On Tournament Behavior in Hedge Funds: High Water Marks, Fund Liquidation, and the Backfilling Bias

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ABSTRACT

We analyze risk shifting by poorly performing hedge funds – and test predictions on the extent to which risk choices are related to the fund's incentive contract, risk of fund closure and dissemination of performance information. Consistent with theoretical arguments, we find that the propensity for losing funds to increase risk is significantly weaker among those that tie the manager's incentive pay to the fund's high-water mark (HWM) – suggesting a possible benefit from such incentive structures – and among funds that face little immediate risk of liquidation. Risk shifting behavior is affected by both absolute and relative fund performance and is found to be more prevalent in the backfilled period, when some funds may be at an incubation stage. Overall, the combination of factors such as high-water mark provisions, low risk of fund closure and the reporting of performance to a database appear to make poorly performing funds more conservative with regard to risk-shifting.

Keywords: Keywords: hedge funds; tournaments; risk-taking; backfilling; high-water marks.

JEL Codes: G11, G12

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Abstract

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Keywords: hedge funds, absolute performance, portfolio choice, high-water mark.

JEL Classification: G11, G12.

I. Introduction

After several years of explosive growth, the hedge fund industry has achieved a size of well over a trillion dollars under management.[1] Not surprisingly, the size of the industry and its potential impact on financial markets has led to heightened regulatory interest in the management and structure of these funds and in their investment and risk-related choices. This is manifest, for instance, in recent legislation to achieve greater transparency of hedge funds and enhanced regulation by the SEC.[2] In this paper our objective is to investigate the risk choices of hedge funds and, in particular, to examine how such decisions are related to incentive contracts, risk of fund closure and dissemination of the fund's performance information. A better understanding of hedge fund risk behavior would be useful for both investors and policy makers: for instance, by identifying factors that may curb 'excessive' risk taking by funds.

Our focus is on the risk-shifting choices by hedge funds that perform poorly, including "tournament behavior": the notion that poor performance relative to peer funds induces funds to increase risk. We also study variance strategies related to absolute performance, using the fund's high-water mark benchmark. The notion underlying risk-shifting is that convex payoffs – whether on account of asymmetric incentive contracts or an asymmetry in the response of investor flows to fund performance – may induce fund managers to increase portfolio risk. Such risk-shifting is likely to be detrimental to the interests of investors; there is also a broader policy concern that hedge funds acting in tandem could increase systemic risk. At the same time, it is recognized that a manager's incentive to elevate risk might be moderated by factors such as his risk-aversion, personal stake and reputational concerns (e.g., Starks (1987) and Carpenter (2000)).

What is the influence of the fund's incentive structure on the risk choices of managers? If risk-shifting is indeed of substantial concern, we might expect compensation arrangements to emerge that mitigate investor concerns, while still providing strong incentives to managers. Hedge funds

[1]The assets managed by the hedge fund industry have ballooned from a few billion dollars in the early 1990s to over a trillion dollars in 2005 (see e.g., The Hedge Fund Reader, August 2005, http://www.hedgefundreader.com/2005/08/hedge_funds_cha.html). After an all-time high of $1.93 trillion in June, 2008, the assets under management have declined to about $1.56 trillion after a drop in performance and fund redemptions in the last quarter of 2008 (Associated Press, January 13, 2009).

[2]Title IV of the Dodd-Frank Wall Street Reform and Consumer Protection Act compels the Securities and Exchange Commission (SEC) to impose reporting requirements on all hedge funds as it deems necessary or appropriate in the public interest or for the assessment of systemic risk.

are commonly, and increasingly, structured with asymmetric performance bonuses in which the rewards are based on exceeding a 'high-water mark' benchmark.[3] Does the form of these incentive contracts mitigate risk-shifting by managers – which could partly account for their popularity – or, to the contrary, does it exacerbate such behavior? These issues are important to understanding the design of hedge fund contracts and the possible benefits, if any, for hedge fund investors.

The (typical) asymmetric incentive contract is generally regarded as inducing managers to increase portfolio risk. However, recent theoretical work on hedge funds suggests that tying the manager's performance bonus to the fund's high-water mark benchmark [henceforth, HWM contract/provision], in conjunction with a relatively long investment horizon, may discourage excessive risk taking by fund managers. For example, Hodder and Jackwerth (2007) show that the incentives to increase risk are particularly strong when the manager faces only a single evaluation period and funds are below their high-water mark benchmark. More recently, Panageas and Westerfield (2009) show that if a manager's horizon is indefinitely long, HWMs can constrain risk taking, even by risk neutral managers. The intuition is that a hedge fund manager, depending on horizon, can be regarded as facing a sequence of options. While a riskier portfolio can increase the probability of crossing the current high-water mark, it also increases the probability that the assets will be worth less and that future options will be more out of the money.

Despite the theoretical interest in asymmetric incentive contracts, there are few empirical studies of risk-shifting behavior by hedge funds. A well-known paper that investigates risk-shifting in hedge funds is Brown, Goetzmann and Park (2001) [henceforth, BGP]. For some of our analysis we follow their approach and examine how mid-year performance, in relative as well as absolute terms, is related to subsequent fund volatility. Our study, however, differs from BGP in important ways and it delivers a number of new and significant results. First, we make use of a broader sample of hedge funds over a longer time period and have information on when the fund starts reporting to the database. Hence, unlike BGP, we are able to investigate and control for the impact of backfilled data in our analysis. This could be important if some of the backfilled data corresponds to an incubation stage, when funds may be more willing to increase risk after a poor performance.[4] Second, our data

[3]This is unlike the symmetric incentive contracts associated with mutual funds. Mutual funds are subject to the Investment Company Act (1940) and must offer only symmetric incentive contracts. A ruling to this effect was made by the SEC in 1971 based on its regulatory authority under the Investment Company Act, 1940 (see Starks, 1987).

[4]The reason is that funds that perform well will likely be launched – while those that do poorly will presumably be closed quietly, without significant reputation or wealth repercussions for fund managers. Evans (2009) finds that

allows us to distinguish between hedge funds that use HWMs to calculate performance bonuses and those that do not (about one third of sample funds) – unlike BGP in which all funds are assumed to use HWMs. In our analysis, funds without HWMs serve as a control group that helps us identify the relation between HWMs and risk choice. Furthermore, we study whether risk-shifting incentives are exacerbated when there is greater likelihood of a fund being liquidated and the manager is, in effect, facing a shortened investment horizon.

Our main source of data is the Lipper/TASS data set over the sample period January 1995 through December 2007. For our empirical analysis of risk-shifting we rely on both contingency table tests, as well as a multivariate regression approach. An advantage of the contingency table tests is that they allow us to directly compare our findings to those in BGP. The regression approach, on the other hand, enables us to control for a variety of factors, e.g., mean-reversion in return volatility (Koski and Pontiff, 1999), autocorrelation-induced biases (Busse, 2001), and investor capital flows (Ferson and Warther, 1996), that might influence the measured change in fund risk.

We report several new empirical findings. First, we find evidence of a substantial bias on account of backfilled data. When the full sample of hedge fund returns is used, our findings are consistent with BGP's conclusions that mid-year changes in hedge fund risk are negatively related to mid-year relative performance ("tournament behavior"). However, the evidence on tournament behavior is far weaker in the subsample that excludes backfilled observations. In fact, the contingency table tests indicate that mid-year relative performance bears no significant relation with the propensity to change fund risk in the period after the fund starts reporting to a database.

Second, we investigate the role of HWMs on risk-shifting in the non-backfilled sample. As noted, incentive pay tied to the high-water mark benchmark may offset fund managers' propensity to increase risk following poor performance. About 65% of the funds in the sample utilize HWMs and our results indicate that these funds exhibit a significantly lower tendency to increase risk following poor relative or absolute performance. Hence, our findings provide support for theoretical models that have argued that HWMs can induce a form of risk-aversion in certain settings. The findings also suggest that the greater use of HWMs by hedge funds over time might be driven, in part, by the preferences of investors for funds that are less likely to engage in risk-shifting.

Third, we follow a two-step procedure and investigate the impact of a greater probability of

fund incubation in the mutual fund industry leads to a 4.7% upward bias in estimates of annual fund returns.

fund liquidation on a manager's risk-shifting incentives. In the first step, we estimate the likelihood that a fund will be liquidated at year-end based upon several fund specific variables, including assets under management, lagged returns, and whether the fund is under-water at the start of the year. We then repeat our risk-shifting tests on subsamples depending on the presence of HWMs and the predicted probability of liquidation. Our results indicate that managers facing a higher risk of liquidation have a greater tendency to increase risk following poor mid-year performance. While HWMs tend to moderate a fund's overall tendency to increase risk, the sensitivity of risk change to liquidation probability is similar across funds with and without HWMs. This indicates that, consistent with theoretical arguments, HWMs are less effective when the fund faces a high risk of fund liquidation.

Our main conclusions are qualitatively unchanged across several variations of our methodology, including repeating our tests on year-by-year or style category subsamples, using smoothing-adjusted returns (see, e.g., Getmansky, Lo, and Makarov (2004)), alternative measures of fund risk changes, and an alternative method of tracking a fund's high-water mark benchmark. We also extend our analysis to examine other plausible determinants of risk-shifting behavior. First, we expand the sample to include the small number of hedge funds that have a 0% performance fee, and find that the risk-shifting of these funds is indeed lower as compared to other funds. Second, we find evidence of significantly lower risk-shifting among managers that report a large investment of personal capital in the fund. Overall, the results of the paper indicate that the type of risk-shifting behavior documented for mutual funds is generally weaker for hedge funds – other than in backfilled data. HWMs and low likelihood of fund closure appear to make poorly performing funds quite restrained with regard to risk-shifting.

The rest of the paper is organized as follows. Section II discusses related literature. Section III describes the data. Section IV discusses the main results on risk-shifting. Section V discusses robustness of and extensions to our main results. Section VI concludes.

II Literature Review

Our paper is related to the substantial literature that examines the influence of past performance and incentive contracts on the risk choices of fund managers.[5] Central to this literature is the notion

[5]See, e.g., Admati and Pfleiderer (1997), Kritzman (1987), Ferguson and Leistikow (1997), Starks (1987), Grinblatt and Titman (1989), Carpenter (2000), and Basak, Pavlova, and Shapiro (2007). For empirical work, see Grinold and

that fund managers may have the incentive to choose investment strategies that, for instance, markedly increase (or decrease) portfolio risk. These risk-shifting strategies may not necessarily be in the interest of fund investors. It is argued that factors such as convex payoffs can induce fund managers to increase portfolio risk. Brown, Harlow, and Starks (1996) [henceforth, BHS] make the argument that mutual fund managers might be especially concerned about their performance relative to that of other funds (i.e., tournaments), thereby inducing relatively poor performers to increase risk. It is recognized, however, that the incentive to increase risk may be curbed by factors such as managerial risk-aversion, managerial stake and reputational concerns (e.g., Starks (1987) and Carpenter (2000)).

Most existing empirical work on risk-shifting focuses on mutual funds. A defining feature of the mutual fund industry is a regulatory prohibition on the use of asymmetric performance bonuses. Instead, mutual fund managers are typically compensated with a fixed management fee, and thus compensation is proportional to assets under management. However, a convex payoff structure can result indirectly if the relation between fund flows and past performance is asymmetric (e.g., Chevalier and Ellison (1997) and Sirri and Tufano (1992)). The idea is that mid-year losers will take higher risk because successful gambles will attract a large amount of capital, while unsuccessful gambles will result in disproportionately fewer outflows. In comparison to mutual funds, a potential advantage of studying risk-shifting in hedge funds is that the vast majority of managers in this industry are compensated by an asymmetric performance bonus (91% in our sample). Therefore, a convex payoff structure follows directly from the compensation contract, and risk-shifting tests do not necessarily depend on a particular flow/performance relation.

There is ongoing debate about the role of performance bonuses on the investment choices of hedge fund managers. The influence of HWMs and other factors on the risk choices of hedge fund managers is analyzed in some recent papers. Of these, Hodder and Jackwerth (2007) analyze the effect of incentive fees, HWMs, and managerial ownership of shares. They show that in some portions of the state space – especially when the manager's investment horizon is short and the fund is below its HWM, the manager takes extreme risks. The manager's proclivity to gamble may also be exacerbated by a 'long bomb' effect, irrespective of horizon. While the manager wins on the

Rudd (1987), Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Orphanides (1996), Elton, Gruber, and Blake (2003), Golec and Starks (2004), Koski and Pontiff (1999), Busse (2001), Kazemi and Li (2007), and Kempf and Ruenzi (2008).

upside, his losses are limited on the downside if, in the absence of incentive pay, the manager prefers to close the fund and pursue outside options. In another recent paper, Panageas and Westerfield (2009) study the optimal portfolio choice of hedge fund managers who are compensated by incentive contracts that tie the manager's bonus to the fund's high-water mark benchmark. They show that if the horizon is long, even risk-neutral managers will not take large risks. The intuition is that hedge fund contracts represent a sequence of options: while a riskier portfolio increases the probability of crossing the current high-water mark benchmark, it also increases the probability that the assets will be lower next period and the future options more out of the money. Our findings are generally consistent with the predictions of these models: it is when the fund is likely to be liquidated, and therefore the manager does not expect to operate the fund for many periods, HWMs are far less effective in moderating risk-shifting following poor performance.

We also expect that having their own investment in the fund would affect a manager's incentives to shift risk. For example, in Carpenter's (2000) model the manager is compensated through an asymmetric bonus fee and faces no explicit downside risk. In that case the manager takes extreme risks when he is further away from the money. In contrast, Basak, Pavlova, and Shapiro (2007) and Hodder and Jackwerth (2007) show that the manager will not necessarily take big gambles when the fund is performing badly as long as he is exposed to some downside risk, either through a personal capital stake in the fund or through management fees based on end-of-period assets. The intuition is that the manager trades off the greater risk-taking incentives of convex compensation with risk aversion, and the latter effect will play a larger role when the option component is farther away from the money. Likewise, Starks (1987) finds that asymmetric incentive fees can motivate managers to choose higher risk levels as compared to symmetric ("fulcrum") incentive fees. Taken together, this suggests that personal stake will tend to moderate risk-shifting behavior in hedge funds.

Other studies of hedge fund contracts include Goetzmann, Ingersoll and Ross (2003), who estimate the implied market value of hedge fund management fees for a given portfolio and analyze the effect of some limited managerial control of fund risk. Also, Aragon and Qian (2008) argue that the HWMs in hedge fund contracts can provide a certification role when information is asymmetric about manager ability.

There is limited empirical work on risk-shifting by hedge fund managers. One well known paper is Brown, Goetzmann and Park (2001) that uses the approach developed by Brown, Harlow, and Starks (1996) to study mutual fund tournament behavior. The paper finds evidence of tournament behavior among hedge funds, though there is no evidence that absolute performance (such as being above or below the high-water mark benchmark) is related to fund volatility. Agarwal, Daniel, and Naik (2002) also report this finding for hedge funds, using an alternative method to estimate HWMs. In our paper we rely, for some of our tests, on an approach similar to that in BGP. However, our focus is on how risk-shifting incentives interact with backfilling, managerial horizon, and whether the manager's performance bonus is tied to the fund's high-water mark benchmark.

Finally, several authors have empirically examined the survival rates of hedge funds. For example, BGP find a positive (negative) relation between fund disappearance and lagged risk (returns). Fung and Hsieh (2000, 2002), Liang (2000), and Getmansky (2004) document a significant relation between fund survival and fund characteristics including investment style, assets, and performance.[6] We extend this work by integrating the estimated fund survival rates into an empirical model of risk-shifting, thereby addressing the theoretical predictions about how a manager's propensity to shift risk in response to past performance might interact with his investment horizon and the likelihood of the fund being liquidated.

III Available Fund Data and Summary Statistics

We describe the data used in our analysis in this section, followed by a discussion of our measures of variance change and sample summary statistics.

III.A Data

The main database used in our empirical analysis is supplied by Lipper/TASS, a major hedge fund data vendor. Although many funds report a performance history prior to 1995, TASS started collecting hedge fund data only in 1994. Therefore, to avoid survivorship bias, our sample period covers January 1995 through December 2007. The final sample contains the 42,392 fund-year observations of 7,626 individual funds, of which 3,167 are 'live' as of August 2, 2008. The remaining funds have ceased reporting to TASS and are considered 'defunct'.

For each fund we observe monthly net-of-fees returns and total assets. There is also a single

[6] See, also, Brown, Goetzmann, and Ibbotson (1999), Gregoriou (2002), Getmansky, Lo, and Mei (2004), Baquero, Horst, and Verbeek (2005), and Grecu, Malkiel, and Saha (2007).

snapshot of organizational characteristics, including the parameters of the fund's compensation contract. Information is available on the fund's incentive fees and whether a high-water mark provision is included in the compensation contract. As noted above, incentive fees provide an important motivation for our analysis of risk-shifting in hedge funds. Therefore, the results presented in Section IV for our main tests correspond to the subsample that excludes all 688 funds that report an incentive fee of zero.[7] We also observe the date on which a fund is added to the TASS database. This allows us to identify backfilled observations that precede the joining date. About half of the median fund's return observations in our sample are backfilled.

It is worth highlighting some of the differences between BGP and our data sample since we later compare some of their findings to our results. The data in BGP comes from TASS as well. However, unlike BGP, our data provides information on the fund manager's compensation contract and on whether an observation is backfilled. Also, our sample period is 1995-2007, while BGP considers the 1989-1998 period. The longer sample period may be important because, as noted by BGP, data prior to 1994 are subject to survivorship bias. For example, in the final year of the BGP sample period (1998), approximately 13.5% of the funds are defunct. In contrast, 58.5% of the funds in the final year of our sample (2007) are in the TASS graveyard.

III.B Tracking the high-water mark benchmark

A key variable of interest here is the extent to which fund investors' assets are below the high-water mark benchmark. This variable is not directly observable from the dataset, but can be indirectly measured using observable data on net-of-fees fund returns. Specifically, we assume the fund is initially at its high-water mark benchmark (i.e, is not "under-water") and solve recursively for the high-water mark level of a fund in year y as follows, where H_y and A_y denote the fund's high-water mark and asset levels, respectively:

$$\begin{aligned} A_y = & \quad A_{y-1} \times (1 + R_y^{\text{net}}) \\ H_y = & \quad \max\{H_{y-1}, A_y\}. \end{aligned} \tag{1}$$

The first expression is intended to capture the asset growth of a representative investor in the fund. This is affected each year by the annual net-of-fees return (R_y^{net}). The second expression reflects the growth in the historical maximum asset level obtained by the fund at the end of each year.

[7]Qualitatively similar results are found when we do not exclude these funds. We also extend our sample to include these funds for additional testing in Section V.

It is difficult to exactly measure a fund's high-water mark due to differences in investor flows, hurdle rates, and frequency at which the high-water mark is reset. In reality, the fund manager usually faces a multiplicity of high-water mark levels, each of which corresponds to a distinct investor clientele. However, an advantage of the approach in Eq. (1) is that it follows BGP's method of calculating the high-water mark benchmark, thereby allowing more direct comparisons with the present analysis. In addition, the actual assets of the fund are not necessary for the calculation (we assume $A_0 = H_0 = 1$). This allows us to avoid dropping observations for which asset level observations in TASS are missing (about 15% of the sample). Nevertheless, our main findings are qualitatively similar when we use a more sophisticated algorithm to measure a fund's high-water mark level.[8]

In analyzing the role of HWMs in the compensation contract, we calculate a high-water mark benchmark for funds without HWM provisions as we do for funds with HWMs. Basically, we track the extent to which a fund is under-water according to Eq. (1) for all funds, and then test whether the risk-shifting activities of under-water funds are different depending on whether a HWM provision is actually included in the compensation contract.

III.C Summary Statistics

Table I presents summary statistics for the full sample of funds. The first set of variables correspond to observable parameters of the compensation contract. Management Fee is compensation to managers based on an annual percentage of the assets under management and has a sample median of 1.50%. Incentive Fee represents the manager's asymmetric performance bonus – that is, the annual percentage of positive profits received by the manager. The incentive fee has a sample median of 20%. Although the vast majority (91%) of funds in our sample have a non-zero incentive fee, there is more variation in whether the fund has a HWM. Specifically, 65% of the funds are not entitled to any performance bonus unless they have recovered all fund losses realized in prior periods. We also report the extent to which a fund's reported track record precedes the date the fund was added to the database and therefore "backfilled". The median proportion of backfilling is 50%. Together, this suggests that backfilling and HWMs can potentially affect inferences made from the full sample of observations.

[8] Please see the Appendix and Section V for details on this procedure.

The average annual return is 9% and the average standard deviation of monthly returns is 4%. The variable Under End measures the percentage difference between a fund's asset level and the fund's high-water mark benchmark at year-end (i.e., $H_y/A_y - 1$). By construction, this variable cannot take negative values and is positively skewed. The median fund is not below-water at year-end, while the average fund is 3% below-water at year-end. Under June measures the mid-year percentage difference between a fund's fund's high-water mark benchmark and its asset level. Specifically,

$$\text{Under June}_y = \frac{H_{y-1}}{A_{y-1} \times (1 + R^{\text{net}}_{\text{June},y})} - 1 \tag{2}$$

where $R^{\text{net}}_{\text{June},y}$ is the cumulative net return over the first six months in year y. Unlike Under End, this variable can be negative, in which case the fund is above-water at mid-year. This distinction allows us to later test how changes in fund risk are related to whether the fund is above or below-water at mid year. The median fund is above-water at mid-year by 3%. This is consistent with the overall positive average returns in our sample. However, there is substantial variation in Under June as reflected by the sample standard deviation of 14% and a sample range with endpoints of -29% and 126%.

The remaining variables reflect fund and fund-family characteristics. Fund Age is defined as the number of months from the fund's inception date, and Fund Size is the fund's estimated assets (in millions of dollars). Both inception date and estimated assets are directly observable from the database. In our sample the median age and size are 31 months and $25.71 million, respectively. We also construct family-level variables from the individual funds of the same management firm. Family Age denotes the number of months from the earliest inception date across all individual funds, while Family Size is the aggregated assets held by individual funds. In our sample, the median Family Age and Family Size are 57 months and $94 million, respectively. Family Complexity denotes the total number of individual funds that are managed by the same management firm. For example, the largest family complex in our sample is 57 funds, while the median family manages three individual funds. Twenty-six percent of the funds in the sample have a lockup provision and the median redemption notice period is 30 days. This is in line with the numbers reported in Aragon's (2007) study of hedge fund share restrictions.

The last two rows summarize variables related to the manager's investment of personal capital in the fund. Personal Capital is a dummy variable that equals one if the fund manager has any personal capital in the fund, and we find that 32% of the managers in our sample respond that they do. Personal Capital Amount is a continuous variable measuring the reported amount of personal capital invested in the fund, and has a sample range from $0 to $300 million. We use this variable to test whether having a personal investment in the fund influences a manager's risk-taking behavior.

IV Risk-taking and mid-year performance

In this section we discuss the methodology and findings from our analysis of risk-shifting incentives in hedge funds. Our focus is on how changes in fund risk between the first and second halves of the year are related to mid-year performance – and how these patterns interact with a fund's decision to advertise to a database, the presence of HWMs in the compensation contract, and the risk of fund closure. We report results using two distinct approaches. First, a contingency table approach that allows for direct comparison with earlier findings in the literature; and second, a regression approach that tests hypotheses in a multivariate setting that controls for various factors that might affect risk-shifting.

IV.A Contingency Table Tests

BHS and BGP show how a 2x2 contingency table can be used to examine risk-shifting in fund management. The logic behind the test is that, if the propensity to change risk is unrelated to mid-year performance, then mid-year losers will be equally likely to show high and low changes in fund risk; and likewise for mid-year winners. Of course, changes in fund risk are unobservable and need to be estimated. The test is based on the risk adjustment ratio (RAR) that is estimated for each fund-year observation. The RAR is defined as

$$RAR_y = \frac{\sigma_{y,2}}{\sigma_{y,1}},$$

where $\sigma_{y,2}$ is the sample standard deviation of a fund's monthly returns during the second semi-annual period of year y, and $\sigma_{y,1}$ is defined similarly for the first semi-annual period. We require that a fund have the full six monthly observations to be included in the estimate of semi-annual standard deviation. In the analysis, we classify funds as high (low) risk-shifters depending on whether the RAR is above (below) the median RAR.

We follow BGP and consider two methods of classifying funds as mid-year losers. First, we use a relative benchmark and classify losing funds as those for which the cumulative monthly raw return over January to June is below the median return of funds over the same period. By construction, therefore, there are an equal number of mid-year losers and winners with respect to the relative benchmark. In this case, the null hypothesis of no risk-shifting is also a hypothesis of no tournament behavior; specifically, whether the mid-year (relative) losers are equally distributed into high and low RAR categories. Second, we use an absolute benchmark where mid-year losers are those for which Under June is greater than zero (i.e., under-water funds) at mid-year. In general, there will not be an equal number of funds classified as losers and winners for the absolute benchmark.[9] In this case, the null hypothesis of no risk-shifting is again a joint test of whether both the mid-year losers and mid-year winners are equally distributed into high and low RAR categories. Tests of the null hypothesis for both relative and absolute benchmarks involve a Chi-square statistic with one degree of freedom.

Table II presents results for contingency table tests where performance is measured relative to the median return across funds by year. By definition of relative performance, the results for mid-year winners are a mirror image of mid-year losers and are not reported. For the full sample (includes backfilled and non-backfilled data), we find that a greater proportion of mid-year losers have high RAR's as compared to low RAR's. For example, over the 1995-2007 period, 51.57% of mid-year losers have above-the-median RARs, as compared to only 48.43% with below-the-median RARs. The Chi-square test statistic of 28.97 leads us to reject at the 1% significance level the null hypothesis of an equal proportion of losers in the RAR groups. This pattern holds in 11 out of 13 years of the full sample.

Panel B shows that similar conclusions are reached when we repeat the analysis on the backfilled sub-sample. Evidence of tournament behavior is actually stronger in the sense that, compared to the full sample, a greater proportion (53.06% vs. 51.57%) of mid-year losers have above-the-median RARs. We again reject the null hypothesis of no tournament behavior at the 1% significance level (Chi-square is 32.43). Taken together, the results reported in Panels A and B are consistent with BGP's findings that high return funds decrease variance while low return funds increase variance.

Panel C presents strikingly different results for the subsample that excludes backfilled observations. Specifically, mid-year losers do not exhibit a strong tendency to have above-the-median RARs. This is evident in a roughly equal split of mid-year losers among low and high RAR cate-

[9] In fact, Table I shows that the majority of funds are absolute winners (i.e., the sample median of Under June is negative) for the full sample of observations.

gories, and an insignificant Chi-square statistic of 0.64. Hence, it appears that hedge funds are less likely to engage in tournament behavior after they initiate reporting to the database. As we have discussed, such a pattern is potentially consistent with backfilled data including an initial period of fund incubation, when fund managers may have far greater incentive to engage in tournament behavior. Perhaps, the risk to managerial reputation and the threat of liquidation by fund investors is greater when manager behavior is made more transparent, and this threat curbs risk-shifting behavior.

Of course, the backfilled period is not necessarily an indication that the fund is in incubator status. A well established fund that is closed to new investments may not feel the need to advertise their fund by reporting performance data to TASS. Nevertheless, the key point here is that the backfilled data provide a very different picture of risk-shifting than the non-backfilled data. Therefore, to ensure that our results are not affected by backfilling, we will exclude backfilled data from all the subsequent analysis in the paper.[10]

We next consider the impact of absolute, rather than relative, mid-year performance. Table III presents results for contingency table tests where mid-year under-performance is measured as being below the fund's HWM benchmark. Panel A reports results for all sample funds. The point estimates suggest that – contrary to the predictions for tournament behavior – under-water funds actually have a lower propensity to fall into the high RAR category as compared to the low RAR category. For example, the fraction is 48.34% over the 1995-2007 period, and we can reject the null hypothesis of no risk-shifting at the 1% level.

The above results indicate that under-water funds, at least those reporting to a database, are more likely to adopt a conservative approach to risk-taking. We next consider the possibility that these findings are largely driven by the majority of funds that compensate managers on the basis of HWMs. For reasons discussed earlier, such funds might be less willing to increase their level of risk. If HWMs affect the risk choice of managers and induce conservative behavior, we would expect such behavior to be stronger among funds in which compensation is actually tied to the

[10]We find similar evidence when we consider absolute performance and analyze the risk-shifting behavior of funds that are above and below their high-water mark benchmarks at mid-year: Funds that are under-water in the backfilled period reveal a tendency to increase risk; however, for non-backfilled observations, the evidence on under-water funds increasing risk is far weaker. We also compared risk-shifting in the backfilled and non-backfilled periods using a multivariate approach where changes in fund risk are regressed on mid-year fund performance and other characteristics such as lagged volatility, fluctuations in return autocorrelation, and investor flows. We again find that risk-shifting behavior is more evident in the backfilled period. These results are available from the authors upon request.

high-water mark. We now proceed to test this prediction.

Panel B shows the test results for the subsample of funds that do not use a high-water mark. As indicated, there is no significant evidence that being above or below the HWM affects risk-shifting for these funds. The picture is quite different for funds with HWMs. The indication from Panel C is that the anti-tournament behavior found for the full sample is largely concentrated in the subsample of funds that actually use high-water marks.

Overall, the evidence reported here for the full sample of observations (i.e., including back-filled data) is consistent with BGP's findings that performance relative to other funds is important. However, our analysis reveals that hedge fund risk-shifting incentives are related in a significant way to whether the fund is in the backfilled period, and also to whether the manager's performance bonus is actually tied to the fund's high-water mark benchmark. Apparently, fund managers exhibit a greater propensity to increase risk following poor performance if they have not already decided to voluntarily report their returns to the database. After excluding backfilled data, we find no evidence that performance relative to other funds is important for risk-shifting. In addition, the evidence in Panels B and C of Table III suggests that the presence of a high-water mark provision in the compensation contract dampens fund managers' incentives to increase fund risk when they are under-water at mid-year.

Our use of a contingency table test methodology was motivated both by its intuitive appeal and because it allows direct comparison with previous findings. The limitation, however, is that the methodology does not allow us to control for fund attributes and other variables that might influence risk-taking, suggesting the need for a multivariate procedure. To this we turn next.

IV.B Multivariate Regressions

In the analysis that follows, we rely on a multivariate regression approach which controls for fund characteristics and other factors that might influence fund risk choices. Specifically, changes in fund risk are regressed on mid-year fund performance and other characteristics such as lagged volatility, fluctuations in return autocorrelation, and investor flows. We begin by investigating whether high-water mark provisions – as suggested by the contingency table results – tend to curb the extent of risk-shifting by funds in response to mid-year performance. We estimate the following pooled cross-sectional regression:

$$\Delta\text{Risk} = \alpha + \beta_1\text{HWM} + \beta_2\text{Perf} + \beta_3\text{Perf*HWM} \\ +\beta_4\text{LagRisk} + \beta_5\Delta\rho + \beta_6\text{Flow} + \Sigma_j\beta_j Dummy_j, \tag{3}$$

where ΔRisk is the difference between the sample standard deviations of monthly returns in the second and first halves of the year (i.e., ΔRisk= $\sigma_{y,2} - \sigma_{y,1}$), HWM is a dummy variable equal to one if the observation corresponds to a fund that uses a high-water mark to calculate incentive fees, LagRisk is the value of the risk variable during the first six months, $\Delta\rho$ is the change in the fund's monthly autocorrelation between the second and first halves of the year, and Flow is the percentage net flow during the second half of the year.[11]

From this regression we can infer the relation between past performance and risk for funds that do not use high-water marks in the compensation contract from Perf. From Perf*HWM, we can infer the incremental effect that a high-water mark provision has on this relation. For performance (Perf) we use relative and absolute measures: RelRnk, AbsWin, or AbsRnk. Here, RelRnk is the fractional rank of the fund's raw return over the first six months relative to other funds during the same period. A negative coefficient on RelRnk implies a propensity to increase risk following poor performance relative the manager's peers, and is therefore indicative of tournament behavior. AbsRnk is the fractional rank of the fund's percentage distance between the fund's level of assets at mid-year from the fund's high-water mark (i.e., the negative of the Under June variable), within the sample of return observations for the full sample period 1995–2007; and AbsWin is an indicator variable that equals one if the fund is above its high-water mark at mid-year. A negative coefficient on AbsRnk or AbsWin implies that funds are prone to increase risk when their mid-year position relative to the high-water benchmark is poor.

We also include lagged risk in our specification to control for mean reversion in risk changes that may be induced by mismeasurement (e.g., Koski and Pontiff (1999), Daniel and Wermers (2000), and Kempf and Ruenzi (2008)). For example, in periods in which measured risk is high, we might expect lower risk in the subsequent period due to mean reversion in the noise component of our estimate. Changes in fund risk can also result from changes in return autocorrelation that are unrelated to risk-shifting. Positive autocorrelation in fund returns can lead to higher return

[11] Koski and Pontiff (1999) and Kempf and Ruenzi (2008) also use ΔRisk. However, we also use as dependent variables the natural logarithm of the risk adjustment ratio (RAR) and the difference of the risk ratios $(\sigma_{y2}/\sigma_{my2}) - (\sigma_{y1}/\sigma_{my1})$, where σ_{mys} is the median sample standard deviation of monthly returns across funds in semi-annual period s of year y. The results are very similar to those reported.

volatility.[12,13] On the other hand, autocorrelation in fund returns may be a symptom of return-smoothing by fund managers, and the measured variance may, therefore, be a downward biased estimate of the true, economic return variance (e.g., Getmansky, Lo, and Makarov (2004)). For these reasons, we therefore include as a separate control variable the intra-year change in estimated monthly return autocorrelation.[14] In our specification we also include second period net flows into the fund because we expect this variable to capture a spurious relation between mid-year performance and changes in fund risk (e.g., Ferson and Warther (1996) and Koski and Pontiff (1999)). For example, in periods in which managers employ a buy-and-hold strategy (and therefore do not actively shift risk), investor net flows into the fund can affect fund risk to the extent that the manager takes time to re-deploy new capital. Finally, we also include dummy independent variables for the year and style category. Standard errors allow for heteroskedasticity, as in White (1980), and also clustering by fund family.

Table IV reports the results from estimating Eq. (3) for the subsample of non-backfilled observations. The results for Models 1-6 indicate that the coefficient is significantly negative for each of the three measures of performance. The interaction term Perf*HWM is, however, significantly positive in all models. Therefore, changes in fund risk are negatively associated with mid-year performance even after the backfilling period. However, this relation is significantly weaker among funds that use HWMs to calculate incentive fees. This result holds for all performance variables. For example, a drop in relative performance rank from 100% to 0% is associated with a 0.78% increase in monthly return standard deviation for funds without HWMs, as compared to only 0.08%

[12] To see this, consider a monthly return process given by $R_t = \rho R_{t-1} + \epsilon_t$, where $\epsilon \sim N(0, \sigma_\epsilon^2)$ and ρ is the autocorrelation. Here expected return $E(R_t) = 0$ and the monthly variance $E(R_t^2) = \frac{\sigma_\epsilon^2}{(1-\rho^2)}$. Hence, keeping the variance of return innovations σ_ϵ^2 fixed, an increase in ρ increases the measured monthly variance. Therefore, intra-year change in estimated monthly return autocorrelation would be expected to be positively correlated with the change in fund risk. In our sample we find that, if anything, stronger fund performance in the first half of the year is associated with an increase in the autocorrelation in the latter half. Such a pattern would tend to bias against our finding tournament and risk-shifting behavior in our sample – since an increase in autocorrelation would tend to increase the measured volatility of returns in the second half of the year.

[13] Busse (2001) studies a related issue in the context of mutual funds. He argues that most of the intra-year risk change in mutual funds is attributable to intra-year changes in daily return autocorrelation caused by changes in the volatility of common stock market risk factors. These specific effects are less likely in the current analysis, because traditional equity market risk factors explain much less of the variation in hedge fund returns.

[14] In the Appendix we use simulations to examine our risk-shifting tests under the null of no risk-shifting while allowing for return-smoothing. Our main finding, discussed in Section V, is that including lagged risk and changes in monthly autocorrelation as independent variables in our multivariate regression model eliminates the biases induced by several forms of return-smoothing. Moreover, in Section V we show that our main results are qualitatively unchanged when we repeat our risk-shifting tests after adjusting the fund returns data for return-smoothing as described in Getmansky, Lo, and Makarov (2004).

when managers are subject to HWMs. Meanwhile, the difference in fund risk changes between funds that are above and below water is -0.56% when HWMs are absent, as compared to -0.26% if the fund has a HWM.

Regarding other variables we find, consistent with mean reversion in measured fund risk, that the coefficient on LagRisk is negative and significant for all specifications. The coefficient on $\Delta\rho$ suggests that intra-year changes in fund volatility are greater among funds experiencing increases in monthly return autocorrelation. This makes sense because, as noted earlier, greater autocorrelation in reported returns leads to greater measured volatility in reported returns. Also, the coefficient on Flow is negative and significant across models and therefore consistent with the flow hypothesis. As shown in Models 1, 3, and 5, however, omitting $\Delta\rho$ and Flow from the regressions has little impact on the coefficient of our key variable (Perf*HWM).

Overall, the results of our pooled regression analysis confirm and extend our initial findings from contingency table tests: Fund managers' incentives to increase risk following poor performance are significantly weaker among funds that tie the manager's incentive pay to the fund's high-water mark benchmark. In the following, we examine the consistency of this pattern across years and style categories.

IV.C Risk-Shifting and HWM Across Years and Styles

In this section we run our main regression model through finer cuts of the data, using year-by-year regressions and style category regressions. To address temporal stability we run Eq. (3) each year for subsamples of funds with and without a HWM. Each year we require each subgroup (i.e., HWM or not) to have at least 60 observations in order to estimate the model in Eq. (3). We produce White (1980) standard errors which are robust to within-style correlation. In Table V we report the estimated coefficients (β_1) on the key variable of interest (Perf). A negative β_1 implies that fund risk tends to increase following poor performance, and is therefore indicative of risk-shifting. We find that the reduced propensity of funds with HWMs to increase risk following poor performance is generally consistent across years. For example, in nine of ten years, we find a positive difference (diff) between the estimated β_1 for funds with (yes) and without (no) a HWM. This difference is also statistically significant in 2001, 2002, and 2004. A similar pattern is observed when risk-shifting is measured with respect to absolute performance (AbsRnk). The final rows of the table report the average of the yearly estimates. The average yearly risk-shifting coefficient is negative and significant for the sample of funds without HWMs, but not significant for the sample of funds with HWMs.[15]

Next we estimate Eq. (3) for all funds within each style category and for subsamples of funds with and without a HWM. We produce White (1980) standard errors which are robust to within-year correlation. We again require both subgroups (i.e., HWM or not) to have at least 60 observations each in order to estimate the model in Eq. (3). In Table VI we find that the lower risk-shifting of HWM funds is generally consistent across fund style categories. For example, we find reduced risk-shifting in response to relative performance in nine of ten style categories. The difference is significant for the Emerging Markets, Fun of Funds, Long/Short Equity Hedge, and Multi-Strategy styles. The one exception is Fixed Income Arbitrage, where HWMs are associated with larger, though insignificant, risk-shifting. We find similar evidence when measuring performance using the rank of absolute performance (AbsRnk) or the above/below water dummy (AbsWin). The final rows of the table report the average of the style-by-style estimates. Across styles, risk-shifting behavior is negative and significant for the sample of funds without HWMs, but less negative and not significant for the sample of funds with HWMs. The differences are positive and significant. Overall the results show that the main message from Table IV is consistent for the vast majority of years and style categories in our sample.

IV.D Fund Liquidation and Risk-Shifting

In this section we examine whether the relation between mid-year performance and changes in fund risk is affected by the threat of fund liquidation. Hodder and Jackwerth (2007) and Panageas and Westerfield (2009) show that risk-taking can be significantly reduced if a manager expects to operate the fund over multiple periods. Therefore, we expect risk-shifting to be more pronounced among funds with a comparatively high probability of liquidation, where managers are likely to have shorter expected horizons. However, we note that a high likelihood of liquidation might have a far stronger effect on risk-taking than when a horizon is short due to innocuous reasons, such as a manager facing retirement. The reason is that if the fund has recently suffered large losses and is about to be closed due to investor redemptions, the manager may have the incentive to take

[15] The results for the above/below water dummy (AbsWin) are very similar to AbsRnk and are not reported to conserve space.

disproportionately large risks. This is because managers may see little downside to increasing risk if the fund is already facing liquidation and the manager has outside opportunities. Meanwhile, on the upside, a superior performance may help the manager avert fund closure and receive performance-linked compensation.[16]

In the first step, we estimate the probability that the fund is liquidated at year-end, conditional on information available at mid-year. We measure fund liquidation using the joint condition that a fund is defunct (i.e., has stopped reporting from the database) and that TASS provides "Fund liquidated" as the reason for defunct fund status. Specifically, we estimate the following probit model:

$$P\left(LIQ_{iy} = 1 | X_{iy} = x_{iy}\right) = \Phi\left(x'_{iy}\beta\right),$$

where

$$LIQ_{iy} = \begin{cases} 1 & \text{if fund } i \text{ is liquidated at the end of year } y \\ 0 & \text{if otherwise} \end{cases}$$

and Φ is the cumulative distribution function of the standard normal distribution, and x_{iy} is a vector of fund i's characteristics that are measurable at the middle of year y.[17]

We consider several fund specific variables to determine fund liquidation. The first set of variables are measured in June of the current year. Under June is defined above and is the mid-year percentage distance between the fund's asset level and its high-water mark. Under June* is an alternative measure of distance from a high-water mark and is described in the Appendix. Raw Return June is the fund's cumulative monthly raw return between January and June. The second set of variables are measured at the end of the previous year. Under Water is an indicator variable that equals one if the the fund is under-water. Under Water* is defined similarly using the alternative method of calculating distance from a high-water mark and is described in the Appendix. Raw Return and Excess Return refer to the lagged annual raw return and return in excess of the annual return of a value-weighted portfolio of funds of the same style. Volatility is the

[16]While managers near retirement may have short horizons, they are also likely to have a substantial stake in the fund and thus less incentive to take risk. In Section V we extend our main analysis to study the influence of a personal stake in the fund on a manager's risk-shifting behavior.

[17]Of the 4,459 defunct funds in our sample, 1,750 (39%) are classified by TASS as "Fund Liquidated". Getmansky, Lo, and Mei (2004) argue that the vast majority of the remaining 2,709 defunct funds that are classified as either "closed to new investment" (9 funds), "merged into another entity" (97 funds), "dormant" (4 funds), "no longer reporting" (1,610 funds), "unable to contact fund" (740 funds), or "unknown" (249 funds), are also plausibly liquidated. For this reason we repeated all of our tests after treating all 4,135 defunct funds as liquidated. Our qualitative results are unchanged using this method and are available upon request.

yearly estimate of the fund's monthly return standard deviation. All variables (excluding indicator variables) are standardized to have a zero mean and variance of one across funds.

We use the estimated coefficients from the probit model to compute a fund's probability of liquidation in our second stage analysis of risk-shifting. We avoid any future information when estimating the liquidation probability. Each year, we re-estimate the probit model using a 3-year rolling estimation window and define ProbLiq as the fitted values obtained from the estimated coefficients.[18] In Table VII we report the average of the yearly estimates obtained from our rolling estimation procedure. We report t-statistics of the averages to draw inferences.[19] The probit model is separately estimated depending on whether the manager's incentive fee is tied to a high-water mark (Panel B) or not (Panel A). We require each subgroup to have at least 30 live and 30 dead funds to estimate the probit model.

For both subgroups, we find that Raw Return and Fund Size are negative predictors of fund disappearance. For example, the probability that a fund without a high-water mark will disappear falls by 1.86% per one standard deviation improvement in mid-year performance. Larger funds are also less likely to disappear. For example, among funds with high-water marks, disappearance probability falls by 2.98% per one standard deviation increase in Fund Size. The positive coefficient on Under Water indicates that funds are more likely to be liquidated if they begin the year under their high-water mark. However, this effect is only statistically significant for funds that actually use a HWM provision to calculate the manager's performance bonus (Panel B). We estimate that funds that are below water at the end of the previous year are between 1.38% and 2.84% more likely to disappear from the database, depending on the model.

Overall, we find that several variables in the probit model are significant in explaining the variation in fund liquidation. As discussed above, the liquidation probability estimated by our model might therefore provide explanatory power for risk-shifting behavior as, for example, a proxy for fund distress or a manager's horizon. Our next step is to estimate the probability of fund liquidation for each fund and year given fund characteristics at mid-year and the previous year-end. We then repeat the regression analyses of mid-year risk-shifting, incorporating the estimated

[18]Our findings are similar when we use alternative estimation windows, including an extending window, or if we define ProbLiq as the fitted values from a one-time estimation using all the data.

[19]We adjusted the standard errors for the estimated first-order autocorrelation in the estimated slopes. Following Fama and French (2002), Chakravarty, Gulen, and Mayhew (2004), and Petersen (2008), and others, we first estimated the autocorrelation of the yearly coefficients (ρ), and then multiplied the estimated standard error of the average coefficient by $\sqrt{(1+\rho)/(1-\rho)}$.

liquidation probability.

To investigate the impact of liquidation probability on the relation between prior fund performance and changes in fund risk, we estimate the following pooled cross-sectional regression

$$\begin{aligned} \Delta\text{Risk} = \quad & \alpha + \beta_1 \text{ProbLiq} + \beta_2 \text{Perf} + \beta_3 \text{Perf*ProbLiq} \\ + \quad & \beta_4 \text{LagRisk} + \beta_5 \Delta\rho + \beta_6 \text{Flow} + \Sigma_j \beta_j Dummy_j, \end{aligned} \tag{4}$$

where ProbLiq is the fractional rank of the estimated probability of fund disappearance relative to other funds at mid-year. As noted above, the probability of fund closure is obtained from a probit model that is estimated each year using only the data from the prior three years to avoid the use of any future information.

The regression model is estimated separately for funds with and without high-water mark provisions. In the regression model β_2, the coefficient on Perf, will allow us to infer the relation between past performance and risk change for funds with the lowest probability of disappearance. The coefficient β_3 on the interaction variable Perf*ProbLiq captures the incremental effect that an increase in disappearance probability has on this relation. Finally, the coefficient β_1 on ProbLiq reflects the relation between disappearance probability and the change in fund risk. The regression includes the volatility and flow variables employed in earlier risk change regressions, as well as dummy variables for year and style categories.

Panel A of Table VIII reports the results from estimating Eq. (4) for the subsample of funds that do not use high-water marks. The results for Models 1-6 indicate that $\beta_1 > 0$ and $\beta_3 < 0$. Therefore, changes in fund risk are positively related to the fund's probability of termination, and the propensity for mid-year losers to increase risk is stronger among funds that are more likely to be liquidated at year-end. For example, Model 6 predicts that a drop in absolute performance rank from 100% to 0% is associated with an insignificant 0.26% decrease in fund risk for funds with the lowest predicted probability of disappearance. Meanwhile, for funds with the highest likelihood of liquidation, the same performance drop is associated with a significant 1.81% increase in fund risk. These patterns hold for all performance variables, though the interaction term for relative performance rank is not statistically significant. Overall, the results indicate that risk-shifting incentives are significantly lower when there is only a remote possibility of liquidation.

Panel B of Table VIII reports the results from estimating Eq. (4) for the subsample of funds that use high-water marks. Our findings from Table IV indicate that the propensity for mid-year losers to increase risk is lower among funds with high-water marks. This is consistent with the new results, as the coefficients on each performance variable in Models 1, 3, and 5 are lower in Panel B as compared to Panel A. However, as in Panel A, we again find that $\beta_1 > 0$ and $\beta_3 < 0$ for funds with high-water mark provision. For example, the results for Model 6 suggest that a drop in absolute performance rank from 100 to 0 is associated with a significant 0.62% decrease in fund risk for funds with the lowest predicted probability of liquidation. Hence, the HWM in conjunction with a low risk of closure, tends to make a manager more risk-averse following a poor performance. On the other hand, for funds with the highest likelihood of liquidation, the same drop is associated with a significant increase in fund risk of 0.92% . Therefore, even though the propensity for mid-year losers to increase risk is weaker among funds that use high-water marks, the sensitivity of the risk shifting behavior to liquidation probability (indicated by β_3), appears similar across the two groups.

We interpret these results as supportive of the theoretical arguments advanced in Hodder and Jackwerth (2007) and Panageas and Westerfield (2009) that there is an interaction between horizon and the ability of HWMs to curb risk-taking behavior. When the horizon is relatively long, risk-shifting might not be a concern since a HWM induces managers to become more risk-averse. This is consistent with our evidence. In addition, the findings are also supportive of managers taking disproportionately large risks when the fund is substantially underwater or has recently suffered large losses and is about to be closed due to investor redemptions.

V Robustness and Extensions

In this section we discuss robustness tests and extensions to our main findings. First, we repeat our main tests using an alternative measure of the deviation of a fund's assets from its high-water mark. Second, we expand the sample to include funds that do not have an incentive fee, and compare the risk-shifting incentives of these funds to ones that use incentive fees in the compensation contract. We also extend our analysis to see whether risk-shifting is related to the personal capital the manager has invested in the fund. Third, we repeat our main risk-shifting tests after adjusting reported returns for the specific form of return-smoothing described by Getmansky, Lo, and Makarov (2004). Lastly, we discuss the results of a simulation exercise to examine the robustness of our test methodology to several forms of time-variation in return-smoothing, including cases in which the return-smoothing is highly correlated with past performance.[20]

In Table IX we report results using an alternative measure of absolute performance outlined in the Appendix. The main difference from the method outlined in Eq. (1) is that it allows for investor-specific high-water mark benchmarks that result from differences in the timing of investor capital flows into and out of the fund. The qualitative results are the same. Specifically, there is less risk-shifting by funds with high-water mark provisions and those with a lower likelihood of being terminated.

We next expand our sample to include the 688 funds with a zero percent incentive fee. For this expanded sample we estimate the following pooled regression model:

$$\begin{aligned}\Delta\text{Risk} = \quad & \alpha + \beta_1\text{Perf} + \beta_2\text{IFEE} + \beta_3\text{HWM} + \beta_4\text{log(1+Personal Capital Amount)} + \beta_5\text{Perf*IFEE} \\ & +\beta_6\text{Perf*HWM} + \beta_7\text{Perf*log(1+Personal Capital Amount)} + \text{Control Variables,}\end{aligned} \tag{5}$$

where IFEE is a dummy variable equal to one if the observation corresponds to a fund that has an incentive fee larger than zero. As control variables we include LagRisk, $\Delta\rho$, Flow, and also dummy independent variables for year and style categories. In this regression we can infer the relation between past performance and risk for funds with no incentive fee from Perf. From Perf*IFEE, we can infer the incremental effect that an asymmetric incentive fee has on this relation in the absence of a high-water mark provision. From Perf*HWM, we can infer the incremental effect that a high-water mark provision has on this relation.[21] Finally, from Perf*log(1+Personal Capital Amount), we can infer the incremental effect that a personal capital investment has on the relation between changes in fund risk and mid-year performance.

Table X reports the results from estimating Eq. (5) for the sample funds. The results for Models 1-6 indicate that the interaction term Perf*IFEE is significantly negative. Therefore, changes in fund risk are more strongly negatively associated with mid-year performance for funds with incentive pay. In fact, Models 1 and 5 do not detect any significant relation between risk changes and relative performance among funds that do not have an incentive bonus. The estimated coefficients for LagRisk, $\Delta\rho$, Flow, year and style dummies are suppressed for brevity.

[20] As further robustness we repeated our tests on fund subsamples depending on whether the fund is domiciled offshore, and therefore might cater to a somewhat different investor clientele than onshore funds. Consistent with our findings in Table IV, we find that high-water marks are associated with significantly less risk-shifting in both the offshore and onshore fund subsamples. This suggests that our findings are not affected by a fund's domicile and are robust, for instance, to a potential misclassification of which players are competing in the same tournament.

[21] This is true because a fund cannot have a high-water mark provision without a positive incentive fee; i.e., $IFEE = 0$ implies $HWM = 0$.

The interaction term Perf*HWM is, however, significantly positive in each case. Therefore, the risk-shifting behavior among funds with incentive pay is significantly weaker when high-water marks are used to calculate incentive fees. This result holds for all performance variables. For example, Model 1 predicts that a drop in relative performance rank from 100% to 0% is associated with an insignificant 0.12% increase in monthly return standard deviation of funds without incentive pay, as compared to a significant 0.76% increase for managers with incentive pay that is not tied to the fund's high-water mark. On the other hand, in the presence of incentive pay and high-water mark provisions, this figure drops to an insignificant -0.08%.

As discussed in Section II, we expect that having a personal investment in the fund would dampen the manager's incentives to shift risk. Consistent with this prediction, we also find that risk-shifting is less evident among managers with larger investments of personal capital in the fund. This is reflected in the positive and significant coefficient on Perf*log(1+Personal Capital Amount).[22] In economic terms, the reduction in risk-shifting associated with a doubling of a manager's personal stake is roughly half of that of adding a high-water mark provision to the manager's incentive fee. Hence, it appears that ownership of a relatively small stake in the fund might not have a meaningful effect on the risk shifting incentives of managers. The limited usage of manager personal capital observed in the sample could be the result of resource constraints as well as managerial risk aversion, if having a significant part of his wealth tied up in the fund could make the manager overly cautious.

Getmansky, Lo, and Makarov (2004) develop a model of return-smoothing behavior in hedge funds that predicts downward biases in estimates of return volatility. Specifically, they assume that the fund's reported monthly return (R^o) satisfies,

$$R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \theta_2 R_{t-2} \tag{6}$$

where R is the fund's true, unobservable monthly return, $\theta_j \in [0,1],\ j = 0,1,2$, and $\theta_0 + \theta_1 + \theta_2 = 1$. The parameters θ_j are interpreted as the speed at which information is reflected in reported returns. For example, θ_0 is the fraction of a fund's economic return that is contemporaneously reflected in its reported return. Assuming the true economic returns are independent and identically distributed, the model implies that the reported return variance will be lower than the true return variance.

[22] We find similar results when we use a dummy variable that equals one if the manager reports any positive amount of personal capital investment in the fund.

Specifically, $V(R^o) = \left(\theta_0^2 + \theta_1^2 + \theta_2^2\right) V(R) \leq V(R)$. Thus, the smoothing model predicts that changes in reported return variance will also be lower than changes in true return variance. If the degree of smoothing is correlated with our main variables of interest (e.g., high-water marks, fund horizon), then our main results might be driven by a smoothing bias.

To address this issue we repeat our main risk-shifting tests using smoothing-adjusted returns. First, we obtain the maximum likelihood estimates $(\hat{\theta}_0, \hat{\theta}_1, \hat{\theta}_2)$ of the smoothing parameters in Eq. (6), assuming that de-meaned economic returns are mean-zero, normal random variables. We require each fund in the estimation to have at least 24 monthly return observations. Next, we calculate adjusted returns recursively from Eq. (6) as follows:

$$R_t = \begin{cases} R_t^o / \hat{\theta}_0, & t = 0; \\ \left(R_t^o - \hat{\theta}_1 R_{t-1}\right) / \hat{\theta}_0, & t = 1; \\ \left(R_t^o - \hat{\theta}_1 R_{t-1} - \hat{\theta}_2 R_{t-2}\right) / \hat{\theta}_0, & t \geq 2 \end{cases}$$

Table XI presents the results for the key variables in our risk-shifting tests using smoothing-adjusted returns. The qualitative results are the same. Specifically, the propensity to increase risk following poor performance is lower among funds with high-water mark provisions and those with a lower likelihood of being terminated.

To further address the issue of return-smoothing we conduct a simulation exercise. The model outlined in Getmansky, Lo, and Makarov (2004) and implemented above assumes that the degree of return-smoothing is constant over time for a given fund. Therefore, in our simulation we extend the model to allow for several forms of time-variation in return-smoothing, including cases of extreme dependence between return-smoothing and a fund's past performance. Our results from this exercise suggest that including the LagRisk and $\Delta\rho$ variables together in our multivariate regression tests effectively eliminates several forms of smoothing-induced biases in estimates of risk-shifting. The details of the simulation and results are discussed in the Appendix and reported in Tables XI and XII.

Overall, the results confirm and extend the findings from our main tests: Fund managers' incentives to increase risk following poor performance are significantly weaker among funds that either do not use incentive pay, combine incentive pay with a high-water mark provision, or have a substantial personal stake in the fund. These results are insensitive to the way in which we measure the distance between fund's current assets and the fund's high-water mark level, and also to the potential biases from return-smoothing.

VI Conclusions

Previous studies report a negative relation between changes in fund risk and mid-year relative fund performance ("tournament" behavior). We find evidence of such risk-shifting in hedge funds and show that it is affected by both absolute and relative fund performance. This risk-shifting is found to be more prevalent in the backfilled period, when some funds may be at an incubation stage. Consistent with theoretical arguments, the propensity for losing funds to increase risk is significantly weaker among those that tie the manager's incentive pay to the fund's high-water mark and among funds that face little immediate risk of liquidation. These findings suggest that fund investors may favor the use of HWMs since they appear to curb risk-shifting, possibly accounting for the increasing popularity of HWMs among hedge funds.

Our findings suggest that there must be significant costs to resetting the HWM or in shutting down and restarting a fund that falls well below its HWM. Clearly, the HWM provision would be much less effective as an incentive device in ex-ante terms if managers believed that the HWM could be easily overridden, whether by resetting or by closing and restarting a similar fund. The reason might be the existence of significant costs/legal issues that make this difficult. In part the costs may be of a reputational nature – so that a family that resets a fund's HWM or restarts the fund, hurts its credibility with investors with regard to the use of HWMs in its other funds.

Our results have general policy implications with regard to potential changes in the regulation of hedge funds. One is that if there are changes in the disclosure requirements with regard to, say, performance, asset holdings and expenses, they should apply to all funds in the incubation process as well. As we have discussed, the evidence of risk-shifting by funds in the backfilled data could, at least to an extent, be the result of hedge funds being more willing to increase the risk of funds in incubation and cherry pick the ones that do well. If fund families were required, for instance, to report the outcomes of all incubated funds, this could moderate the incentives of fund families to engage in risk-shifting.

A second observation concerns the issue of whether risk-shifting by hedge funds has implications for systemic risk. This issue has featured prominently in recent legislative calls for regulators to monitor hedge funds' contribution to systemic risk. In this regard, our finding that absolute poor performance is associated with funds increasing risk is relevant. The reason is that it suggests a possible pathway for risk-shifting incentives of individual funds to have system-wide implications – since a large economic shock could potentially induce many funds with poor absolute performance to increase risk at the same time. Hence, transparency and the presence of high water marks, which appear effective at curbing risk-shifting, might be deserving of policy support. Also, constraints on the nature of incentive contracts, such as limiting the use of asymmetric contracts in hedge funds and other industries, might well be counterproductive (asymmetric contracts are, for example, ruled out for mutual funds). It remains an open question, however, as to why high-water marks, as opposed to other provisions (e.g., clawbacks), have emerged as the preferred device to curb risk-shifting incentives in hedge fund performance contracts.

Appendix

A.1. Alternative high-water mark benchmark

In this appendix we describe the alternative method used to track a fund's high-water mark benchmark. The approach is similar in spirit to the procedure used in Agarwal, Daniel, and Naik (2009). The main difference from the method outlined in Eq. (1) is that here we allow for investor-specific high-water mark benchmarks that result from differences in the timing of investor capital flows into and out of the fund. In this case, we define the fund's overall position relative to its high-water mark benchmark as a weighted average of the individual investor class positions. Let K_y denote the number of investor classes in the fund at the end of each year y. Each class k will differ depending on 1) the time of entrance into the fund, 2) the current asset level of the class ($A_{k,y}$), and 3) the high-water mark level of the class ($H_{k,y}$). We define the year-end fund-level distance between the current assets and the high-water mark level as the weighted average of class-level distances:

$$\text{Under End}^*_y = \sum_{k=1}^{K_y} w_{k,y} \times \left(\frac{H_{k,y}}{A_{k,y}} - 1\right)$$

where $w_{k,y} = A_{k,y}/\sum_{k=1}^{K_y} A_{k,y}$ is the proportion of fund investor assets held by the k'th investor class at the end of year y.

We define two additional variables that measure the fund's overall position relative to its high-water mark benchmarks. Both of these variables appear in Table VII. First, Under Water$^*_y$ is a dummy variable that equals one if at least one investor class is under-water at the end of year y; i.e., if UnderEnd$^*_y > 0$. Second, the fund's overall mid-year position in year y is defined as the weighted average percentage distance between the mid-year asset levels and high-water mark benchmarks across investor classes:

$$\text{Under June}^*_y = \sum_{k=1}^{K_{y-1}} w_{k,\text{June},y} \times \left(\frac{H_{k,y-1}}{A_{k,\text{June},y}} - 1\right)$$

where $w_{k,\text{June},y} = A_{k,\text{June},y}/\sum_{k=1}^{K_{y-1}} A_{k,\text{June},y}$, $A_{k,\text{June},y} = A_{k,y-1} \times (1+R_{\text{June},y})$, and $R_{\text{June},y}$ denotes the cumulative gross return of the fund over the first half of year y.

A complication here is that K_y, $A_{k,y}$, $H_{k,y}$, and gross returns are not directly observable from the dataset. Therefore, we measure these variables indirectly using observable information on net returns, assets under management, and the parameters of the compensation contract. First, we compute the total management and incentive fees paid by each investor class as follows:

$$\begin{aligned} \text{mfee}_{ky} &= m \times A_{k,y} \\ \text{pfee}_{ky} &= p \times \max\{A_{k,y} \times (1+R_y) - H_{k,y}, 0\} \end{aligned}$$

where R_y is the annual gross return on the fund's portfolio (i.e., gross of fees paid to the manager), and m and p denote the fixed management fee and incentive fee, respectively. The new net asset and high-water level of investor group k are updated recursively as follows:

$$\begin{aligned} A_{k,y} &= A_{k,y-1} \times (1+R_y) - \left(\text{mfee}_{ky} + \text{pfee}_{ky}\right) \\ H_{k,y} &= H_{k,y-1} + \max\{A_{k,y} - H_{k,y-1}, 0\} \end{aligned}$$

Next, we update the personal capital invested by the manager as follows:

$$PC_y = PC_{y-1} \times (1+R_y) + \sum_{k=1}^{K_{y-1}} \text{pfee}_{ky} \times (1 - 0.35 \times (1 - \text{OFF}))$$

where OFF is an indicator that equals one if the fund is domiciled offshore. Here, the assumption is that the manager uses all after-tax incentive fees to buy new shares in the fund. The income tax for onshore funds is assumed to be 35%.

We solve for R_y numerically by comparing the implied net return with the actual net return that is observable from the database. Specifically, we compute the implied net fund return as

$$\frac{\sum_{k=1}^{K_{y-1}} A_{k,y} + PC_{y-1} \times (1 + \hat{R}_y)}{\sum_{k=1}^{K_{y-1}} A_{k,y-1} + PC_{y-1}} - 1$$

where $\hat{R}_y$ is an estimate for the gross return. We repeat this procedure until the absolute difference between the implied and actual net returns is less than 1e-04.

The net flow into the fund is defined as the difference between the end-of-year assets and the sum of existing investors' assets plus manager's personal capital. Specifically,

$$\text{Flow}_y = A_y - \left(\sum_{k=1}^{K_{y-1}} A_{k,y} + PC_y \right)$$

where A_y is the total fund assets reported to TASS at the end of year y. If Flow_y is positive, then the fund has gained a new investor class ($K_{y-1} + 1$) with beginning net asset and high-water mark level equal to Flow_y. If Flow_y is negative, then no new investors are added. Instead, the asset level of the earliest investor class is reduced by the amount of negative flow, if possible. If the absolute magnitude of Flow_y exceeds the asset level of the earliest investor class, then the earliest investor class is considered retired, and the residual negative flow is applied to the next earliest investor class, and so on. In the event that all investor classes are retired, then any residual outflow is applied to the manager's personal capital in the fund.

Finally, to start the algorithm, we initially assume that the fund is endowed with a single investor class on the earliest observation date for that fund in our sample, and that on this date the high-water mark for this investor is equal to the current asset level. We also assume the manager has no personal capital invested with the fund on the initial observation date.

A.2. Return-smoothing simulation exercise

In this exercise we generate monthly fund returns under the null of no risk-shifting while allowing for return-smoothing. We show that biases in risk-shifting estimates can result from certain forms of return smoothing, but that including lagged risk and autocorrelation as control variables in the regression tests effectively eliminates these biases. We assume that the log monthly fund return (R) is a normal random variable, and that the difference between R and the observable return reported to TASS (R^o) is captured by a binary random variable θ as follows:

$$R_t^o = \theta_t \times R_t + (1 - \theta_{t-1}) \times R_{t-1} \tag{7}$$

where $\theta_t \in \{\bar{\theta}, \underline{\theta}\}, 0 < \underline{\theta} < \bar{\theta} < 1$, represents the fraction of a fund's economic return that is contemporaneously reflected in its reported return. Therefore, $\theta_t = \bar{\theta}$ corresponds to a high liquidity, low return-smoothing month; and vice versa for $\underline{\theta}$. The conditional distribution for smoothing parameter is denoted by

$$Pr\{\theta_t = \bar{\theta} | R_t < 0\} = p^-; \quad Pr\{\theta_t = \bar{\theta} | R_t > 0\} = p^+$$

The special case, $p^- = p^+ = 0$, corresponds to the Getmansky, Lo, and Makarov (2004) smoothing model, where the number of smoothing lags is 1 and the smoothing parameter is a constant parameter $\underline{\theta}$.

We implement the simulation exercise as follows. First, we draw 12,000 independent observations of monthly fund returns (R) from the normal distribution with a mean and standard deviation of 0.32% and 3.36%, respectively.[23] Next, we draw 12,000 independent observations of θ from the conditional distribution (p^-, p^+) given R. Next we calculate the sequence of 12,000 reported monthly fund returns according to Eq. (7). We then divide the sequence of 12,000 monthly reported returns into the 1,000 non-overlapping sequences of 12 monthly reported returns. Each of these represents a fund-year observation (y). For each fund-year observation, we calculate cumulative returns, standard deviation of returns, and autocorrelation using the six observations in each of the two halves of the year. Finally, we run the following regression model to test the risk-shifting hypothesis:

$$\hat{\sigma}_2(y) - \hat{\sigma}_1(y) = \alpha + \beta R_1(y) + \gamma_1 \hat{\rho}_1(y) + \gamma_2 \hat{\rho}_2(y) + \gamma_3 \hat{\sigma}_1(y) + \epsilon(y) \tag{8}$$

where $\hat{\sigma}_1$ and $\hat{\rho}_1$ represent the estimated standard deviation and autocorrelation, respectively, of monthly reported returns in the first half of the year; $\hat{\sigma}_2$ and $\hat{\rho}_2$ are defined the same for the second half of the year; and R_1 is the total reported return during the first half of the year. The above regression can be thought of as a single time-series regression of 1,000 years of data for a single fund or, equivalently, a pooled regression using 10 years of data for 100 funds. We repeat the whole experiment 2,000 times, each time drawing a new sample of R, θ, running the regression model in Eq. (8), and storing the OLS t-ratios for each regression. At the end, we have 2,000 t-ratios for each estimate of $\beta, \gamma_1, \gamma_2, \gamma_3$.

Case 1: Variable smoothing independent of fund returns.
In this case we assume $p^- = p^+ = p$. Thus, the extent of smoothing can change over time but does not depend on fund performance. We also assume $\bar{\theta} = 1$, so that the high liquid, low return-smoothing environment is the special case in which true returns are completely reflected in reported returns. We consider several cases depending on $\underline{\theta}$ and p. The results are reported in Table XII. Specifically, the table gives the rejection rates of one-sided tests of the null hypothesis of no risk-shifting at the 1%, 2.5%, and 5% significance levels. For each $(p, \underline{\theta})$ combination, rejection rates are reported for three specifications depending on coefficient restrictions in the above regression model: Model 1 restricts $\gamma_1 = \gamma_2 = \gamma_3 = 0$; Model 2 restricts $\gamma_1 = -\gamma_2$; and Model 3 is unrestricted. p is the probability of the fund experiencing no return smoothing (i.e., $\bar{\theta} = 1$); and $\underline{\theta}$ is the smoothing parameter when there is smoothing. From the table we see that in almost all cases the most restrictive model (1) performs quite well in the sense that the actual rejections rates are basically the same as what one expects under the null hypothesis. For example, when the no-smoothing state is most likely ($p = 0.90$) and high smoothing is moderate ($\underline{\theta} = 0.75$), the rejection rate is 2.45% for a one-sided test with a 2.5% critical value. In fact, only when the high smoothing state is extreme ($\underline{\theta} = 0.50$) and either state is equally likely ($p = 0.50$) do we observe dramatic departures of actual rejection rates from asymptotic significance levels. For example, in this case it appears that the restricted model (1) rejects the null of no risk-shifting over 13% of the time for a significance level of 5%. In contrast, the less restricted models (2 and 3) do well in every case. In fact, the bias in rejection rates from model 1 is effectively eliminated in all cases after including monthly return volatility and autocorrelation as control variables in the risk-shifting tests.

Case 2: Variable smoothing depends on fund returns.
In this case we do not assume $p^- = p^+$. Thus, the extent of smoothing changes over time and depends on fund performance. We again fix $\bar{\theta} = 1$, and also that $\underline{\theta} = 0.75$. Thus, smoothing can fluctuate between two states: no smoothing ($\theta = 1$) and a situation in which only 75% of true returns are reflected contemporaneously in reported returns. We consider several cases depending on p^- and p^+. The results are reported in Table XIII. In contrast to Case 1 where even the restricted model (1) delivers rejection rates consistent with asymptotic significance levels, the rejection rates reported for the restricted model (1) are now significantly biased towards rejecting the null of no

[23]These numbers are the averages across funds in our sample, of each fund's time-series sample mean and standard deviation of smoothing-adjusted monthly fund returns. Smoothing-adjusted returns are calculated using the procedure described in the (constant) smoothing model in Eq. (6).

risk-shifting. In every case, we can reject a one-sided test of no risk-shifting at least 43% of the time at the 5% significance level. This suggests that return-based estimates of risk-shifting in hedge funds are prone to serious biases if return-smoothing is correlated with fund returns. However, the results also show the these biases are effectively eliminated in the unrestricted models 2 and 3, in which first half return volatility and either changes in return autocorrelation (model 2) or levels of return autocorrelation (model 3) are included as control variables in the risk-shifting tests. In fact, except for the most extreme cases of negative correlation between fund returns and return smoothing does the rejection rate for the unrestricted model 3 exceed 6% for a one-sided test at the 5% significance level.

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Table I

Summary Statistics

This table reports summary statistics of key variables calculated from the raw sample of 7,658 hedge funds over the 1989-2007 period. Incentive Fee and Management Fee are the incentive fee and management fee, respectively. IFEE is an indicator variable that equals one if the fund has an incentive fee. HWM is an indicator variable that equals one if the fund manager's incentive fee is tied to the fund's high-water mark. Backfilled Freq is the proportion of a fund's monthly return observations that precede the date the fund was added to the database. Annual Return is the average net-of-fees compounded monthly return over each available year in a fund's sample period. Standard Deviation is the average yearly estimate of the standard deviation of monthly fund returns. UnderEnd is the average year-end percentage difference between a fund's asset level and its high-water mark. UnderJune is the average mid-year percentage difference between a fund's asset level and its high-water mark at the previous year-end. Age, Size, and Complexity variables are measured at the midpoint of each fund's available time series observations. Fund Age is the number of months from a fund's inception date; and Fund Size is the total assets under management (in millions of dollars). Family age is the number of months from the earliest inception date across all funds under the same fund family. Family size is the total net assets (in millions of dollars) under management, aggregated across all funds under the same management firm. Family complexity is the median number of individual funds under management by the same family. Lockup is an indicator that equals one if the fund has a lockup provision. Notice is the fund's redemption notice period in days. Personal Capital is an indicator variable that equals one if the fund manager invests personal capital into the fund. Personal Capital Amount is the reported amount of personal capital invested by the manager into the fund (in $ millions).

Characteristic	N	Mean	StDev	Median	Min	Max
Management Fee (%)	7623	1.48	0.69	1.50	0.00	10.00
Incentive Fee (%)	7622	16.49	7.01	20.00	0.00	50.00
IFEE	7622	0.91	0.29	1.00	0.00	1.00
HWM	7623	0.65	0.48	1.00	0.00	1.00
Backfilled Freq	7626	0.56	0.27	0.50	0.00	1.00
Annual Return	7626	0.09	0.13	0.08	-0.99	5.23
Standard Deviation	7623	0.04	0.03	0.02	0.00	0.74
UnderEnd	7626	0.03	0.09	0.00	0.00	1.07
UnderJune	7614	0.00	0.14	-0.03	-0.29	1.26
Fund Age	7626	39.97	30.51	31.00	1.00	299.00
Fund Size	5589	96.10	279.47	25.71	0.00	6995.04
Family Age	7580	71.11	51.09	57.00	1.00	332.00
Family Size	5744	713.42	3656.85	94.14	0.00	144942.70
Family Complexity	7580	6.01	8.74	3.00	1.00	57.00
Lockup?	7626	0.26	0.44	0.00	0.00	1.00
Notice	7626	35.06	29.42	30.00	0.00	365.00
Personal Capital?	7626	0.32	0.47	0.00	0.00	1.00
Personal Capital Amount	7626	0.58	6.06	0.00	0.00	300.00

Table II

Below Median Mid-Year Performance and Subsequent Volatility Change

The table reports the proportion of sample funds falling in each risk-adjustment ratio (RAR) classification for funds with returns that fall below the median return over January to June in a given year. Panels A, B and C correspond to the full sample, the sub-sample of backfilled observations, and the sub-sample that excludes backfilled observations, respectively. January to June return is defined as the total fund return measured over the first six month of each each year, and is measured relative to a benchmark of the median fund return over that six-month period. RAR is calculated each year as the ratio of the standard deviation of monthly fund returns over the second six-month period to the standard deviation of monthly fund returns over the first six-month period. RAR Low corresponds to observations less than the median for all funds in the calendar year, and RAR High corresponds to observations greater than or equal to the median. The Chi-square numbers represent the $\chi^2(1)$ statistics from the 2x2 contingency table. +, *, and ** indicate rejections of a two-sided test of the null hypothesis of an equal number of funds within each group at 10%, 5%, and 1% significance levels, respectively.

	Panel A: Full Sample			Panel B: Backfilled			Panel C: Backfill-Free		
Year	RAR Low	RAR High	Chi-Square	RAR Low	RAR High	Chi-Square	RAR Low	RAR High	Chi-Square
1995	49.77	50.23	0.01	50.29	49.71	0.04	0.00	100.00	3.94*
1996	45.40	54.60	8.83**	46.92	53.08	2.59	39.78	60.22	7.76**
1997	48.11	51.89	1.81	45.97	54.03	4.84*	52.43	47.57	0.88
1998	48.63	51.37	1.04	48.59	51.41	0.62	47.06	52.94	1.53
1999	46.52	53.48	7.92**	46.06	53.94	5.19*	48.73	51.27	0.41
2000	42.98	57.02	37.64**	42.07	57.93	27.29**	45.48	54.52	5.60*
2001	47.71	52.29	4.49*	45.35	54.65	5.94*	51.47	48.53	0.70
2002	49.01	50.99	0.95	50.24	49.76	0.03	48.50	51.50	1.14
2003	41.10	58.90	91.43**	40.92	59.08	28.30**	41.38	58.62	46.84**
2004	49.04	50.96	1.20	48.38	51.62	0.84	49.74	50.26	0.05
2005	54.90	45.10	35.30**	54.85	45.15	5.04*	57.03	42.97	45.54**
2006	49.32	50.68	0.68	52.50	47.50	0.70	48.39	51.61	2.97+
2007	50.90	49.10	1.04	-	-	-	51.65	48.35	3.24+
1995–07	48.43	51.57	28.97**	46.94	53.06	32.43**	49.66	50.34	0.64

Table III

Above/Below High Water Mark at Mid-Year and Subsequent Volatility Change

The table reports the proportion of sample funds with an above-the-median risk-adjustment ratio (RAR) for fund subsamples, depending on whether the fund is below or above its high-water mark benchmark over January to June in a given year. A fund's high-water mark benchmark in a given year is the maximum net asset value obtained since fund inception and is calculated in Eq. (1). Panels A corresponds to the full sample of funds. Panels B and C correspond to funds subsamples, depending on whether a HWM provision is actually included in the manager's compensation contract. Backfilled data are dropped from the analysis. RAR is calculated each year as the ratio of the standard deviation of monthly fund returns over the second six-month period to the standard deviation of monthly fund returns over the first six-month period. The Chi-square numbers represent the $\chi^2(1)$ statistics from the 2 x 2 contingency tables. +, *, and ** indicate rejections of a two-sided test of the null hypothesis of an equal percentage of funds within each group at the 10%, 5%, and 1% significance levels, respectively.

	Panel A: All Funds			Panel B: Funds without HWMs			Panel C: Funds with HWMs		
Year	Below-water	Above-water	Chi-square	Below-water	Above-water	Chi-square	Below-water	Above-water	Chi-square
1995	100.00	25.00	3.94*	100.00	25.00	3.94*	–	–	–
1996	64.58	44.93	5.50*	67.39	43.55	7.63**	50.00	50.00	0.00
1997	50.68	49.83	0.02	49.25	50.19	0.02	66.67	47.50	0.77
1998	43.40	53.46	4.29*	43.36	53.91	4.01*	37.50	53.33	1.32
1999	46.32	51.58	1.48	44.03	53.05	3.49+	58.06	48.25	0.94
2000	51.77	49.13	0.42	50.84	49.51	0.08	51.06	49.67	0.03
2001	50.55	49.79	0.04	52.00	48.80	0.42	51.00	49.56	0.06
2002	48.47	51.39	1.14	51.97	48.10	0.85	46.76	52.68	2.66
2003	52.50	48.90	1.78	52.60	48.53	0.81	54.37	48.27	3.26+
2004	48.80	50.70	0.65	50.22	50.00	0.00	47.50	51.38	1.89
2005	42.21	54.50	32.04**	38.34	57.19	17.10**	43.21	53.83	18.47**
2006	61.29	47.62	30.61**	72.94	45.70	21.16**	58.64	48.17	14.82**
2007	30.56	52.16	48.43**	30.56	51.58	5.89*	31.35	52.19	39.22**
1995–07	48.34	50.66	6.93**	49.78	50.19	0.08	47.67	50.82	7.87**

Table IV

Regressions of Change in Risk on Past Performance in the Same Calendar Year and High-water Marks in Incentive Compensation

Results of regression analyses testing the relation between the change in risk variable between the first six months and the second six months of the year, and hedge fund performance during the first six months of the year. The dependent variable is the change in risk variable between the first six months and the second six months of the year. Risk is measured as the sample standard deviation of the monthly raw return. Independent variables include a dummy variable equal to one if the fund has a high-water mark (HWM) and a dummy variable equal to one if the fund's assets at mid-year are below their high-water mark (AbsWin). RelRnk is the fractional rank of the fund's raw return in the first six months relative to that of all other funds. AbsRnk is the fractional rank of the distance of a fund's net assets at mid-year to its high-water mark measured at the end of the previous year. LagRisk is the value of the risk variable during the first six months. $\Delta\rho$ is the change in the fund's estimated monthly return autocorrelation between the first and second halves of the year. Flow is the percentage net flow in the second half of the year. Each regression also includes dummy independent variables (not reported) for years and fund style categories. Dependent variables are windsorized at the 1% level. t-statistics (reported below each coefficient) are produced from White (1980) standard errors which are robust to within-family correlation. +, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
RelRnk	-0.0076	-0.0078				
	5.34**	5.33**				
RelRnk*HWM	0.0066	0.007				
	4.32**	4.45**				
AbsWin			-0.0056	-0.0056		
			6.77**	6.66**		
AbsWin*HWM			0.0028	0.003		
			3.08**	3.19**		
AbsRnk					-0.0081	-0.0082
					5.73**	5.69**
AbsRnk*HWM					0.0049	0.0053
					3.18**	3.37**
LagRisk	-0.2355	-0.2317	-0.2509	-0.2468	-0.2417	-0.2377
	14.98**	14.49**	15.83**	15.32**	15.56**	15.07**
$\Delta\rho$		0.0004		0.0004		0.0004
		1.06		1.26		1.18
Flow		-0.001		-0.0009		-0.0008
		3.24**		2.82**		2.50*
HWM	-0.0028	-0.0029	-0.0014	-0.0015	-0.0017	-0.0019
	3.08**	3.18**	1.62	1.67+	1.96+	2.09*
Intercept	-0.0177	-0.0175	0.0041	-0.0177	-0.0179	-0.0178
	2.57*	2.54*	0.85	2.47*	2.59**	2.57*
Observations	15957	14576	15961	14576	15957	14576
R-squared	0.26	0.25	0.26	0.25	0.26	0.25
Style fixed effects?	yes	yes	yes	yes	yes	yes
Year fixed effects?	yes	yes	yes	yes	yes	yes

Table V

Risk-Shifting and High-Water Marks: Stability of Results Across Years

This table reports results from the following yearly regression for each high-water mark category (yes or no):

$$\Delta\text{Risk} = \alpha + \beta_1\text{Perf} + \beta_2\text{LagRisk} + \beta_3\Delta\rho + \beta_4\text{Flow} + \Sigma_j\beta_j\text{Style Dummy}_j,$$

The dependent variable in all regressions is the individual fund's change of risk between the first and second part of a year measured as the sample standard deviation of the monthly raw return in the second half of the year less that of the first half of the year. The independent variables are the performance rank of this fund (Perf), the risk of the fund in the first part of the year (LagRisk), the change in the fund's estimated monthly return autocorrelation between the first and second halves of the year ($\Delta\rho$), the percentage net flow in the second half of the year (Flow). and style fixed effects. To save space we only report the estimated coefficient on Perf (Risk Shifting Coefficient). A negative coefficient indicates that fund risk increases following poor performance. We report the results from defining Perf as either RelRnk or AbsRnk. RelRnk is the fractional rank of the fund's raw return in the first six months relative to that of all other funds. AbsRnk is the fractional rank of the distance of a fund's net assets at mid-year to its high-water mark measured at the end of the previous year. t-statistics (reported below each coefficient) are produced from White (1980) standard errors which are robust to within-style correlation. The final two rows report the average of the yearly coefficients and the corresponding t-statistic for whether the average is different from zero.+, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

			Risk Shifting Coefficient (β_1)					
	N		Perf=RelRnk			Perf=AbsRnk		
year	no	yes	no	yes	diff	no	yes	diff
1998	380	90	-0.0046	-0.0021	0.0025	-0.0005	0.0038	0.0043
			-1.10	-0.24	0.35	-0.13	0.38	0.44
1999	476	143	-0.0107	-0.0197	-0.0090	-0.0130	-0.0148	-0.0018
			-1.33	-1.53	-1.00	-10.51**	-2.26*	-0.28
2000	475	191	-0.0073	-0.0015	0.0058	-0.0060	-0.0086	-0.0026
			-2.62*	-0.54	1.23	-2.58*	-3.17**	-0.68
2001	413	315	-0.0074	0.0038	0.0112	-0.0136	0.0045	0.0181
			-1.29	1.08	2.16+	-2.07+	1.13	2.33*
2002	553	738	-0.0273	-0.0038	0.0235	-0.0218	-0.0036	0.0183
			-3.43**	-0.68	3.39**	-3.85**	-0.95	3.36**
2003	508	1017	-0.0071	-0.0049	0.0021	-0.0087	-0.0066	0.0021
			-0.91	-2.05+	0.27	-2.28*	-4.14**	0.51
2004	514	1301	-0.0100	-0.0044	0.0056	-0.0139	-0.0055	0.0084
			-2.78*	-1.33	2.24*	-3.96**	-1.53	3.75**
2005	483	1599	0.0033	0.0039	0.0007	0.0002	0.0047	0.0045
			0.93	3.25**	0.22	0.03	2.35*	0.94
2006	484	1934	-0.0066	-0.0051	0.0015	-0.0067	-0.0060	0.0007
			-2.83*	-2.20*	0.78	-2.85*	-2.60*	0.44
2007	436	2024	0.0052	0.0061	0.0010	0.0052	0.0053	0.0001
			1.20	1.99+	0.20	0.91	1.68	0.01
Averages across years			-0.0072	-0.0028	0.0045	-0.0079	-0.0027	0.0052
			-2.61*	-1.22	1.68	-3.09*	-1.23	2.18+

Table VI

Risk-Shifting and High-Water Marks: Stability of Results Across Style Categories

This table reports results from the following style-by-style regression for each high-water mark category (yes or no):

$$\Delta\text{Risk} = \alpha + \beta_1\text{Perf} + \beta_2\text{LagRisk} + \beta_3\Delta\rho + \beta_4\text{Flow} + \Sigma_j\beta_j\text{Year Dummy}_j,$$

The dependent variable in all regressions is the individual fund's change of risk between the first and second part of a year measured as the sample standard deviation of the monthly raw return in the second half of the year less that of the first half of the year. The independent variables are the performance rank of this fund (Perf), the risk of the fund in the first part of the year (LagRisk), the change in the fund's estimated monthly return autocorrelation between the first and second halves of the year ($\Delta\rho$), the percentage net flow in the second half of the year (Flow). and style fixed effects. To save space we only report the estimated coefficient on Perf (Risk Shifting Coefficient). A negative coefficient indicates that fund risk increases following poor performance. We report the results from defining Perf as either RelRnk or AbsRnk. RelRnk is the fractional rank of the fund's raw return in the first six months relative to that of all other funds. AbsRnk is the fractional rank of the distance of a fund's net assets at mid-year to its high-water mark measured at the end of the previous year. t-statistics (reported below each coefficient) are produced from White (1980) standard errors which are robust to within-year correlation. The final two rows report the average of the style-by-style coefficients and the corresponding t-statistic for whether the average is different from zero. +, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

			Risk Shifting Coefficient (β_1)					
	N		Perf=RelRnk			Perf=AbsRnk		
Style Category	no	yes	no	yes	diff	no	yes	diff
Convertible Arbitrage	195	388	-0.0066	0.0031	0.0097	-0.0026	0.0027	0.0053
			-0.71	0.71	0.84	-0.34	0.67	0.53
Emerging Markets	477	492	-0.0112	0.0029	0.0141	-0.0150	-0.0010	0.0140
			-1.28	0.40	2.19+	-2.90*	-0.16	2.12+
Equity Market Neutral	234	591	-0.0069	0.0005	0.0074	-0.0098	-0.0012	0.0086
			-1.84+	0.14	1.56	-2.00+	-0.28	1.77
Event Driven	433	966	-0.0070	-0.0024	0.0046	-0.0095	-0.0035	0.0060
			-2.32*	-1.06	1.17	-3.48**	-1.13	1.35
Fixed Income Arbitrage	168	506	0.0043	0.0003	-0.0040	0.0065	-0.0037	-0.0102
			0.48	0.07	-0.43	0.96	-1.78	-1.42
Fund of Funds	1008	1774	-0.0020	0.0076	0.0096	-0.0038	0.0037	0.0074
			-0.70	1.73	1.94+	-1.09	0.66	1.30
Global Macro	255	395	-0.0084	-0.0026	0.0058	-0.0152	-0.0045	0.0107
			-1.21	-0.73	0.70	-2.67*	-1.30	1.55
Long/Short Equity Hedge	1599	3243	-0.0097	-0.0040	0.0057	-0.0091	-0.0039	0.0052
			-2.50*	-1.02	2.69*	-3.97**	-1.11	2.43*
Managed Futures	608	492	-0.0156	-0.0024	0.0132	-0.0148	-0.0032	0.0116
			-2.04+	-0.62	1.47	-2.29*	-0.78	1.57
Multi-Strategy	199	478	-0.0128	0.0004	0.0132	-0.0120	0.0015	0.0135
			-1.71	0.14	1.88+	-1.56	0.52	1.82+
Averages Across Styles			-0.0076	0.0003	0.0079	-0.0085	-0.0013	0.0072
			-4.28**	0.31	4.65**	-3.94**	-1.40	3.30**

Table VII

Fund Liquidation and Fund Return, Risk, and Other Characteristics

This table reports the output from a standard Probit regression that examines the relation between fund disappearance in a given year and lagged observations of fund characteristics. The dependent variable is an indicator that equals one if the fund is liquidated (as classified by TASS in the second half of the current year. The first set of explanatory variables are measured in June of the current year. Under June and Under June* measure the percentage distance between the fund's high-water mark and asset levels. Raw Return June is the cumulative monthly raw return over the first half of the year. Fund Age June is the number of monthly return observations since the fund's inception date. Fund Size June is the funds estimated asset value (in millions of dollars). The next set of variables are measured at the end of the previous year. Under Water and Under Water* are indicator variables that take the value of one if the funds assets are below the funds high-water mark. Raw Return and Excess Return refer to the annual raw return and return in excess of the annual return of a value-weighted portfolio of funds of the same style, respectively. Volatility is the yearly estimate of the fund's monthly return standard deviation. Family Size and Family Age are the fund family's estimated asset value (in millions of dollars) and number of monthly return observations reported by the fund family since the earliest inception date across all funds in the same family, respectively. Family Complexity is the number of funds managed by the same fund family. Lockup is an indicator variable that takes the value of one if the fund has lockup; Notice is the funds redemption notice period (in days); and Capital is an indicator variable that equals one if the fund manager invests personal capital into the fund. All age, size, and complexity variables are natural logarithms of the corresponding variables. All variables (excluding indicator variables) are standardized to have a zero mean and variance of one across funds. Marginal effects are reported for each variable. For the indicator variables, discrete marginal effects are reported. Each regression also includes dummy independent variables (not reported) for fund style categories. The probit model is estimated each year using a rolling three year window. The table reports averages of the yearly coefficient estimates of the probit model and t-statistics of the averages to draw inferences. Standard errors of the average coefficients are adjusted for the estimated autocorrelation of the coefficients. The model is estimated on fund sub-samples depending on whether the manager's performance bonus is tied to the fund's high-water mark (HWM= 1) or not (HWM= 0). Both sub-samples exclude backfilled observations. +, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

Table VII

Variables	Panel A: HWM= 0 1	2	Panel B: HWM= 1 3	4
Variables Measured in June				
Under June	-0.0290		-0.0111	
	-0.88		-0.67	
Under June*		-0.0134		0.0015
		-0.71		0.33
Raw Return June	-0.0186	-0.0168	-0.0152	-0.0194
	-4.46**	-5.05**	-0.59	-1.53
Fund Age June	0.0044	0.0039	-0.0031	-0.0036
	3.19*	2.53*	-2.13+	-1.76
Fund Size June	-0.0430	-0.0423	-0.0298	-0.0270
	-12.83**	-8.45**	-10.09**	-11.81**
Variables Measures at End of Previous Year				
Under Water?	0.0326		0.0284	
	1.72		3.00*	
Under Water?*		0.0244		0.0138
		1.00		5.24**
Raw Return	-0.0113	-0.0176	-0.0153	-0.0199
	-0.99	-1.36	-0.40	-1.52
Excess Return	-0.0033	0.0010	0.0072	0.0043
	-0.32	0.08	0.95	0.71
Volatility	-0.0088	-0.0085	-0.0110	-0.0114
	-2.41*	-3.12*	-14.54**	-18.33**
Family Age	-0.0262	-0.0269	-0.0094	-0.0095
	-8.86**	-7.66**	-2.96*	-3.70**
Family Size	0.0131	0.0129	0.0043	0.0026
	5.52**	5.48**	1.13	1.07
Family Complexity	0.0039	0.0044	0.0075	0.0081
	0.65	0.82	10.51**	15.17**
Fund Characteristic Variables				
Lockup?	-0.0140	-0.0128	-0.0065	-0.0081
	-4.10**	-4.77**	-2.30+	-1.27
Notice	-0.0140	-0.0146	-0.0043	-0.0027
	-2.61*	-2.47*	-2.71*	-3.48*
Personal Capital?*	-0.0095	-0.0089	-0.0123	-0.0113
	-0.56	-0.49	-10.90**	-23.34**
Pseudo-R2	0.2024	0.2020	0.1738	0.1697
Style fixed effects?	yes	yes	yes	yes

Table VIII

Regressions of Change in Risk on Past Performance in the Same Calendar Year and Relation to Probability of Liquidation

The table reports the results from the pooled least squares regression model:

$$\begin{aligned}\Delta\text{Risk} = &\ \alpha + \beta_1\text{ProbLiq} + \beta_2\text{Perf} + \beta_3\text{Perf*ProbLiq} \\ + &\ \beta_4\text{LagRisk} + \beta_5\Delta\rho + \beta_6\text{Flow} + \Sigma_j\beta_j Dummy_j,\end{aligned}$$

The dependent variable is the change in risk variable between the first six months and the second six months of the year. Risk is measured as the sample standard deviation of the monthly raw return. Independent variables include ProbLiq-the fractional rank of the estimated probability of fund disappearance relative to other funds and measured at the end of first six months of the year. The predicted probability of fund disappearance is obtained from the estimated coefficients of a standard Probit model summarized in Table VII. These coefficients are estimated each year using rolling three year windows. Other variables include a dummy variable equal to one if the fund's assets at mid-year are below their high-water mark (AbsWin). RelRnk is the fractional rank of the fund's raw return in the first six months relative to that of all other funds. AbsRnk is the fractional rank of the distance of a fund's net assets at mid-year to its high-water mark measured at the end of the previous year. Each regression also includes the following independent variables (not reported): LagRisk is the value of the risk variable during the first six months; $\Delta\rho$ is the change in the fund's estimated monthly return autocorrelation between the first and second halves of the year; Flow is the percentage net flow in the second half of the year; and also dummy independent variables (not reported) for years and fund style categories. Panels A and B correspond to fund subsamples depending on whether the manager's performance bonus is tied to the fund's high-water mark ($HWM = 1$) or not ($HWM = 0$). Both sub-samples exclude backfilled observations. t-statistics (reported below each coefficient) are produced from White (1980) standard errors which are robust to within-family correlation. +, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: HWM= 0	1	2	3	4	5	6
RelRnk	-0.0089	-0.0014				
	5.56**	0.49				
RelRnk*ProbLiq		-0.0076				
		1.40				
AbsWin			-0.0057	0.0002		
			6.30**	0.12		
AbsWin*ProbLiq				-0.008		
				2.57*		
AbsRnk					-0.0102	0.0026
					5.91**	0.79
AbsRnk*ProbLiq						-0.0207
						3.37**
ProbLiq		0.0052		0.0064		0.0103
		1.41		1.90+		2.71**
Intercept	0.026	0.0322	0.0263	0.0301	0.0275	0.0287
	3.83**	5.51**	3.84**	4.95**	4.10**	5.00**
Observations	5200	2603	5200	2603	5200	2603
R-squared	0.25	0.27	0.25	0.28	0.25	0.28
Style fixed effects?	yes	yes	yes	yes	yes	yes
Year fixed effects?	yes	yes	yes	yes	yes	yes
Other control variables?	yes	yes	yes	yes	yes	yes

Table VIII

cont.

Panel B: HWM= 1	1	2	3	4	5	6
RelRnk	-0.0001	0.0071				
	0.18	4.16**				
RelRnk*ProbLiq		-0.0133				
		4.72**				
AbsWin			-0.0026	0.0008		
			4.53**	0.65		
AbsWin*ProbLiq				-0.0061		
				3.32**		
AbsRnk					-0.0022	0.0062
					2.32*	3.38**
AbsRnk*ProbLiq						-0.0154
						5.38**
ProbLiq		0.0068		0.0035		0.007
		4.03**		1.94+		4.16**
Intercept	0.0104	-0.0071	0.0127	-0.0042	0.0118	-0.0064
	2.09*	1.1	2.42*	0.63	2.28*	0.98
Observations	9376	6633	9376	6633	9376	6633
R-squared	0.26	0.31	0.27	0.31	0.26	0.31
Style fixed effects?	yes	yes	yes	yes	yes	yes
Year fixed effects?	yes	yes	yes	yes	yes	yes
Other control variables?	yes	yes	yes	yes	yes	yes

Table IX

Regressions of Change in Risk on Past Performance by High-water Mark and Horizon Using Alternative Measure of Distance from Fund High-water Marks

Results of regression analyses testing the relation between the change in risk variable between the first six months and the second six months of the year, and hedge fund performance during the first six months of the year. The dependent variable is the change in risk variable between the first six months and the second six months of the year. Risk is measured as the sample standard deviation of the monthly raw return. Independent variables include a dummy variable equal to one if the fund has a high-water mark (HWM) and a dummy variable equal to one if the fund's assets at mid-year are below their high-water mark (AbsWin). AbsRnk is the fractional rank of the distance of a fund's net assets at mid-year to its high-water mark measured at the end of the previous year. High-water mark benchmarks are tracked according to the procedure outlined in the Appendix. Each regression also includes the following independent variables (not reported): LagRisk is the value of the risk variable during the first six months; $\Delta\rho$ is the change in the fund's estimated monthly return autocorrelation between the first and second halves of the year; Flow is the percentage net flow in the second half of the year; and also dummy independent variables (not reported) for years and fund style categories. Dependent variables are windsorized at the 1% level. The sample excludes backfilled observations. Panel A corresponds to all funds. Panels B and C correspond to fund subsamples depending on whether the manager's performance bonus is tied to the fund's high-water mark (HWM= 1) or not (HWM= 0). t-statistics (reported below each coefficient) are produced from White (1980) standard errors which are robust to within-family correlation. +, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: All Funds		Panel B: HWM= 0		Panel C: HWM= 1	
	1	2	3	4	5	6
AbsWin	-0.0063		-0.0018		-0.0002	
	6.86**		0.85		0.14	
AbsWin*HWM	0.0038					
	3.55**					
AbsWin*ProbLiq			-0.006		-0.0042	
			1.71+		1.75+	
AbsRnk		-0.0079		0.0005		0.006
		5.38**		0.13		3.17**
AbsRnk*HWM		0.0061				
		3.79**				
AbsRnk*ProbLiq				-0.0157		-0.0144
				2.58*		4.79**
HWM	-0.002	-0.0021				
	1.94+	2.32*				
ProbLiq			0.0045	0.0075	0.0018	0.0061
			1.18	1.99*	0.76	3.44**
Intercept	0.0055	0.005	0.0265	0.0252	-0.0033	-0.0062
	1.04	0.96	4.44**	4.58**	0.49	0.97
Observations	13978	13978	2529	2529	6448	6448
R-squared	0.26	0.26	0.28	0.28	0.31	0.31
Other control variables?	yes	yes	yes	yes	yes	yes

Table X

Regressions of Change in Risk on Past Performance by High-water Mark and Presence of an Incentive Fee and Manager's Personal Capital

The table presents results from the pooled least squares regression model:

$$\Delta\text{Risk} = \alpha + \beta_1\text{Perf} + \beta_2\text{IFEE} + \beta_3\text{HWM} + \beta_4\log(1{+}\text{Personal Capital Amount}) + \beta_5\text{Perf*IFEE} + \beta_6\text{Perf*HWM} + \beta_7\text{Perf*}\log(1{+}\text{Personal Capital Amount}) + \text{Control Variables},$$

The dependent variable is the change in risk variable between the first six months and the second six months of the year. Risk is measured as the sample standard deviation of the monthly raw return. Independent variables include a dummy variable equal to one if the fund has a positive incentive fee (IFEE), a dummy variable equal to one if the manager's incentive fee is tied to the fund's high-water mark benchmark (HWM), the natural logarithm of the dollars of personal capital invested by the manager into the fund (Personal Capital Amount), and a dummy variable equal to one if the fund's assets at mid-year are below their high-water mark (AbsWin). RelRnk is the fractional rank of the fund's raw return in the first six months relative to that of all other funds. AbsRnk is the fractional rank of the distance of a fund's net assets at mid-year to its high-water mark measured at the end of the previous year. Each regression also includes the following independent variables (not reported): LagRisk is the value of the risk variable during the first six months;$\Delta\rho$ is the change in the fund's estimated monthly return autocorrelation between the first and second halves of the year; Flow is the percentage net flow in the second half of the year; and also dummy independent variables (not reported) for years and fund style categories. Dependent variables are windsorized at the 1% level. The sample excludes backfilled observations. t-statistics (reported below each coefficient) are produced from White (1980) standard errors which are robust to within-family correlation. +, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

	Perf=RelRnk		Perf=AbsWin		Perf=AbsRnk	
	1	2	3	4	5	6
Perf	-0.0012	-0.0012	-0.0027	-0.0027	-0.0029	-0.0029
	0.47	0.49	2.39*	2.40*	1.54	1.55
Perf*IFEE	-0.0064	-0.0064	-0.003	-0.003	-0.0055	-0.0055
	2.25*	2.25*	2.19*	2.19*	2.37*	2.37*
Perf*HWM	0.0068	0.0064	0.003	0.0029	0.0053	0.0049
	4.38**	4.15**	3.19**	3.00**	3.38**	3.12**
Perf*Log(1+Personal Capital Amount)		0.0026		0.0013		0.0029
		2.48*		2.01*		2.83**
IFEE	0.0025	0.0025	0.0015	0.0015	0.002	0.002
	1.64	1.64	1.1	1.11	1.47	1.47
HWM	-0.0028	-0.0026	-0.0015	-0.0014	-0.0019	-0.0017
	3.07**	2.87**	1.65+	1.52	2.09*	1.86+
Log(1+Personal Capital Amount)		-0.0013		-0.0008		-0.0015
		2.16*		1.4		2.45*
Intercept	-0.0142	-0.0142	-0.0134	-0.0134	-0.0139	-0.0139
	2.19*	2.18*	2.04*	2.03*	2.14*	2.13*
Observations	16204	16204	16204	16204	16204	16204
R-squared	0.26	0.26	0.27	0.27	0.26	0.26
Other control variables?	yes	yes	yes	yes	yes	yes

Table XI

Regressions of Change in Risk Using Smoothing-Adjusted Returns

Results of regression analyses testing the relation between the change in risk variable between the first six months and the second six months of the year, and hedge fund performance during the first six months of the year. Returns are smoothing-adjusted using the model of Getmansky, Lo, and Makarov (2004) and defined in Eq. (6). The dependent variable is the change in risk variable between the first six months and the second six months of the year. Risk is measured as the sample standard deviation of the monthly raw return. Independent variables include first half performance (Perf), a dummy variable equal to one if the fund has been added to the database (Added), a dummy variable equal to one if the manager's incentive fee is tied to the fund's high-water mark benchmark (HWM), and the probability that the fund will disappear from the database (ProbLiq). Each regression also includes LagRisk, Flow, $\Delta\rho$, and dummy independent variables (not reported) for year and fund style categories. The performance variables is either a dummy variable equal to one if the fund's assets at mid-year are below their high-water mark (AbsWin), the fractional rank of the fund's raw return in the first six months relative to that of all other funds (RelRnk), or the fractional rank of the distance of a fund's net assets at mid-year to its high-water mark measured at the end of the previous year (AbsRnk). Panels B-D exclude backfilled data. Dependent variables are windsorized at the 1% level. t-statistics (reported below each coefficient) are produced from White (1980) standard errors which are robust to within-family correlation. +, *, and ** denote significance at the 10%, 5%, and 1% levels, respectively.

	Perf=RelRnk		Perf=AbsWin		Perf=AbsRnk	
Panel A: Effect of High-Water Mark (HWM)						
Perf	-0.0026	-0.0079	-0.0036	-0.0058	-0.0052	-0.0089
	2.91**	4.76**	6.24**	5.95**	4.96**	5.31**
Perf*HWM		0.0083		0.0035		0.0065
		4.52**		3.29**		3.51**
HWM		-0.0037		-0.0019		-0.0026
		3.56**		1.95+		2.47*
Observations	14420	14420	14420	14420	14420	14420
Panel C: Funds With H=0, Effect of Distress (ProbLiq)						
Perf	-0.0098	-0.0007	-0.006	-0.0002	-0.0114	0.0034
	5.25**	0.21	5.48**	0.1	5.50**	0.88
Perf*ProbLiq		-0.0123		-0.0077		-0.0247
		2.02*		2.11*		3.53**
ProbLiq		0.0084		0.0072		0.0131
		2.00*		1.88+		2.94**
Observations	5142	2594	5142	2594	5142	2594
Panel D: Funds With H=1, Effect of Distress (ProbLiq)						
Perf	0.0009	0.0081	-0.0024	0.0007	-0.0019	0.0069
	1.00	3.94**	4.02**	0.45	1.78+	3.17**
Perf*ProbLiq		-0.0133		-0.0049		-0.0154
		3.86**		2.38*		4.53**
ProbLiq		0.006		0.0016		0.0062
		3.02**		0.84		3.19**
Observations	9344	6601	9344	6601	9344	6601

Table XII

Simulation Results Allowing Variable Smoothing Independent of Fund Returns

The table reports results from the simulation exercise allowing for variable smoothing independent of fund returns (case 1). Details of the procedure are provided in the Appendix. The table gives the rejection rates of one-sided tests of the null hypothesis of no risk-shifting at the 1%, 2.5%, and 5% significance levels. This test uses estimates of the β coefficient in the following regression model:

$$\hat{\sigma}_2(y) - \hat{\sigma}_1(y) = \alpha + \beta R_1(y) + \gamma_1 \hat{\rho}_1(y) + \gamma_2 \hat{\rho}_2(y) + \gamma_3 \hat{\sigma}_1(y) + \epsilon(y)$$

where $\hat{\sigma}_1$ and $\hat{\rho}_1$ represent the estimated standard deviation and autocorrelation, respectively, of monthly reported returns in the first half of the year; $\hat{\sigma}_1$ and $\hat{\rho}_1$ are defined the same for the second half of the year; and R_1 is the total reported return during the first half of the year. We repeat the whole experiment 2,000 times, each time drawing a new sample of R, θ, and running the regression model in Eq. (8). Each time we store the OLS t-ratios for each regression. At the end, we have 2,000 t-ratios for each estimate of $\beta, \gamma_1, \gamma_2, \gamma_3$. The table reports t-ratios for three specifications depending on coefficient restrictions in the above regression model: Model 1 restricts $\gamma_1 = \gamma_2 = \gamma_3 = 0$; Model 2 restricts $\gamma_1 = -\gamma_2$; and Model 3 is unrestricted. p is the probability of the fund experiencing no return smoothing (i.e., $\bar{\theta} = 1$); and $\underline{\theta}$ is the smoothing parameter when there is smoothing.

$p = 0.90$		$\underline{\theta} = 0.90$			$\underline{\theta} = 0.75$			$\underline{\theta} = 0.50$	
	1	2	3	1	2	3	1	2	3
$t(\hat{\beta}) \leq$-2.326	1.00%	0.95%	0.95%	0.90%	0.75%	0.75%	1.70%	0.70%	0.65%
$t(\hat{\beta}) \leq$-1.96	2.40%	2.70%	2.70%	2.45%	2.30%	2.35%	3.85%	1.80%	1.80%
$t(\hat{\beta}) \leq$-1.645	5.20%	5.15%	5.00%	5.05%	4.65%	4.50%	7.20%	4.40%	4.55%
$t(\hat{\beta}) \geq$1.645	4.95%	4.50%	4.50%	5.95%	5.95%	5.95%	3.35%	4.80%	4.65%
$t(\hat{\beta}) \geq$1.96	2.70%	2.85%	2.85%	3.00%	3.30%	3.25%	1.70%	2.20%	2.20%
$t(\hat{\beta}) \geq$2.326	1.35%	1.20%	1.20%	1.40%	1.30%	1.35%	0.60%	1.00%	0.95%
$p = 0.75$		$\underline{\theta} = 0.90$			$\underline{\theta} = 0.75$			$\underline{\theta} = 0.50$	
	1	2	3	1	2	3	1	2	3
$t(\hat{\beta}) \leq$-2.326	1.40%	0.95%	0.95%	1.90%	1.30%	1.25%	2.15%	1.00%	1.05%
$t(\hat{\beta}) \leq$-1.96	3.45%	2.40%	2.40%	4.30%	3.15%	3.15%	5.25%	1.95%	2.05%
$t(\hat{\beta}) \leq$-1.645	6.00%	4.35%	4.35%	6.85%	6.10%	6.00%	9.95%	3.95%	4.00%
$t(\hat{\beta}) \geq$1.645	5.50%	5.30%	5.35%	3.45%	5.05%	5.00%	2.15%	4.80%	4.90%
$t(\hat{\beta}) \geq$1.96	3.15%	3.05%	3.05%	1.85%	2.65%	2.70%	0.70%	2.05%	1.95%
$t(\hat{\beta}) \geq$2.326	1.40%	1.55%	1.55%	1.00%	0.85%	0.80%	0.30%	0.70%	0.75%
$p = 0.50$		$\underline{\theta} = 0.90$			$\underline{\theta} = 0.75$			$\underline{\theta} = 0.50$	
	1	2	3	1	2	3	1	2	3
$t(\hat{\beta}) \leq$-2.326	0.70%	0.85%	0.85%	1.35%	1.00%	1.00%	3.50%	1.00%	1.00%
$t(\hat{\beta}) \leq$-1.96	2.30%	2.55%	2.55%	2.90%	2.05%	2.05%	8.05%	2.10%	2.10%
$t(\hat{\beta}) \leq$-1.645	5.25%	4.80%	4.75%	5.90%	4.40%	4.35%	13.20%	4.85%	4.85%
$t(\hat{\beta}) \geq$1.645	5.30%	5.80%	5.80%	4.60%	5.75%	5.75%	1.75%	4.55%	4.50%
$t(\hat{\beta}) \geq$1.96	2.75%	2.90%	3.05%	2.40%	2.90%	2.95%	0.70%	2.30%	2.30%
$t(\hat{\beta}) \geq$2.326	1.30%	1.35%	1.35%	0.95%	1.30%	1.40%	0.30%	0.80%	0.80%

Table XIII

Simulation Results Allowing Variable Smoothing to Depend on Fund Returns

The table reports results from the simulation exercise allowing for variable smoothing that depends on fund returns (case 2). Details of the procedure are provided in the Appendix. The table gives the rejection rates of one-sided tests of the null hypothesis of no risk-shifting at the 1%, 2.5%, and 5% significance levels. This test uses estimates of the β coefficient in the following regression model:

$$\hat{\sigma}_2(y) - \hat{\sigma}_1(y) = \alpha + \beta R_1(y) + \gamma_1 \hat{\rho}_1(y) + \gamma_2 \hat{\rho}_2(y) + \gamma_3 \hat{\sigma}_1(y) + \epsilon(y)$$

where $\hat{\sigma}_1$ and $\hat{\rho}_1$ represent the estimated standard deviation and autocorrelation, respectively, of monthly reported returns in the first half of the year; $\hat{\sigma}_1$ and $\hat{\rho}_1$ are defined the same for the second half of the year; and R_1 is the total reported return during the first half of the year. We repeat the whole experiment 2,000 times, each time drawing a new sample of R, θ, and running the regression model in Eq. (8). Each time we store the OLS t-ratios for each regression. At the end, we have 2,000 t-ratios for each estimate of $\beta, \gamma_1, \gamma_2, \gamma_3$. The table reports t-ratios for three specifications depending on coefficient restrictions in the above regression model: Model 1 restricts $\gamma_1 = \gamma_2 = \gamma_3 = 0$; Model 2 restricts $\gamma_1 = -\gamma_2$; and Model 3 is unrestricted. p^+ is the probability of the fund experiencing no return smoothing (i.e., $\bar{\theta} = 1$) conditional on positive fund returns; and p^- is the probability of the fund experiencing no return smoothing (i.e., $\bar{\theta} = 1$) conditional on negative fund returns. The smoothing parameter in the high smoothing state ($\underline{\theta}$) is fixed at 0.75 for all cases.

p^+=0.75		p^-=0.50			p^-=0.25			p^-=0	
	1	2	3	1	2	3	1	2	3
$t(\hat{\beta}) \leq$-2.326	7.35%	1.00%	1.00%	36.80%	0.90%	0.80%	83.10%	1.40%	1.10%
$t(\hat{\beta}) \leq$-1.96	13.65%	2.60%	2.60%	50.05%	3.55%	3.15%	90.45%	3.80%	2.50%
$t(\hat{\beta}) \leq$-1.645	22.95%	5.05%	4.95%	62.85%	6.55%	6.25%	94.85%	7.75%	4.90%
$t(\hat{\beta}) \geq$1.645	0.85%	4.60%	4.60%	0.05%	4.60%	5.30%	0.00%	3.35%	4.90%
$t(\hat{\beta}) \geq$1.96	0.30%	2.20%	2.30%	0.00%	2.10%	2.60%	0.00%	1.40%	2.15%
$t(\hat{\beta}) \geq$2.326	0.00%	0.95%	0.95%	0.00%	0.90%	1.10%	0.00%	0.50%	0.75%
p^+=0.90		p^-=0.50			p^-=0.25			p^-=0	
	1	2	3	1	2	3	1	2	3
$t(\hat{\beta}) \leq$-2.326	14.50%	1.05%	0.95%	49.70%	1.15%	1.05%	88.40%	1.80%	1.30%
$t(\hat{\beta}) \leq$-1.96	24.70%	2.65%	2.60%	63.30%	3.30%	3.00%	94.15%	3.75%	2.95%
$t(\hat{\beta}) \leq$-1.645	35.35%	4.50%	4.50%	75.55%	6.10%	5.70%	97.20%	7.25%	5.45%
$t(\hat{\beta}) \geq$1.645	0.10%	4.10%	4.45%	0.00%	3.60%	3.85%	0.00%	4.20%	5.25%
$t(\hat{\beta}) \geq$1.96	0.05%	2.30%	2.45%	0.00%	1.90%	2.10%	0.00%	2.05%	3.00%
$t(\hat{\beta}) \geq$2.326	0.00%	0.85%	0.90%	0.00%	0.60%	0.75%	0.00%	0.70%	1.15%
p^+=1.00		p^-=0.50			p^-=0.25			p^-=0	
	1	2	3	1	2	3	1	2	3
$t(\hat{\beta}) \leq$-2.326	20.35%	0.90%	0.90%	58.35%	1.35%	1.10%	93.60%	1.70%	1.30%
$t(\hat{\beta}) \leq$-1.96	32.20%	2.85%	2.80%	72.25%	3.10%	2.80%	97.20%	3.95%	2.95%
$t(\hat{\beta}) \leq$-1.645	43.85%	5.65%	5.70%	82.20%	6.00%	5.25%	98.60%	7.70%	6.15%
$t(\hat{\beta}) \geq$1.645	0.10%	4.60%	4.60%	0.05%	3.85%	4.10%	0.00%	3.10%	4.65%
$t(\hat{\beta}) \geq$1.96	0.05%	2.15%	2.15%	0.00%	2.30%	2.45%	0.00%	1.85%	2.25%
$t(\hat{\beta}) \geq$2.326	0.00%	0.80%	0.80%	0.00%	0.80%	1.00%	0.00%	0.80%	1.20%