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

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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 sample of hedge fund daily returns from Bloomberg, we find a seasonal pattern in their risk taking. During earlier months of a year, poorly performing funds reduce 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, poorly performing funds gamble for resurrection by increasing risk. It is largely achieved by increasing exposure to market factors, and can be linked to stronger indirect managerial incentives during the second half of a year.

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.[1] 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

[1] 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).

(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. 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.[2] 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

[2] 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.

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 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.[3]

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.

[3]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.

2 Related literature and problem setting

Our paper is grounded in the extensive theoretical research on the optimal managerial response to incentives.[4] 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 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

[4] 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.

of a hedge fund manager.[5] 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.

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

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

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.[6]

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 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

[6]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.

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.[7] We do not find any evidence for a backfilling bias at any horizon in our sample of hedge funds. In particular, we cannot reject a hypothesis of mean equality between the returns of funds during the first half year, a year, and two years and the rest of the sample period. Hence, we do not delete initial return observations for the following analysis.[8]

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 differ-

[7] 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 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.

[8] Another potential issue is a kink in the return distribution around zero, which can be mechanically introduced by a subtraction of accrual incentive fees from the reported returns by well performing hedge funds (Jorion and Schwarz 2014). This, however, does not constitute a problem for our analysis. As will be shown later in the paper, the key results are associated with the regions of poor fund performance, which are not affected by accrual incentive fees.

ences 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. For example, 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%. 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. The median management fee of 1.5% and incentive fee of 20% of the funds in our sample are the same as those of funds reporting on a monthly basis. 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.[9] Funds in the two groups exhibit similar performance patterns. The correlation between average cross-sectional returns across these samples is 93%.[10] This suggests that the sample of daily reporting hedge funds, apart from containing generally less risky and less profitable funds, is comparable to the conventionally used hedge fund samples in terms of the average return dynamics and hedge fund characteristics.

[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,

[9] Our comparison group includes funds that report to five commercial databases: BarclayHedge, Eurekahedge, 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.

[10] 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%.

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. 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.[11]

[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

[11] As a robustness check, we repeat the analysis using a reduced sample from which potential multiple share classes of the same fund are excluded. The results remain virtually unchanged from those reported in the paper, and are discussed in Online Appendix available at the journal webpage https://financialreview.poole.ncsu.edu.

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 pronounced, despite some variation in the estimated factor loadings.[12]

4 Methodology

We measure hedge fund risk as the standard deviation of daily returns within one month.[13] 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:

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

where α_i and α_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 ($Value_{i,t_-}$). 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

[12] Detailed results are reported in Online Appendix.

[13] In Online Appendix we use alternative risk measures, including return left semi-standard deviation and Value-at-Risk. The key results hold for these measures, too.

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.[14] 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:

$$Value_{i,t_-} = \frac{\prod_{k=0}^{t-1} CR_{i,k}}{HWM_{i,t_-}}. \tag{2}$$

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_τ being the daily return of hedge fund i earned on day τ of month t.

The relation between fund value relative to the HWM and managerial risk taking is captured by a nonparametric function $f_k(Value_{i,t_-})$. 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.[15] 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 sample.[16] 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,

[14] Our results are robust to different specifications of the HWM. See Online Appendix for more details.

[15] 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.

[16] Partial autocorrelations capture the relation between the values at lag zero and higher-order lags in isolation of the lags in between.

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 $DeltaCorr_{i,t}$ to control for variations in the observed risk levels which arise from changes in serial correlations rather than from managerial risk shifting.[17] 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 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

[17] 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.

$$Flow_{i,t-1} = \frac{AuM_{i,t_-} - AuM_{i,t-1_-}CR_{i,t-1}}{AuM_{i,t-1_-}} \ , \tag{3}$$

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:

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

Here κ indicates the average incremental risk taking in a given interval of fund values and δ indicates the slope of the fund-risk to value relation within this interval.[18]

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,

[18] We also employ a piecewise continuous specification of the model as explained in Online Appendix and obtain qualitatively similar results.

a nonparametric kernel regression of the residuals on the corresponding fund value is estimated.[19]

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

For the kernel regression, we use a Gaussian kernel with a fixed bandwidth of 0.07.[20] 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 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

[19] 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 α-s, β-s, and θ-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.

[20] 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.

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.[21]

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) and significant at the 1% level. Thus, after liquidation of presumably more liquid assets, the remaining hedge fund portfolio is riskier.[22]

[21] 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).

[22] 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.

[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 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.[23] 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 quarter at a fund value of 0.60 of the HWM. The corresponding coefficients κ of –0.45 and δ 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

[23] 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.

hedge funds.[24] 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 manages 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 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).[25] In choosing the

[24] Hodder et al. (2014), for example, report that an average fund of hedge funds holds only 24 individual funds.

[25] 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

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:

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

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).

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

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]

flow-performance relation. Therefore, we measure the latter in accordance to our measurement of the former.

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 the 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.[26]

If the indirect incentives do indeed play such an important role, we should observe a

[26]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.

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 a proxy for EPS 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.[27] 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.[28]

[Table 8 around here]

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

[27]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.

[28]Detailed results for unconstrained styles are reported in Online Appendix.

at the 1% level) for "good" and "bad" years respectively, and during the forth 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.[29]

[Table 9 around here]

The results corroborate our hypothesis of a dominant role of indirect managerial incentives towards the end of a calender 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 investment horizons optimally reduce the fund risk to avoid liquidation. Fund liquidation is extremely costly for managers, as they lose a potentially 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

[29] In Online Appendix 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.

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 other variables instead 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.[30] 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 γ) 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:

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

For example, for management fees, a negative and significant γ_{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

[30] See, for example, Liang and Park (2010) among others. Another potential determinant of the 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.

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.[31]

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 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.[32] The model fit depends on the fund style, with the average adjusted R-square varying from 5%

[31]The high nonlinearity of managerial risk taking suggests that a linear statistical identification can be misleading. See Online Appendix for the related results.

[32]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 Online Appendix and are qualitatively similar to those discussed in this section.

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).

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 forth quarter, we can see that the maximum increase in the market risk is about 23% with respect to the expected level of market risk ($e^{0.60-0.66\cdot0.6} = 1.23$), whereas the maximum increase in the idiosyncratic risk is just 13% ($e^{0.34-0.36\cdot0.6} = 1.13$). 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 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.[33] 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 disproportionally exposed to market risk, as compared to their average exposure.

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.

[33]Looking further into scalability of investment strategies, we show in Online Appendix 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.

6.1 *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 γ capturing the impact of an indicator variable taking a value of one for funds having a HWM. The estimated coefficients remain virtually unchanged from those of the main results in Table 5, and are not reported for the sake of space. 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.

Similarly, we use a dummy variable indicating the existence of a positive incentive fee[34] and still do not find any significant relation between charging incentive fees and increasing risk at the end of a year.

These findings 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

[34] 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.

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 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 12 reports the estimation results.

[Table 12 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.[35] 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 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

[35] 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.

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, investors 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.

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Table 1: Descriptive statistics for the hedge fund sample

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.

	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

Table 2: Descriptive statistics for hedge fund risk

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.

	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

Table 3: Descriptive statistics across hedge fund styles

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.

	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

Table 4: Panel regressions of hedge fund risk

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 statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(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	

Table 5: Piecewise regressions of residual hedge fund risk

The table reports estimation results for piecewise linear regressions of residual fund RISK as discussed in Section 4. κ-s correspond to the constant terms, and δ-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 statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

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

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

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 statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	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	

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

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 measures 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 statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	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	

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

The table reports estimation results for piecewise linear regressions of residual fund RISK. κ-s stand for the constant terms, δ-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 statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

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

Table 9: Risk taking across different investment opportunities regimes

The table reports estimation results for piecewise linear regressions of residual fund RISK. κ-s stand for the constant terms, δ-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 statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

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

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

The table reports estimation results for piecewise linear regressions of residual fund RISK. κ stands for the constant term, δ 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, γ is the estimate for the dummy, which indicates funds with higher than median management fee. In Panel B, γ indicates funds with higher than median notice period prior to redemption. In Panel C, γ 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 statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

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

Table 11: Market vs. idiosyncratic risk taking

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). κ stands for the constant term, δ 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 statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

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

Table 12: Performance - risk relation in monthly reporting funds

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 (ΔSTD_{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.

	(I) ΔSTD_{July}		(II) $\Delta STD_{January}$	
$AbsWin$	-2.35***	(-20.56)	0.70***	(8.29)
$AbsWin \cdot HWM$	0.38***	(2.86)	-1.09***	(-11.28)
STD_{t-1}	-0.43***	(-164.35)	-0.29***	(-92.55)
$Flow$	-0.00	(-0.71)	-0.00	(-0.68)
HWM	-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	

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%.

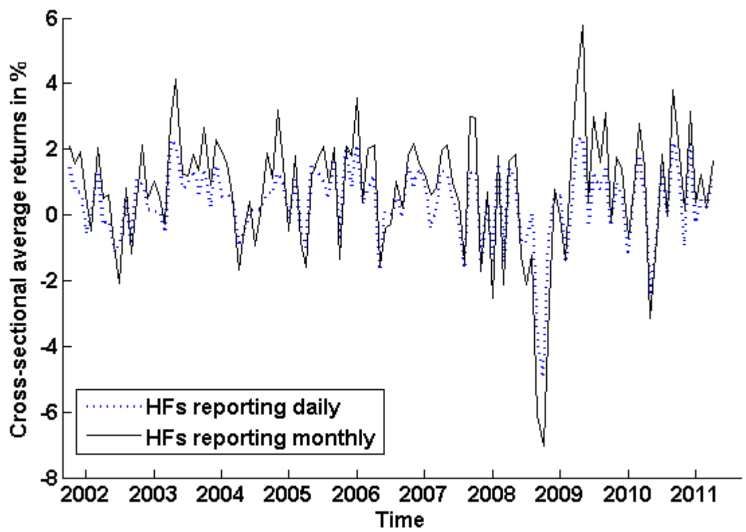


Figure 2: Distribution of styles of daily and monthly reporting hedge funds

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").

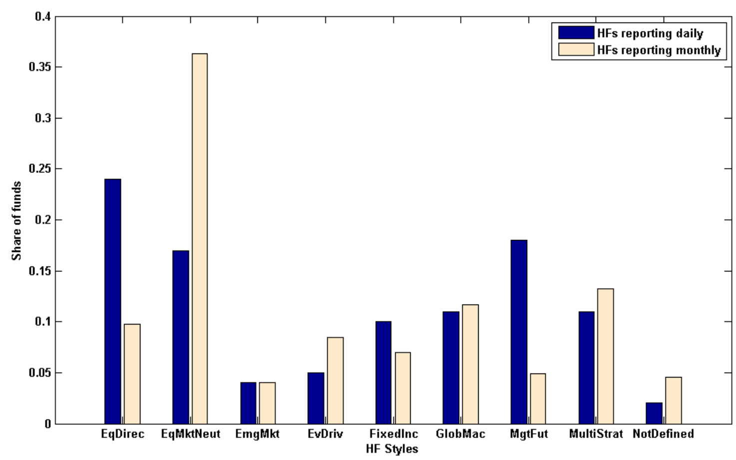
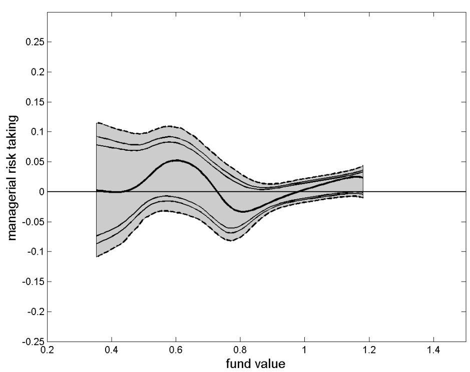
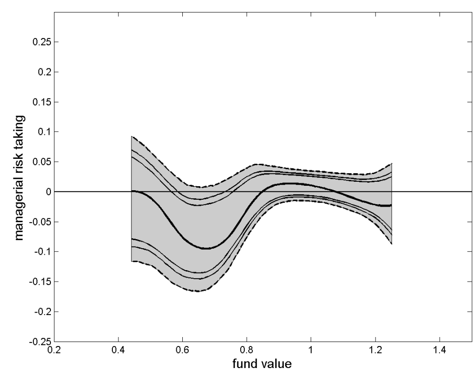


Figure 3: Managerial risk taking: quarter-wise

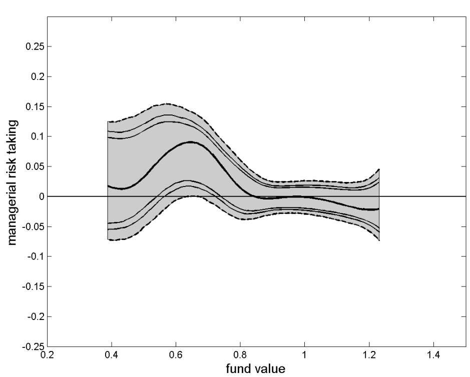
The figure plots the result of the kernel regression specified in Section 4 for the different quarters of a year. On the horizontal axis is the fund value relative to the HWM. On the vertical axis is the managerial risk taking contained in the residuals from a panel regression of RISK (the natural logarithm 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.



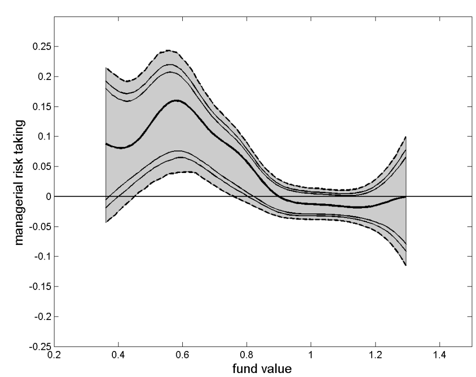
(a) Quarter 1



(b) Quarter 2



(c) Quarter 3



(d) Quarter 4

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.

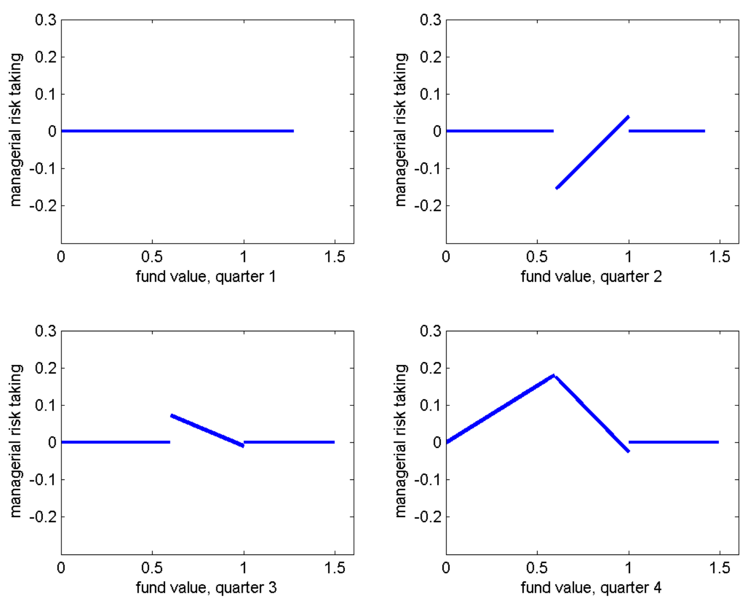
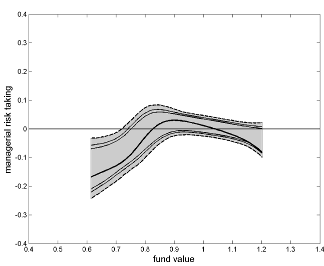
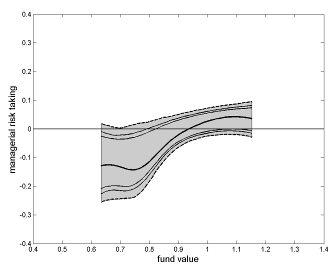


Figure 5: Managerial risk taking: month-wise

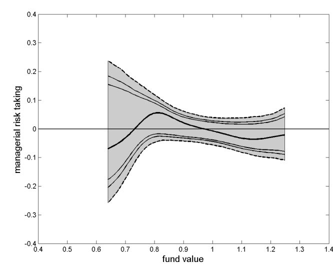
The figure plots the results of kernel regressions specified in Section 4 for each month in the second and the fourth quarter of a year. On the horizontal axis is the fund value relative to the HWM. On the vertical axis is the managerial risk taking contained in the residuals from a panel regression 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.



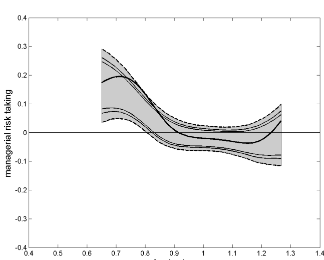
(a) April



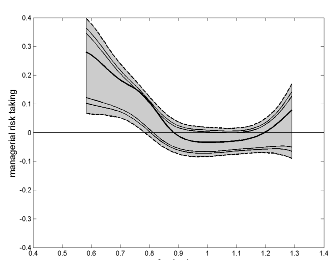
(b) May



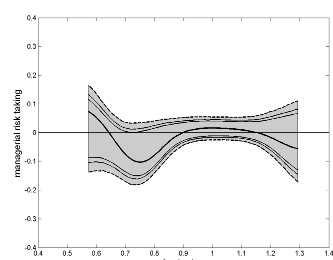
(c) June



(d) October



(e) November



(f) December