2083	2,364.1	416	331.9	(17.92)
2011	2060	2,613.5	412	903.9	(48.81)
2012	2033	2,457.2	406	399.8	(21.59)
2013	2041	2,666.3	408	585.8	(31.63)

Table 11: Falsification test

This table summarizes the results from a falsification test via a bootstrapping exercise. The boostrapping exercise randomly assigns each fund to one of 57 benchmarks, and a total of 500 different randomization trials are performed. For each of the 500 random assignments, quantile regression at the median and pooled OLS regression are performed. These regression specifications are the same as those used in column (I) of Table 4 and in Column (III) of Table 3. Then, we provide the 5th and 95th percentiles of the point estimates associated with the distance variable from the 500 random benchmark assignments exercise. We also provide the coefficient estimate of the distance variable from our baseline quantile and pooled OLS regressions.

Confidence Interval from Random Benchmark Assignments Exercise

	5%	95%	Original Estimate
Quantile regression (*Distance*)	-0.447	-0.289	-1.007
Pooled OLS regression (*Distance*)	-0.613	-0.351	-2.396

Table 12: Temporal stability analysis

This table shows the robustness of the results for the different sub-periods. A quantile regression is estimated where the conditional median function, $Q_{0.5}(.|.)$, is specified as

$$Q_{0.5}(dependent_{j,t}|I_{t,}) = a_t + c_1 * distance_{j,t} + c_2 * exret_{j,t} + \gamma * Controls.$$

The dependent variable is the ratio of the standard deviation of tracking errors in the second half of the year to that from the first half of the year. The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero. The controls include *Exp ratio*, *Turn ratio*, *Shareclass*, *Log age*, *Log size*, and *Flows*. *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; and *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. In Panel A, we drop each calendar year from the sample, in turn, and estimate the quantile regression. The coefficient of *Distance* variable is reported for each year of exclusion. In Panel B, we report the results from a bootstrapping exercise. For each iteration, we randomly draw 27,141 fund-year observations (size of our sample) from our original sample and estimate a quantile regresion. We perform 500 iterations. Mean and the standard deviation of the 500 estimates are reported. In Panel C, we split the sample into four sub-periods and report the coefficient of *Distance* variable for each period. All the specifications have time-fixed effects and the bootstrapped standard errors are reported in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

Panel A : Excluding each year

Year Excluded	Distance Coefficient
2000	-1.154***
2001	-0.932***
2002	-0.664***
2003	-1.193***
2004	-1.007***
2005	-1.006***
2006	-1.045***
2007	-1.019***
2008	-0.972***
2009	-1.010***
2010	-0.998***
2011	-0.990***
2012	-1.011***
2013	-1.006***

Panel B: Bootstrapped results

	Coefficient	Standard Error
Distance	-1.017***	(0.142)

Panel C: Sub-Period

	2000-2003	2004-2006	2007 - 2010	2011-2013
Distance	-0.985***	-3.559***	-1.705***	-4.607***
	(0.290)	(1.027)	(0.258)	(0.762)

Table 13: Robustness: dependent variable

This table lists the results of a quantile regression at the median given in Eq. (5). Column (I) considers only the subsample of funds with zero or positive excess returns. Column (II) considers only the subsample of funds with negative excess returns. Column (III) uses the absolute values of the excess returns. Column (IV) uses the months until July as the first half of the year. The dependent variable in all specifications is the ratio of the standard deviation of tracking errors from the second half of the year to that from the first half of the year. The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; and *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. All the specifications have time-fixed effects and the bootstrapped standard errors are reported in parentheses. Panel B provides the results of a quantile regression at the median for funds with different investment styles. Only the coefficient of *Distance* is reported in Panel B. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

Panel A

	(I) Above	(II) Below	(III) Absolute	(IV) 7 month
Exret	-0.116**	0.578***	0.099***	-0.014
	(0.047)	(0.055)	(0.027)	(0.048)
Distance				-2.637***
				(0.326)
$\|Exret\|$			-0.306***	
			(0.029)	
Exp ratio	0.677**	0.348	0.329**	1.131***
	(0.283)	(0.201)	(0.149)	(0.37351)
Turn ratio	-0.003	0.001	-0.001	-0.003**
	(0.002)	(0.001)	(0.001)	(0.001)
Shareclass	-0.007	-0.012***	-0.009***	-0.007**
	(0.005)	(0.004)	(0.002)	(0.003)
Log size	-0.004***	-0.002	-0.003***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Log age	0.001	0.006**	0.004**	-0.009
	(0.002)	(0.003)	(0.002)	(0.007)
Flows	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	14,015	13,126	27,141	27,141
$Pseudo\, R^2$	0.42	0.33	0.38	0.02

Panel B: Risk shifting by fund style

	Cap Based	Growth	Growth & Income	Income	Others
Distance	-0.958***	-0.931***	-1.502**	-4.661**	-1.019
	(0.337)	(0.134)	(0.718)	(1.863)	(0.768)

Table 14: Robustness: time-series correction

This table lists the results of a quantile regression at the median given in Eq. (5). The dependent variable in columns (I), (II) and(III) is the ratio of the standard deviation of tracking errors from the second half of the year to that from the first half of the year. The variable *Exret* is the fund's first-half return in excess of its own self-designated benchmark; *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero; *Exp ratio* is the expense ratio of the fund at the beginning of the year; *Turn ratio* is the turnover ratio of the fund at the beginning of the year; *Shareclass* is a dummy variable that takes a value of one if the fund has multiple share classes; *Log age* is the log of the fund's age; *Log size* is the log of the fund's TNA at the beginning of the year; and *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1}-TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. *Risk* is the standard deviation of the fund's returns for the first half of the year. In Column (I) we drop the observations of the last two months of the year to compute the dependent variable (RAR). In Column (II), we use the residuals from the moving average process to compute the dependent variable (see Eq. (10)). All the specifications have time-fixed effects and the bootstrapped standard errors are reported in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I) Window Dressing	(II) Return Correlation	(III) Reversion
Distance	-1.117***	-1.075***	-0.935***
	(0.124)	(0.142)	(0.123)
Exret	0.135***	0.111***	0.080***
	(0.034)	(0.029)	(0.026)
Exp ratio	0.292*	0.273*	0.312*
	(0.168)	(0.148)	(0.156)
Turn ratio	-0.004*	-0.002	-0.002
	(0.002)	(0.001)	(0.001)
Shareclass	-0.005	-0.008***	-0.007***
	(0.003)	(0.002)	(0.002)
Log size	-0.002***	-0.002***	-0.003***
	(0.001)	(0.001)	(0.001)
Log age	0.002	0.003	0.004
	(0.003)	(0.003)	(0.002)
Flows	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Risk			-0.567
			(0.579)
Observations	27,141	27,139	27,141
Pseudo R^2	0.37	0.38	0.38

Table 15: Robustness: sorting bias

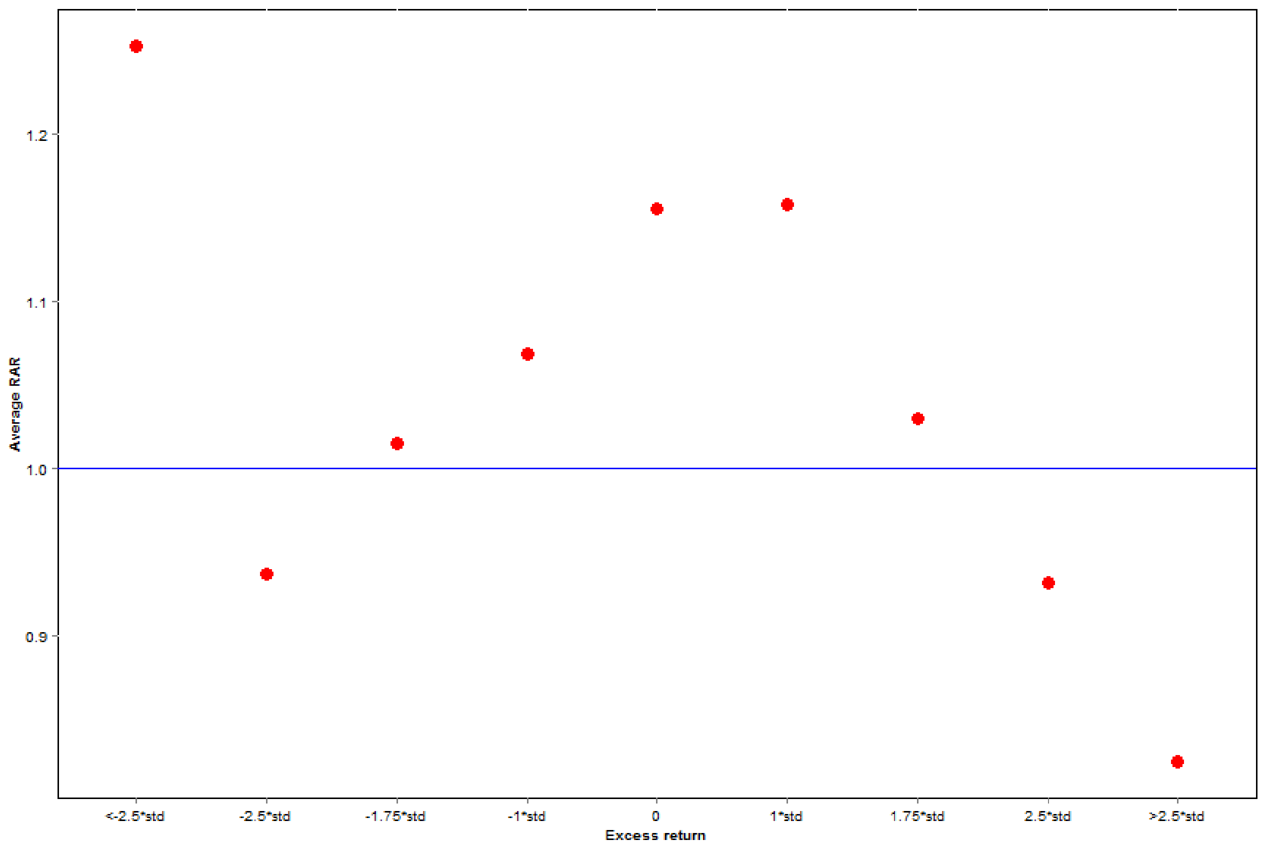
This table reports risk-shifting behavior results using active portfolio changes, as specified in Eq. (13). The dependent variable is portfolio weight changes, defined as the dollar value difference between December and June shareholdings indexed by the total value of the equity holdings in December (Eq. (12)). *Adj.Ret.* (AR) and *Adj.Std.* (AS) are the security level excess first-half return and standard deviation over the portflio average. *Distance* is the square of the fund's return in excess of its benchmark and it measures the extent to which the excess return deviates from zero. $Distance * AR$ and $Distance * AS$ are interaction terms between *Distance* and *Adj.Ret.* and *Adj.Std.*, respectively. *Flows* is the new money into fund j, defined as $\frac{TNA_{j,t+1} - TNA_{j,t}(1+r_{j,t+1})}{TNA_{j,t}}$, during the first half of the year. Column (I) presents the OLS results, where coefficients are computed using Fama and MacBeth (1973) and standard errors (reported in parentheses) are computed using Newey-West with three lags. Column (II) has the quantile regression results. This specification has time-fixed effects and the bootstrapped standard errors are reported in parentheses. The significance levels are denoted by *, **, and *** and indicate whether the results are statistically different from zero at the 10%, 5%, and 1% significance levels, respectively.

	(I) OLS	(II) Quantile
$Distance * AS$	-1.028**	-0.051***
	(0.377)	(0.013)
Adj.Std.	0.016***	0.001***
	(0.003)	(0.001)
Distance	-0.033	0.001***
	(0.02)	(0.001)
$Distance * AR$	-0.053**	0.001
	(0.019)	(0.001)
Adj.Ret.	-0.001	0.001***
	(0.001)	(0.001)
Flows	0.001***	0.001***
	(0.001)	(0.001)
Observations	1.96 M	1.96 M

Figure 1: Risk shifting behavior

The graph below plots the average RAR value for the different partitions of the excess return distribution. The variable RAR is the ratio of the tracking error, as in Eq. (2). Excess return is the difference between fund's return and its self-reported benchmark. Funds are grouped into one of nine bins. Funds are grouped under $<$-2.5σ category if their mid-year returns is 2.5 standard deviations below zero. Funds with mid-year returns between 1.75 standard deviations and 2.5 standard deviations below zero are grouped under -2.5σ, those having returns between 1.75 standard deviations and 1 standard deviation below zero are under -1.75σ, and those with returns between 1 standard deviation and 0.25 standard deviation below zero are under -1σ. Similarly, funds are labeled 1σ, 1.75σ, 2.5σ, and $>$2.5σ if their mid-year returns are between 1 standard deviation and 0.25 standard deviation, 1.75 standard deviations and 1 standard deviation, 1.75 standard deviations and 2.5 standard deviations, and more than 2.5 standard deviations above zero, respectively. Funds with mid-year excess returns between 0.25 standard deviation below and above zero are characterized as 0. Panel B tabulates the numbers and percentages of observations in each of the bins, as well as their average RAR values.

Panel A



Panel B

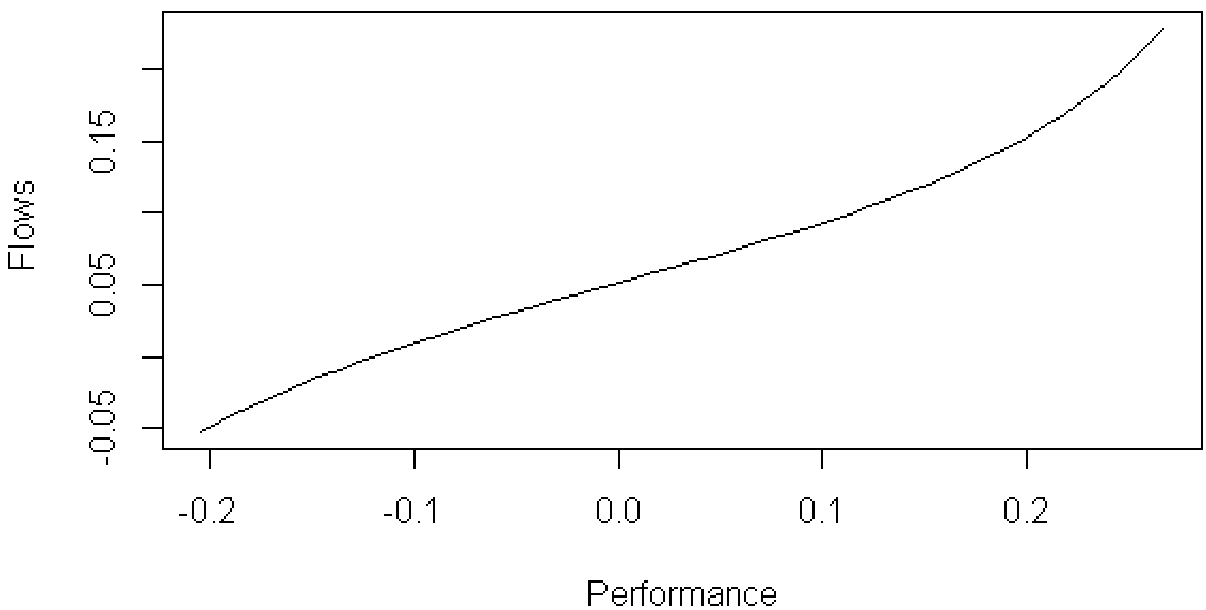
	$<$-2.5σ	-2.5σ	-1.75σ	-1σ	0	1σ	1.75σ	2.5σ	$>$2.5σ
# of obs	329	433	1438	7065	9841	7206	1961	759	617
% of obs	1.11	1.46	4.85	23.83	33.19	24.30	6.61	2.56	2.08
Average RAR	1.30	0.94	1.02	1.07	1.16	1.15	1.02	0.93	0.81

Figure 2: Flow-performance relation

Plotted is the nonparametric relation between flow and performance estimated using the following semiparametric specification:

$$\text{Flows}_{j,t+1} = f(r_{j,t} - b_{j,t}) + cX + e_{j,t},$$

where $\text{Flows}_{j,t+1}$ is percentage flows to fund j in year $t+1$ and $(r_{j,t} - b_{j,t})$ is return of the fund in excess of its benchmark for the previous year t. X represents a vector of control variables which include benchmark adjusted returns of year $t+1$ and $t-1$, natural logarithm of the ratio of the TNA of the fund to the cross-sectional mean TNA ($\log(\text{assets}_{j,t})$), the growth in total assets under management by the mutual fund industry ($\text{IndustryGrowth}_{t+1}$), and the natural logarithm of the age of the fund ($\log(\text{age}_{j,t})$).



AppendixA. Exchange option

An exchange option is a security in which the long position has the option to exchange one risky asset for another. This payoff is similar to the payoff of portfolio managers who earn a bonus when the fund's returns are greater than the benchmark returns. Managers will exchange the return of the portfolio for the return of the benchmark.

Margrabe (1978) prices a similar asset, where the two assets the portfolio,P, and the benchmark, B, have the following dynamics:

$$dP = \mu_p P dt + \sigma_p P dW_p$$

$$dB = \mu_b B dt + \sigma_b B dW_b$$

where the Brownian motion driving the two asset prices is correlated, that is, $dW_p dW_b = \rho$. The price of this exchange option, EO, is given by the following equation:

$$EO = PN(d_1) - BN(d_2)$$

where

$$d_1 = \frac{\ln\left(\frac{P}{B}\right) + \frac{\sigma^2}{2}T}{\sigma\sqrt{T}},$$

$$d_2 = d_1 - \sigma\sqrt{T}. \tag{A.1}$$

In the above formula,

$$\sigma = \sqrt{\sigma_p^2 + \sigma_b^2 - 2\sigma_b\sigma_p\rho},$$

$$N(x) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{x} e^{-\frac{s^2}{2}} ds,$$

and

$$N'(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}.$$

The first object of interest is the sensitivity of the exchange option to the volatility of the risky portfolio (σ_p). One should also note that the following expressions are true:

$$\frac{\partial}{\partial \sigma_p}\left(\frac{1}{2}\sigma^2 T\right) = T \times (\sigma_p - \sigma_b \rho), \tag{A.2}$$

$$\frac{\partial}{\partial \sigma_p}(\sigma) = \frac{1}{\sigma}(\sigma_p - \sigma_b \rho), \tag{A.3}$$

$$\frac{\partial}{\partial \sigma_p}\left(\frac{1}{\sigma}\right) = \frac{-1}{\sigma^3}(\sigma_p - \sigma_b \rho), \tag{A.4}$$

$$\frac{\partial}{\partial \sigma_p}(N(d_1)) = N'(d_1)\frac{(\sigma_p - \sigma_b \rho)}{\sigma}\left(\sqrt{T} - \frac{d_1}{\sigma}\right), \tag{A.5}$$

and

$$\frac{\partial}{\partial \sigma_p}(N(d_2)) = N'(d_2)\frac{(\sigma_p - \sigma_b \rho)}{\sigma}\left(-\frac{d_1}{\sigma}\right). \tag{A.6}$$

Based on these expressions, we can compute the response of the exchange option to the change in the volatility of manager's portfolio

$$\frac{\partial EO}{\partial \sigma_p} = P\left(N'(d_1)\frac{(\sigma_p - \sigma_b \rho)}{\sigma}\left(\sqrt{T} - \frac{d_1}{\sigma}\right)\right) - B\left(N'(d_2)\frac{(\sigma_p - \sigma_b \rho)}{\sigma}\left(-\frac{d_1}{\sigma}\right)\right).$$

Note that the following identity holds:

$$N'(d_2)B - N'(d_1)P = 0.$$

Using the above expressions, we obtain the "vega" of the option as follows:

$$\upsilon = \frac{\partial EO}{\partial \sigma_p} = PN'(d_1)\frac{(\sigma_p - \sigma_b \rho)}{\sigma}\sqrt{T}. \tag{A.7}$$

Where is the vega maximized?

Eq. (A.7) clearly shows that the value of the manager's option increases as the manager increases the value of his or her portfolio volatility. However, the following economic question still remains: For what value of the portfolio does the manager have the most incentive to increase portfolio risk? The derivative of vega(υ) with respect to the portfolio price leads us to the following first-order condition:

$$\frac{\partial \upsilon}{\partial P} = \frac{\partial}{\partial P}\left(\frac{\partial EO}{\partial \sigma_p}\right) = \frac{(\sigma_p - \sigma_b \rho)}{\sigma}\sqrt{T} \times \frac{\partial}{\partial P}(PN'(d_1)) = 0.$$

Solving the above equation yields

$$\ln\left(\frac{P}{B}\right) = \frac{\sigma^2}{2}T.$$

Therefore, the value of the portfolio for which the portfolio's volatility is most valuable is given by

$$P = Be^{\frac{\sigma^2}{2}T} \approx B. \tag{A.8}$$

AppendixB. Information regarding hand-collected incentive data

Summary Statistic based on the hand collected incentive data			
Group 1 : No performance based compensation	Number of observations with no performance based compensation	2846	
	Subtotal		2846
Group 2 : Performance based - partial	Funds having performance based compensation but no additional data provided	681	
	Funds providing compensation by comparing performance only against an index benchmark - but index not clearly specified	245	
	Funds providing compensation by comparing performance only against a peer benchmark - but peer universe not clearly specified	497	
	Funds providing compensation by comparing performance against both a peer and an index benchmark - but benchmarks not clearly specified	1131	
	Subtotal		2554
Group 3 : Performance based - Clear	Funds providing compensation by comparing performance only against an index benchmark - index is clearly mentioned	2197	
	Funds providing compensation by comparing performance only against a peer benchmark - peer universe clearly mentioned	1462	
	Funds providing compensation by comparing performance against both a peer and an index benchmark - both benchmarks clear	2496	
	Subtotal		6155
Total			11555

AppendixC. Examples of compensation contract types from the SAI

Case 1. No performance based compensation

Chase Mid-Cap Growth Fund in 2010: Portfolio Manager Compensation

The portfolio managers receive a fixed base salary and are entitled to participate in company-sponsored pension and 401(k) plans commensurate with the other employees of the firm. The firm matches a portion of the employees' contributions to the 401(k) plan. No portion of the fixed base salary of the portfolio managers is tied to the management or the performance of the Funds or to the performance of the Advisor's separately managed accounts.

Case 2. Performance based compensation with no or unclear benchmark

AllianceBernstein Growth Fund in 2010: Portfolio Manager Compensation

The Adviser's compensation program for investment professionals is designed to be competitive and effective in order to attract and retain the highest caliber employees. The compensation program for investment professionals is designed to reflect their ability to generate long-term investment success for our clients, including shareholders of the AllianceBernstein Mutual Funds. ...

Investment professionals' annual compensation is comprised of the following:

(i) Fixed base salary: This is generally the smallest portion of compensation. The base salary is a relatively low, fixed salary within a similar range for all investment professionals. The base salary is determined at the outset of employment based on level of experience, does not change significantly from year-to-year and hence, is not particularly sensitive to performance.

(ii) Discretionary incentive compensation in the form of an annual cash bonus: ... This portion of compensation is determined subjectively based on qualitative and quantitative factors. In evaluating this component of an investment professional's compensation, the Adviser considers the contribution to his/her team or discipline as it relates to that team's overall contribution to the long-term investment success, business results and strategy of the Adviser. Quantitative factors considered include, among other things, relative investment performance (e.g., by comparison to competitor or peer group funds or similar styles of investments, and appropriate, broad-based or specific market indices), and consistency of performance. ...

Case 3. Performance based compensation with clear benchmark

American Century Ultra Fund in 2010: Portfolio Manager Compensation

American Century Investments portfolio manager compensation is structured to align the interests of portfolio managers with those of the shareholders whose assets they manage. ...

(i) Base Salary: Portfolio managers receive base pay in the form of a fixed annual salary.

(ii) Bonus: A significant portion of portfolio manager compensation takes the form of an annual incentive bonus tied to performance. Bonus payments are determined by a combination of factors. One factor is fund investment performance. Fund investment performance is generally measured by a combination of one- and three-year pre-tax performance relative to various benchmarks and/or internally-customized peer groups, such as those indicated below. . . .

Fund	*Benchmarks*	*Peer Group*
Ultra Fund	***Russell 1000 Growth Index***	***Morningstar Large-Cap Growth***

Portfolio managers may have responsibility for multiple American Century Investments mutual funds. In such cases, the performance of each is assigned a percentage weight appropriate for the portfolio manager's relative levels of responsibility. Portfolio managers also may have responsibility for other types of similarly managed portfolios. If the performance of a similarly managed account is considered for purposes of compensation, it is either measured in the same way as a comparable American Century Investments mutual fund (i.e., relative to the performance of a benchmark and/or peer group) or relative to the performance of such mutual fund. ...

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