Recovering Managerial Risk Taking from Daily Hedge Fund Returns: Incentives at Work?*

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Abstract

Analyzing a sample of hedge funds reporting daily returns to Bloomberg, we document a strong seasonal pattern in managerial risk taking. During earlier months of a year, poorly performing funds reduce their risk. The reduction is stronger for funds with higher management fees, shorter redemption notice 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. The increase is not purely driven by high-water mark provisions, pointing towards the existence of other incentives, like reporting good performance at year end.

Key words: Hedge funds; Risk Taking; Incentives; Seasonality

1 Introduction

Typical compensation contracts of hedge fund managers[1] create complex incentive schemes, which theoretically induce highly nonlinear managerial risk taking (e.g., Hodder and Jackwerth (2007), and Lan, Wang, and Yang (2013)). In this paper, we analyze the dynamic risk taking by hedge fund managers empirically and address its *intra-year* variation. We use a previously unattended sample of daily hedge fund returns from Bloomberg. While the hedge funds in our sample behave 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 as the intra-month return standard deviation.

We document a strong seasonal pattern in the risk taking, which is a nonlinear function of fund performance relative to the HWM. Conditional on fund underperformance relative to the high-water mark (henceforth HWM), hedge fund managers increase the fund risk, which is consistent with theoretical predictions in Hodder and Jackwerth (2007) and Buraschi, Kosowski, and Sritrakul (2014). This relation holds, however, only during later months of a year, whereas the aforementioned models predict a uniform risk increase throughout the year. During earlier months of a year, poorly performing funds, on the contrary, reduce their risk. Such risk alteration is consistent with the predictions in Lan, Wang, and Yang (2013). Comparing the assumptions underlying the different models suggests that at the beginning of a year, fund managers perceive their evaluation horizon as very long, and seek to reduce the fund liquidation probability to keep earning management fees. Towards the end of a year poorly performing managers perceive their investment horizon as rather short. This finding reveals that none of the elaborate currently existing models of hedge fund risk taking alone

[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 calculate as a share of the fund's profits in excess of a high-water mark (previously achieved end-of-year maximum net asset value), which is often paid at the end of a calendar year.

captures the full variation of actual managerial risk taking. This points towards the potential existence of additional incentives, not included in the models.

Looking further into the incentives to reduce the risk in case of poor performance during earlier month of a year, we show that funds, which charge higher management fees, exhibit a stronger risk reduction. Similarly, funds with a shorter notice period prior to redemption, recently deteriorating performance, and younger age also exhibit a stronger risk reduction, which is potentially driven by a higher liquidation probability of such funds. Remarkably, these factors do not have any impact on the documented risk increase at the end of a year; here all poorly performing managers gamble for resurrection.

The end of year gamble by poorly performing funds is not (purely) driven by the existence of high-water marks and incentive fees provisions. It is strongly pronounced for funds not charging incentive fees, too. This finding points towards the existence of other incentives (not directly linked to the managerial compensation scheme) that induce higher risk taking at the end of a calendar year. These can include reputational concerns, as the majority of hedge funds provide end-of-year reports to their clients. Remarkably, funds that exhibit higher return correlations with the market show a stronger risk increase at year end. These funds seem to follow more conventional strategies, which potentially allow for a more flexible risk adjustment.

The documented risk alterations are economically significant and range from a 14% decline to a 20% increase relative to the expected level of risk. They contribute to our understanding of the mechanism of risk changes in hedge funds throughout a year and suggest that a negative association between changes in risk from the first to the second half of a year and fund performance documented by previous research (e.g., Aragon and Nanda (2012)) is driven not only by the excessive risk taking during later months of a year, but also by risk reductions earlier in a year.

2 Related Literature and Hypotheses Development

One of the first models, which covers most of the characteristics of a typical incentive contract of a hedge fund[2] in a one-period as well as in a multi-period setting, is Hodder and Jackwerth (2007). The optimal risk taking is obtained for a risk-averse hedge fund manager, who has some personal wealth invested in the fund, receives a management fee as well as an inventive fee that is tied to a HWM, and possesses an option to liquidate the fund at her own discretion. The optimization is performed on a discretized grid of fund values and time. With a three year valuation horizon and incentive fee calculation and 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.

Hodder and Jackwerth (2007) do not consider investors' behavior in response to hedge fund performance. Empirically, however, investors respond to good fund performance by capital inflows, and tend do redeem shares upon poor performance (Ding, Getmansky, Liang, and Wermers (2009)). Although this response could be a minor issue for short valuation horizons, as redemptions are often restricted by lock-up and notice periods, it could have a substantial effect for longer horizons.

[2]While there is a vast literature on the optimal response to more general incentive schemes (see, e.g., Harris and Raviv (1979), Gibbons and Murphy (1992), Ross (2004), Basak, Pavlova, and Shapiro (2008) among others), here we focus on the most relevant models for hedge funds only.

A step forward in this direction is made by Buraschi, Kosowski, and Sritrakul (2014). 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,[3] 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 optimal investment problem is then solved using the martingale approach developed in Cox and Huang (1989). The theoretical solution of Buraschi, Kosowski, and Sritrakul (2014) suggests the highest risk taking at a fund value of approximately 60% of the HWM, with the risk taking still being bounded. Compared to Hodder and Jackwerth (2007), where a poorly performing manager keeps increasing investment risk at lower fund values right until she optimally chooses to liquidate the fund and take-up outside opportunities, the investors' and brokers' options to redeem shares and suspend financing in Buraschi, Kosowski, and Sritrakul (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.

The above mentioned papers suggest the following testable hypotheses:

Hypothesis A(i): *The average managerial risk taking is higher if the hedge fund value is below the HWM.*

Hypothesis A(ii): *Below the HWM, the relationship between fund value relative to the HWM and managerial risk taking is not linear but bell-shaped.*

Lan, Wang, and Yang (2013) take a different avenue in modeling optimal hedge fund risk taking. The key difference to the aforementioned models is the infinite valuation horizon of

[3] The model is based on Koijen (2014), who develops a structural model for optimal portfolios of mutual fund managers, taking into account managerial skill, incentives, and risk preferences.

the manager. Instead of maximising the utility at some terminal date, they maximize 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 stylized facts 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. This model provides a competing hypothesis:

Hypothesis B: *The average managerial risk taking is lower for hedge fund values below the HWM.*

Hypothesis A would be consistent with a relatively short valuation horizon of fund managers, whereas *Hypothesis B* would suggest the managers have a much longer valuation horizon. The impact of the managerial valuation horizon can, indeed, be substantial as Panageas and Westerfield (2009) show. The authors consider optimal portfolio allocations for a risk-neutral manager disregarding personal managerial investments in the fund and management fees. They show, that even in such an extreme setting, an option like compensation contract results in infinitely high risk taking, only if the managerial valuation horizon is finite. With an infinite horizon, the optimal portfolio is constant with bounded risk.

The scope of the existing empirical evidence on the managerial response to incentives in hedge funds is determined by the availability of hedge fund data. Generally, hedge fund return data are available only at a monthly frequency. Most of the existing studies choose to analyze changes in fund risk (measured as the return standard deviation) from the first half of a year to the second half of a year, with each of the standard deviation estimates being based on six monthly return observations only. With such a research design, Brown, Goetzmann, and Park (2001) find tournament behaviour 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, Daniel, and Naik (2002) find similar results in their sample of hedge funds. More recently, however, Aragon and Nanda (2012) and Buraschi, Kosowski, and Sritrakul (2014) do find evidence of endogenous and state dependent risk shifting. Buraschi, Kosowski, and Sritrakul (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 our empirical empirical investigation.

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 and confirm an average negative relation between fund relative-to-peers performance and risk changes. The risk shifting is, however, mitigated for hedge funds with a HWM provision and low risk of immediate liquidation, as well as for managers with a large personal capital 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.

The existing empirical research does not consider the intra-year variation of risk taking in detail. We expect, however, that seasonality in risk taking might be rather pronounced in light of the existing evidence on seasonality in reported returns. Agarwal, Daniel, and Naik (2011) find that hedge funds (especially those with low incentives and high opportunities to manipulate returns) underreport good returns, smooth performance throughout a year, and then inflate December returns by adding the underreported portion of returns.[4] The authors also find some weak evidence of hedge funds inflating December returns through "borrowing" from January returns. Ben-David, Franzoni, Landier, and Moussawi (2013) suggest possible stock price manipulations by large hedge funds that have to file end-of-quarter long equity holdings with the SEC through 13F reports. Stocks held by the hedge funds exhibit excessive price pressure during the last trading day of the quarter and earn abnormal returns, which are rapidly reverted during the first trading day following the quarter end. The majority of funds does not need to file quarterly reports with the SEC, but they still provide investors with end-of-year reports. Such reporting may induce changes in managerial investment behaviour. For example, Patton and Ramadorai (2013) show that hedge funds reporting voluntarily on a monthly basis to commercial databases vary their factor exposures within months.

Reporting particularly good results at year end to the investors contributes to managerial reputation as well as increases immediately paid fees. Besides the aforementioned direct manipulations, higher (on average) end-of-year returns can also be achieved by increasing the riskiness of the underlying portfolio. This leads us to a conjecture, that *Hypothesis A(i)* is more likely to hold at the end of a year, rather than at the beginning of a year.

3 Data

Our sample consists of 714 single- and multi-strategy hedge funds retrieved from Bloomberg 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 man-

[4]In our sample of hedge funds the reported average returns in December are also significantly higher than during all other months. This indicates that the funds in our sample exhibit general patterns common to the funds reporting on a monthly basis. Inflated returns reported in December do not influence our risk-related results, as the return STD is computed every month and it takes into consideration mean differences, as will be discussed later.

agement, together with some static information on fund characteristics, like the levels of the management and incentive fee, the use of a HWM, as well as 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.[5] We do not find any evidence for a backfilling bias at any horizon in our sample of hedge funds. Hence, we do not delete initial return observations for the following analysis.

Table 1 summarizes the sample and reports the descriptive statistics of the hedge fund returns. The median returns for EUR hedge funds are lower than for USD hedge funds, which is partially due to inflation differences between the U.S. and the Euro-zone, and partially due to differences across the implemented strategies by the funds. Compared to hedge funds that report on a monthly basis to commercial databases commonly used in the hedge fund literature, the hedge funds in our sample seem to be slightly less profitable and less risky.[6] This difference is consistent with the funds in our sample being more transparent and liquid, and, thus, able to report on a daily basis. Despite slightly lower levels of overall risk, we expect the risk shifting patterns to be comparable to the funds reporting on a monthly frequency, due to similar managerial incentive schemes. Table 2 also reports the cross-sectional average descriptive statistics of intra-month return standard deviations.

[Tables 1 and 2 around here]

[5] We, first, delete all zero returns. Then, the average number of non-reporting days is not allowed to exceed 5/4 (at least 4 return observations per week on average), the maximum gap is 9 trading days (the fund never misses reporting for 2 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 4 per week for the shortest month) and an AuM observation within the first and last 5 trading days of the month to obtain a monthly flow estimate. We exclude one fund with less than one year of reported returns.

[6] Hodder, Jackworth, and Kolokolova (2013) 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%.

Figure 1 depicts the time series of average monthly returns of hedge funds in our sample and funds reporting on a monthly basis.[7] Funds in both groups exhibit similar performance patterns. The correlation between average cross-sectional returns across these samples is 93%.[8] This suggests that the sample of daily reporting hedge funds, apart from containing generally less risky and less profitable funds, is not systematically different from the conventionally used hedge fund samples.

[Figure 1 around here]

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

[Table 3 around here]

We compare the distribution of fund styles in the samples of daily reporting funds and funds reporting monthly to commercial databases and depict it in Figure 2. There is a difference in the percentage of Directional Equity and Equity Market Neutral funds across the two databases. These styles account for 24% and 17% respectively of daily reported funds and for 10% and 36% of monthly reporting styles. This discrepancy, however, might

[7] 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, Jackworth, and Kolokolova (2013). The time period is matched to the one of our sample of daily reporting hedge funds.

[8] The tail behaviour 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%.

be driven by variations in style labeling across different database. Altogether, equity funds cover the largest and rather similar shares across both samples – 41% of daily reporting funds and 46% of monthly reporting funds. Another exception is Managed Futures funds that are relatively over-represented in the sample of daily reporting funds accounting for 18% of the sample, whereas they account for 5% of the sample of monthly reporting funds. Other styles have very similar distribution 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.

[Figure 2 around here]

4 Methodology

We measure hedge fund risk as the standard deviation of daily returns within one month. For each hedge fund in our sample, a time-series of such monthly risk estimates is constructed. For the ease of presentation, we will henceforth refer to the natural logarithm of the intra-month standard deviation of daily hedge fund returns as "RISK". In contrast, 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.

$$
\begin{aligned}
RISK_{i,t} &= \alpha_i + \alpha_t + \sum_{j=1}^{3} \beta_j RISK_{i,t-j} + \theta_1 DeltaCorr_{i,t} + \theta_2 ln(AuM_{i,t_-}) \\
&+ \theta_3 OutflowLarge_{i,t-1} + \sum_{k=1}^{K} f_k(Value_{i,t_-}) I_k + \varepsilon_{i,t} \ , \qquad (4.1)
\end{aligned}
$$

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 ($Value_{i,t_-}$). Here the minus sign as a sub-index in t_- indicates the beginning of month t. For each fund the HWM is initially set to 1. It is then reset every 1st of January to the level of the cumulative return, if it exceeds the previous HWM, and it is kept unchanged if the cumulative return is below the previous HWM.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:

$$
Value_{i,t_-} = \frac{\prod_{k=0}^{t-1} CR_{i,k}}{HWM_{i,t}}. \qquad (4.2)
$$

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 drives of hedge fund risk levels. In the time-series dimension, we expect RISK to be persistent.[9] To quantify the actual persistence in hedge fund risk, we

[9] There is strong evidence on the predictability of second moments in equity markets, e.g. Christoffersen and Diebold (2006) and Christoffersen, Diebold, Mariano, Tay, and Tse (2007). Persistence in stock return

estimate the partial serial correlation at the first 5 lags of RISK for each hedge fund in our sample.[10] The fractions of negative and significant partial serial correlations are negligible and the fractions of significantly positive coefficients drop after the third lag to only 3% at lag 4. These results suggest that RISK follows an AR(3) process and we include three lagged values of RISK as explanatory variables in the panel regression.

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

The time series of the cross-sectional average RISK share the same dynamics with RISK of the MSCI-World index. The correlation coefficients between the series range from 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.[11] As an additional control variable, we include the natural logarithm

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, Gorovyy, and van Inwegen (2011) document stability of hedge fund leverage. The substantial transaction costs can also prevent frequent portfolio alterations.

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

[11] There are different potential reasons for a change in the serial correlation. A variation in the true

of the AuM of fund i at the beginning of month t ($ln(AuM_{i,t_-})$) in the regression. The variable captures 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

$$Flow_{i,t-1} = \frac{AuM_{i,t_-} - AuM_{i,t-1_-}CR_{i,t-1}}{AuM_{i,t-1_-}} \ , \tag{4.3}$$

where $CR_{i,t}$ is the cumulative return earned by fund i over month t. We then include a dummy variable, which indicates a flow below –5% and serves as a proxy for large outflows ($OutflowLarge_{i,t}$).

The analysis above allows us to capture potential nonlinearities in the relationship of fund risk and value. In order to give a more precise quantification of the strength of risk shifting, we repeat the analysis using a piecewise linear specification for the residuals instead of a kernel regression. We analyze the residuals from the linear part of Equation 4.1 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);

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 not equally spaced observations of daily returns within consecutive months. If the reporting frequency has any information on hedge fund risk, it will be also picked up by the change in the return serial correlation.

(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 and bootstrapped standard errors:

$$\hat{e}_{i,t} = \begin{cases} \kappa_{low} + \delta_{low} Value_{i,t_-} + \eta_{i,t} & \text{if } Value_{i,t_-} < \bar{V} \\ \kappa_{mid} + \delta_{mid} Value_{i,t_-} + \eta_{i,t} & \text{if } \bar{V} < Value_{i,t_-} < 1 \\ \kappa_{high} + \delta_{high} Value_{i,t_-} + \eta_{i,t} & \text{if } Value_{i,t_-} > 1 \ . \end{cases} \tag{4.4}$$

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

4.2 Estimation

The regression in Equation 4.1 is estimated in two steps. First, RISK is regressed on all covariates excluding fund value. Then, the residuals from this regression ($\hat{e}_{i,t}$) are grouped according to calendar quarters or months. For each of the related four or twelve groups, a nonparametric kernel regression of the residuals on the corresponding fund value is estimated.[12]

$$\hat{e}_{i,t} I_k = f_k(Value_{i,t_-}) I_k + \eta_{i,t,k} \tag{4.5}$$

For the kernel regression, we use a Gaussian kernel with a fixed bandwidth of 0.07.[13]

[12] The variable $Value$ in our regressions is not strongly correlated with other explanatory variables, and the first step estimation does not suffer from the 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 the ones reported in the paper.

[13] Cross-validations conducted separately for different quarters and months yield optimal bandwidths ranging from 0.01 to 0.11. To make sure that our results for different periods are not driven by differential

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.

Note that in the linear part of the Equation 4.1, the lagged values of RISK are correlated with the error term, which biases OLS estimates (Nickell (1981)). The most prominent solutions to this dynamic panel bias are GMM estimation techniques (e.g. Arellano and Bond (1991)) or an explicit bias correction (e.g. Kiviet (1995)). The former, however, is designed for small T panels and the latter is only feasible with balanced panels. Nickell (1981) derives an expression for the bias and shows that it approaches zero as T tends to infinity. In a simulation study, Judson and Owen (1999) show that for unbalanced panels, a fixed effects model outperforms the other alternatives already 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.[14]

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.

[14] 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)).

5 Empirical Results: Seasonality

5.1 Managerial Risk-Taking: Quarter-Wise

Column (I) in Table 4 reports the estimation results based on the linear part of Equation 4.1. 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 forced liquidation of presumably more liquid assets, the remaining hedge fund portfolio is riskier.[15]

[Table 4 around here]

Figure 3 plots the estimated kernel regression of residual risk taking. Here fund and time fixed effect, 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]

[15] We also include in the regression the fund flow directly as defined in Equation 4.3 at times $(t-1)$ and $(t-2)$, as well as an indicator function for negative flow. In unreported results, none of these variables turns significant. Also, neither outflows preceded by poor performance, nor cumulative flows are driving the risk increase.

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. This finding supports our *Hypothesis B* and is consistent with Lan, Wang, and Yang (2013).

Moving further 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, consistent with *Hypothesis A(i)*. Below the HWM the risk shifting does not increase monotonically, instead it is bell-shaped as suggested by *Hypothesis A(ii)*, consistent with the predictions of Buraschi, Kosowski, and Sritrakul (2014).

We do not document 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, e.g., by the one-period model of 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 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.[16] 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).

Overall, the documented seasonality in risk taking together with the existing theoretical models suggests that the *perceived* managerial valuation horizon can vary over a year. While at the beginning of a year managers might see themselves as operating long-term funds, by the end of the year, poorly performing funds might be treated more like short term projects for the managers. We will address other possible determinants for the observed seasonality in Section 6 in more detail.

5.2 Economic Significance of Managerial Risk Taking

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 the standard deviation thereof is 0.42%. Other things being equal, a one standard deviation increase in the risk at time t will

[16] 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 with their explanatory power concentrated at the first lag, suggesting a truly short-term effect.

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, that the maximum 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, the maximum risk increase achieved in the fourth quarter is 20% of the expected level of risk ($e^{+0.48-0.50 \cdot 0.50} = 1.20$).

Thus, investors should be aware of managerial risk taking as it is strongly pronounced even on average. 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.

6 Determinants of Changes in Hedge Fund Risk

The documented seasonality in hedge fund risk taking is, to the best of our knowledge, a novel empirical result. In this section, we take a closer look at its determinants.

6.1 Management Fees and Survival Probability

Poorly performing hedge fund managers with very long (infinite) investment horizons optimally reduce the fund risk in order to avoid liquidation (Lan, Wang, and Yang (2013)). Fund liquidation is extremely costly for mangers as they loose an infinite stream of future management and incentive fees. Management fees, in particular, account for 75% of the total managerial surplus according to the model. The higher the management fee, the more a manager looses in case of fund liquidation. This suggests:

Hypothesis C: *Below the HWM, hedge funds with higher management fees exhibit a stronger risk reduction during the second quarter.*

Similarly, those funds that face a higher liquidation probability at the beginning of a year should have stronger incentives to reduce risk and to improve the chances of survival.[17] Comparing the attrition rates in our sample we find that in an average year, only 38.1% of all defunct funds "die" during the first half of a year, while 61.9% "die" during the second half. The difference is statistically significant (p-value 4.31%). At the same time, we do not observe any significant intra-year variation for hedge fund inceptions and fund flows.

Directly relating the managerial decision to alter fund risk to estimated liquidation probabilities in a regression framework might be inaccurate due to endogeneity. Actual fund survival depends on fund risk, which is, in turn, an optimal managerial response to the fund liquidation probability. We use three instruments that are negatively related to the liquidation probability, but are not directly affected by the risk taking decisions of a manager: notice period prior to redemption, recent fund performance, and fund age.[18]

Hypothesis D: *Below the HWM, hedge funds with a longer notice period prior to redemption, positive returns over the previous quarter, and older age exhibit a milder risk reduction during the second quarter.*

In order to test *Hypotheses C* and *D*, we use the piecewise linear specification as in Equation 4.4. For each fund value range we introduce four indicator variables in turn (denoted by γ-s) and estimate Equation 6.1 given below. The indicator variables represent funds with (1) higher than median management fees ($MgtFeeLarge$) to test *Hypothesis C*, (2) higher than median notice periods prior to redemption ($NoticeLarge$), (3) positive cumulative

[17] Liang and Park (2010), among others, find positive relation between fund liquidation probability and fund risk.

[18] Another potential instrument linked to liquidation probability is managerial personal investment in a fund (Aragon and Nanda (2012)). This information, however, is not available for our sample of hedge funds.

returns over the preceding quarter (equivalent to increasing fund values relative to the HWM, $\Delta Value_{t_-} > 0$), and (4) larger than median age ($AgeLarge$) to test *Hypothesis D*.

$$\hat{e}_{i,t} = \begin{cases} \kappa_{low} + \gamma_{low} + \delta_{low} Value_{i,t_-} + \eta_{i,t} & \text{if } Value_{i,t_-} < 0.6 \\ \kappa_{mid} + \gamma_{mid} + \delta_{mid} Value_{i,t_-} + \eta_{i,t} & \text{if } 0.6 < Value_{i,t_-} < 1 \\ \kappa_{high} + \gamma_{high} + \delta_{high} Value_{i,t_-} + \eta_{i,t} & \text{if } Value_{i,t_-} > 1 \ . \end{cases} \tag{6.1}$$

For example, for $MgtFeeLarge$ 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 Tables 6 and 7. Consistent with *Hypothesis C*, hedge funds charging higher than median management fees show a stronger decline in the risk taking during the second quarter conditional on being below the HWM. The corresponding coefficient of -0.05 is significant at the 10% level. Hedge funds that are likely to face a lower liquidation probability because of a longer notice period prior to redemption, positive cumulative returns over the preceding quarter, and older age show a less pronounced risk decline during the second quarter of a year confirming *Hypothesis D*. The coefficients of $+0.13$, $+0.06$, and $+0.07$ in Table 7, 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.

[Tables 6 and 7 around here]

These findings contribute to a further discussion of Aragon and Nanda (2012), who document 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 may be driven not only by the excessive risk taking during the second half-year, but also by a risk reduction during earlier months. And it is the earlier risk reduction that is more pronounced for funds with higher liquidation probability, and not the later risk increase.

6.2 High-Water Mark and Incentive Fees

Managers of funds with a HMW provision possess not a single incentive option, but a sequence of multiple future incentive options (Panageas and Westerfield (2009)). They avoid excess risk taking throughout a year, to minimize the likelihood of losing their future compensation options. This result is consistent with the empirical findings of Aragon and Nanda (2012) 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. We test this proposition in our time-varying setting.

Hypothesis E: *Below the HWM, hedge funds with a high-water mark provision exhibit a less pronounced risk increase at the end of a year.*

We test this hypothesis using Equation 6.1, with γ-s taking a value of one for funds having a HWM provision ($HaveHWM$). The results are reported in Panel A of Table 8. The estimated coefficients remain virtually unchanged as compared to the main results in Table 5. This suggests that, overall, hedge funds that do have and funds that do not have a HWM provision adjust their risk taking in a similar way, depending on their cumulative performance and the time of a year. A HWM provision indeed somewhat offsets the risk increase during the second half of a year consistent with *Hypothesis D* and the prior findings. However, the effect is detected only during the third quarter with the corresponding loading of -0.04 being significant at the 10% level. The risk mitigating incentives provided by the HWM provisions are not sufficient to prevent managers from risk shifting towards the very end of a year. If managers enter the fourth quarter with a fund under water, they significantly increase fund risk regardless of the existence of a HWM provision in the fund.

[Table 8 around here]

In Panel B of Table 8 we perform a similar analysis but use a dummy variable indicating the existence of a positive incentive fee ($HaveIveFee$).[19] The estimation results are somewhat more noisy during the first quarter, but we still do not find any significant relation between charging incentive fees and increasing risk at the end of a year.

The findings above suggest that the increased risk taking at the end of a year may not be solely driven by the incentives provide by managerial option-like compensation contracts. To further investigate this issue, we exclude all funds that do not report a positive incentive fee from the sample and repeat the complete analysis starting from the estimation of the parameters of the linear part of the panel regression. We then further reduce the sample to include only funds that do explicitly report a nonzero incentive fee as well as the use of a HWM. The general risk taking pattern remains largely unaffected.

The findings confirm a minor role of the incentive option – tied to a HWM or not – for seasonal changes in the managerial risk taking. There seem to be other incentives that induce risk shifts towards the end of a year. As pointed out by Chevalier and Ellison (1997), the convexity in the managerial compensation can be induced by a flow-performance relationship even without an explicit incentive fee. At the same time, managers may face pure "reporting" incentives. Reporting better figures to client at a year end may lead to an improvement of the managerial reputation, which in turn could, for example, make the launching of consecutive

[19]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, i.e. may or may not charge an incentive fee.

funds easier.

6.3 Scalability of Investment Strategy

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

Hypothesis F: *Below the HWM, hedge funds with a higher return correlation with the market exhibit a stronger risk increase at the end of a year.*

Again, we estimate Equation 6.1 using an indicator variable $CorrHigh$ taking a value of one if the fund's returns have higher than median correlation with the market returns. The results reported in Table 9 suggest that indeed such hedge funds exhibit a stronger risk increase during the last quarter of a year. The corresponding coefficient of $+0.05$ is significant at the 5% level. Interestingly, the risk shifting during third quarter is reduced by the same magnitude. The result may suggest that those funds that can easily level up their risk do not need to adjust it early. Instead, they can scale the risk up right when they need it – at the end of a year.

[Table 9 around here]

7 Robustness Checks

In this section, we, first, present a month-wise refinement of the main results. We then use the linear specification for the relation between a fund value and risk taking, which allows us to directly compare our results with the ones obtained by previous research based on monthly hedge fund data. We also perform several robustness checks with respect to methodology and sample filtering, which are reported in Appendix. The results are predominantly inline with the main conclusions.

7.1 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 substantially 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.

[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 forth quarter, conditional on the fund value being substantially 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 additional managerial risk taking 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 only 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. At the same time, early adjustments make sure that the alternations in fund risk do not strongly transmit to subsequent quarters, where the desired risk levels can be different. 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 alter fund risk swiftly.

7.2 Linear Specification for the Fund Value Relative to the High-Water Mark

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

We modify Equation 4.1 to include a linear specification for the relationship between fund value and the managerial risk taking to the following form

$$\begin{aligned} RISK_{i,t} &= \alpha_i + \alpha_t + \sum_{j=1}^{3} \beta_j RISK_{i,t-j} + \theta_1 DeltaCorr_{i,t} + \theta_2 ln(AuM_{i,t_-}) \\ &+ \theta_3 OutflowLarge_{i,t-1} + \kappa Value_{i,t_-} + \varepsilon_{i,t} \ . \end{aligned} \tag{7.1}$$

The estimation results reported in Column (I) of Table 10 show that on average, across all fund values and time, we find a negative relationship between fund profitability and risk taking. This finding is consistent with the research that uses a linear statistical identification (e.g., Aragon and Nanda (2012)). The loading on $Value_{i,t_-}$ of -0.19 is significant at the 1% level. The other estimated parameters remain largely unchanged as compared to our main results in Table 4.

[Table 10 around here]

We run the linear regression 7.1 for the non-crisis period only, the coefficient estimate for the value variable, albeit still negative, becomes insignificant, while the truly nonlinear managerial risk taking is still present (Appendix A.3). Besides hiding the truly nonlinear nature of the managerial risk taking, a linear specification can, hence, fail to identify managerial risk taking altogether, which could explain the insignificant results in some earlier papers (e.g. Brown, Goetzmann, and Park (2001) or Agarwal, Daniel, and Naik (2002)). This problem seems to be more pronounced for samples that lack a significant fraction of poorly performing funds, i.e. sample periods that are characterized by bullish markets.

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

We now investigate the impact of hedge fund fixed characteristics, such as fees, size, and notice period prior to the redemption. We re-estimate the panel regression specified in Equation 7.1 and include interaction terms between the fund value variable and (1) a dummy for the use of a HWM; (2) a dummy for the incentive fee being above the median; (3) a dummy for the management fee being above the median; and (4) a dummy for the notice period being above the median. The results are reported in Table 11.

[Table 11 around here]

Consistent with Aragon and Nanda (2012), in this specification, the existence of the HWM seems to mitigate the risk shifting incentives of hedge fund managers (Column (I) of Table 11). The corresponding loading on the interaction term is positive (+0.15) and significant at the 10% level. Similarly, high management fees mitigate the impact of fund value with the associated loading of +0.17 being significant at the 5% level. High incentives fees and long notice periods, to the contrary, amplify the effect of the fund value, with estimated coefficients of -0.48 and -0.20, which are significant at the 10% and 5% levels, respectively.

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

8 Conclusion

We use a previously unattended dataset of daily hedge fund returns from Bloomberg, which allows us to construct time-series of monthly risk estimates for individual hedge funds and recover the complete surface of managerial risk taking across fund values and time of a year. The risk taking is highly nonlinear and exhibits a strong seasonal pattern. At the beginning of a year, poorly performing funds *decrease* the risk taking, especially if they are threatened by the risk of immediate liquidation. Towards the end of a year such funds, on the contrary, *increase* the risk. Such risk shifting is pronounced for hedge funds with all types of compensation contacts and with all investment styles, and it is even stronger for funds that follow strategies more closely linked to the equity market. This finding contributes to our understanding of the economics behind the previously documented negative association between changes in risk from the first to the second half of a year and fund performance (Aragon and Nanda (2012)). It seems to be driven not only by the excessive risk taking during later months of a year, but also by risk reductions earlier in a year. Given high nonlinearity of managerial risk taking, a linear statistical identification can be misleading.

The estimated maximum average risk shifts are economically significant and span from a 14% decrease to a 20% increase relative to the expected risk levels. Investors and creditors should be aware of the dynamic managerial risk taking and assess the implications of their operational risk for their portfolios, standard compensation practices, and credit risk. Regulators might be interested in monitoring situations, in which a large fraction of hedge funds slides into the areas of the state space that induce high risk taking, as this can result in systemic concern. Our findings also contribute to an on-going discussion on mandatory reporting and disclosure by hedge funds. They indicate that scheduled reporting (although seeking to achieve transparency) might induce (unwanted) changes in the investment behaviour of fund managers.

Our results throughout the paper are robust to various changes in the methodology and sample filtering. Whenever we obtain results in a form directly comparable to the earlier empirical findings for hedge fund risk based on widely used monthly hedge fund return data, they are predominantly in line. Hence, although being technically restricted to our sample of more transparent and less volatile hedge funds reporting on a daily basis, we are confident, that our findings (at least qualitatively) transfer to the larger part of the hedge fund universe with monthly reporting.

References

Agarwal, V., N. D. Daniel, and N. Y. Naik (2002). On determinants of money flow and risk-taking behavior in the hedge fund industry. Working Paper, Georgia State University.

Agarwal, V., N. D. Daniel, and N. Y. Naik (2004). Flows, performance, and managerial incentives in hedge funds. Working Paper, Georgia State University.

Agarwal, V., N. D. Daniel, and N. Y. Naik (2011). Do hedge funds manage their reported returns? *Review of Financial Studies 24*(10), 3281–3320.

Ang, A., S. Gorovyy, and G. B. van Inwegen (2011). Hedge fund leverage. *Journal of Financial Economics 102*(1), 102–126.

Aragon, G. O. and V. K. Nanda (2012). Tournament behavior in hedge funds: High-water marks, fund liquidation, and managerial stake. *Review of Financial Studies 25*(3), 937–974.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies 58*(2), 277–297.

Basak, S., A. Pavlova, and A. Shapiro (2008). Offsetting the implicit incentives: Benefits of benchmarking in money management. *Journal of Banking and Finance 32*(9), 1883–1893.

Ben-David, I., F. Franzoni, A. Landier, and R. Moussawi (2013). Do hedge funds manipulate stock prices? *The Journal of Finance 68*(6), 2383–2434.

Billio, M., M. Getmansky, and L. Pelizzon (2012). Dynamic risk exposures in hedge funds. *Computational Statistics & Data Analysis 56*(11), 3517–3532.

Brown, S. J., W. N. Goetzmann, and J. Park (2001). Careers and survival: Competition and risk in the hedge fund and CTA industry. *Journal of Finance 56*(5), 1869–1886.

Buraschi, A., R. Kosowski, and W. Sritrakul (2014). Incentives and endogenous risk taking: A structural view of hedge funds alphas. *Journal of Finance*, forthcoming.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance 52*(1), 57–82.

Chevalier, J. and G. Ellison (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy 105*(6), 1167–1200.

Christoffersen, P. F. and F. X. Diebold (2006). Financial asset returns, direction-of-change forecasting, and volatility dynamics. *Management Science 52*(8), 1273–1287.

Christoffersen, P. F., F. X. Diebold, R. S. Mariano, A. S. Tay, and Y. K. Tse (2007). Direction-of-change forecasts based on conditional variance, skewness and kurtosis dynamics: international evidence. *Journal of Financial Forecasting 1*(2), 1–22.

Cox, J. C. and C. Huang (1989). Optimal consumption and portfolio policies when asset prices follow a diffusion process. *Journal of Economic Theory 49*(1), 33–83.

Ding, B., M. Getmansky, B. Liang, and R. R. Wermers (2009). Investor flows and share restrictions in the hedge fund industry. Working Paper, University of Massachusetts at Amherst.

Fung, W. and D. A. Hsieh (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies 14*(2), 313–341.

Gibbons, R. and K. J. Murphy (1992). Optimal incentive contracts in the presence of career concerns: Theory and evidence. *Journal of Political Economy 100*(3), 468–505.

Harris, M. and A. Raviv (1979). Optimal incentive contracts with imperfect information. *Journal of Economic Theory 20*(2), 231–259.

Hodder, J. E. and J. C. Jackwerth (2007). Incentive contracts and hedge fund management. *Journal of Financial and Quantitative Analysis 42*(4), 811–826.

Hodder, J. E., J. C. Jackwerth, and O. Kolokolova (2013). Recovering delisting returns of hedge funds. *Journal of Financial and Quantitative Analysis*, forthcoming.

Judson, R. A. and A. L. Owen (1999). Estimating dynamic panel data models: a guide for macroeconomists. *Economics Letters 65*(1), 9–15.

Kiviet, J. F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. *Journal of Econometrics 68*(1), 53–78.

Koijen, R. S. (2014). The cross-section of managerial ability and risk preferences. *The Journal of Finance 69*(3), 1051–1098.

Kolokolova, O. (2011). Strategic behavior within families of hedge funds. *Journal of Banking & Finance 35*(7), 1645–1662.

Lan, Y., N. Wang, and J. Yang (2013). The economics of hedge funds. *Journal of Financial Economics 110*(2), 300–323.

Liang, B. and H. Park (2010). Predicting hedge fund failure: A comparison of risk measures. *Journal of Financial and Quantitative Analysis 45*(1), 199–222.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica 49*(6), 1417–1426.

Panageas, S. and M. M. Westerfield (2009). High-water marks: High risk appetites? Convex compensation, long horizons, and portfolio choice. *The Journal of Finance 64*(1), 1–36.

Patton, A. J. and T. Ramadorai (2013). On the high-frequency dynamics of hedge fund risk exposures. *Journal of Finance 68*(2), 597–635.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies 22*(1), 435–480.

Robinson, P. M. (1988). Root-n-consistent semiparametric regression. *Econometrica 56*(4), 931–954.

Ross, S. A. (2004). Compensation, incentives, and the duality of risk aversion and riskiness. *The Journal of Finance 59*(1), 207–225.

Teo, M. (2010). The liquidity risk of liquid hedge funds. *Journal of Financial Economics 100*(1), 24–44.

Warther, V. A. (1995). Aggregate mutual fund flows and security returns. *Journal of Financial Economics 39*(2-3), 209–235.

Yatchew, A. (2003). *Semiparametric Regression for the Applied Econometrician.* Cambridge: Cambridge University Press.

A Appendix

A.1 Hedge Fund Style

We consider variations in the changes in risk with respect to fund style. In the Equation 6.1 we use dummy variables for each of the reported styles, respectively. As the data requirements are substantial (we need to make sure that in each quarter for each fund value band we have enough observations in each style) we are not able to single out all the reported styles. However, we are able to estimate the regression for the three largest styles: Directional Equity ($EqDirec$), Equity Market Neutral ($EqMktNeu$), and Managed Futures ($ManFut$). Whenever one of those styles is singled out, the average risk shifting pattern among all other funds constitutes the reference case. Table 12 reports the results.

[Table 12 around here]

There exist some statisticlly significant differences among hedge funds reporting different styles. Directional Equity funds, for example, behave differently than other funds above the HWM. We see higher risk taking during the first quarter (+0.10), lower risk taking in the second and the third quarters (-0.09 and -0.11 respectively). Poorly performing Equity Market Neutral funds are somewhat less disposed to increase risk during the fourth quarter of a year (with the loading of -0.07 significant at the 5% level). Managed Futures funds have stronger risk reduction in the second quarter in case of poor performance. The corresponding loading of -0.08 is significant at the 1% level. However, these differences in the magnitude of risk-shifting across different hedge fund styles cannot drive away the main seasonal pattern of risk taking.

A.2 Alternative Specifications of the High-Water Mark

In the main specification, the HWM is set to 1 at hedge fund origination. It then increases to the highest net asset value achieved by the end of December each year. This type of HWM would correspond to investors that initially joined the fund. However, if investors purchase fund shares later on, they can have different HWMs. Therefore, we employ several other procedures to estimate a HWM, which attempt to capture the average HWM for money invested in the fund at different times. Similar to the main specification, we re-set the HWM every January to the highest value of the cumulative return achieved during the previous years. However, instead of considering the compete return history of a fund since inception, we use only the two or three preceding years. To make sure the intra-year variations found for managerial risk taking are not influenced by the end-of-year resetting of the HWM, we also consider resetting the HWM every month to the highest cumulative return earned since inception, as well as over the last two and three years. The results remain virtually unchanged compared to our main specification for fund values below the HWM.[20]

A.3 Excluding the Crisis Period

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

The results from the linear part of the regression are generally consistent with the ones

[20] When resetting the HWM at monthly frequency we lack observations with fund values above the HWM and we can consider only the results below the HWM.

reported in Table 4, with the minor difference, that the third lag of the dependent variable is, albeit still positive, no longer significant. When we exclude the observations from the crisis period, a much lower fraction of fund-month observations lie in the low fund value region. During the complete sample period, about 7% of all sample observations are in the area of fund values between 0.4 and 0.8, whereas when the crisis period is excluded, this share drops to below 2%. The total number of remaining observations in this area is then clearly too low to obtain meaningful kernel regression results. Therefore, we use the piecewise linear specification for the value variable in the form of Equation 4.4, and find a significant risk decline for low fund values relative to the HWM at the beginning of a year, and a significant risk increase towards the end of a year. The risk decline is shifted forward and is now pronounced during the first quarter of a year, whereas risk increase is still strongly pronounced only during the fourth quarter.

A.4 Piecewise Continuous Linear Specification for Managerial Risk Taking

We re-estimate a piecewise linear specification of the model given in Equation 4.4, but this time we require that the resulting regression line is piecewise continuous. We impose continuity restrictions at the breakpoints, and obtain the following regression for each quarter of a year:

$$\hat{e}_{i,t} = \kappa + \delta_{low} Value_{i,t_-} + \delta_{mid}(Value_{i,t_-} - 0.6)^+ + \delta_{high}(Value_{i,t_-} - 1)^+ + \eta_{i,t} \quad . \tag{A.1}$$

Figure 6 depicts the resulting regression lines, where we set insignificant regression coefficients to zero. The results support the main findings in Section 5 from the kernel regression and the unrestricted version of the piecewise linear specification. We see a risk decline for poorly performing funds during the second quarter and a risk increase during the fourth quarter of a year.

[Figure 6 around here]

A.5 Alternative Risk Measures

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

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

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

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

$$RISK^{M}_{i,t} = ln\left(\frac{STD_{i,t}}{STD(Market)_t}\right). \tag{A.2}$$

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

We also adjust hedge funds' returns for market movements and other risk factors by using an asset pricing model. We fit the Carhart (1997) 4-factor model to daily returns of each hedge fund, and then repeat our analysis using the residuals from this model instead of the returns themselves. The results for the managerial risk taking remain qualitalively unchanged.

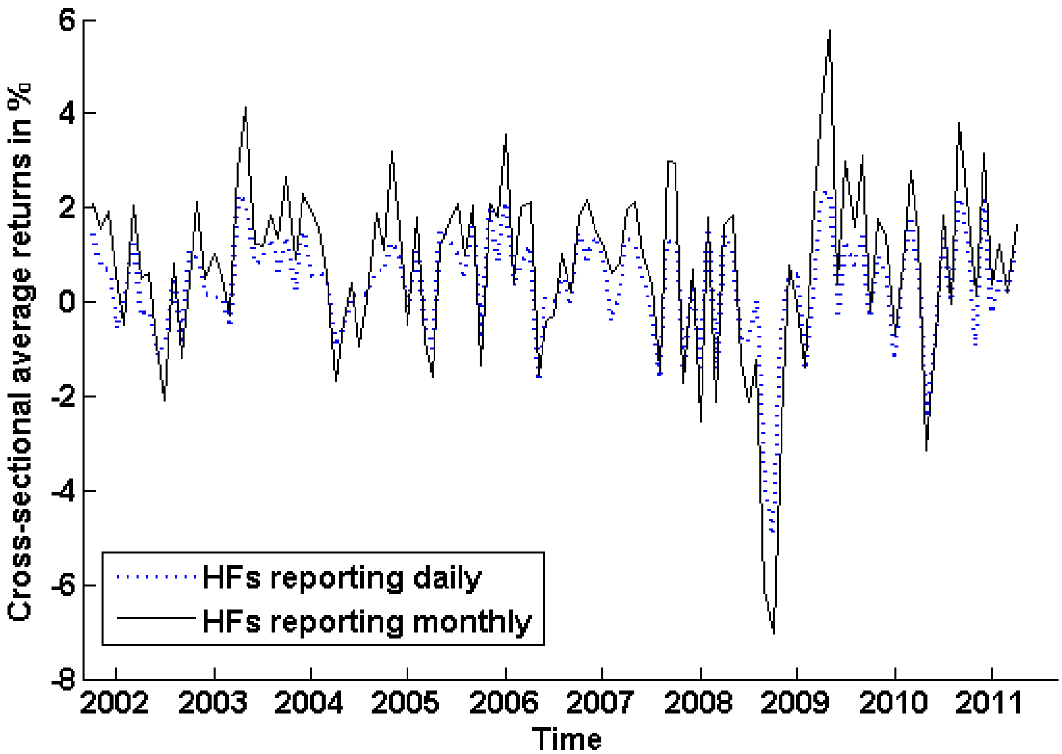
A.6 Controlling For Possible Multiple Share Classes

Hedge fund investment companies often control more than one hedge fund (Kolokolova (2011)). Such multiple funds can be either self-contained individual products or different share classes of the same fund. The sample used in the paper contains 195 unique investment companies. 85 of them control a single fund, 42 control two funds, and 68 control more than two funds. In order to identify potential multiple share classes of the same fund, for each pair of funds belonging to the same investment company we compute return correlations. The mean return correlation of such funds is 0.83, and it ranges from as low as -1 to as high as +1. We consider funds exhibiting pairwise return correlations higher than 98% and exclude one fund from each such pair with the shorter return history. In total, we exclude 207 hedge funds, and repeat the complete analysis based on the remaining sample. Results in Table 13 indicate no qualitative change to the main conclusion of the paper when the reduced sample is used.

[Table 13 around here]

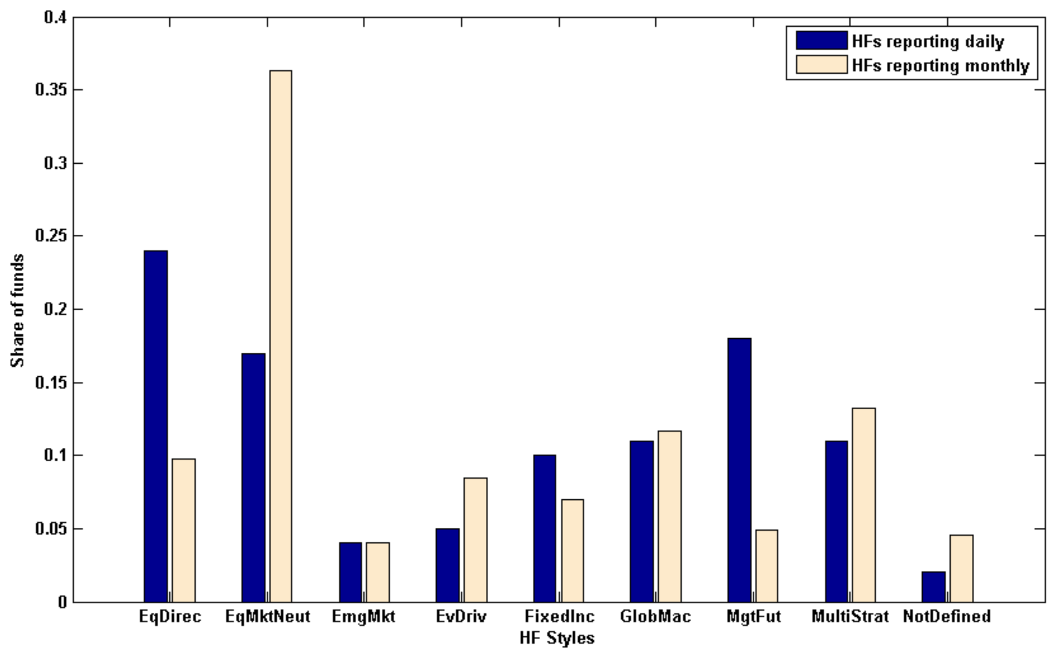
Figures

Figure 1: **Time Series of Average Returns of "Daily" and "Monthly" Hedge Funds**



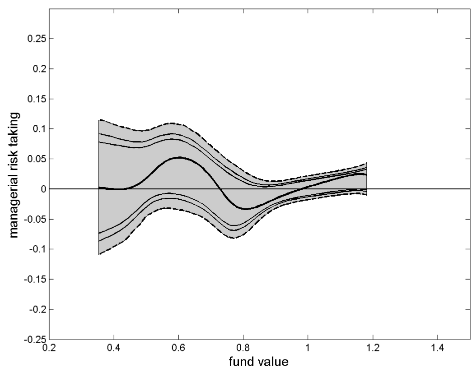
The figure presents time series plots of cross-sectinal average monthly returns from the funds in our sample (reporting daily to Bloomberg) as well as from funds reporting monthly to the commertial databases as defined in Section 3 between October 2001 and April 2011. The correlation between the two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

Figure 2: **Distribution of Styles of "Daily" and "Monthly" Hedge Funds**

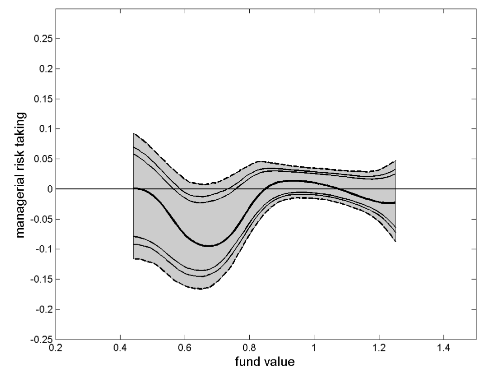


The figure presents the reported styles distributions of funds in our sample (reporting daily to Bloomberg) as well as of funds reporting monthly to commertial databases as described in Section 3 between October 2001 and April 2011. The abbreviations stand for: EqDirec – Directional Equity, EqMktNeu – Equity Market Neutral, EmgMkt – Emerging Markets, EvDriv – Event Driven, FixedInc – Fixed Income, GlobMac – Global Marco, MgtFut – Managed Futures, MultiStrat – Multy Strategy, NotDefined - funds that do not clearly state their style or the style cannot be classified within any of the groups above, for example "Tail Risk".

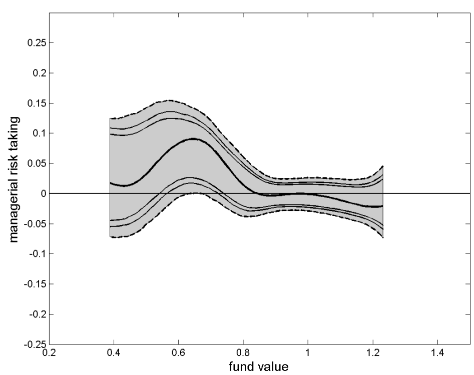
Figure 3: **Managerial Risk Taking: Quarter-Wise**



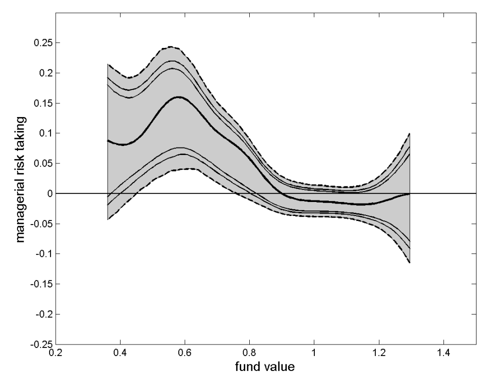
(a) Quarter 1



(b) Quarter 2



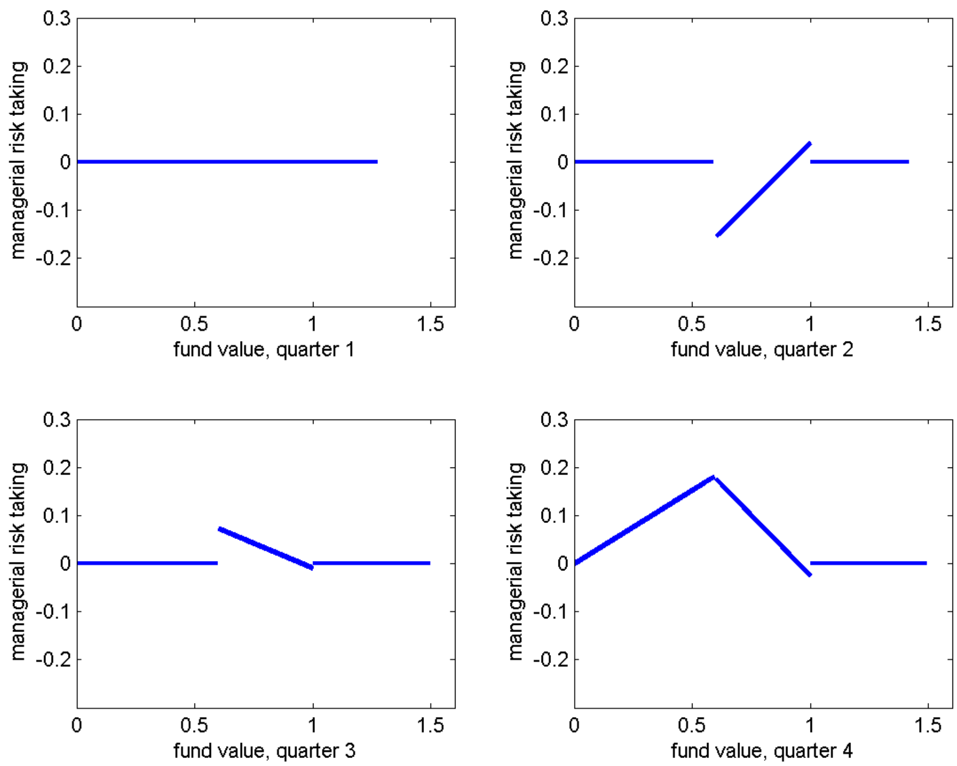
(c) Quarter 3



(d) Quarter 4

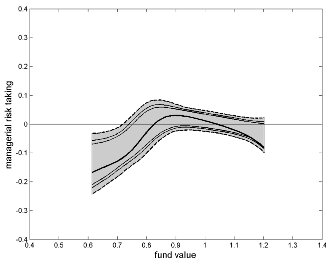
The figure plots the result of the kernel regression specified in Section 4 for the different quarters of a year. On the horizontal axis is the fund value relative to the HWM. On the vertical axis is the managerial risk taking contained in the residuals from a panel regression of RISK (the natural logarithm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

Figure 4: **Managerial Risk Taking: Piecewise Linear Specification**

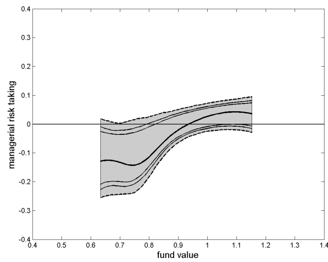


The figure plots the regression results for managerial risk taking on the fund value relative to the HWM as specified in the piecewise panel regression in Equation 4.4 for four quarters of a year. The linear relation between fund value relative to the HWM and RISK (the natural logarithm of the intra-month 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.

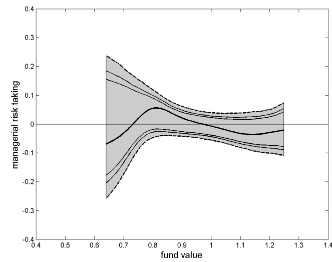
Figure 5: **Managerial Risk Taking: Month-Wise**



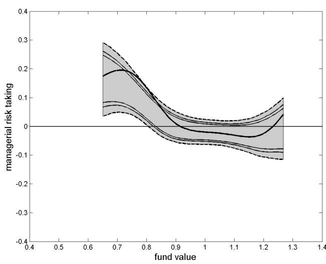
(a) April



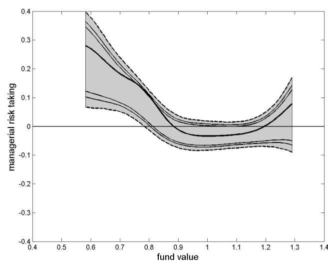
(b) May



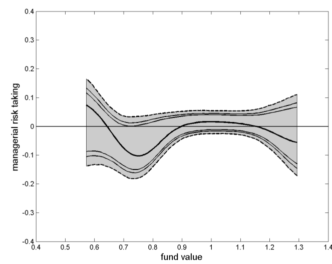
(c) June



(d) October



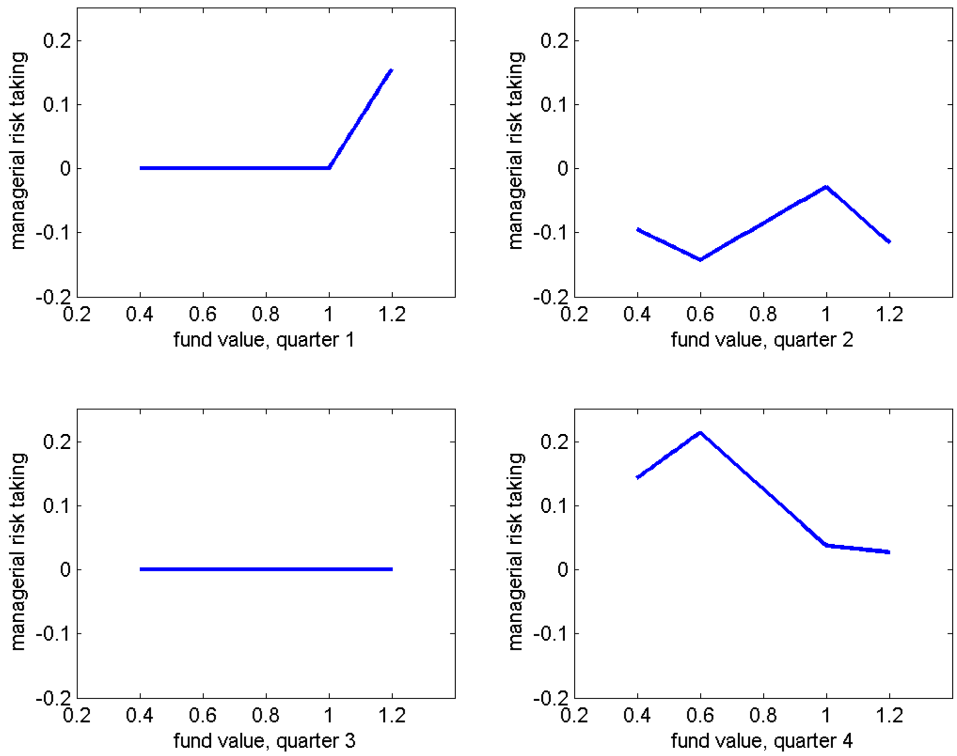
(e) November



(f) December

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 5 observations.

Figure 6: **Managerial Risk Taking: Piecewise Continuous Linear Specification**



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

Tables

Table 1: **Descriptive Statistics for Hedge Fund Sample**

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

Panel A reports the general characteristics of the hedge funds in our sample, including the average fund size, life time in years, usage of a HWM and an incentive fee, etc. Here 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 boarders in the European Union, being authorized in only a single member state. Panels B and C report the descriptive statistics of daily and monthly hedge fund returns in percent per day and month, respectively.

Table 2: **Descriptive Statistics for Hedge Fund Risk**

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

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

Table 3: **Descriptive Statistics Across Hedge Fund Styles**

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

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

Table 4: **Panel Regressions of Hedge Fund Risk**

	(I)		(II)	
$RISK_{t-1}$	+0.50 ***	(+53.07)	+0.50 ***	(+50.76)
$RISK_{t-2}$	+0.09 ***	(+8.74)	+0.10 ***	(+9.01)
$RISK_{t-3}$	+0.07 ***	(+7.19)	+0.07 ***	(+7.20)
$DeltaCorr_t$	+0.03 **	(+2.13)	+0.03 **	(+2.10)
$ln(AuM_{t\_})$	-0.01	(-1.36)	-0.01	(-1.28)
$OutflowLarge_{t-1}$	+0.03 ***	(+2.59)	+0.03 ***	(+2.59)
$ExcessPerf_{t-1}$			-0.27 ***	(-2.80)
R-sqr.	0.90		0.90	
Rbar-sqr.	0.89		0.89	
Nobs	10'141		10'141	

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

Table 5: **Piecewise Regressions of Residual Hedge Fund Risk**

	Q1		Q2		Q3		Q4	
$ConstLow$	-0.02	(-0.58)	+0.01	(+0.22)	+0.04	(+1.05)	-0.05	(-0.77)
$Value_t\_Low$	+0.13	(+1.27)	+0.07	(+0.69)	+0.00	(+0.02)	+0.31 **	(+2.04)
$ConstMiddle$	+0.01	(+0.09)	-0.45 ***	(-3.68)	+0.20 *	(+1.72)	+0.48 ***	(+3.87)
$Value_t\_Middle$	-0.03	(-0.29)	+0.49 ***	(+3.71)	-0.21 *	(-1.67)	-0.50 ***	(-3.74)
$ConstHigh$	-0.52	(-1.46)	+0.32	(+1.29)	+0.32	(+1.23)	-0.00	(-0.03)
$Value_t\_High$	+0.53	(+1.52)	-0.31	(-1.31)	-0.31	(-1.26)	-0.01	(-0.08)

The table reports estimation results for piecesise linear regressions of residual fund RISK as discussed in Section 4. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 6: **Determinants of Residual Hedge Fund Risk: Management Fee**

	Q1		Q2		Q3		Q4	
$ConstLow$	-0.03	(-0.37)	+0.05	(+0.66)	-0.05	(-0.71)	-0.03	(-0.26)
$MgtFeeLarge \cdot I_{Value_t\_Low}$	+0.00	(+0.04)	-0.04	(-0.64)	+0.10	(+1.64)	-0.02	(-0.26)
$Value_t\_Low$	+0.14	(+1.12)	+0.04	(+0.35)	+0.09	(+0.74)	+0.28	(+1.58)
$ConstMiddle$	+0.02	(+0.15)	-0.40 ***	(-3.19)	+0.21 *	(+1.80)	+0.47 ***	(+3.72)
$MgtFeeLarge \cdot I_{Value_t\_Middle}$	-0.01	(-0.46)	-0.05 *	(-1.88)	-0.02	(-0.72)	+0.03	(+1.16)
$Value_t\_Middle$	-0.04	(-0.32)	+0.46 ***	(+3.40)	-0.21 *	(-1.72)	-0.50 ***	(-3.69)
$ConstHigh$	-0.48	(-1.36)	+0.29	(+1.17)	+0.36	(+1.38)	+0.01	(+0.09)
$MgtFeeLarge \cdot I_{Value_t\_High}$	+0.03	(+1.55)	-0.02	(-0.81)	+0.03	(+0.97)	+0.02	(+0.75)
$Value_t\_High$	+0.49	(+1.40)	-0.28	(-1.15)	-0.36	(-1.44)	-0.03	(-0.23)

The table reports estimation results for piecesise linear regressions of residual fund RISK as discussed in Section 6. $MgtFeeLarge$ indicates funds with higher than median management fee. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 7: **Determinants of Residual Hedge Fund Risk: Notice Period, Performance, Age**

	Q1		Q2		Q3		Q4	
Panel A: Notice Period Effect								
$ConstLow$	+0.04	(+0.53)	+0.05	(+0.64)	+0.08	(+0.97)	-0.13	(-1.36)
$NoticeLarge \cdot I_{Value_t\_Low}$	-0.04	(-0.69)	-0.04	(-0.51)	-0.02	(-0.32)	+0.08	(+1.01)
$Value_t\_Low$	-0.05	(-0.36)	-0.08	(-0.47)	-0.12	(-0.73)	+0.45 **	(+2.22)
$ConstMiddle$	-0.11	(-1.28)	-0.49 ***	(-4.57)	+0.17 *	(+1.66)	+0.44 ***	(+3.83)
$NoticeLarge \cdot I_{Value_t\_Middle}$	-0.01	(-0.54)	+0.13 ***	(+3.87)	-0.03	(-1.02)	-0.00	(-0.08)
$Value_t\_Middle$	+0.11	(+1.21)	+0.53 ***	(+4.57)	-0.19	(-1.63)	-0.47 ***	(-3.76)
$ConstHigh$	-0.35	(-0.69)	+0.13	(+0.43)	+0.40	(+1.33)	+0.12	(+0.68)
$NoticeLarge \cdot I_{Value_t\_High}$	-0.04	(-0.89)	-0.03	(-0.61)	-0.04	(-0.78)	-0.03	(-0.92)
$Value_t\_High$	+0.38	(+0.75)	-0.14	(-0.48)	-0.38	(-1.33)	-0.13	(-0.74)
Panel B: Recent Performance Effect								
$ConstLow$	+0.04	(+0.78)	+0.05	(+1.07)	+0.04	(+0.97)	-0.01	(-0.12)
$\Delta Value_{t\_} > 0 \cdot I_{Value_t\_Low}$	-0.08 *	(-1.68)	-0.09 *	(-1.73)	+0.04	(+0.82)	-0.13 **	(-2.36)
$Value_t\_Low$	-0.02	(-0.18)	+0.03	(+0.23)	-0.10	(-0.93)	+0.33 **	(+2.37)
$ConstMiddle$	-0.11	(-1.23)	-0.45 ***	(-4.17)	+0.18 *	(+1.67)	+0.44 ***	(+3.88)
$\Delta Value_{t\_} > 0 \cdot I_{Value_t\_Middle}$	-0.02	(-0.93)	+0.06 ***	(+2.84)	-0.03	(-1.53)	-0.02	(-0.67)
$Value_t\_Middle$	+0.11	(+1.20)	+0.47 ***	(+4.06)	-0.18	(-1.57)	-0.46 ***	(-3.70)
$ConstHigh$	-0.22	(-0.42)	+0.13	(+0.43)	+0.40	(+1.33)	+0.12	(+0.66)
$\Delta Value_{t\_} > 0 \cdot I_{Value_t\_High}$	+0.04	(+1.26)	-0.02	(-0.33)	-0.12 ***	(-3.55)	-0.05	(-1.59)
$Value_t\_High$	+0.23	(+0.45)	-0.12	(-0.43)	-0.29	(-1.00)	-0.08	(-0.47)
Panel C: Age Effect								
$ConstLow$	-0.01	(-0.16)	+0.04	(+0.40)	+0.01	(+0.15)	-0.09	(-0.87)
$AgeLarge \cdot I_{Value_t\_Low}$	-0.01	(-0.17)	-0.03	(-0.35)	+0.03	(+0.36)	+0.04	(+0.52)
$Value_t\_Low$	+0.13	(+1.13)	+0.06	(+0.56)	+0.02	(+0.16)	+0.33 **	(+2.10)
$ConstMiddle$	+0.05	(+0.46)	-0.49 ***	(-3.99)	+0.19	(+1.58)	+0.44 ***	(+3.40)
$AgeLarge \cdot I_{Value_t\_Middle}$	-0.05 **	(-2.57)	+0.07 ***	(+2.88)	+0.01	(+0.25)	+0.04	(+1.41)
$Value_t\_Middle$	-0.05	(-0.41)	+0.49 ***	(+3.74)	-0.20	(-1.58)	-0.48 ***	(-3.50)
$ConstHigh$	-0.56	(-1.54)	+0.31	(+1.27)	+0.33	(+1.28)	-0.00	(-0.03)
$AgeLarge \cdot I_{Value_t\_High}$	-0.03	(-1.58)	-0.02	(-0.97)	-0.04	(-1.39)	+0.00	(+0.11)
$Value_t\_High$	+0.59	(+1.65)	-0.29	(-1.23)	-0.30	(-1.23)	-0.01	(-0.09)

The table reports estimation results for piecesise linear regressions of residual fund RISK as discussed in Section 6. In Panel A $NoticeLarge$ indicates funds with higher than median notice period prior to redemption. In Panel B $\Delta Value_{t\_} > 0$ captures funds with positive cumulative return over the preceeding quarter. In Panel C $AgeLarge$ indicates funds older than the median fund at the beginnig of a quarter. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 8: **Determinants of Residual Hedge Fund Risk: HWM, Incentive Fees**

	Q1		Q2		Q3		Q4	
Panel A: HWM Effect								
$ConstLow$	-0.02	(-0.55)	+0.01	(+0.25)	+0.04	(+1.02)	-0.04	(-0.76)
$HaveHWM \cdot I_{Value_t\_Low}$	-0.03	(-0.63)	+0.02	(+0.33)	-0.05	(-0.81)	-0.04	(-0.47)
$Value_t\_Low$	+0.18	(+1.42)	+0.04	(+0.25)	+0.06	(+0.48)	+0.35 **	(+2.00)
$ConstMiddle$	+0.01	(+0.09)	-0.44 ***	(-3.57)	+0.22 *	(+1.92)	+0.48 ***	(+3.85)
$HaveHWM \cdot I_{Value_t\_Middle}$	-0.00	(-0.01)	-0.01	(-0.62)	-0.04 *	(-1.91)	+0.01	(+0.52)
$Value_t\_Middle$	-0.03	(-0.29)	+0.49 ***	(+3.70)	-0.21 *	(-1.67)	-0.51 ***	(-3.76)
$ConstHigh$	-0.51	(-1.43)	+0.30	(+1.19)	+0.32	(+1.24)	-0.03	(-0.20)
$HaveHWM \cdot I_{Value_t\_High}$	-0.01	(-0.30)	+0.02	(+0.65)	-0.00	(-0.08)	+0.03	(+1.41)
$Value_t\_High$	+0.53	(+1.51)	-0.30	(-1.24)	-0.31	(-1.27)	-0.00	(-0.01)
Panel B: Incentive Fee Effect								
$ConstLow$	-0.03	(-0.61)	+0.02	(+0.48)	+0.04	(+1.05)	-0.05	(-0.78)
$HaveIveFee \cdot I_{Value_t\_Low}$	-0.10	(-1.49)	+0.19 **	(+2.55)	-0.07	(-1.23)	+0.05	(+0.59)
$Value_t\_Low$	+0.30 *	(+1.95)	-0.22	(-1.43)	+0.10	(+0.75)	+0.22	(+1.04)
$ConstMiddle$	-0.00	(-0.04)	-0.43 ***	(-3.41)	+0.22 *	(+1.86)	+0.46 ***	(+3.66)
$HaveIveFee \cdot I_{Value_t\_Middle}$	+0.02	(+0.70)	-0.02	(-0.80)	-0.02	(-0.73)	+0.02	(+0.85)
$Value_t\_Middle$	-0.03	(-0.26)	+0.48 ***	(+3.65)	-0.21 *	(-1.72)	-0.51 ***	(-3.73)
$ConstHigh$	-0.55	(-1.55)	+0.32	(+1.29)	+0.31	(+1.19)	-0.01	(-0.04)
$HaveIveFee \cdot I_{Value_t\_High}$	+0.06 ***	(+3.11)	-0.04 *	(-1.68)	-0.05 *	(-1.74)	+0.02	(+0.74)
$Value_t\_High$	+0.52	(+1.49)	-0.28	(-1.19)	-0.27	(-1.09)	-0.02	(-0.14)

The table reports estimation results for piecesise linear regressions of residual fund RISK as discussed in Section 6. In Panel A $HaveHWM$ indicates funds that report having a high-water mark provision. In Panel B $HaveIveFee$ indicates funds that report non-zero incentive fees. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 9: **Determinants of Residual Hedge Fund Risk: Market Correlation**

	Q1		Q2		Q3		Q4	
$ConstLow$	-0.01	(-0.08)	+0.02	(+0.30)	+0.08	(+1.50)	+0.00	(+0.02)
$CorrHigh \cdot I_{Value_t\_Low}$	-0.03	(-0.34)	-0.01	(-0.22)	-0.07	(-1.06)	-0.08	(-0.97)
$Value_t\_Low$	+0.16	(+1.26)	+0.09	(+0.71)	+0.06	(+0.49)	+0.35 **	(+2.24)
$ConstMiddle$	+0.05	(+0.44)	-0.41 ***	(-3.13)	+0.27 **	(+2.29)	+0.37 ***	(+2.79)
$CorrHigh \cdot I_{Value_t\_Middle}$	-0.02	(-1.12)	-0.02	(-0.92)	-0.05 ***	(-2.62)	+0.05 **	(+2.12)
$Value_t\_Middle$	-0.06	(-0.55)	+0.46 ***	(+3.32)	-0.26 **	(-2.05)	-0.42 ***	(-2.95)
$ConstHigh$	-0.52	(-1.44)	+0.32	(+1.31)	+0.30	(+1.16)	-0.00	(-0.01)
$CorrHigh \cdot I_{Value_t\_High}$	+0.01	(+0.84)	+0.02	(+0.99)	-0.03	(-0.95)	+0.02	(+0.82)
$Value_t\_High$	+0.53	(+1.48)	-0.33	(-1.36)	-0.29	(-1.15)	-0.02	(-0.14)

The table reports estimation results for piecesise linear regressions of residual fund RISK as discussed in Section 6. $CorrHigh$ indicates funds that exhibit higher than median return correlation with the market (MSCI-World index). The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 10: **Panel Regression of Hedge Fund Risk with a Linear Specification for Fund Value**

	(I)		(II)	
$RISK_{t-1}$	+0.50 ***	(+50.54)	+0.50 ***	(+51.85)
$RISK_{t-2}$	+0.09 ***	(+8.88)	+0.09 ***	(+9.14)
$RISK_{t-3}$	+0.07 ***	(+6.99)	+0.07 ***	(+7.27)
$DeltaCorr_t$	+0.03 **	(+2.11)	+0.03 **	(+2.24)
$ln(AuM_{t\_})$	0.00	(-0.97)	0.00	(-1.01)
$OutflowLarge_{t-1}$	+0.02 **	(+2.18)	+0.02 **	(+2.13)
$Value_{t\_}$	-0.19 ***	(-3.96)	-0.17 ***	(-3.36)
$ExcessPerf_{t-1}$			-0.19 *	(-1.92)
R-sqr.	0.90		0.90	
Rbar-sqr.	0.89		0.89	
Nobs	10'141		10'141	

The table reports estimation results for panel regressions of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) on the fund value relative to the high-water mark, a set of dynamic explanatory variables and controls. The regression includes fund and time fixed effects. Compared to the main panel regression in Equation 7.1, the fund value variable has a linear relation to managerial risk taking. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 11: **Panel Regressions of Hedge Fund Risk with a Linear Specification for Fund Value and Interaction Terms**

	(I)		(II)		(III)		(IV)	
$RISK_{t-1}$	+0.50 ***	(+50.62)	+0.50 ***	(+49.01)	+0.50 ***	(+47.81)	+0.50 ***	(+49.86)
$RISK_{t-2}$	+0.09 ***	(+8.87)	+0.09 ***	(+8.67)	+0.09 ***	(+8.90)	+0.09 ***	(+9.22)
$RISK_{t-3}$	+0.07 ***	(+7.07)	+0.07 ***	(+7.08)	+0.07 ***	(+7.30)	+0.07 ***	(+7.12)
$DeltaCorr_t$	+0.03 **	(+2.02)	+0.03 **	(+2.16)	+0.03 **	(+2.15)	+0.03 **	(+2.11)
$ln(AuM_{t\_})$	0.00	(-0.94)	0.00	(-0.98)	0.00	(-0.91)	0.00	(-1.10)
$OutflowLarge_{t-1}$	+0.02 **	(+2.27)	+0.02 **	(+2.13)	+0.02 **	(+2.10)	+0.02 **	(+2.28)
$Value_{t\_}$	-0.28 ***	(-4.08)	-0.18 ***	(-3.86)	-0.27 ***	(-4.21)	-0.12 **	(-2.16)
$Value_{t\_} \times HWM$	+0.15 *	(+1.73)						
$Value_{t\_} \times IveFeeLarge$			-0.48 **	(-1.99)				
$Value_{t\_} \times MmtFeeLarge$					+0.17 **	(+2.00)		
$Value_{t\_} \times NoticeLarge$							-0.20 **	(-2.23)
R-sqr.	0.90		0.90		0.90		0.90	
Rbar-sqr.	0.89		0.89		0.89		0.89	
Nobs	10'141		10'141		10'141		10'141	

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

Table 12: **Determinants of Residual Hedge Fund Risk: Fund Style**

	Q1		Q2		Q3		Q4	
Panel A: Directional Equity								
$ConstLow$	-0.03	(-0.68)	+0.01	(+0.22)	+0.05	(+1.11)	-0.05	(-0.79)
$EqDirec \cdot I_{Value_t\_Low}$	+0.07	(+1.16)	+0.07	(+1.06)	-0.05	(-0.81)	+0.02	(+0.25)
$Value_t\_Low$	+0.10	(+0.96)	+0.03	(+0.22)	+0.03	(+0.28)	+0.29 *	(+1.90)
$ConstMiddle$	+0.01	(+0.09)	-0.45 ***	(-3.68)	+0.16	(+1.41)	+0.46 ***	(+3.69)
$EqDirec \cdot I_{Value_t\_Middle}$	-0.00	(-0.03)	-0.01	(-0.42)	+0.04	(+1.45)	+0.03	(+0.88)
$Value_t\_Middle$	-0.03	(-0.29)	+0.49 ***	(+3.73)	-0.18	(-1.41)	-0.49 ***	(-3.61)
$ConstHigh$	-0.56	(-1.59)	+0.27	(+1.07)	+0.27	(+1.03)	-0.01	(-0.05)
$EqDirec \cdot I_{Value_t\_High}$	+0.10 ***	(+4.37)	-0.09 ***	(-2.76)	-0.11 ***	(-2.94)	-0.01	(-0.35)
$Value_t\_High$	+0.56	(+1.60)	-0.25	(-1.03)	-0.25	(-1.01)	-0.01	(-0.04)
Panel B: Equity Market Neutral								
$ConstLow$	-0.03	(-0.57)	+0.01	(+0.19)	+0.04	(+0.97)	-0.04	(-0.75)
$EqMktNeu \cdot I_{Value_t\_Low}$	-0.01	(-0.14)	-0.23 *	(-1.86)	-0.17	(-1.43)	+0.02	(+0.16)
$Value_t\_Low$	+0.14	(+1.23)	+0.11	(+1.04)	+0.04	(+0.38)	+0.30 *	(+1.87)
$ConstMiddle$	+0.00	(+0.02)	-0.45 ***	(-3.66)	+0.20 *	(+1.72)	+0.48 ***	(+3.90)
$EqMktNeu \cdot I_{Value_t\_Middle}$	+0.02	(+0.80)	-0.01	(-0.31)	+0.02	(+0.95)	-0.07 **	(-2.51)
$Value_t\_Middle$	-0.03	(-0.26)	+0.49 ***	(+3.71)	-0.21 *	(-1.73)	-0.48 ***	(-3.58)
$ConstHigh$	-0.52	(-1.45)	+0.32	(+1.30)	+0.31	(+1.21)	+0.02	(+0.10)
$EqMktNeu \cdot I_{Value_t\_High}$	+0.01	(+0.44)	+0.01	(+0.42)	+0.11 ***	(+2.83)	-0.07 **	(-2.12)
$Value_t\_High$	+0.53	(+1.51)	-0.32	(-1.32)	-0.32	(-1.31)	-0.02	(-0.16)
Panel C: Managed Futures								
$ConstLow$	+0.06	(+0.79)	+0.01	(+0.11)	-0.03	(-0.35)	-0.05	(-0.56)
$ManFut \cdot I_{Value_t\_Low}$	-0.08	(-1.36)	+0.00	(+0.01)	+0.07	(+1.15)	+0.01	(+0.12)
$Value_t\_Low$	+0.02	(+0.13)	+0.08	(+0.56)	+0.08	(+0.60)	+0.32 *	(+1.71)
$ConstMiddle$	+0.01	(+0.09)	-0.38 ***	(-3.03)	+0.19	(+1.61)	+0.45 ***	(+3.57)
$ManFut \cdot I_{Value_t\_Middle}$	+0.00	(+0.01)	-0.08 ***	(-2.80)	+0.01	(+0.48)	+0.04	(+1.27)
$Value_t\_Middle$	-0.03	(-0.29)	+0.43 ***	(+3.24)	-0.20	(-1.58)	-0.49 ***	(-3.53)
$ConstHigh$	-0.49	(-1.34)	+0.31	(+1.23)	+0.32	(+1.23)	+0.01	(+0.07)
$ManFut \cdot I_{Value_t\_High}$	+0.01	(+0.48)	-0.00	(-0.14)	+0.00	(+0.01)	+0.03	(+0.95)
$Value_t\_High$	+0.50	(+1.40)	-0.31	(-1.24)	-0.31	(-1.26)	-0.03	(-0.20)

The table reports estimation results for piecesise linear regressions of residual fund RISK as discussed in Section 6. In Panel A $EqDirec$ indicates Directional Equity funds, in Panel B $EqMktNeu$ indicates Equity Market Neutral funds, in Panel C $ManFut$ indicates Managed Futures funds. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table 13: **Piecewise Regressions of Residual Hedge Fund Risk Excluding Potential Multiple Fund Share Classes**

	Q1		Q2		Q3		Q4	
ConstLow	-0.02	(-0.51)	+0.01	(+0.18)	+0.04	(+1.08)	-0.04	(-0.73)
$Value_{t\_}Low$	+0.10	(+0.95)	+0.07	(+0.61)	+0.02	(+0.23)	+0.34 **	(+2.18)
ConstMiddle	-0.01	(-0.09)	-0.34 **	(-2.35)	+0.02	(+0.11)	+0.55 ***	(+3.32)
$Value_{t\_}Middle$	-0.01	(-0.04)	+0.38 **	(+2.44)	-0.00	(-0.02)	-0.58 ***	(-3.23)
ConstHigh	-0.71	(-1.62)	+0.31	(+1.08)	+0.14	(+0.53)	-0.02	(-0.13)
$Value_{t\_}High$	+0.72 *	(+1.68)	-0.31	(-1.12)	-0.15	(-0.59)	+0.01	(+0.03)

The table reports estimation results for piecesise linear regressions of residual fund RISK with 207 hedge funds exhibiting return correlations above 98% with other funds within the same investment company excluded from the sample. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.