

# A time to scatter stones, and a time to gather them: the annual cycle in hedge fund risk taking\*

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## Abstract

Analyzing a novel sample of hedge fund daily returns from Bloomberg, we show a seasonal pattern in their risk taking. During earlier months of a year, poorly performing funds reduce their risk. The reduction is stronger for funds with higher management fees, shorter redemption periods, and recently deteriorating performance, consistent with a managerial aversion to early fund liquidation. Towards the end of a year, all poorly performing funds gamble for resurrection by increasing risk. The risk increase can be linked to indirect managerial incentives, which become stronger during the second half of a year, and it is largely achieved by increasing exposure to market factors.

*Key words:* hedge funds, risk taking, incentives, seasonality

*JEL:* G11, G23

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# 1 Introduction

The optimal managerial action in response to incentives is a timeless topic in management science. Hedge funds have gained a lot of attention in the recent years, as they provide a natural playground for such analysis. On the one hand, typical compensation contracts of hedge fund managers create complex incentive schemes.<sup>1</sup> On the other hand, being loosely regulated, hedge fund managers have direct control over the fund risk.

There is ongoing debate in the theoretical literature on the optimal response of hedge fund managers to performance. The literature generally predicts two alternative reactions to poor performance. Offensive (increasing) risk taking is expected for fund managers with a finite optimization horizon (Hodder and Jackwerth 2007, Buraschi et al. 2014). Defensive (decreasing) risk taking is expected for managers with an infinite optimization horizon (Lan et al. 2013).

Besides making contradictory theoretical predictions, recent literature also highlights the importance of indirect managerial incentives. Lim et al. (2016) analyze managerial incentives resulting from investor inflows in response to good performance. They find that the indirect link between compensation and performance via future fees on inflows creates stronger incentives than the direct link from the incentive contract.

The empirical evidence on the magnitude and the pattern of risk taking is, however, still scarce. Some papers do not find any significant performance-risk relation at all (Brown et al. 2001), while others find offensive risk taking (Aragon and Nanda 2012, Buraschi et al. 2014). We aim at closing this gap in the literature and recovering the full pattern of managerial risk taking empirically.

We use a previously unexamined sample of daily hedge fund returns from Bloomberg.

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<sup>1</sup>A typical compensation contract includes a management fee, which is a constant share of the fund's assets paid out on a pro rata temporis basis, and a performance fee, calculated as a share of the fund's profits in excess of a high-water mark (previously achieved end-of-year maximum net asset value), often paid at the end of a calendar year. Theoretically, such a compensation structure induces highly nonlinear managerial risk taking (e.g., Hodder and Jackwerth 2007, Panageas and Westerfield 2009, Lan, Wang, and Yang 2013).

While the hedge funds in our sample are very similar to the majority of funds reporting monthly returns with respect to their risk taking, the higher reporting frequency allows us to estimate fund risk on a monthly basis. A semi-parametric panel regression approach allows us to capture nonlinearities in the performance–risk relation. This setup further enables us to analyze potential mechanisms behind the observed risk shifts.

Thereby, we make several contributions to the literature. We reveal a highly nonlinear performance-risk relation with a strong seasonal pattern over the course of a calendar year. Conditional on fund underperformance relative to the high-water mark (henceforth HWM), hedge fund managers reduce the risk during earlier months of a year, but strongly increase it towards the end of a year.<sup>2</sup> The risk alterations are economically significant and range from an average 14% decline to a 20% increase relative to the expected level of risk. The observed nonlinearity offers a potential explanation for the absence of significant results in some previous papers that use linear specifications. And the detected seasonality allows reconciling theoretical predictions on offensive versus defensive risk taking.

Our additional tests suggest that during earlier months of a year, hedge fund managers are mainly concerned with fund survival. Consistent with the theoretical predictions in Lan et al. (2013), funds with a shorter notice period prior to redemption, recently deteriorating performance, or younger age, corresponding to a higher liquidation probability, exhibit a stronger risk reduction. During later months of a year, the focus of poorly performing fund managers shifts towards delivering high returns. We find that the flow–performance relation becomes stronger towards the end of a year, compared to the beginning of a year. Such seasonal variation in the flow–performance sensitivity impacts the trade-off between implicit and explicit incentives of fund managers. Accordingly, the end-of-year risk increase is driven by funds that are not capacity constrained and are expected to have a higher flow–performance sensitivity (Lim et al. 2016). It is also more pronounced during times when

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<sup>2</sup>We also detect a similar seasonal pattern using a larger group of hedge funds reporting conventionally on a monthly basis (see Section 6.3). The lower frequency of reporting, however, does not allow for an analysis as detailed as for the group of daily reporting funds.

the market performs poorly and the competition for investor flows becomes more severe. Remarkably, the end-of-year gamble by poorly performing funds is independent from the actual compensation structure and strongly pronounced for funds not charging incentive fees, too. Our results confirm a material impact of indirect flow-related incentives (Lim et al. (2016)) which are especially pronounced towards the end of the year.<sup>3</sup>

Our analysis also offers insights in the operational implementation of risk shifts. De-risking during the first half of a year is achieved by proportionally reducing exposure to market risk factors and idiosyncratic risk. Increasing the risk towards the end of a year, however, is disproportional. The increase in market risk is almost twice the idiosyncratic risk increase. Thus, hedge fund investors should not only be aware of seasonal variations in the risk taking, but also of a changing risk composition underling the returns over the course of a calendar year.

## 2 Related Literature and Problem Setting

Our paper is grounded in the extensive theoretical research on the optimal managerial response to incentives.<sup>4</sup> The predictions of the existing theoretical models range from offensive risk taking, with poorly performing managers gambling for resurrection by increasing fund risk, to defensive risk taking, with poorly performing managers reducing fund risk. Various factors and model assumptions, such as the existence of a single versus multiple consecutive incentive options, finite versus in(de)finite optimization horizons, the existence and attractiveness of outside opportunities for a manager, and the rules for fund termination determine the expected shape of the performance-risk relation.

The length of the optimization horizon has a crucial impact on the predicted risk taking. Finite horizons generally induce more aggressive risk taking. Carpenter (2000) shows that a

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<sup>3</sup>Chevalier and Ellison (1997) were one of the first to suggest that convexity of fund flows implicitly creates convexity of managerial compensation even in the absence of a HWM provision.

<sup>4</sup>While there is a vast literature on the optimal response to more general incentive schemes (see, for example, Harris and Raviv (1979), Gibbons and Murphy (1992), Ross (2004), Basak et al. (2008) among others), here we focus on the most relevant models for hedge funds only.

risk-averse manager, with a finite optimization horizon and a single incentive option linked to a HWM, will infinitely increase the risk as the fund value approaches zero. Hodder and Jackwerth (2007) solve a one-period and a multi-period optimization problem of a risk-averse manager on a discretized grid of fund values. In their model a manager has some personal wealth invested in the fund, receives a management fee, as well as an incentive fee tied to a HWM, and a discretionary option to liquidate the fund. With a three-year valuation horizon and incentive fee calculation together with HWM resetting at the end of every year, the managerial risk taking increases if the fund value is substantially below the HWM. It reflects managerial gambling at a point where the fund is close to liquidation. The simulation results by Hodder and Jackwerth (2007) suggest that the liquidation boundary, endogenously chosen by managers, lies between fund values of 50% to 60% of the corresponding HWM. Unlike the theory of Carpenter (2000), the risk increase at low fund values is still bounded.

Buraschi et al. (2014) further incorporate investor flows into the optimization problem of a hedge fund manager.<sup>5</sup> The goal of their paper is to find an appropriate adjustment of hedge fund performance for managerial risk taking. The authors develop a structural model of optimal risk taking which considers a typical hedge fund incentive contract, but does not explicitly include the manager's personal investment in a fund. Instead of an option for the manager to liquidate the fund, the authors model investors' redemptions and potential brokerage funding restrictions through short put option positions. The theoretical solution of Buraschi et al. (2014) suggests that the highest risk taking occurs at a fund value of approximately 60% of the HWM, with the risk taking being bounded. Compared to Hodder and Jackwerth (2007), where a poorly performing manager keeps increasing investment risk at lower fund values right until optimally choosing to liquidate the fund and take-up outside opportunities, the investors' and brokers' options to redeem shares and suspend financing in Buraschi et al. (2014) result in a gradual risk reduction after the fund value drops below a certain point and approaches the strike of the short put option.

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<sup>5</sup>Empirically, investors respond to good fund performance by providing capital inflows, and tend to redeem shares upon poor performance (Ding et al. 2009).

Managers with an infinite horizon behave in a more risk-averse manner. In Lan et al. (2013), a fund manager has an infinite horizon and instead of maximizing the utility at some terminal date, maximizes the present value of an infinite stream of management and incentive fees. The infinite investment horizon makes early liquidation of a fund extremely costly, and results in risk-averse behavior even for a risk-neutral manager. This leads to lower risk taking at fund values below the HWM. In this continuous time structural model, the authors also incorporate other characteristics of managerial investment strategies and compensation contracts, including the existence of alpha-generating strategies, drawdown and fund liquidation triggered by poor performance, leverage constraints, managerial ownership, inflows in response to good performance, as well as an endogenous managerial option to liquidate and re-start the fund at a cost.

There is also a growing body of empirical studies on managerial risk taking in hedge funds. Generally, hedge fund return data are available only at a monthly frequency. Most of the existing studies choose to analyze changes in fund risk (measured as the return standard deviation) from the first half of a year to the second half of a year, with each of the standard deviation estimates being based on six-monthly return observations only. With such a research design, Brown et al. (2001) find tournament behavior among hedge funds, but no relation of fund risk to absolute performance. The significance of a negative relation between the relative fund performance during the first half of a year and changes in return volatility vanishes after conditioning on the estimated HWM. Agarwal et al. (2002) find similar results in their sample of hedge funds. More recently, however, Aragon and Nanda (2012) and Buraschi et al. (2014) do find evidence of endogenous and state dependent risk shifting.<sup>6</sup>

The paper by Aragon and Nanda (2012) is most closely related to our work. The authors investigate changes in hedge fund return standard deviations from the first to the second half

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<sup>6</sup>Buraschi et al. (2014) focus on differences in the overall hedge fund return volatilities measured across a whole year and they treat all observations alike in terms of time to expiration of the nearest managerial incentive option. The results are then used for performance adjustments and are, thus, not directly comparable to ours.

of a year in a panel regression framework. They confirm an average negative relation between relative-to-peers performance and risk changes. The risk shifting is, however, mitigated by a HWM provision and a low risk of immediate liquidation, as well as for managers with a large personal stake invested in the fund. The authors also repeat the analysis using the absolute fund performance, measured by an indicator variable of fund value being below the HWM in the middle of a year, and confirm a negative relation.

Besides contradictory theoretical predictions and the limited empirical support for offensive risk taking by underperforming funds, our analysis is also motivated by the findings in Lim et al. (2016). The authors highlight the importance of indirect incentives through a positive flow-performance relation. In our paper we take an agnostic view point. We use a novel sample of higher frequency hedge fund returns, which allows us to reveal the exact shape of this highly debated risk-taking pattern. We seek to answer the questions of when, how, and by how much exactly hedge fund managers change the risk (if at all) in response to performance.

### 3 Data

Our sample consists of data retrieved from Bloomberg on 714 single- and multi-strategy hedge funds that report their returns on a daily basis in either USD or EUR from October 1, 2001 through April 29, 2011. We retrieve time series of daily hedge fund returns and assets under management (AuM), together with some static information on fund characteristics, such as the levels of the management and incentive fee, the use of a HWM, and the length of the lock-up and notice periods. The sample period starts once the number of fund-month observations for our main variable of interest (RISK) discussed later eventually remains above 50 in every month. The sample contains only individual hedge funds and no funds of funds. It is cleaned to ensure regular reporting.<sup>7</sup> We do not find any evidence for a

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<sup>7</sup>We first delete all zero returns. Then the average number of non-reporting days is not allowed to exceed 5/4 (at least four return observations per week on average), the maximum gap is nine trading days (the fund

backfilling bias at any horizon in our sample of hedge funds. Hence, we do not delete initial return observations for the following analysis.

Table 1 summarizes the sample and reports descriptive statistics of the hedge fund returns. The median returns for EUR hedge funds are lower than for USD hedge funds, which is partly due to inflation differences between the US and the Eurozone, and partly to differences across the implemented strategies by the funds. Compared to hedge funds that report on a monthly basis to commercial databases commonly used in the hedge fund literature, the hedge funds in our sample seem to be slightly less profitable and less risky.<sup>8</sup> This difference is consistent with the funds in our sample being more transparent and liquid, and thus being able to report on a daily basis. Despite slightly lower levels of overall risk, we expect the risk-shifting patterns to be comparable to the funds reporting on a monthly frequency, due to similar managerial incentive schemes. Table 2 reports the cross-sectional average descriptive statistics of intra-month return standard deviations.

[Tables 1 and 2 around here]

Figure 1 depicts the time series of average monthly returns of hedge funds in our sample and funds reporting on a monthly basis.<sup>9</sup> Funds in the two groups exhibit similar performance patterns. The correlation between average cross-sectional returns across these samples is 93%.<sup>10</sup> This suggests that the sample of daily reporting hedge funds, apart from contain-

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never misses reporting for two weeks or more), and the standard deviation must lie below 0.5 (reporting gaps do not occur frequently). We require at least 15 daily return observations per month (at least four per week for the shortest month) and an AuM observation within the first and last five trading days of the month to obtain a monthly flow estimate. We exclude one fund with less than one year of reported returns. Within a group of hedge funds generally reporting on a daily basis, the number of zero returns can be correlated with fund liquidity. However, as we cannot guarantee the actual reporting frequency while loading the data, the only way to filter out funds reporting on a daily as opposed to a weekly or monthly basis is to impose the filters as discussed above.

<sup>8</sup>Hodder et al. (2014) report that for their combined sample of hedge funds the mean (median) return of USD funds is 0.55% (0.50%) with a corresponding standard deviation of 4.60%.

<sup>9</sup>Our comparison group includes funds that report to five commercial databases: BarclayHedge, Eureka-hedge, Morningstar, HFR, and TASS, which is an updated version of the database used in Hodder et al. (2014). The time period is matched to the one of our sample of daily reporting hedge funds.

<sup>10</sup>The tail behavior is also very similar. The correlation between 5% quantiles of the cross-sectional return distributions is 87%, and the correlation of the 95% quantiles is 78%.



ing generally less risky and less profitable funds, is not systematically different from the conventionally used hedge fund samples.

[Figure 1 around here]

Hedge funds following different strategies exhibit different risk-return profiles. Our sample covers a wide range of hedge fund investment styles. Based on Bloomberg’s classification, we assign each fund to one of nine categories (including “Not defined”), as reported in Table 3. The highest mean return of 0.69% per month is earned by the Emerging Markets hedge funds, whereas the Managed Futures funds exhibit the highest return standard deviation of 5.77% per month.

[Table 3 around here]

We compare the distribution of fund styles in the samples of daily reporting funds and funds reporting monthly to commercial databases and depict the result in Figure 2. There is a difference in the share of directional equity and equity market neutral funds across the two databases. These styles account for 24% and 17% of the daily reporting funds, respectively, and for 10% and 36% of the monthly reporting funds. This discrepancy, however, might be driven by variations in style labeling across different databases. Altogether, equity funds account for the largest (and rather similar) share of both samples – 41% of daily reporting funds and 46% of monthly reporting funds. Another exception is managed futures funds, which are relatively over-represented in the sample of daily reporting funds, accounting for 18% of the sample whereas they account for only 5% of the sample of monthly reporting funds. Other styles have very similar distributions across the sample. Despite some differences, our sample of daily reporting hedge funds is not biased towards a single hedge fund style. It covers the whole spectrum of styles similar to other widely used samples of monthly reporting funds.<sup>11</sup>

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<sup>11</sup>As a robustness check, we also repeat the analysis using a reduced sample from which potential multiple share classes of the same fund are excluded as discussed in Appendix A. The results remain virtually unchanged from those reported in the paper.

[Figure 2 around here]

Last but not least, we compare the average loadings on the Fung and Hsieh (2004) seven factors of the funds in our sample with those reporting monthly. While estimating the regressions, we aggregate the daily returns to monthly to assure comparability of the estimates. Overall, consistent with the descriptive statistics, hedge funds in our sample have significantly lower alphas than the corresponding funds reporting monthly, with the exception of fixed income funds. Two styles, namely, emerging markets and managed futures, exhibit substantial differences in their risk profile across the two data sources. They have significantly different loadings on most of the risk factors. The differences for other styles, which constitutes the largest share of our sample, are not very propounded, despite some variation in the estimated factor loadings. Detailed results are reported in Appendix B.

## 4 Methodology

We measure hedge fund risk as the standard deviation of daily returns within one month.<sup>12</sup> For each hedge fund in our sample, a time series of monthly risk estimates is constructed. For ease of presentation, we will refer to the natural logarithm of the intra-month standard deviation of daily hedge fund returns as “RISK”. Uncapitalized “risk”, will still be used to refer to the general notion of investment risk.

### 4.1 Model specification

We employ a semi-parametric fixed-effect panel regression approach to analyze the managerial risk taking in response to incentives, with RISK being the dependent variable:

$$RISK_{i,t} = \alpha_i + \alpha_t + \sum_{j=1}^3 \beta_j RISK_{i,t-j} + \theta_1 DeltaCorr_{i,t} + \theta_2 \ln(AuM_{i,t-})$$

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<sup>12</sup>In Appendix C we use alternative risk measures, including return left semi-standard deviation and Value-at-Risk. The key results hold for these measures, too.

$$+ \theta_3 \text{OutflowLarge}_{i,t-1} + \sum_{k=1}^K f_k(\text{Value}_{i,t-}) I_k + \varepsilon_{i,t} , \quad (1)$$

where  $\alpha_i$  and  $\alpha_t$  are the fund and time fixed effects, respectively.

To identify risk shifting caused by the convex compensation contract, we use the value of the fund  $i$  relative to its HWM at the beginning of a month ( $\text{Value}_{i,t-}$ ). The minus sign as a sub-index in  $t_-$  indicates the beginning of month  $t$ . For each fund the HWM is set to 1 at inception. It is then reset every 1st of January to the level of the cumulative return (earned since inception), if it exceeds the previous HWM, and it is kept unchanged if the cumulative return is below the previous HWM.<sup>13</sup> The fund value relative to the HWM is then the ratio of the total cumulative return of the hedge fund (that would correspond to the net asset value of 1 unit invested in the fund at origination) over the corresponding HWM:

$$\text{Value}_{i,t-} = \frac{\prod_{k=0}^{t-1} CR_{i,k}}{HWM_{i,t-}}. \quad (2)$$

where  $CR_{i,t}$  is the cumulative return earned by fund  $i$  over month  $t$ .  $CR_{i,t} = \prod_{\tau} (1 + r_{i,\tau})$  with  $r_{\tau}$  being the daily return of hedge fund  $i$  earned on day  $\tau$  of month  $t$ .

The relation between fund value relative to the HWM and managerial risk taking is captured by a nonparametric function  $f_k(\text{Value}_{i,t-})$ . The function is allowed to vary over  $K$  periods of a year, with  $I_k$  indicating either the different quarters ( $K = 4$ ) or months ( $K = 12$ ).

We control for other drivers of hedge fund risk levels. In the time series dimension, we expect RISK to be persistent.<sup>14</sup> To quantify the actual persistence in hedge fund risk, we estimate the partial serial correlation at the first five lags of RISK for each hedge fund in our

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<sup>13</sup>Our results are robust to different specifications of the HWM. See Appendix D for more details.

<sup>14</sup>There is strong evidence on the predictability of second moments in equity markets, for example in Christoffersen and Diebold (2006) and Christoffersen et al. (2007). Persistence in stock return volatilities translates into persistence of hedge fund return volatilities if fund portfolios do not change rapidly. Following one investment strategy consistently could result in stable levels of fund risk, too, even if the underlying securities in the portfolio often change. Teo (2010) finds that the liquidity risk exposure of hedge fund portfolios is persistent. Ang et al. (2011) show the stability of hedge fund leverage. Substantial transaction costs can also prevent frequent portfolio alterations.

sample.<sup>15</sup> The fractions of negative and significant partial serial correlations are negligible and the fractions of significantly positive coefficients drop after the third lag to only 3% at lag 4. These results suggest that RISK follows an AR(3) process and we include three lagged values of RISK as explanatory variables in the panel regression.

In such a dynamic panel regression, fund-specific effects are correlated with regressors, which renders random-effect models inconsistent. Fixed-effect models, however, do not allow for a joint analysis of time-variant and time-invariant regressors (such as fund characteristics). Hence, we include fund fixed effects in the panel regression, which capture variations in the average level of risk due to fund style, fees, redemption period, currency, and all other time-invariant characteristics, such as the manager’s general appetite for risk.

The time series of the cross-sectional average RISK shares the same dynamics with the RISK of the MSCI World index. The correlation coefficients between the series range from 0.80 for MSCI-World and EUR funds to 0.84 for MSCI-World and USD funds. We include fixed effects in the time dimension in the regression, which control for variations in the market conditions and all other period specific effects jointly affecting all hedge funds.

Following Aragon and Nanda (2012), we include the change in intra-month return first-order serial correlations as an additional variable  $\Delta Corr_{i,t}$  to control for variations in the observed risk levels which arise from changes in serial correlations rather than from managerial risk shifting.<sup>16</sup> We also include the natural logarithm of the AuM of fund  $i$  at the beginning of month  $t$   $\ln(AuM_{i,t-})$  in the regression to capture potential changes in the risk-taking pattern that result from fund size variations over time.

We also consider the impact of fund outflows on risk taking. Substantial redemptions force hedge funds to liquidate positions. To minimize the liquidation costs, managers are

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<sup>15</sup>Partial autocorrelations capture the relation between the values at lag zero and higher-order lags in isolation of the lags in between.

<sup>16</sup>There are different potential reasons for a change in the serial correlation. A variation in the true underlying return generating process due to a deliberate change in the fund strategy by the managers can cause such a change. However, a change in the estimated correlation coefficient can be also artificially caused by observations of daily returns not being equally spaced within consecutive months. If the reporting frequency has any information on hedge fund risk, it will also be picked up by the change in the return serial correlation.

likely to close the most liquid positions first. The liquid positions are often among the less risky components of the fund’s portfolio within each asset class. Thus, the remaining portfolio contains relatively fewer liquid assets and a larger share of riskier assets and it might take some time for the management to return to the desired level of risk. To address the fund-flow related risk changes, we calculate the fund flow over the previous month as

$$Flow_{i,t-1} = \frac{AuM_{i,t-} - AuM_{i,t-1-} CR_{i,t-1}}{AuM_{i,t-1-}} , \quad (3)$$

We then include a dummy variable, which indicates a flow below  $-5\%$  and serves as a proxy for large outflows ( $OutflowLarge_{i,t}$ ).

This semi-parametric analysis allows us to capture potential nonlinearities in the relation between fund risk and value. To give a more precise quantification of the strength of risk shifting, we repeat the analysis using a piecewise linear specification instead of a kernel regression. We analyze the residuals from the linear part of Equation (1) for the different quarters of a year and allow the estimated coefficients on the value variable to vary within three intervals: (1) fund value below  $\bar{V}$  (expressed in percent relative to the HWM); (2) fund value between  $\bar{V}$  and the HWM; and (3) fund value above the HWM. The choice of the breakpoint value  $\bar{V}$  will be motivated by the kernel regression results. For each quarter of a year, we estimate the following regression with bootstrapped standard errors:

$$\hat{e}_{i,t} = \begin{cases} \kappa_{low} + \delta_{low} Value_{i,t-} + \eta_{i,t} & \text{if } Value_{i,t-} < \bar{V} \\ \kappa_{mid} + \delta_{mid} Value_{i,t-} + \eta_{i,t} & \text{if } \bar{V} < Value_{i,t-} < 1 \\ \kappa_{high} + \delta_{high} Value_{i,t-} + \eta_{i,t} & \text{if } Value_{i,t-} > 1 . \end{cases} \quad (4)$$

Here  $\kappa$  indicates the average incremental risk taking in a given interval of fund values and  $\delta$  indicates the slope of the fund-risk to value relation within this interval.<sup>17</sup>

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<sup>17</sup>We also employ a piecewise continuous specification of the model as explained in Appendix E and obtain qualitatively similar results.

## 4.2 Semi-parametric estimation

The regression in Equation (1) is estimated in two steps. First, *RISK* is regressed on all covariates excluding fund value. Then, the residuals from this regression ( $\hat{e}_{i,t}$ ) are grouped according to calendar quarters or months. For each of the related four or twelve groups, a nonparametric kernel regression of the residuals on the corresponding fund value is estimated.<sup>18</sup>

$$\hat{e}_{i,t}I_k = f_k(Value_{i,t-})I_k + \eta_{i,t,k} \quad (5)$$

For the kernel regression, we use a Gaussian kernel with a fixed bandwidth of 0.07.<sup>19</sup> We restrict the support for our estimates to the closed interval, on which at least five observations are contained in each bandwidth window, to avoid inference over areas with few observations. We follow Yatchew (2003, p.161) to obtain bootstrapped confidence bounds around the estimated functions  $\hat{f}_k$ . The procedure employs undersmoothing and a wild bootstrap with 10,000 iterations to correct for the asymptotic bias of the estimator and allow for heteroscedasticity of the residuals. Unlike for asymptotic procedures, the estimated bounds are not simply equidistant from the regression line (see Yatchew (2003, p.162, Figure 8.1)), but use information contained in the actual observations, especially on higher-order moment properties. In some rare cases (few and extreme observations, strong curvature), the conservative confidence interval can lie closer to zero and not contain the regression line itself

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<sup>18</sup>The variable *Value* in our regressions is not strongly correlated with other explanatory variables, and the first-step estimation does not suffer from an omitted variable bias if *Value* is excluded. We also employ the three-stage approach of Robinson (1988) used in Chevalier and Ellison (1997). We (1) estimate separate kernel regressions of *RISK* and the control variable on *Value*; (2) obtain estimates of  $\alpha$ -s,  $\beta$ -s, and  $\theta$ -s by regressing the first-stage *RISK*-residuals on controls' residuals; (3) compute residuals  $\hat{e}_{i,t}$  as the difference between  $RISK_{i,t}$  and the linear part estimated in (2). The obtained estimates are very similar to those reported in the paper.

<sup>19</sup>Cross-validations conducted separately for different quarters and months yield optimal bandwidths ranging from 0.01 to 0.11. To ensure that our results for different periods are not driven by differential smoothing, we keep the bandwidth fixed for all kernel regressions. From manually comparing regression results and trading-off smoothness and variance for all bandwidths within the range suggested by cross-validation, we chose 0.07 as our fixed bandwidth. As a robustness check, we re-estimate the regressions with smaller bandwidths of 0.05 and larger bandwidth of 0.09. Our findings remain qualitatively the same.

anymore.

Note that in the linear part of Equation (1), the lagged values of RISK are correlated with the error term, which biases OLS estimates (Nickell 1981). The most prominent solutions to this dynamic panel bias are GMM estimation techniques (e.g., Arellano and Bond 1991) or an explicit bias correction (e.g., Kiviet 1995). The former, however, is designed for small  $T$  panels and the latter is only feasible with balanced panels. Nickell (1981) derives an expression for the bias and shows that it approaches zero as  $T$  tends to infinity. In a simulation study, Judson and Owen (1999) show that for unbalanced panels, a fixed-effects model already outperforms the other alternatives for  $T = 30$ . Therefore, we can well neglect the dynamic panel bias in our regression (with  $T = 115$ ) and employ OLS. Bootstrapped panel robust standard errors take care of potentially remaining serial correlation and heteroscedasticity in the errors.<sup>20</sup>

## 5 Empirical Results

### 5.1 Seasonal pattern in managerial risk taking

Column (I) in Table 4 reports the estimation results based on the linear part of Equation (1). Consistent with the time series analysis of hedge fund risk, past values of RISK are important predictors of the current risk level. The explanatory power is decreasing in the lag length. The first lag obtains the highest loading of 0.50, and it decreases to 0.09 and 0.07 for the second and the third lags, respectively. All three loadings are highly significant. We do not find any significant effect of variations in fund size on hedge fund risk in our sample, while our control variable *DeltaCorr* is positively related to hedge fund risk and significant at the 5% level. Outflows exceeding 5% of the AuM over the previous month lead to a significant increase in the fund risk. The corresponding loading is positive (0.03)

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<sup>20</sup>At the same time, we find that OLS standard errors are virtually identical to the bootstrapped ones, which indicates that our model does not produce serially correlated errors (Petersen 2009).

and significant at the 1% level. Thus, after liquidation of presumably more liquid assets, the remaining hedge fund portfolio is riskier.<sup>21</sup>

[Table 4 around here]

Figure 3 plots the estimated kernel regression of residual risk taking. Here, fund and time fixed effects, risk persistence, effects of flows and size are already controlled for. The results are presented for four quarters of a year separately, together with 1%, 5%, and 10% confidence bounds around the regression lines.

[Figure 3 around here]

The figure suggests a clear seasonal pattern in risk taking. During the first quarter of a year, the fund value relative to the HWM does not seem to have any significant impact on the hedge fund risk at any conventional confidence level. During the second quarter managers tend to decrease the risk if the fund value is some 25% below the HWM with the minimum achieved at a value of about 60% of the HWM. The decrease is significant at the 5% level. Towards the end of a year, the managerial risk taking reverts. It increases if a hedge fund is substantially below the HWM. The increase is significant at the 5% level during the third quarter, and highly significant during the fourth quarter. Below the HWM, the risk shifting does not increase monotonically. Instead, it is bell-shaped, as suggested by Buraschi et al. (2014).

We do not find significant managerial risk changes around the HWM itself in any quarter. The existence of the incentive option induces neither a risk increase just below the HWM (to push the incentive option into the money), nor a risk reduction right above the HWM (to lock in the incentive pay) as suggested, for example, by the one-period model in Hodder

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<sup>21</sup>We include in the regression the fund flow directly as defined in Equation (3) at times  $(t-1)$  and  $(t-2)$ , as well as an indicator function for negative flow. In unreported results, none of these variables turns out to be significant. Also, neither outflows preceded by poor performance nor cumulative flows are driving the risk increase.



and Jackwerth (2007). Significant alternations of fund risk take place only when funds are substantially underperforming and their very existence is under question.

The results obtained using the piecewise linear specification confirm the documented pattern. We choose a breakpoint  $\bar{V}$  of 0.60 and report the estimated coefficients in Table 5. Figure 4 depicts the resulting regression lines, where we set insignificant regression coefficients to zero.

[Table 5 around here]

[Figure 4 around here]

To account for potential tournament behavior among hedge funds (Aragon and Nanda 2012) we include the cumulative return earned by fund  $i$  over month  $t$  in excess of the average cumulative industry return ( $ExcessPerf_{i,t}$ ) as an additional control and report the results in Column (II) of Table 4. Consistent with the previous studies, the short-term performance relative to the competitors is negatively related to fund risk.<sup>22</sup> The resulting kernel regression lines remain qualitatively unchanged as compared to our main results. This finding complements Aragon and Nanda (2012): the tournament behavior phenomenon has both a short-term driver (recent underperformance relative to the industry), as well as a longer-term driver (absolute fund success captured by fund value relative to the HWM).

## 5.2 Magnitude of managerial risk shifts

Consider a hedge fund that reports its performance in USD. The average intra-month standard deviation of daily returns of such a fund is 0.74% and its standard deviation is 0.42%. Other things being equal, a one standard deviation increase in the risk at time  $t$  will result in a 25% increase in the risk during the following month ( $e^{0.50 \cdot \ln((0.74+0.42)/0.74)} = 1.25$ ).

According to Table 5, the highest risk decline for an average fund happens in the second

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<sup>22</sup>In unreported results, we find that other performance proxies (e.g., dummy variables for underperformance, or relative performance based on Sharpe and Sortino ratios) are also significant. Their explanatory power is concentrated at the first lag, as it is for the reported measure, suggesting a truly short-term effect.

quarter at a fund value of 0.60 of the HWM. The corresponding coefficients  $\kappa$  of  $-0.45$  and  $\delta$  of  $+0.49$  imply a 14% decline relative to its expected level ( $e^{-0.45+0.49 \cdot 0.60} = 0.86$ ). Similarly, an average fund increases the risk in the fourth quarter up to 20% of the expected level of risk ( $e^{+0.48-0.50 \cdot 0.60} = 1.20$ ).

Thus, investors should be aware of managerial risk shifting, as it is strongly pronounced even on average. It may be even more severe in smaller and less diversified portfolios of hedge funds.<sup>23</sup> Also, as pointed out by Aragon and Nanda (2012), if a substantial fraction of hedge funds slides into a portion of the state space that induces high risk taking, this might be of systemic concern.

### 5.3 Potential drivers of seasonal risk shifting

Our finding of seasonality in hedge fund risk taking is, to the best of our knowledge, a novel empirical result. We now take a closer look at the potential drivers and determinants.

#### 5.3.1 *Direct vs. Indirect Managerial Incentives*

Explicit managerial compensation contracts provide managers with complex risk-taking incentives, which are extensively discussed in the literature. Throughout our paper, we compare our empirical results to the theoretical predictions, but find that none of the suggested models can explain the full pattern of the managerial risk taking we reveal.

At the same time, a substantial share of managerial wealth is generated due to fund inflows, which mainly arrive in response to good performance. According to Lim et al. (2016), the thereby created flow related indirect incentives are at least 1.4 times larger than the direct incentives from the immediate compensation. They are more pronounced for funds with stronger flow-performance sensitivity (FPS).

We test if our findings on intra-year variation of hedge fund risk taking can be linked to time varying indirect incentives to fund managers. We estimate a panel regression of monthly

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<sup>23</sup>Hodder et al. (2014), for example, report that an average fund of hedge funds holds only 24 individual funds.

percentage flows ( $Flow_{i,t}$ ) on fund performance measured at the end of the previous month ( $Perform_{i,t-1}$ ) and a set of controls. We measure fund performance by either its monthly return (to proxy for short-term performance) or fund value relative to the HWM as of the end of the month (to capture long-term cumulative fund performance).<sup>24</sup> In choosing the control variables, we closely follow Ding et al. (2009) and include the natural logarithm of the standard deviation of the past month returns ( $\ln STD_{t-1}$ ), the natural logarithm of last month standard deviation of the returns on the S&P 500 index ( $\ln STDSP500_{t-1}$ ), fund age in months ( $Age_{t-1}$ ), the natural logarithm of the fund's AuM ( $\ln AuM_{t-1}$ ), a dummy variable indicating if the fund is using a HWM ( $HWM$ ), the levels of management and incentive fees in percent ( $MgtFee$  and  $IncFee$ ), the length of the notice period prior to redemption in months ( $Redem$ ), contemporaneous average percentage flow to other funds following the same style ( $SlyteFlow_t$ ), and the past month return on the MSCI World index ( $MSCIRet_{t-1}$ ). The corresponding regression specification is, thus:

$$Flow_{i,t} = a + b \cdot Perform_{i,t-1} + c \cdot Controls_{i,t} + \varepsilon_{i,t} \quad (6)$$

We next allow the FPS to change from the first to the second half of a year. We first estimate the regression in Equation (6) based on information only from the first halves of years, and then repeat the estimation using the information from the second halves only. In this specification, the factor loadings on all other variables are also allowed to change. In another specification, we use all the data simultaneously, but include a dummy variable for second year halves and an interaction term between this dummy and fund performance as detailed in Equation (7).

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<sup>24</sup>The sensitivity of flows to lagged performance might exist for other flow and performance metrics, measurement horizons, and lag lengths. Our aim here is not to analyze all the determinants of this relationship, but instead to test if observed changes in the risk-performance relation can be attributed to changes in the flow-performance relation. Therefore, we measure the latter in accordance to our measurement of the former.

$$Flow_{i,t} = a_0 + a_1 \cdot \mathcal{I}_{July-Dec} + (b_0 + b_1 \cdot \mathcal{I}_{July-Dec})Perform_{i,t-1} + c \cdot Controls_{i,t} + \varepsilon_{i,t} \quad (7)$$

Here, the indicator function  $\mathcal{I}_{July-Dec}$  takes a value of one during second halves of each year. If there is no seasonal variation in flow-performance relation,  $b_1$  should turn insignificant. Tables 6 and 7 report the estimation results for Equations (6) and (7), respectively.

[Tables 6 and 7 around here]

The sub-period analysis in Table 6 suggests that there is no significant relation between monthly flows and previous month performance during the first half of a year, whereas the FPS is positive and significant during the second half of a year. The corresponding coefficients on return and value of +0.09 and +0.05 are significant at the 10% and 1% levels, respectively. Fund value relative to the HWM has a stronger statistical support than fund return, suggesting that although flows respond to past performance only during the second half of a year, investors are not myopic and care relatively more about long-term fund performance (captured through the value variable) rather than the immediate short-term performance. The results reported in Table 7 corroborate this finding, with the interaction term between past performance and the second year-half dummy being significantly positive for fund value relative to the HWM.

Thus, the flow analysis suggests that in our sample of liquid hedge funds FPS is varying within a year. It becomes stronger towards the end of a year, making indirect managerial incentives more relevant as compared to the beginning of a year. Given the suggested importance of indirect incentives (Lim et al. 2016), such seasonality in FPS may well be a driver of seasonality in managerial response to poor fund performance. Observing insignificant FPS during the first half of a year, managers may care less about delivering high returns during that period and focus more on fund survival – a proposition we test in the Section 5.3.2. Towards the end of a year, the indirect flow-related incentives start playing a role,

and managerial focus can shift towards delivering higher returns.<sup>25</sup>

If the indirect incentives do indeed play such an important role, we should observe a stronger seasonal pattern for funds with higher expected FPS. Relating risk taking to the estimated individual fund FPS is, however, empirically challenging. The estimated FPS will depend on the returns, which are driven by the optimal managerial response to fund FPS, creating endogeneity. Thus, one has to use an instrument which is not directly related to managerial actions during the life time of a fund. Lim et al. (2016) show that hedge funds that are not capacity constrained exhibit a stronger FPS. Following this research and the classification suggested in Ding et al. (2009), we classify funds into capacity constrained and capacity unconstrained subgroups. The capacity constrained group contains the Emerging Market, Event Driven, and Fixed Income funds from our sample (132 funds). The unconstrained group contains Equity Directional, Equity Market Neutral, Global Macro, Managed Futures, and Multi Strategy funds (565 funds). We repeat the piecewise linear analysis separately for these two subgroups of funds. The significance of the seasonal pattern disappears for the constrained subgroup of funds.<sup>26</sup> The seasonal pattern remains virtually unchanged for the capacity unconstrained funds. The estimation results are reported in Table 8. Only the estimates for the fund value between 0.6 and 1 are reported for the ease of reading from now on.<sup>27</sup>

[Table 8 around here]

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<sup>25</sup>Investigating the reasons for the seasonality in the flow-performance sensitivity is an interesting research question, which lies, however, beyond the scope of this paper. It is related to the behavior of fund investors, rather than fund managers. There is extensive literature on window dressing by institutional investors suggesting that institutions that report on an annual basis tend to overinvest in well performing assets towards the end of a year, to make their portfolios look better by the reporting date. Lakonishok et al. (1991), for example, show that window dressing by institutional investors is more likely to occur at the end of the fourth quarter of the year. As the sample of hedge funds used in this paper covers liquid hedge funds, which usually do not have any reported lock-up periods and have only short notice periods, these funds could be used for window dressing by their investors similar to other asset classes. For mutual funds, Franzoni and Schmalz (2017) show that the FPS is state varying and exhibits a hump-shaped relation to aggregate risk realizations.

<sup>26</sup>Partly, the absence of significant results can be attributed to the very small sample size. Also, it does not allow us to estimate the regression for fund values below 0.6.

<sup>27</sup>Detailed results for unconstrained styles are reported in Appendix F.

We next check if variations in the investment opportunity set can be linked to the documented seasonality. Generally, one can expect that during deteriorating market conditions investors become more sensitive to fund performance. To this end, we split the whole sample into two sub-samples according to the annual MSCI-World return being above/below the median. We repeat the piecewise linear analysis for each of these sub-samples. The seasonality in risk taking is seen in both sub-samples. However, it is stronger during the years with low investment opportunities. Table 9 reports the results. During the second quarter, the slope coefficients on  $Value_{t-}$  are 0.37 (significant at the 5% level) and 0.63 (significant at the 1% level) for “good” and “bad” years respectively, and during the fourth quarter the corresponding slope coefficients are -0.42 (significant at the 10% level) and -0.54 (significant at the 1% level). During years of poor market performance (and likely lower investor capital available), fund managers are more concerned about fund survival than during the better years and reduce risk more strongly at the beginning of the year. At the same time, the competition for investor inflows during “bad” years is also stronger, which leads to higher risk taking at the end of a year of poorly performing funds as compared to “good” years.<sup>28</sup>

[Table 9 around here]

The results corroborate our hypothesis of a dominant role of indirect managerial incentives towards the end of a calendar year.

### 5.3.2 *Management Fees and Liquidation Probability*

Now we test for evidence on a managerial focus on fund survival during the first half-year – a proposition stemming from the insignificance of the FPS during the beginning of a year. We suggest, that if hedge fund managers care more about survival than returns during the beginning of a year, they are likely to behave as suggested by the model of Lan et al. (2013). Here, poorly performing hedge fund managers with very long (infinite) investment

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<sup>28</sup>In Appendix G we exclude the financial crises period from July 2007 onwards from the analysis, and find that the observed seasonality is not only driven by poor performance during crisis years.

horizons optimally reduce the fund risk to avoid liquidation. Fund liquidation is extremely costly for managers, as they lose an infinite stream of future management and incentive fees. Management fees, in particular, account for 75% of the total managerial surplus according to the model. The higher the management fee, the more the manager loses in case of fund liquidation. We expect that below the HWM, hedge funds with higher management fees exhibit a stronger risk reduction at the beginning of a year.

Similarly, a stronger risk reduction during the early part of a year may be expected for funds with a higher liquidation probability. Directly relating the managerial decision to alter fund risk to estimated liquidation probabilities in a regression framework, however, might be inaccurate due to endogeneity. Actual fund survival depends on fund risk, which is, in turn, an optimal managerial response to the fund liquidation probability. We use three instruments that are negatively related to the liquidation probability, but are not directly affected by the future risk-taking decisions of a manager: notice period prior to redemption, recent fund performance, and fund age.<sup>29</sup> We expect that below the HWM, hedge funds with a longer notice period prior to redemption, positive returns over the previous quarter, or older age exhibit a milder risk reduction at the beginning of a year.

To test these corollaries, we use a similar piecewise linear specification as in Equation (4). For each fund value range, we introduce four indicator variables in turn (denoted by  $\gamma$ ) and estimate Equation (8). The indicator variables represent funds with (1) higher than median management fees, (2) higher than median notice periods prior to redemption, (3) positive cumulative returns over the preceding quarter, and (4) larger than median age:

$$\hat{e}_{i,t} = \begin{cases} \kappa_{low} + \gamma_{low} + \delta_{low}Value_{i,t-} + \eta_{i,t} & \text{if } Value_{i,t-} < \bar{V} \\ \kappa_{mid} + \gamma_{mid} + \delta_{mid}Value_{i,t-} + \eta_{i,t} & \text{if } \bar{V} < Value_{i,t-} < 1 \\ \kappa_{high} + \gamma_{high} + \delta_{high}Value_{i,t-} + \eta_{i,t} & \text{if } Value_{i,t-} > 1 \end{cases} \quad (8)$$

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<sup>29</sup>See, for example, Liang and Park (2010) among others. Another potential instrument linked to liquidation probability is managerial personal investment in a fund (Aragon and Nanda 2012). This information, however, is not available for our sample of hedge funds.

For example, for management fees, a negative and significant  $\gamma_{mid}$  in the second quarter implies that hedge funds with higher management fees reduce risk more strongly during the second quarter, if their value is below the HWM.

The estimation results are reported in Table 10. Consistent with our expectations, hedge funds charging higher than median management fees show a stronger decline in risk taking during the second quarter, conditional on being below the HWM. The corresponding coefficient of  $-0.05$  is significant at the 10% level. Hedge funds that are likely to face a lower liquidation probability, because of a longer notice period prior to redemption, positive cumulative returns over the preceding quarter, or older age, show a less pronounced risk decline during the second quarter of a year. The coefficients of  $+0.13$ ,  $+0.06$ , and  $+0.07$ , respectively, are all highly significant. Remarkably, we do not detect any significant impact of these factors on risk-shifting behavior at the end of a year, which again points towards a dominant role of the indirect flow-related incentives at the end of a year.

[Table 10 around here]

These findings supplement the results by Aragon and Nanda (2012), who report that changes in fund risk (between the first six months and the second six months of a year) are positively related to the fund liquidation probability. Our results suggest that this relation is not primarily driven by excessive risk taking during the second half-year, but mainly by a risk reduction during earlier months.<sup>30</sup>

## 5.4 Implementation of risk shifts

We now take a closer look at the exact mechanism of risk shifting. Do managers change the riskiness of their portfolios by proportionally changing the exposure to all the risk factors, or do they overweigh/underweigh some factors? If the latter is true, not only does the overall portfolio risk exhibit a seasonal pattern, but also the relative composition of risk factors

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<sup>30</sup>The high nonlinearity of managerial risk taking suggests that a linear statistical identification can be misleading. See Appendix H for the related results.



changes throughout a year, which may further complicate the risk-management problem on the investor side.

In order to address this issue, using daily returns of each hedge fund we fit the Carhart (1997) 4-factor model. As our main results suggest that the riskiness of hedge funds varies at least on a quarterly basis, we allow the factor loadings to change each quarter, too.<sup>31</sup> The model fit depends on the fund style, with the average adjusted R-square varying from 5% for Fixed Income Directional funds to 26% for Equity Directional funds, based on quarterly regressions. The average loadings on the market factor vary from 0.004 for Fixed Income Directional funds to 0.22 to Equity Directional Funds. We decompose the hedge fund daily returns into their fitted component, driven by (time varying) exposure to the market factors, and the residual or idiosyncratic component, which is orthogonal to the factors used in the model. We then repeat our analysis of risk taking based on the fitted component of returns and the residual component. Table 11 reports the estimation results of the piecewise liner specification based on fitted return values (Panel A) and residuals (Panel B).

[Table 11 around here]

During the second quarter underperforming funds reduce both market and idiosyncratic risk to the same extent. The corresponding constant terms and slope coefficients are very similar in absolute values between the two regression specifications, and are not statistically different from each other.

During the third quarter, underperforming funds start to increase their market risk exposure. The corresponding level and slope coefficients of +0.43 and -0.46 are highly statistically significant for the residual RISK based on the fitted return values (Panel A). The corresponding estimates for the idiosyncratic part of risk are close to zero and are not statistically significant (Panel B).

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<sup>31</sup>As a robustness check, we allow factor loading to change every months and use an alternative model specification, namely, a reduced form of Fung and Hsieh (2004) seven factor model, following Patton and Ramadorai (2013). The results are reported in Appendix I and are qualitatively similar to those discussed in this section.

During the fourth quarter of a year, underperforming funds increase both market and idiosyncratic components of the total portfolio risk. However, the corresponding loadings for the market risk component are almost twice as large in the absolute values than those of the idiosyncratic component of risk. Their difference is also statistically significant at the 5% level. Looking at the economic differences in the changes of different types of risk during the fourth quarter, we can see that the maximum increase in the market risk is about 23% with respect to the expected level of market risk ( $e^{0.60-0.66 \cdot 0.6} = 1.23$ ), whereas the maximum increase in the idiosyncratic risk is just 13% ( $e^{0.34-0.36 \cdot 0.6} = 1.13$ ). Towards the end of a year, underperforming funds increase both their exposure to market risk factors and the idiosyncratic part of their total risk. The increase in the market risk exposure is, however, significantly stronger.

When focusing on the major risk shifts observed, declining risk in the second quarter and increasing risk in the fourth quarter of a year by poorly performing funds, our results provide two insights in the risk-shifting mechanism. First, the seasonal pattern is still observed in both fitted values and the residuals. Thus when changing the risk taking, hedge fund managers adjust both their exposure to market risks as well as the idiosyncratic risk. Second, the results are consistent with fund investment strategies being scalable downwards, for example, by reducing leverage, resulting in proportional decline in market and idiosyncratic components in quarter two, but not as easily scalable upwards, for example, because of the limited availability of arbitrage opportunities, resulting in disproportional increase in market exposure in quarter four.<sup>32</sup> Investors in hedge funds should therefore be aware that not only the riskiness of the underperforming hedge funds increases towards the end of a year, but also that such funds are likely to become disproportionately exposed to market risk, as compared to their average exposure.

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<sup>32</sup>Looking further into scalability of investment strategies, we show in Appendix J that poorly performing funds with more market-driven returns do indeed exhibit stronger increase in the risk taking in the fourth quarter of a year.

## 6 Robustness Checks

In this section, we analyze the impact of the HWM and incentive fees on the seasonality in managerial risk taking and present refined month-wise results. We then discuss the implications of our findings for the majority of hedge funds that report on a monthly basis to commercial databases.

### 6.1 High-water mark and incentive fees

Managers of funds with a HWM provision possess not a single incentive option, but a sequence of multiple future incentive options. By excessive risk taking, they may lose their future compensation options. The empirical findings of Aragon and Nanda (2012) show, accordingly, that the existence of a HWM mitigates the relative risk increase from the first to the second half of a year by poorly performing funds. Thus, one can expect that below the HWM, hedge funds with a HWM provision exhibit a less pronounced risk increase at the end of a year.

We test this proposition using Equation (8), with  $\gamma$  capturing the impact of an indicator variable taking a value of one for funds having a HWM. The results are reported in Panel A of Table 12. The estimated coefficients remain virtually unchanged from those of the main results in Table 5. This suggests that, overall, hedge funds that do have a HWM provision and those that do not adjust their risk taking in a similar way, depending on their cumulative performance and the time of year. A HWM provision somewhat offsets the risk increase during the second half of a year, consistent with the prior findings. However, the effect is detected only during the third quarter, with the corresponding loading of  $-0.04$  being significant at the 10% level. The risk-mitigating incentives provided by the HWM provisions are not sufficient to prevent managers from risk shifting towards the very end of a year. If managers enter the fourth quarter with a fund under water, they significantly increase fund risk regardless of the existence of a HWM provision in the fund.

[Table 12 around here]

In Panel B of Table 12 we show the results of a similar analysis but use a dummy variable indicating the existence of a positive incentive fee<sup>33</sup> and still do not find any significant relation between charging incentive fees and increasing risk at the end of a year.

The findings above confirm a minor role of the incentive option – tied to a HWM or not – for seasonal changes in managerial risk taking, and again point towards the importance of indirect flow-related incentives which increases towards the end of a year.

## **6.2 Seasonal pattern in managerial risk taking: month-wise refinement**

We show that managers significantly decrease fund risk during the second quarter and increase the risk during the fourth quarter, if a fund is below the HWM. Now, we take a closer look at the two quarters and re-estimate the corresponding kernel regressions for each month separately. Figure 5 reports the estimated regression lines, together with 1%, 5%, and 10% confidence bounds. As we keep the requirement of a minimum of five observations per bandwidth window, the support of the month-wise estimates shrinks compared to the quarter-wise results. The regression line also does not lie within the bootstrapped confidence bounds in some cases, confirming that the monthly analysis suffers from a lack of observations.

[Figure 5 around here]

Despite lower numbers of observations at the edges, the pattern of low risk taking in the second quarter and high risk taking in the fourth quarter, conditional on the fund value being below the HWM, remains pronounced. At the same time, the results suggest that the decision to alter the portfolio risk is taken at the beginning of a respective quarter. For

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<sup>33</sup>In our sample, about 30% of the hedge funds do not report a positive incentive fee. Some of these funds report a zero incentive fee, while others do not provide any information, that is, they may or may not charge an incentive fee.

the second quarter, we observe a managerial risk reduction in April which is significant at the 1% level. In May, the decrease is still pronounced, being significant at the 5% level. In June, we do not find any risk alterations distinguishable from zero-mean noise around the expected level of risk. A similar pattern emerges in the fourth quarter. The increase in risk taking is highly significant in October and November, and it vanishes in December.

Fund managers seem to act rather early in moving the fund risk up and down towards the desired levels. If they want to increase fund risk towards the end of a year in response to a low fund value, it does not seem to be sufficient to switch to a riskier investment strategy in December. The time may be too short for the realized returns to cover past losses. Given risk persistence, assigning more weight to riskier assets in October and November assures that the portfolio risk remains high in December as well, and no additional risk increase is required in December. Technically speaking, a desired level of expected future fund risk is achieved by adding a desired shock to the autoregressive process in foresight. This finding stands in stark contrast to the assumption of the theoretical models that hedge fund managers are able to alter fund risk swiftly.

### **6.3 Seasonal pattern in managerial risk taking: monthly reporting funds**

In this section, we check if the seasonality in managerial response to poor performance is pronounced only for hedge funds reporting on daily basis, or if it is a common phenomenon for more conventional funds reporting on a monthly basis too. Using the merged hedge fund database of Hodder et al. (2014), we repeat the analysis of Aragon and Nanda (2012). First, we relate the changes of standard deviations of hedge fund returns from the first to the second half-year to the fund performance in the middle of a year using the “absolute win” specification of Table 2 in Aragon and Nanda (2012). Fund performance is proxied by a dummy variable *AbsWin* taking a value of one, if the fund value is above the HWM. We then consider changes in return standard deviations from the second half of a year to the

first half of the following year, given the fund performance at the end of the first year. If the seasonality in risk taking is pronounced for funds reporting on a monthly basis, we expect to find a negative relation between performance and risk in the first specification, consistent with Aragon and Nanda (2012), but a positive relation in the second specification. We include other control variables following Aragon and Nanda (2012), together with time and style fixed effects. Table 13 reports the estimation results.

[Table 13 around here]

Indeed, the signs flip across the two specifications. The loading on the performance measure changes from negative ( $-2.35$ ) to positive ( $0.70$ ) and is highly significant. The product of the performance and the existence of a HWM flips the sign, too, and the existence of the HWM changes its sign from negative to positive.<sup>34</sup> Thus, although the lower frequency of data does not allow us to conduct a more detailed analysis of the intra-year variation in managerial risk taking, the results above indicate that the seasonality is generally also strongly pronounced in the sample of conventional hedge funds reporting on a monthly basis. The rotations between fund performance, HWM, and future changes in the risk taking change the signs depending on the time of a year the performance and risk are being measured.

## 7 Conclusion

A previously unexamined data set of daily hedge fund returns from Bloomberg allows us to construct time series of monthly risk estimates for individual hedge funds. Using a semi-parametric estimation approach, we can, thus, recover the complete structure of managerial risk taking across fund values and time of a year. The revealed risk taking is highly nonlinear and exhibits a strong seasonal pattern. At the beginning of a year, managers of poorly

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<sup>34</sup>We use a different time span and a different database from the original paper of Aragon and Nanda (2012), as well as returns in percent rather than in percentage points; we do not seek to exactly reproduce the numerical results of Aragon and Nanda (2012). Instead, we check if our results are qualitatively consistent with those of Aragon and Nanda (2012), that is, if we obtain the same signs of the significant regression coefficients.

performing funds decrease the risk. Towards the end of a year, on the contrary, managers of such funds increase the risk. The estimated average risk shifts are economically significant and range from a 14% decrease to a 20% increase relative to the expected risk levels.

Our key result is robust to various changes in the methodology and sample filtering. A more restrictive analysis based on monthly reporting funds confirms seasonality in the managerial response to incentives for conventionally used hedge fund databases, too.

The observed seasonal risk-taking pattern differs from the predictions of the existing theoretical models, none of which explicitly predicts seasonality. It further confirms the importance of indirect managerial incentives. At the beginning of a year, poorly performing funds focus more on fund liquidation probability. Towards the end of a year, the fund flow performance sensitivity increases, shifting the focus towards return generation and leading to excessive risk taking of underperforming funds, regardless of their actual fee structure.

Another take away is that hedge fund risk cannot be manipulated as rapidly as assumed by the theoretical models. Even in the sample of very liquid hedge funds used in this paper, we find that the risk levels are highly persistent. In order to achieve a desired level of risk by the end of a quarter, managers act early and start risk adjustment at the beginning of the respective quarter. Also, the core investment strategies seem to be easily scalable downwards, but not upwards. The risk increases are achieved by a disproportional increase in the market risk.

Our paper suggests several avenues for future research. First and foremost, the reasons underlying seasonality in the flow-performance sensitivity should be investigated. This would complement our results on seasonality in the managerial response to poor performance, as well as findings on other types of seasonal variations in hedge funds' reported returns, such as December return spikes (Agarwal et al. 2011), quarter-end stock price manipulations (Ben-David et al. 2013), and within-month risk-factor exposure variation (Patton and Ramadorai 2013).

Another question is related to the observed investors' dilemma. On the one hand, in-

vestors direct capital into funds, delivering the desired risk-return profile. On the other hand, flows induce risk changes, ranging from a reduction of the core exposure to pumping up funds with market risks, which alter the targeted profile. This adds another aspect to the lasting problem of the optimal alignment of managerial actions to the interests of investors. It points towards a solution beyond the mere adjustment of the compensation scheme, and calls for the control over the indirect flow-related incentives.

From the investors' point of view, another highly relevant question is in which situations additional risk or a risk reduction is or is not desirable. This hinges on the more general question about optimal leverage and the resulting risk-return pattern for levered funds from an investors perspective.

Our findings also contribute to an ongoing discussion on mandatory reporting and disclosure rules for hedge funds, which may provide pure "reporting incentives" to fund managers. Reporting better figures to clients at a year-end may lead to an improvement of managerial reputation, which in turn could, for example, make the launching of subsequent funds easier. Such scheduled reporting, although seeking to achieve transparency, might induce (unwanted) changes in the investment behavior of fund managers.

Generally, investors and creditors should all be aware of the dynamic managerial risk taking and assess the implications of this operational risk for their portfolios, standard compensation practices, credit risk, and optimal timing of redemptions. Regulators might also be interested in monitoring situations, in which a large fraction of hedge funds slides into an area of the state space that induces high risk taking, as this can result in systemic concern, especially during bad years.



# Appendix

## A Controlling for Possible Multiple Share Classes

Hedge fund investment companies often control more than one hedge fund (Kolokolova 2011). Such multiple funds can be either self-contained individual products or different share classes of the same fund. The sample used in the paper contains 195 unique investment companies: 85 of them control a single fund, 42 control two funds, and 68 control more than two funds. To identify potential multiple share classes of the same fund, for each pair of funds belonging to the same investment company we compute return correlations. The mean return correlation of such funds is 0.83, and it ranges from as low as almost -1 to as high as almost +1. We consider funds exhibiting pairwise return correlations higher than 98% and exclude one fund from each such pair with the shorter return history. In total, we exclude 207 hedge funds, and repeat the complete analysis based on the remaining sample. Results indicate no qualitative change to the main conclusion of the paper when the reduced sample is used.

## B Comparison of Risk Factor Loadings

We aggregate daily returns of the hedge funds in our sample to a monthly frequency and estimate the Fung and Hsieh (2004) seven factor model for each fund over its entire life. We repeat the estimation using a merged database of hedge funds reporting on a monthly basis. The database comprises five commercial databases (BarclayHedge, Eurekahedge, Morningstar, HFR, and TASS) over the same time period as the daily reporting hedge funds in our sample. Table 14 reports the estimated mean factor loadings and their differences across two data sources. Overall, the hedge funds reporting daily have significantly smaller average alphas, which are also often negative. Emerging markets and managed futures are the two styles that exhibit the most pronounced difference in their risk profile, with most of the loadings being statistically significantly different across the data bases. Other styles have

more comparable average factor loadings, which are often not significantly different across the two data sets.

[Table 14 around here]

## C Alternative Risk Measures

We consider two different measures for hedge funds risk. Instead of RISK (the natural logarithm of the intra-month standard deviation of daily hedge fund returns), we first use the natural logarithm of the intra-month left semi-standard deviation of daily returns, which takes only negative deviations from the mean into account. Second, we use the 10% Value-at-Risk ( $VaR_{10\%}$ ) computed for each month.

The results for the semi-standard deviation remain virtually unchanged as compared to the overall return standard deviation.

The results for the linear part of the panel regression for  $VaR_{10\%}$  also remain similar to our main results.  $VaR_{10\%}$  is persistent, with all three lags of the variable being positively and highly significantly related to its current value. The kernel regression results (as well as the piecewise linear results) become much noisier. The reason is that we use a rather imprecise sample  $VaR$  estimate. The number of observations per month ranges from 15 to 22, and thus,  $VaR_{10\%}$  corresponds to the second lowest return earned during a given month. Nevertheless, we still observe a significant risk increase in the last quarter of a year and a significant risk decline during the second quarter.

Throughout the paper, we analyze the absolute level of hedge fund risk. We also show that the cross-sectional average hedge fund risk is highly correlated with market risk. Time fixed effects in our panel regressions are supposed to control for all period-specific effects, including market risk. We repeat the analysis using a relative specification of hedge fund risk with respect to market risk. For each month, we calculate the ratio of the intra-month standard deviation of fund returns over the intra-month standard deviation of the returns

on the MSCI World Index, and then take the natural logarithm thereof:

$$RISK_{i,t}^M = \ln \left( \frac{STD_{i,t}}{STD(Market)_t} \right). \quad (9)$$

The results remain virtually unchanged as compared to the main results in Table 4, which indicates that the time dummies fully capture the impact of changing market risk over time.

## D Alternative Specifications of the High-water Mark

In the main specification, the HWM is set to 1 at hedge fund origination. It then increases to the highest net asset value achieved by the end of December each year. This type of HWM corresponds to investors that initially joined the fund. However, if investors purchase fund shares later on, they can have different HWMs. Therefore, we employ several other procedures to estimate a HWM, which attempt to capture the average HWM for money invested in the fund at different times. Similar to the main specification, we reset the HWM every January to the highest value of the cumulative return achieved during the previous years. However, instead of considering the complete return history of a fund since inception, we use only the two or three preceding years. To make sure the intra-year variations found for managerial risk taking are not influenced by the end-of-year resetting of the HWM, we also consider resetting the HWM every month to the highest cumulative return earned since inception, as well as over the last two and three years. The results remain virtually unchanged compared to our main specification for fund values below the HWM.<sup>35</sup>

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<sup>35</sup>When resetting the HWM at monthly frequency we lack observations with fund values above the HWM and we can consider only the results below the HWM.

## E Piecewise Continuous Linear Specification for Managerial Risk Taking

We re-estimate a piecewise linear specification of the model given in Equation (4) of the main paper, but this time we require that the resulting regression line is piecewise continuous. We impose continuity restrictions at the breakpoints, and obtain the following regression for each quarter of a year:

$$\hat{e}_{i,t} = \kappa + \delta_{low} Value_{i,t-} + \delta_{mid}(Value_{i,t-} - \bar{V})^+ + \delta_{high}(Value_{i,t-} - 1)^+ + \eta_{i,t} . \quad (10)$$

Figure 6 depicts the resulting regression lines, where we set insignificant regression coefficients to zero. The results support the main findings from the kernel regression and the unrestricted version of the piecewise linear specification. We see a risk decline for poorly performing funds during the second quarter and a risk increase during the fourth quarter of a year.

[Figure 6 around here]

## F Hedge Fund Style

This section analyzes variations in the seasonal risk-taking pattern with respect to fund style. We augment Equation (8) of the main paper and use dummy variables for each of the reported styles, one at a time. As the data requirements are substantial (we need to make sure that in each quarter for each fund value band we have enough observations in each style) we are not able to single out all the reported styles. We are able to estimate the regression for the three largest styles: directional equity, equity market neutral, and managed futures. All these styles belong to the capacity unconstrained hedge fund styles (Ding et al. 2009).

Whenever one of those styles is singled out, the average risk-shifting pattern among all other funds constitutes the reference case. Table 15 reports the results.

[Table 15 around here]

There are statistically significant differences among hedge funds reporting different styles. Managers of poorly performing equity market neutral funds are somewhat less disposed to increase risk during the fourth quarter of a year (with the loading of  $-0.07$  significant at the 5% level). This finding is consistent with our result that the risk increase at the end of a year is disproportionably driven by increase in market risk. Those funds that try to preserve their market neutrality even when performing poorly, do not increase the risk to the same extent as their peers that simply take more market risk. Managed Futures funds have a stronger risk reduction in the second quarter in case of poor performance. The corresponding loading of  $-0.08$  is significant at the 1% level. All the differences in the magnitude of risk-shifting across different hedge fund styles, however, cannot drive away the main seasonal pattern of risk taking.

## **G Excluding the Crisis Period**

The first signs of financial turmoil appeared in July 2007, a year before the collapse of Lehman Brothers. The TED spread (the spread between three-month LIBOR and three-month T-bill rates) spiked up and one month later both the U.S. Federal Reserve and the European Central Bank injected some 90bn USD into financial markets. We exclude observations from July 2007 onwards from the sample and repeat the analysis.

The results from the linear part of the regression are consistent with those reported in Table 4, with the minor difference that the third lag of the dependent variable is no longer significant, albeit still positive. When we exclude the observations from the crisis period, a much lower fraction of fund-month observations lie in the low fund value region. During the complete sample period, about 7% of all sample observations are in the area of fund

values between 0.4 and 0.8, whereas when the crisis period is excluded, this share drops to below 2%. The total number of remaining observations in this area is then clearly too low to obtain meaningful kernel regression results. Therefore, we use the piecewise linear specification for the value variable in the form of Equation (4) of the main paper, and find a significant risk decline for low fund values relative to the HWM at the beginning of a year, and a significant risk increase towards the end of a year. The risk decline is shifted forward and is now pronounced during the first quarter of a year, whereas the risk increase is still strongly pronounced only during the fourth quarter.

## H Linear Specification for the Fund Value Relative to the High-water Mark

Our main analysis differs from earlier empirical research with respect to data and methodology. In this section, we use a linear specification of the relation between fund value relative to the HWM and risk. This allows us to directly compare our findings to those of earlier papers and analyze the drivers of differential results.

We modify Equation (1) of the main paper to include a linear specification for the relation between fund value and the managerial risk taking to the following form:

$$\begin{aligned}
 RISK_{i,t} &= \alpha_i + \alpha_t + \sum_{j=1}^3 \beta_j RISK_{i,t-j} + \theta_1 DeltaCorr_{i,t} + \theta_2 \ln(AuM_{i,t-}) \\
 &+ \theta_3 OutflowLarge_{i,t-1} + \kappa Value_{i,t-} + \varepsilon_{i,t} .
 \end{aligned} \tag{11}$$

The estimation results reported in Column (I) of Table 16 show that on average, across all fund values and time, we find a negative relation between fund profitability and risk taking. This finding is consistent with the research that uses a linear statistical identification (e.g., Aragon and Nanda 2012). The loading on  $Value_{i,t-}$  of  $-0.19$  is significant at the 1% level.

The other estimated parameters remain largely unchanged as compared to our main results in Table 4.

[Table 16 around here]

When we run the linear regression in Equation (11) for the non-crisis period only, the coefficient estimate for the value variable becomes insignificant, while the truly nonlinear managerial risk taking is still present (Appendix G). This means that besides hiding the truly nonlinear nature of the managerial risk taking, a linear specification can fail to identify managerial risk taking altogether, which could explain the insignificant results in some earlier papers (e.g., Brown et al. 2001, Agarwal et al. 2002). This problem seems to be more pronounced for samples that lack a significant fraction of poorly performing funds, that is, sample periods that are characterized by bullish markets.

We then include the relative fund performance with respect to peers into the regression. Similar to our previous findings, both the fund value relative to the HWM and the short-term performance relative to the industry are negatively related to fund risk. The coefficients of  $-0.17$  and  $-0.19$  are significant at the 1% and 10% levels, respectively (Column (II), Table 16).

We now analyze the impact of hedge fund fixed characteristics, such as fees, size, and notice period prior to redemption. We re-estimate the panel regression specified in Equation (11) and include interaction terms between the fund value variable and (1) a dummy for the use of a HWM; (2) a dummy for the incentive fee being above the median; (3) a dummy for the management fee being above the median; and (4) a dummy for the notice period being above the median. The results are reported in Table 17.

[Table 17 around here]

Consistent with Aragon and Nanda (2012), in this specification, the existence of the HWM mitigates the risk-shifting incentives of hedge fund managers (Column (I) of Table

17). The corresponding loading on the interaction term is positive (+0.15) and is significant at the 10% level. Similarly, high management fees mitigate the impact of fund value, with the associated loading of +0.17 being significant at the 5% level (Column (III)). High incentive fees and long notice periods, by contrast, amplify the effect of the fund value, with estimated coefficients of  $-0.48$  and  $-0.20$ , which are significant at the 10% and 5% levels, respectively (Columns (II) and (IV)).

Overall, our results are consistent with earlier empirical research. This shows that the funds in our sample, with respect to risk taking, behave like funds that report on a monthly basis to more widely used databases. At the same time, using the linear specification does not allow the capture of truly nonlinear risk taking and seasonality in the impact of various fixed hedge fund characteristics. The interpretation of the economic mechanism of risk shifting might be misleading if the true seasonality is not taken into account.

## **I Alternative Model Specifications for Systematic Risk**

In Section 5.4, we fit a Carhart (1997) four factor model to the daily return of hedge funds in our sample, allowing the loadings to vary each quarter. Now, we repeat the analysis allowing the loadings to change every month. We next use the Fung and Hsieh (2004) model instead of the Carhart (1997) model. As the trend-following factors are available only on monthly frequency, we follow Patton and Ramadorai (2013) and use the first four factors of the model only. Both models provide a comparable fit to the data in terms of adjusted R-square. The Carhart (1997) model fits equity-related styles better: the mean adjusted R-squares for equity directional, equity market neutral, and emerging markets styles are 0.26, 0.12, and 0.13, compared to 0.24, 0.08, and 0.10 for the reduced Fung and Hsieh (2004) model. The latter model provides, however, a better fit for fixed income funds, with the adjusted R-square being 0.11, compared to 0.05 of the Carhart (1997) model. Table 18 reports the estimation results of the piecewise linear specification based on fitted return



values (Panels A1 and B1) and residuals (Panels A2 and B2) of the two models. Overall, similar to the previously discussed results, we find seasonality in RISK of both fitted values and residuals, with the RISK increase at the end of the year being significantly stronger in fitted values than in residuals.

[Table 18 around here]

## J Scalability of the Investment Strategy

The overall portfolio risk can be changed by loading more or less on the core investment strategy while keeping it unchanged, by changing the core investment strategy (e.g., using riskier assets), or by a combination of the two. For many funds, the first option may seem preferable as it does not require additional research into new core assets. However, not all funds are equally able to scale their core strategy (e.g., through leverage). It is likely to be easier, for example, for funds with long only equity positions as compared to event-driven funds that bet on special corporate events. We expect that a risk increase towards year-end should be more pronounced for funds that can easily scale their strategy. As we do not observe the exact portfolio composition of hedge funds, we compute correlations between their reported returns and the market (proxied by the MSCI World Index). Funds exhibiting a higher correlation with the market are likely to follow more “conventional” strategies, which can be easier to scale. We thus expect that below the HWM, hedge funds with a higher return correlation with the market will exhibit a stronger risk increase at the end of a year.

We estimate Equation (8) of the main paper using an indicator variable taking a value of 1 if the fund’s returns have higher than median correlation with the market returns. The results reported in Table 19 suggest that such hedge funds do indeed exhibit a stronger risk increase during the last quarter of a year. The corresponding coefficient of +0.05 is significant at the 5% level. Interestingly, the risk shifting during the third quarter is reduced

by the same magnitude. Those funds that can easily level up their risk do not need to adjust it early. Instead, they can scale the risk up right when they need it – at the end of a year.

[Table 19 around here]

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Table 1: Descriptive statistics for the hedge fund sample

	EUR			USD		
	All	Live	Dead	All	Live	Dead
Panel A: Sample						
Funds	400	285	115	314	178	136
Monthly STD obs.	14,728	10,951	3,777	10,073	5,962	4,111
Mean life time	3.35	3.38	3.26	2.90	2.92	2.88
Median management fee (%)	1.5	1.5	1.5	1.5	1.5	1.3
Have incentive fee	284	209	75	222	131	91
Median incentive fee (%)	20	20	20	20	20	20
Have HWM	234	175	59	201	112	89
Mean notice period (days)	24	19	38	15	15	14
UCITS & SICAV	90	81	9	131	73	58
Report AuM	371	278	93	164	105	59
Monthly AuM obs.	8,544	7,063	1,481	3,370	2,184	1,186
Mean AuM (mil. USD)	369.52	431.73	150.56	103.70	135.11	43.80
Panel B: Daily returns						
Mean	0.01	0.02	-0.01	0.01	0.03	-0.01
Median	0.02	0.02	0.01	0.03	0.04	0.01
Min.	-77.69	-77.69	-32.18	-50.12	-50.12	-45.51
Max.	43.32	43.32	26.21	76.24	45.80	76.24
STD	0.56	0.58	0.50	0.89	0.76	1.06
Skewness	-0.39	-0.25	-0.75	-0.25	-0.28	-0.20
Kurtosis	23.01	19.37	32.02	26.01	18.24	36.17
Sharpe ratio	0.02	0.04	-0.03	0.02	0.04	-0.01
Panel C: Monthly returns						
Mean	0.23	0.40	-0.22	0.21	0.55	-0.24
Median	0.24	0.34	0.11	0.39	0.54	0.23
Min.	-77.85	-77.85	-40.34	-66.28	-50.53	-66.28
Max.	57.80	40.90	57.80	94.83	94.83	55.54
STD	2.39	2.49	2.16	3.67	3.34	4.09
Skewness	-0.43	-0.36	-0.62	-0.31	-0.23	-0.41
Kurtosis	4.77	4.61	5.15	4.36	4.00	4.84
Sharpe ratio	0.06	0.16	-0.19	0.07	0.17	-0.06

Panel A reports the general characteristics of the hedge funds in our sample, including the average fund size, lifetime in years, usage of a HWM, an incentive fee, etc. SICAV and UCITS are types of an open-ended collective investment vehicle operating in Western Europe. UCITS directives allow investment funds to freely operate across the borders in the European Union, being authorized in only a single member state. Panels B and C report the descriptive statistics of daily and monthly hedge fund returns in percent per day and month, respectively.

Table 2: Descriptive statistics for hedge fund risk

	EUR			USD		
	All	Live	Dead	All	Live	Dead
Mean	0.47	0.50	0.42	0.74	0.67	0.83
Median	0.42	0.44	0.35	0.63	0.59	0.67
Min.	0.19	0.21	0.15	0.31	0.32	0.29
Max.	1.39	1.45	1.24	2.15	1.68	2.75
STD	0.25	0.26	0.25	0.42	0.30	0.58

The table reports descriptive statistics of hedge fund risk. Hedge fund risk is estimated on a monthly basis as the intra-month standard deviation of daily returns. The underlying daily returns are measured in percent per day.

Table 3: Descriptive statistics across hedge fund styles

	Funds	Mean	Median	Min	Max	STD
Panel A: Daily returns						
Eq Directional	168	0.03	0.03	-16.94	26.84	1.03
Eq Mkt Neutral	120	0.01	0.01	-50.12	76.24	1.16
Emerg Mkt	30	0.03	0.03	-18.51	14.11	0.90
Event Driven	34	0.02	0.02	-45.51	11.12	0.63
Fixed Income	68	0.01	0.01	-42.22	45.80	0.46
Global Macro	76	0.01	0.01	-14.38	17.60	0.86
Mgd Futures	125	0.02	0.02	-77.69	43.32	1.52
Multi Strat	76	0.00	0.01	-34.33	20.71	0.73
Not Defined	17	-0.01	0.01	-16.24	18.54	1.01
Panel B: Monthly returns						
Eq Directional	168	0.64	0.46	-35.76	30.40	4.33
Eq Mkt Neutral	120	0.06	0.14	-66.28	55.54	4.01
Emerg Mkt	30	0.69	0.42	-34.79	28.78	4.21
Event Driven	34	0.39	0.50	-44.77	14.71	3.09
Fixed Income	68	0.25	0.26	-41.99	94.83	2.62
Global Macro	76	0.28	0.32	-32.20	25.38	3.84
Mgd Futures	125	0.30	0.28	-77.85	57.80	5.77
Multi Strat	76	0.09	0.24	-37.95	26.84	3.27
Not Defined	17	-0.10	0.17	-45.48	14.69	5.24

The table reports the descriptive statistics of hedge fund returns separately for different hedge fund styles. Funds are classified in one of eight style groups according to the investment strategy reported to Bloomberg. The last group contains hedge funds for which no strategy classification is provided. Panel A is based on daily hedge fund returns, and Panel B is based on monthly returns. Returns are expressed in percent per day and month, respectively.



Table 4: Panel regressions of hedge fund risk

	(I)	(II)
$RISK_{t-1}$	+0.50 *** (+53.07)	+0.50 *** (+50.76)
$RISK_{t-2}$	+0.09 *** (+8.74)	+0.10 *** (+9.01)
$RISK_{t-3}$	+0.07 *** (+7.19)	+0.07 *** (+7.20)
$DeltaCorr_t$	+0.03 ** (+2.13)	+0.03 ** (+2.10)
$\ln(AuM_{t-})$	-0.01 (-1.36)	-0.01 (-1.28)
$OutflowLarge_{t-1}$	+0.03 *** (+2.59)	+0.03 *** (+2.59)
$ExcessPerf_{t-1}$		-0.27 *** (-2.80)
R-sqr.	0.90	0.90
Rbar-sqr.	0.89	0.89
Nobs	10,141	10,141

The table reports estimation results for panel regressions of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) on a set of dynamic explanatory variables and controls. The regressions include fund and time fixed effects. The regressions and the included variables are described in Section 4. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 5: Piecewise regressions of residual hedge fund risk

	Q1		Q2		Q3		Q4	
$\kappa_{low}$	-0.02	(-0.58)	+0.01	(+0.22)	+0.04	(+1.05)	-0.05	(-0.77)
$\delta_{low}$	+0.13	(+1.27)	+0.07	(+0.69)	+0.00	(+0.02)	+0.31 **	(+2.04)
$\kappa_{mid}$	+0.01	(+0.09)	-0.45 ***	(-3.68)	+0.20 *	(+1.72)	+0.48 ***	(+3.87)
$\delta_{mid}$	-0.03	(-0.29)	+0.49 ***	(+3.71)	-0.21 *	(-1.67)	-0.50 ***	(-3.74)
$\kappa_{high}$	-0.52	(-1.46)	+0.32	(+1.29)	+0.32	(+1.23)	-0.00	(-0.03)
$\delta_{high}$	+0.53	(+1.52)	-0.31	(-1.31)	-0.31	(-1.26)	-0.01	(-0.08)

The table reports estimation results for piecewise linear regressions of residual fund RISK as discussed in Section 4.  $\kappa$ -s correspond to the constant terms, and  $\delta$ -s are the slope coefficients for  $Value_{t-}$ . The subscripts *low*, *mid*, and *high* capture fund values below 0.6, between 0.6 and 1, and above 1, respectively. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 6: Intra-year variation in flow-performance sensitivity: sub-periods

	$Ret_{t-1}$		$Value_{t-1}$	
Panel A: January to June				
$a$	+0.04 **	(+2.11)	+0.04 *	(+1.83)
$b$	+0.01	(+0.22)	+0.00	(+0.05)
$\ln STD_{t-1}$	+0.01 ***	(+4.10)	+0.01 ***	(+4.00)
$\ln STDSP500_{t-1}$	-0.00	(-1.08)	-0.00	(-1.07)
$Age_{t-}$	-0.00 ***	(-7.47)	-0.00 ***	(-7.20)
$\ln AuM_{t-}$	-0.00	(-0.32)	-0.00	(-0.32)
$HWM$	-0.00	(-0.69)	-0.00	(-0.70)
$MgtFee$	+0.01 **	(+2.40)	+0.01 **	(+2.38)
$IncFee$	-0.00	(-1.47)	-0.00	(-1.46)
$Redemption$	-0.00	(-0.40)	-0.00	(-0.39)
$StyleFlow_t$	+0.90 ***	(+38.94)	+0.90 ***	(+38.94)
$MSCIRet_{t-1}$	+0.01	(+0.26)	+0.01	(+0.31)
R-sqr.	0.23		0.23	
Rbar-sqr.	0.23		0.23	
Nobs	6,047		6,047	
Panel B: July to December				
$a$	+0.07 ***	(+2.72)	+0.04	(+1.41)
$b$	+0.09 *	(+1.83)	+0.05 ***	(+3.24)
$\ln STD_{t-1}$	+0.00 **	(+2.43)	+0.01 ***	(+2.99)
$\ln STDSP500_{t-1}$	-0.00	(-0.22)	+0.00	(+0.16)
$Age_{t-}$	-0.01 ***	(-9.75)	-0.01 ***	(-8.72)
$\ln AuM_{t-}$	-0.01 ***	(-5.26)	-0.01 ***	(-5.51)
$HWM$	-0.01 *	(-1.81)	-0.01 *	(-1.81)
$MgtFee$	+0.00	(+0.17)	+0.00	(+0.51)
$IncFee$	-0.00	(-0.04)	-0.00	(-0.19)
$Redemption$	+0.00	(+0.16)	+0.00	(+0.57)
$StyleFlow_t$	+0.87 ***	(+34.19)	+0.87 ***	(+34.23)
$MSCIRet_{t-1}$	+0.01	(+0.14)	+0.04	(+0.72)
R-sqr.	0.21		0.21	
Rbar-sqr.	0.20		0.21	
Nobs	5,586		5,586	

The table reports estimation results for pooled panel regressions of monthly percentage fund flow onto fund performance and a set of controls. In the first column, performance is measured as past month return in percent ( $Ret_{t-1}$ ). In the second column, performance is measured as fund values relative to the HWM at the end of the previous month ( $Value_{t-1}$ ). Panel A reports the results based on months January to June, and Panel B is based on months July to December.  $a$  is a constant term in the regression, and  $b$  is the slope coefficient on previous month performance as in Equation (6). The t-statistics are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 7: Intra-year variation in flow-performance sensitivity: Joint specification

	$Ret_{t-1}$		$Value_{t-1}$	
$a_0$	+0.05 ***	(+3.52)	+0.06 ***	(+3.00)
$a_1$	-0.00	(-0.39)	-0.05 **	(-2.45)
$b_0$	+0.02	(+0.37)	+0.00	(+0.14)
$b_1$	+0.07	(+1.03)	+0.05 **	(+2.40)
$\ln STD_{t-1}$	+0.01 ***	(+4.64)	+0.01 ***	(+5.02)
$\ln STDSP500_{t-1}$	-0.00	(-0.99)	-0.00	(-0.83)
$Age_{t-}$	-0.01 ***	(-12.23)	-0.01 ***	(-11.30)
$\ln AuM_{t-}$	-0.00 ***	(-3.93)	-0.00 ***	(-4.11)
$HWM$	-0.01 *	(-1.79)	-0.01 *	(-1.79)
$MgtFee$	+0.00 *	(+1.85)	+0.00 **	(+2.06)
$IncFee$	-0.00	(-1.05)	-0.00	(-1.17)
$Redemption$	-0.00	(-0.21)	+0.00	(+0.09)
$StyleFlow_t$	+0.89 ***	(+51.96)	+0.89 ***	(+52.03)
$MSCIRet_{t-1}$	+0.01	(+0.18)	+0.02	(+0.55)
R-sqr.	0.22		0.22	
Rbar-sqr.	0.21		0.22	
Nobs	11,633		11,633	

The table reports estimation results for pooled panel regressions of monthly percentage fund flow onto fund performance and a set of controls. In the first column, performance is measured as past month return in percent ( $Ret_{t-1}$ ). In the second column, performance is measured as fund values relative to the HWM at the end of the previous month ( $Value_{t-1}$ ).  $a_0$  states for the constant in the regression,  $a_1$  indicates the loading on the dummy for the second half-year.  $b_0$  and  $b_1$  are the slope coefficients on the previous month performance measure and its interaction with the second year-half dummy respectively, as in Equation (7). The t-statistics are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 8: Risk taking in capacity constrained and unconstrained hedge funds

	Q1		Q2		Q3		Q4	
Panel A: Capacity constrained hedge funds								
$\kappa_{mid}$	+0.65	(+1.51)	+0.94 *	(+1.69)	-1.08 *	(-1.69)	+0.65	(+1.29)
$\delta_{mid}$	-0.75 *	(-1.65)	-0.93	(-1.60)	+1.01	(+1.52)	-0.67	(-1.25)
Panel B: Capacity unconstrained hedge funds								
$\kappa_{mid}$	-0.07	(-0.65)	-0.56 ***	(-4.59)	+0.18 *	(+1.67)	+0.47 ***	(+3.75)
$\delta_{mid}$	+0.06	(+0.53)	+0.60 ***	(+4.55)	-0.17	(-1.41)	-0.50 ***	(-3.63)

The table reports estimation results for piecewise linear regressions of residual fund RISK.  $\kappa$ -s stand for the constant terms,  $\delta$ -s are slope coefficients on  $Value_{t-}$ . The subscript *mid* captures fund values between 0.6 and 1, as specified in Equation (4). Panel A is based on hedge funds following capacity constrained styles. Panel B is based on capacity unconstrained funds. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 9: Risk taking across different investment opportunities regimes

	Q1	Q2	Q3	Q4
Panel A: Years with low investment opportunities				
$\kappa_{mid}$	-0.19 (-1.31)	-0.59 *** (-3.30)	+0.27 * (+1.82)	+0.51 *** (+3.40)
$\delta_{mid}$	+0.18 (+1.14)	+0.63 *** (+3.30)	-0.29 * (-1.81)	-0.54 *** (-3.26)
Panel B: Years with high investment opportunities				
$\kappa_{mid}$	+0.25 (+1.26)	-0.32 ** (-2.17)	+0.06 (+0.33)	+0.39 * (+1.80)
$\delta_{mid}$	-0.30 (-1.30)	+0.37 ** (+2.25)	-0.04 (-0.23)	-0.42 * (-1.77)

The table reports estimation results for piecewise linear regressions of residual fund RISK.  $\kappa$ -s stand for the constant terms,  $\delta$ -s are slope coefficients on  $Value_{t-}$ . The subscript *mid* captures fund values between 0.6 and 1, as specified in Equation (4). Panel A is based on years with low investment opportunities (MSCI World Index returns being below the median). Panel B is based on years with high investment opportunities (MSCI World Index returns above the median). The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 10: Determinants of residual hedge fund risk: management fee, notice period, performance, age

	Q1	Q2	Q3	Q4
Panel A: Management fee effect				
$\kappa_{mid}$	+0.02 (+0.15)	-0.40 *** (-3.19)	+0.21 * (+1.80)	+0.47 *** (+3.72)
$\gamma_{mid}$	-0.01 (-0.46)	-0.05 * (-1.88)	-0.02 (-0.72)	+0.03 (+1.16)
$\delta_{mid}$	-0.04 (-0.32)	+0.46 *** (+3.40)	-0.21 * (-1.72)	-0.50 *** (-3.69)
Panel B: Notice period effect				
$\kappa_{mid}$	-0.11 (-1.28)	-0.49 *** (-4.57)	+0.17 * (+1.66)	+0.44 *** (+3.83)
$\gamma_{mid}$	-0.01 (-0.54)	+0.13 *** (+3.87)	-0.03 (-1.02)	-0.00 (-0.08)
$\delta_{mid}$	+0.11 (+1.21)	+0.53 *** (+4.57)	-0.19 (-1.63)	-0.47 *** (-3.76)
Panel C: Recent performance effect				
$\kappa_{mid}$	-0.11 (-1.23)	-0.45 *** (-4.17)	+0.18 * (+1.67)	+0.44 *** (+3.88)
$\gamma_{mid}$	-0.02 (-0.93)	+0.06 *** (+2.84)	-0.03 (-1.53)	-0.02 (-0.67)
$\delta_{low}$	+0.11 (+1.20)	+0.47 *** (+4.06)	-0.18 (-1.57)	-0.46 *** (-3.70)
Panel D: Age effect				
$\kappa_{mid}$	+0.05 (+0.46)	-0.49 *** (-3.99)	+0.19 (+1.58)	+0.44 *** (+3.40)
$\gamma_{mid}$	-0.05 ** (-2.57)	+0.07 *** (+2.88)	+0.01 (+0.25)	+0.04 (+1.41)
$\delta_{low}$	-0.05 (-0.41)	+0.49 *** (+3.74)	-0.20 (-1.58)	-0.48 *** (-3.50)

The table reports estimation results for piecewise linear regressions of residual fund RISK.  $\kappa$  stands for the constant term,  $\delta$  is the slope coefficient on  $Value_{t-}$ . The subscript  $mid$  captures fund values between 0.6 and 1, as specified in Equation (8). In Panel A,  $\gamma$  is the estimate for the dummy, which indicates funds with higher than median management fee. In Panel B,  $\gamma$  indicates funds with higher than median notice period prior to redemption. In Panel C,  $\gamma$  captures funds with positive cumulative return over the preceding quarter. In Panel D it indicates funds older than the median fund at the beginning of a quarter, as specified in Equation (8). The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 11: Market vs. idiosyncratic risk taking

	Q1	Q2	Q3	Q4
Panel A: Incremental RISK of fitted returns				
$\kappa_{mid}$	-0.00 (-0.02)	-0.50 *** (-4.14)	+0.43 *** (+3.32)	+0.60 *** (+4.08)
$\delta_{mid}$	-0.00 (-0.04)	+0.54 *** (+4.13)	-0.46 *** (-3.30)	-0.66 *** (-4.09)
Panel B: Incremental RISK of residual returns				
$\kappa_{mid}$	+0.14 (+1.39)	-0.51 *** (-4.59)	+0.03 (+0.31)	+0.34 *** (+2.80)
$\delta_{mid}$	-0.16 (-1.52)	+0.56 *** (+4.65)	-0.02 (-0.20)	-0.36 *** (-2.70)

The table reports estimation results for piecewise linear regressions of residual fund RISK based on fitted returns from the Carhart (1997) regression (Panel A) and the corresponding residuals (Panel B).  $\kappa$  stands for the constant term,  $\delta$  is the slope coefficient on  $Value_{t-}$ . The subscript  $mid$  captures fund values between 0.6 and 1, as specified in Equation (4). The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.



Table 12: Determinants of residual hedge fund risk: HWM, incentive fees

	Q1		Q2		Q3		Q4	
	Panel A: HWM effect							
$\kappa_{mid}$	+0.01	(+0.09)	-0.44 ***	(-3.57)	+0.22 *	(+1.92)	+0.48 ***	(+3.85)
$\gamma_{mid}$	-0.00	(-0.01)	-0.01	(-0.62)	-0.04 *	(-1.91)	+0.01	(+0.52)
$\delta_{mid}$	-0.03	(-0.29)	+0.49 ***	(+3.70)	-0.21 *	(-1.67)	-0.51 ***	(-3.76)
	Panel B: Incentive fee effect							
$\kappa_{mid}$	-0.00	(-0.04)	-0.43 ***	(-3.41)	+0.22 *	(+1.86)	+0.46 ***	(+3.66)
$\gamma_{mid}$	+0.02	(+0.70)	-0.02	(-0.80)	-0.02	(-0.73)	+0.02	(+0.85)
$\delta_{mid}$	-0.03	(-0.26)	+0.48 ***	(+3.65)	-0.21 *	(-1.72)	-0.51 ***	(-3.73)

The table reports estimation results for piecewise linear regressions of residual fund RISK.  $\kappa$  stands for the constant term,  $\delta$  is the slope coefficient on  $Value_{t-}$ . The subscript  $mid$  captures fund values between 0.6 and 1. In Panel A,  $\gamma$  is the estimate of the dummy variable indicating funds that report having a HWM provision. In Panel B,  $\gamma$  indicates funds that report a non-zero incentive fee, as specified in Equation (8). The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 13: Performance - risk relation in monthly reporting funds

	(I)		(II)	
	$\Delta STD_{July}$		$\Delta STD_{January}$	
<i>AbsWin</i>	-2.35***	(-20.56)	0.70***	(8.29)
<i>AbsWin</i> · <i>HWM</i>	0.38***	(2.86)	-1.09***	(-11.28)
<i>STD</i> <sub><i>t</i>-1</sub>	-0.43***	(-164.35)	-0.29***	(-92.55)
<i>Flow</i>	-0.00	(-0.71)	-0.00	(-0.68)
<i>HWM</i>	-0.32**	(-2.32)	1.09***	(10.16)
$\Delta\rho$	0.17***	(8.48)	0.06***	(2.81)
Constant	3.22***	(19.64)	0.55***	(4.19)
R-sqr.	0.37		0.15	
Rbar-sqr.	0.37		0.15	
Nobs	70,135		68,402	

The table reports estimation results for linear panel regressions of changes in return standard deviation from the first to the second half of a year ( $\Delta STD_{July}$ ) and from the second half of a year to the first half of the following year ( $\Delta STD_{January}$ ). *AbsWin* is a dummy variable that takes a value of one, if the fund value is above the HWM at the middle or the end of the year (Columns (I) and (II) respectively). The control variables are chosen to match those used in Aragon and Nanda (2012). *Flow* is the percentage fund net flow during the second (Column (I)) or the first (Column (II)) half of the year.  $\Delta\rho$  is the change in the fund's monthly return serial correlation between the corresponding halves of the year.

Table 14: Factor loadings of daily and monthly reporting hedge funds

	<i>Alpha</i>	<i>Mrk - Rf</i>	<i>SMB</i>	<i>BOND</i>	<i>CREDIT</i>	<i>PTFSBD</i>	<i>PTFSFX</i>	<i>PTFSCOM</i>
EqDirec	Daily	+30.41	-3.54	+111.04	-135.49	-3.91	+3.05	-0.97
	Monthly	+36.24	-12.60	+153.94	-207.05	-1.12	+0.27	-0.31
	Diff	-0.64**	+9.06	-42.91	+71.56	-2.79**	+2.78*	-0.67
EqMktNeut	Daily	+14.42	+3.28	-39.42	-130.47	-0.95	-1.05	+0.06
	Monthly	+31.73	-9.72	+73.78	-255.79	-0.88	-0.12	+0.31
	Diff	-17.32***	+13.00	-113.20*	+125.31	-0.07	-0.92	-0.26
EmgMkt	Daily	+13.49	-17.35	+175.58	-187.10	-12.27	+8.24	-5.09
	Monthly	+46.30	+13.15	-27.34	-489.82	-0.46	-1.49	+0.23
	Diff	-1.49***	-30.49***	+202.92*	+302.71*	-11.81***	+9.74***	-5.32***
EvDriv	Daily	+28.95	-6.77	+102.28	-146.33	+0.36	-0.29	-2.23
	Monthly	+24.75	-5.82	+26.52	-311.09	-1.49	+0.54	-0.29
	Diff	-0.51**	+4.21	+75.76	+164.77	+1.85	-0.83	-1.94
FixedInc	Daily	+6.66	+2.54	+19.87	-87.58	-0.56	-0.59	-1.00
	Monthly	+10.51	+3.82	-62.22	-369.75	-1.42	-0.82	-0.67
	Diff	-3.86	-1.28	+82.09	+282.16**	+0.86	+0.24	-0.33
GlobMac	Daily	+24.24	+8.95	+39.44	-216.20	-0.19	-2.88	+3.60
	Monthly	+13.92	+4.55	+53.12	-44.59	+1.21	+0.94	+3.41
	Diff	+10.32	+4.40	-13.68	-171.62	-1.41	-3.82*	+0.20
MgtFut	Daily	+48.16	+26.36	-514.80	-865.95	+7.85	-7.98	+14.70
	Monthly	+11.02	+1.84	+104.27	-30.23	+3.62	+0.72	+6.31
	Diff	+37.14***	+24.52***	-619.07**	-835.71***	+4.23	-8.70***	+8.40**
MultiStrat	Daily	+29.33	+6.24	-60.96	-15.79	-0.12	-2.62	+3.38
	Monthly	+13.18	+2.25	-0.49	-245.66	-1.11	+0.24	-0.80
	Diff	-1.05***	+16.15**	-60.47	+229.88	+1.00	-2.86*	+4.19**

The table reports the average loadings on the Fung and Hsieh (2004) seven factors across different hedge fund styles. The model is estimated based on monthly returns of the funds in our sample (initially reporting daily) as well as for funds reporting monthly to commercial databases as described in Section 3, between October 2001 and April 2011. The abbreviations stand for: EqDirec – directional equity; EqMktNeut – equity market neutral; EmgMkt – emerging markets; EvDriv – event driven; FixedInc – fixed income; GlobMac – global macro; MgtFut – managed futures; MultiStrat – multi strategy. *Alpha* is a constant term in the regression; *Mkr - Rf* is the excess return of the S&P500 index; *SMB* is the size factor, the difference between monthly total returns on the Russell 2000 and S&P500 indices; *BOND* is the bond factor, the monthly change in the 10-year Treasury constant maturity yield; *CREDIT* is the credit factor, the monthly change in the difference between the Moody's Baa yield and the 10-year Treasury constant maturity yield; *PTFSBD*, *PTFSFX*, and *PTFSCOM* are bond, currency, and commodity trend-following factors, respectively, as downloaded from the David A. Hsieh web page <https://faculty.fuqua.duke.edu/~dah7/HFData.htm>. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 15: Determinants of residual hedge fund risk: fund style

	Q1	Q2	Q3	Q4
Panel A: Directional equity				
$\kappa_{low}$	+0.01 (+0.09)	-0.45 *** (-3.68)	+0.16 (+1.41)	+0.46 *** (+3.69)
$\gamma_{low}$	-0.00 (-0.03)	-0.01 (-0.42)	+0.04 (+1.45)	+0.03 (+0.88)
$\delta_{low}$	-0.03 (-0.29)	+0.49 *** (+3.73)	-0.18 (-1.41)	-0.49 *** (-3.61)
Panel B: Equity market neutral				
$\kappa_{mid}$	+0.00 (+0.02)	-0.45 *** (-3.66)	+0.20 * (+1.72)	+0.48 *** (+3.90)
$\gamma_{mid}$	+0.02 (+0.80)	-0.01 (-0.31)	+0.02 (+0.95)	-0.07 ** (-2.51)
$\delta_{mid}$	-0.03 (-0.26)	+0.49 *** (+3.71)	-0.21 * (-1.73)	-0.48 *** (-3.58)
Panel C: Managed futures				
$\kappa_{mid}$	+0.01 (+0.09)	-0.38 *** (-3.03)	+0.19 (+1.61)	+0.45 *** (+3.57)
$\gamma_{mid}$	+0.00 (+0.01)	-0.08 *** (-2.80)	+0.01 (+0.48)	+0.04 (+1.27)
$\delta_{mid}$	-0.03 (-0.29)	+0.43 *** (+3.24)	-0.20 (-1.58)	-0.49 *** (-3.53)

The table reports estimation results for piecewise linear regressions of residual fund RISK.  $\kappa$  stands for the constant term,  $\delta$  is the slope coefficient on  $Value_{t-}$ . The subscript *mid* captures fund values between 0.6 and 1. In Panel A,  $\gamma$  is the estimate of the dummy variable indicating directional equity funds. In Panel B,  $\gamma$  indicates equity market neutral funds. In Panel C, it represents managed futures funds, as specified in Equation (8). The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 16: Panel regression of hedge fund risk with a linear specification for fund value

	(I)		(II)	
<i>RISK</i> <sub><i>t</i>-1</sub>	+0.50 ***	(+50.54)	+0.50 ***	(+51.85)
<i>RISK</i> <sub><i>t</i>-2</sub>	+0.09 ***	(+8.88)	+0.09 ***	(+9.14)
<i>RISK</i> <sub><i>t</i>-3</sub>	+0.07 ***	(+6.99)	+0.07 ***	(+7.27)
<i>DeltaCorr</i> <sub><i>t</i></sub>	+0.03 **	(+2.11)	+0.03 **	(+2.24)
<i>ln(AuM</i> <sub><i>t</i>-</sub> )	0.00	(-0.97)	0.00	(-1.01)
<i>OutflowLarge</i> <sub><i>t</i>-1</sub>	+0.02 **	(+2.18)	+0.02 **	(+2.13)
<i>Value</i> <sub><i>t</i>-</sub>	-0.19 ***	(-3.96)	-0.17 ***	(-3.36)
<i>ExcessPerf</i> <sub><i>t</i>-1</sub>			-0.19 *	(-1.92)
R-sqr.	0.90		0.90	
Rbar-sqr.	0.89		0.89	
Nobs	10,141		10,141	

The table reports estimation results for panel regressions of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) on the fund value relative to the HWM, a set of dynamic explanatory variables and controls. The regression includes fund and time fixed effects. Compared to the main panel regression in Equation (11), the fund value variable has a linear relation to managerial risk taking. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 17: Panel regressions of hedge fund risk with a linear specification for fund value and interaction terms

	(I)	(II)	(III)	(IV)
$RISK_{t-1}$	+0.50 *** (+50.62)	+0.50 *** (+49.01)	+0.50 *** (+47.81)	+0.50 *** (+49.86)
$RISK_{t-2}$	+0.09 *** (+8.87)	+0.09 *** (+8.67)	+0.09 *** (+8.90)	+0.09 *** (+9.22)
$RISK_{t-3}$	+0.07 *** (+7.07)	+0.07 *** (+7.08)	+0.07 *** (+7.30)	+0.07 *** (+7.12)
$DeltaCorr_t$	+0.03 ** (+2.02)	+0.03 ** (+2.16)	+0.03 ** (+2.15)	+0.03 ** (+2.11)
$\ln(AuM_{t-})$	0.00 (-0.94)	0.00 (-0.98)	0.00 (-0.91)	0.00 (-1.10)
$OutflowLARGE_{t-1}$	+0.02 ** (+2.27)	+0.02 ** (+2.13)	+0.02 ** (+2.10)	+0.02 ** (+2.28)
$Value_{t-}$	-0.28 *** (-4.08)	-0.18 *** (-3.86)	-0.27 *** (-4.21)	-0.12 ** (-2.16)
$Value_{t-} \times HWM$	+0.15 * (+1.73)			
$Value_{t-} \times IveFeeLarge$		-0.48 ** (-1.99)		
$Value_{t-} \times MntFeeLarge$			+0.17 ** (+2.00)	
$Value_{t-} \times NoticeLarge$				-0.20 ** (-2.23)
R-sqr.	0.90	0.90	0.90	0.90
Rbar-sqr.	0.89	0.89	0.89	0.89
Nobs	10,141	10,141	10,141	10,141

The table reports estimation results for panel regressions of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) on the fund value relative to the HWM, a set of dynamic explanatory variables and controls. The regressions include fund and time fixed effects. Additional interaction terms between the fund value variable and several fund characteristics are included. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 18: Market vs. idiosyncratic risk taking: alternative models

	Q1	Q2	Q3	Q4
Panel A1: Incremental RISK of fitted returns, Carhart (1997) model				
$\kappa_{mid}$	-0.08 (-0.56)	-0.46 *** (-2.67)	+0.33 ** (+2.17)	+0.80 *** (+4.71)
$\delta_{mid}$	+0.06 (+0.42)	+0.48 *** (+2.62)	-0.35 ** (-2.13)	-0.85 *** (-4.58)
Panel A2: Incremental RISK of residual returns, Carhart (1997) model				
$\kappa_{mid}$	+0.09 (+0.83)	-0.52 *** (-4.27)	+0.06 (+0.49)	+0.42 *** (+3.30)
$\delta_{mid}$	-0.12 (-0.95)	+0.59 *** (+4.44)	-0.05 (-0.36)	-0.45 *** (-3.23)
Panel B1: Incremental RISK of fitted returns, Fung and Hsieh (2004) model				
$\kappa_{mid}$	+0.18 (+1.10)	-0.84 *** (-5.14)	+0.21 (+1.34)	+0.55 *** (+2.83)
$\delta_{mid}$	-0.20 (-1.17)	+0.90 *** (+5.11)	-0.21 (-1.26)	-0.58 *** (-2.76)
Panel B2: Incremental RISK of residual returns, Fung and Hsieh (2004) model				
$\kappa_{mid}$	+0.13 (+1.01)	-0.35 *** (-2.70)	+0.12 (+0.96)	+0.29 * (+1.90)
$\delta_{mid}$	-0.15 (-1.08)	+0.38 *** (+2.76)	-0.11 (-0.78)	-0.32 * (-1.91)

The table reports estimation results for piecewise linear regressions of residual fund RISK based on fitted returns from the Carhart (1997) regression (Panel A1), the corresponding residuals (Panel A2), and fitted and residual returns from the reduced Fung and Hsieh (2004) regression (Panel B1 and B2) respectively.  $\kappa$  stands for the constant term,  $\delta$  is the slope coefficient on  $Value_{t-}$ . The subscript  $mid$  captures fund values between 0.6 and 1, as specified in Equation (4). The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.

Table 19: Determinants of residual hedge fund risk: market correlation

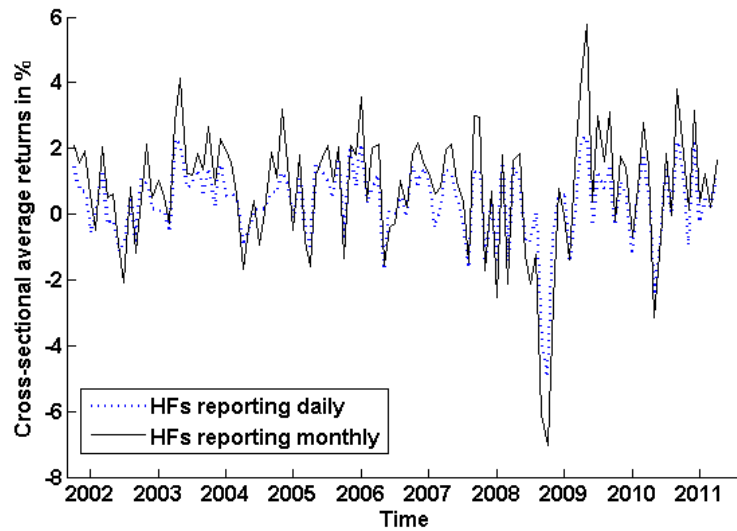
	Q1		Q2		Q3		Q4	
$\kappa_{mid}$	+0.05	(+0.44)	-0.41 ***	(-3.13)	+0.27 **	(+2.29)	+0.37 ***	(+2.79)
$\gamma_{mid}$	-0.02	(-1.12)	-0.02	(-0.92)	-0.05 ***	(-2.62)	+0.05 **	(+2.12)
$\delta_{mid}$	-0.06	(-0.55)	+0.46 ***	(+3.32)	-0.26 **	(-2.05)	-0.42 ***	(-2.95)

The table reports estimation results for piecewise linear regressions of residual fund RISK.  $\kappa$  stands for the constant term,  $\delta$  is the slope coefficient on  $Value_{t-}$ . The subscript  $mid$  captures fund values between 0.6 and 1.  $\gamma$  is the estimate of the dummy variables indicating funds that exhibit higher than median return correlation with the market (MSCI World Index), as specified in Equation (8). The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. \*\*\*, \*\*, and \* indicate significance at the 1%, 5%, and 10% level, respectively.



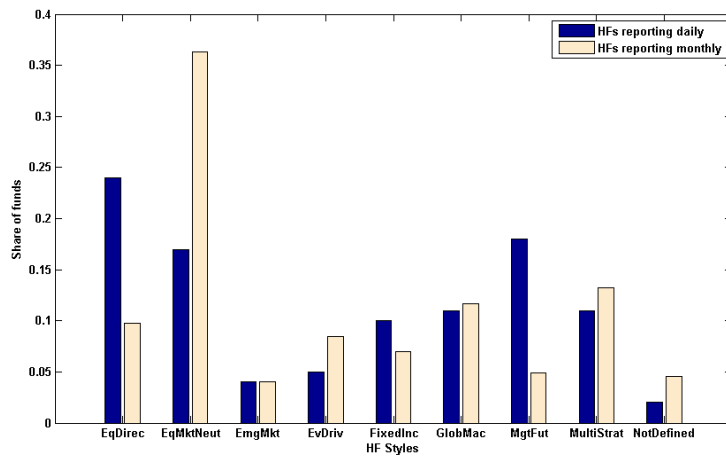
# Figures

Figure 1: Time series of average returns of daily and monthly reporting hedge funds



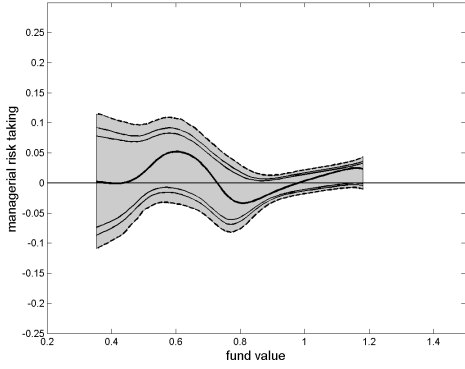
The figure presents the time series of cross-sectional average monthly returns from the funds in our sample (reporting daily to Bloomberg) as well as from funds reporting monthly to the commercial databases as defined in Section 3, between October 2001 and April 2011. The correlation between the two series is 93%.

Figure 2: Distribution of styles of daily and monthly reporting hedge funds

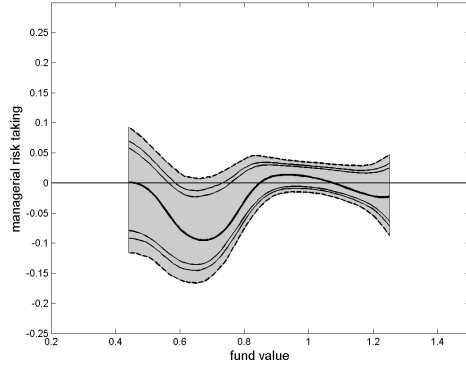


The figure presents the distributions of the reported styles for the funds in our sample (reporting daily) as well as for funds reporting monthly to commercial databases as described in Section 3, between October 2001 and April 2011. The abbreviations stand for: EqDirec – directional equity; EqMktNeut – equity market neutral; EmgMkt – emerging markets; EvDriv – event driven; FixedInc – fixed income; GlobMac – global macro; MgtFut – managed futures; MultiStrat – multi strategy; NotDefined – funds that do not clearly state their style or the style cannot be classified within any of the groups above (e.g, “tail risk”).

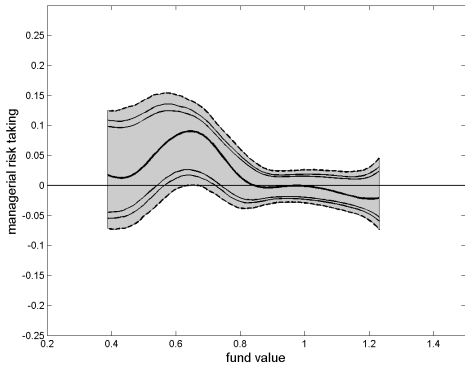
Figure 3: Managerial risk taking: quarter-wise



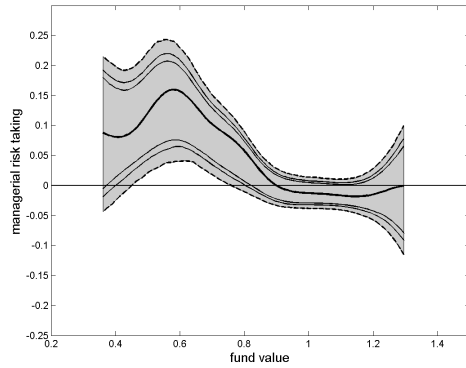
(a) Quarter 1



(b) Quarter 2



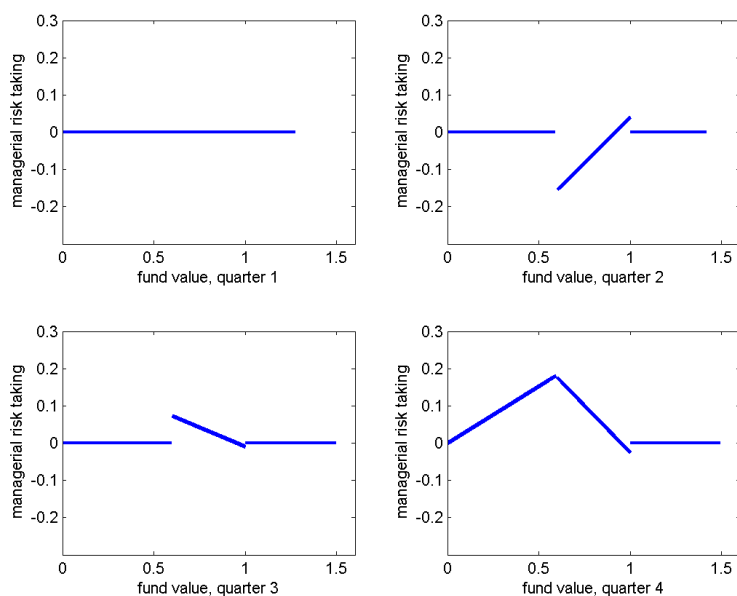
(c) Quarter 3



(d) Quarter 4

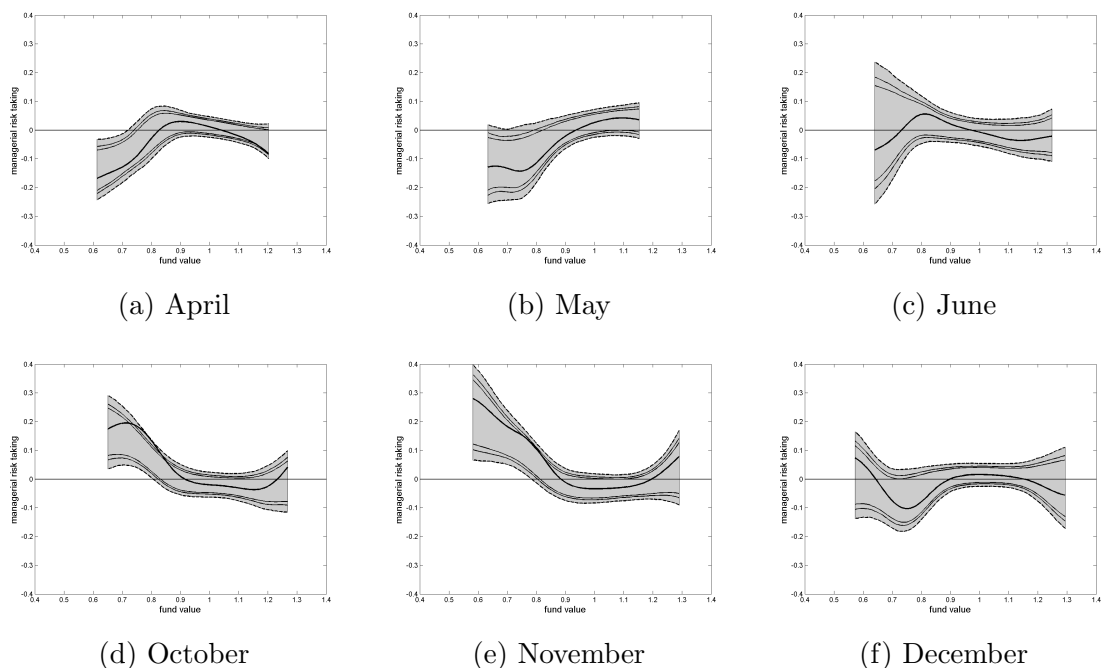
The figure plots the result of the kernel regression specified in Section 4 for the different quarters of a year. On the horizontal axis is the fund value relative to the HWM. On the vertical axis is the managerial risk taking contained in the residuals from a panel regression of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) on other factors explaining dynamic hedge fund risk. The shaded area around the regression line indicates the 1% confidence interval obtained from a bootstrap procedure. The 5% and 10% confidence bounds are given by the additional two lines. The regression uses a Gaussian kernel and a bandwidth of 0.07. The support is restricted to the closed interval on which each bandwidth window contains at least five observations.

Figure 4: Managerial risk taking: piecewise linear specification



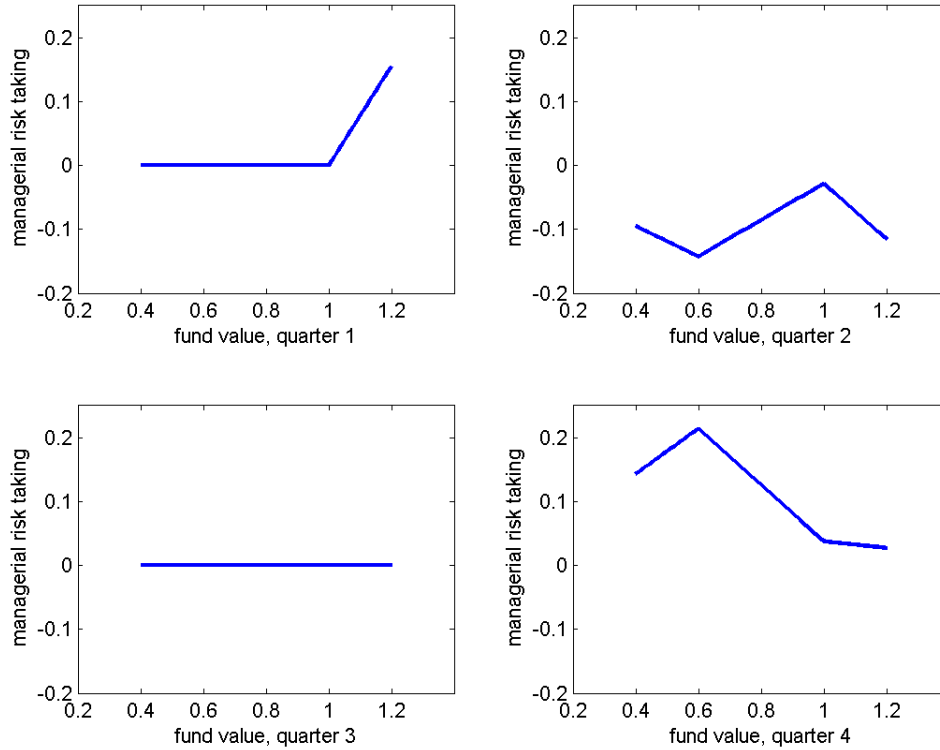
The figure plots the regression results for managerial risk taking on the fund value relative to the HWM as specified in the piecewise panel regression in Equation (4) for four quarters of a year. The linear relation between fund value relative to the HWM and RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) is allowed to vary for fund values below 0.6, between 0.6 and 1, and above 1 without any continuity restriction. On the horizontal axis is the fund value relative to the HWM. On the vertical axis is the managerial incremental risk taking as a function of the fund value. Insignificant regression coefficients are set to zero.

Figure 5: Managerial risk taking: month-wise



The figure plots the results of kernel regressions specified in Section 4 for each month in the second and the fourth quarter of a year. On the horizontal axis is the fund value relative to the HWM. On the vertical axis is the managerial risk taking contained in the residuals from a panel regression of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) on other factors explaining dynamic hedge fund risk. The shaded area around the regression line indicates the 1% confidence interval obtained from a bootstrap procedure. The 5% and 10% confidence bounds are given by the additional two lines. The regression uses a Gaussian kernel and a bandwidth of 0.07. The support is restricted to the closed interval on which each bandwidth window contains at least five observations.

Figure 6: Managerial risk taking: piecewise continuous linear specification



The figure plots the regression results for managerial risk taking on the fund value relative to the HWM as specified in the piecewise continuous panel regression in Equation (10) for four quarters of a year. The relation between fund value relative to the HWM and RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) is allowed to vary for fund values below 0.6, between 0.6 and 1, and above 1. Continuity is required at the breakpoints. On the horizontal axis is the fund value relative to the HWM. On the vertical axis is the managerial incremental risk taking as a function of the fund value. Insignificant regression coefficients are set to zero.