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

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Abstract

Analyzing a sample of hedge funds that report 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 risk reduction is stronger for funds with higher management fees, shorter notice period prior to redemption, and recently deteriorating performance, which is consistent with a managerial aversion to early fund liquidation and loss of future management fees. Towards the end of a year, on the contrary, poorly performing funds gamble for resurrections by increasing risk. The risk increase is not purely driven by a high-water mark provision and incentive fees, and it points towards existing of other incentives, like reporting good performance at a year end.

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1 Introduction

Hedge funds pose a challenging task from a risk management perspective. They are allowed to use exotic financial products of all kinds, they can rapidly change their strategy as well as the exposures to different markets, and often they are highly leveraged. Most managers have some personal wealth invested in their fund, and a typical compensation contract provides them with complex risk taking incentives. They earn a management fee – a constant share of the fund's assets paid out on a pro rata temporis basis, as well as a performance fee – a share of the fund's profits in excess of a high-water mark (previously achieved end-of-year maximum net asset value, henceforth HWM), which is often paid at the end of a calendar year. Such a complex incentive scheme induces highly non-linear managerial risk taking with a strong seasonal pattern. Our paper addresses the *intra-year* variation of HF risk taking.

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 an intra-month return standard deviation.

We document a strong seasonal pattern in risk taking as a function of fund performance relative to its HWM. Conditional on fund underperformance relative to the HWM, hedge fund managers increase the fund risk, which is consistent with theoretical predictions of Hodder and Jackwerth (2007) and Buraschi, Kosowski, and Sritrakul (2012). It happens, however, only during later months of a year (particularly, during the fourth quarter), whereas the aforementioned models predict a uniform risk increase throughout a year. During earlier months of a year (second quarter), poorly performing funds, on the contrary, tend to reduce their risk. This risk down shift seems to be consistent with the predictions of a recent model of Lan, Wang, and Yang (2013). It may suggest that at the beginning of a year, fund managers perceive their evaluation horizon as very long, and seek to reduce fund liquidation probability in order to keep earning management fees, whereas towards the end of a year poorly performing managers perceive their investment horizon as rather short.

Looking further into the incentives to reduce risk by poorly performing funds during earlier month of a year, we document that, indeed, those funds that charge higher management fees are more prone to risk reduction. Similarly, funds with a shorter notice period prior to redemption, recently deteriorating performance, and younger age – thus, with potentially higher liquidation probability – exhibit stronger risk reduction. Remarkably, these factors do not have significant impact on risk increase at the end of a year, where all poorly performing managers gamble for resurrection.

End of year gamble for resurrection by poorly performing funds is not purely driven by the existence of a high-water mark provision and incentive contracts. It is strongly pronounced for funds not charging incentive fees, too. This finding points towards existing of other incentives (not explicitly linked to managerial compensation scheme) that induce higher risk taking at the end of a calendar year. These might include reputation concerns, as majority of hedge funds provide end-of-year reports to their clients. Remarkably, funds exhibiting higher return correlation with the market have stronger risk increase at a year end. Such funds seem to follow more conventional strategies, which risk can be relatively easier adjusted though leverage.

We also document that hedge fund risk is persistent, with the previous three months risk levels having the strongest impact. While finding general persistence in second moments of return distributions is not surprising, we show that managers take it into account when they adjust the fund risk. Risk adjustments happen in advance to assure the desired risk levels at desired times. The second quarter risk decline of poorly performing funds is strongly pronounced in April and May, and not so in June; and the fourth quarter gambling starts as early as October, is pronounced in November, and no additional risk shifts can be detected in December.

2 Related Literature

In this section, we, first, review the theoretical predictions for managerial risk taking in hedge funds. While there is a vast literature on the optimal response to more general incentive schemes[1], we will focus on the most relevant models for hedge funds only. Then, we proceed by summarizing the existing empirical evidence.

One of the first models, which covers most of the main characteristics of a typical incentive contract 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 three year valuation horizon and the incentive fee being calculated and the HWM reset at the end of every year, the managerial risk taking increases if fund value is substantially below the HWM. It reflects managerial gambling at a point, where the fund is close to liquidation. The simulation results of 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.

[1]See, e.g., Harris and Raviv (1979), Gibbons and Murphy (1992), Ross (2004), Basak, Pavlova, and Shapiro (2008) among others.

One limitation of the Hodder and Jackwerth (2007) model is that investor's behavior in response to hedge fund performance is ignored. Generally, investors respond to good fund performance by capital inflows to the fund, and tend do redeem shares after periods of 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.

A step forward in this direction is made by Buraschi, Kosowski, and Sritrakul (2012). Here, the authors search for an appropriate adjustment of hedge fund performance for managerial risk taking. Therefore, they develop a structural model of optimal risk taking.[2] The model considers a typical hedge fund incentive contract but does not explicitly include the manager's personal investment in a fund. The manager does not have an option to liquidate the fund; instead, the authors model investors' redemptions and potential brokerage funding restrictions through short put option positions.[3] 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 (2012) suggests the highest risk taking at a fund value of approximately 60% of the HWM, with the risk taking still being bounded. If the short put options are ignored and only the performance fee is maximized (a long call option only), the model predicts unbounded risk taking. 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 (2012) result in gradual risk reduction after the fund value drops below a certain point and approaches

[2]The model is based on Koijen (2013), who develops a structural model for optimal portfolios of mutual fund managers, taking into account managerial skill, incentives, and risk preferences.

[3]Buraschi, Kosowski, and Sritrakul (2012) also analyze risk shifting empirically. But the authors focus on differences in the overall hedge fund return volatilities measured across a whole year, where they treat all observations alike in terms of time to expiration. The results are then used for performance adjustments and are not directly comparable to our empirical results.

the strike of the short put option.

While Buraschi, Kosowski, and Sritrakul (2012) do not analyze differential times to expiration of the managerial incentive option explicitly, Panageas and Westerfield (2009) focus entirely on the effect of the managerial valuation horizon. They consider the optimal portfolio allocations for a risk-neutral manager disregarding personal managerial investments in the fund and management fees. The authors 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 above mentioned papers suggest the following testable hypotheses:

Hypothesis A: Average managerial risk taking is higher if hedge fund value is below the HWM.

Hypothesis A(1): Below the HWM, the relationship between fund value relative to the HWM and its risk is not linear but bell-shaped.

In a recent paper Lan, Wang, and Yang (2013) take a different avenue in modeling optimal hedge fund risk taking (leverage). The key difference from the models of Hodder and Jackwerth (2007) and Buraschi, Kosowski, and Sritrakul (2012) is the infinite valuation horizon of managers. 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 of a risk-neutral manager. This leads to a *lower* leverage at fund values below the HWM (where the fund liquidation probability is higher). Interestingly, management fees capture 75% of total managerial surplus, with only 25% generated though incentive fees. In this continuous time structural model, the authors also incorporate other stylized facts of managerial investment strategies and compensation contracts, including existence of alpha-generating strategies, drawdown and fund liquidation triggered by poor performance, leverage constraints, managerial ownership, new money inflow in response to good performance, as well as endogenous managerial option to liquidate and re-start the fund at a cost.

This model provides a competing hypothesis:

Hypothesis B: Average managerial risk taking is lower for hedge funds 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 scope of the existing empirical evidence on the managerial response to incentives in hedge funds is limited by the availability of hedge fund data. Generally, hedge fund return data are available only at a monthly frequency. Many of 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 observations only. Brown, Goetzmann, and Park (2001) find tournament behaviour among hedge funds but no relation of fund risk to absolute performance. In particular, the authors show that hedge funds delivering above average performance during the first half of a year, reduce the return volatility during the second half of the year, while those funds exhibiting below average performance, tend to increase return volatility. However, after conditioning on the estimated HWM, the significance of the volatility changes vanishes. Agarwal, Daniel, and Naik (2002) find similar results in their sample of hedge funds, i.e. no relation of risk to fund value relative to the HWM. More recently, however, Aragon and Nanda (2012) and Buraschi, Kosowski, and Sritrakul (2012) do find evidence of endogenous and state dependent risk shifting.

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 performance and risk changes (which would be consistent with general predictions of Hodder and Jackwerth (2007) and Buraschi, Kosowski, and Sritrakul (2012)). They relate the risk changes to managerial incentives and find that the risk shifting is 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 paper focuses on tournament behavior by hedge fund managers; and the main performance measure is the relative rank of a fund with respect to its peers. The authors also repeat the analysis using the absolute fund performance, which is measured by an indicator variable of fund being below the high-water mark in the middle of a year. They find that fund that are below the HWM significantly increase risk raking from the first to the second half of a year.

The existing empirical research does not seem to 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) tend to underreport good returns, thus, smoothing performance, throughout a year and then inflate their December returns by adding the underreported portion of returns back. Such strategy assures higher inflows as investors direct money into funds reporting a greater fraction of positive returns. The authors also find weak evidence of hedge fund inflating December returns through "borrowing" from January returns. Such strategy increases the fees earned during the current year. Supporting this view, Ben-David, Franzoni, Landier, and Moussawi (2013) suggest possible stock price manipulation by large hedge funds that have to file end-of-quarter long equity holdings with 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. Majority of funds that do not have to submit quarterly reports, still provide their investors with end-of-year reports. Reporting particularly good results contributes to managerial reputation as well as increases immediately paid fees. Higher returns in December can be achieved (apart from aforementioned direct manipulations) by increasing the riskiness of the underlying portfolio beforehand. This leads us to a conjecture, that *Hypothesis A* is more likely to hold at the end of a year, rather and at the beginning of a year.

3 Data

3.1 General Properties of Hedge Fund Daily Returns

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.[4] We retrieve time series of daily hedge fund returns and assets under management, 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.

We clean two obvious outliers, where the daily returns exceed 100% and include only hedge funds, which report daily returns regularly over the entire lifetime. To ensure regular daily reporting, we delete all zero return information reported and impose restrictions on the number of trading days between two consecutive reporting dates. The average

[4] The number of hedge funds reporting daily returns to Bloomberg in other currencies is generally small and develops unevenly over time, which is why we use EUR and USD funds only.

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). For the included funds, we later require at least 15 daily return observations per month (at least 4 per week for the shortest month, on average) to obtain a monthly risk estimate, and an AuM observation within the first and last 5 trading days of the month to obtain a monthly flow estimate. We also exclude one fund with less than one year of reported returns.

Hedge funds reporting on a daily basis can be expected to be less opaque than those reporting on a monthly basis. Some of them are SICAVs[5], some work under the UCITS[6] jurisdiction, others may operate through managed accounts. 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.[7] 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 of funds in our sample, we expect the risk shifting patterns to be comparable to the funds reporting on monthly frequency, primarily because of similar

[5]SICAV is a type of an open-ended collective investment vehicle operating in Western Europe.

[6]UCITS directives allow investment funds to freely operate across the boarders in the European Union, being authorized in only a single member state.

[7]Hodder, Jackwerth, 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%.

managerial incentive schemes.[8]

[Insert Table 1 around here]

Further comparing the time-series dynamics of hedge funds returns in our sample and the ones reported on the monthly basis[9] we see that funds in both groups exhibit similar performance patterns. The correlation between average cross-sectional returns across these samples is 93%. The tail behaviour is also very similar with the correlation between returns of the bottom 5% of funds being 87%, and the correlation of the return of the top 5% of funds being 78%. The Figure 1 depicts the time series of average monthly returns of hedge funds in our sample and funds reporting on monthly bases. The two lines are closely related (reflecting the high correlation) and positive and negative spikes in the returns seem to coincide. 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 funds.

[Insert 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 2. 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.

[8] Throughout the paper, we compare our results to earlier results for more traditional hedge fund samples and show that they are in line. Moreover, in the Appendix we will present further evidence, e.g. on the cross-sectional determinants of risk levels, that suggests that our funds behave very much like monthly reporting funds.

[9] Our comparison group includes more that 20000 hedge funds that report to five commercial databases BarclayHedge, Eurekahedge, Morningstar, HFR, and TASS. The time period is matched to the one of our sample of daily reporting hedge funds.

[Insert Table 2 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. We feel, however, that this discrepancy might 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. Other styles have very similar distribution across the sample. The only 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. Despite these differences, our sample of daily reporting hedge funds is not biased towards a single hedge fund style. It covers the whole spectrum of styles as other widely used samples of monthly reporting funds.

[Insert Figure 2 around here]

The main focus of our paper is the risk of the hedge funds. 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. Figure 3 shows an envelope plot of the RISK time series for all individual hedge funds in our sample, revealing considerable cross-sectional variation in hedge fund risk taking.

[Insert Figure 3 around here]

The corresponding cross-sectional average descriptive statistics of the intra-month standard deviations of daily returns are given in Table 3. The average return standard deviations reported are slightly lower than the ones from the previously reported descriptive statistics in Table 1 (0.47% vs. 0.56% for EUR funds and 0.74% vs. 0.89% for USD funds). The differences capture the variations in the average level of hedge funds' returns over time. While for Table 1 only one estimate of return standard deviation is computed across the complete return history of each fund, the monthly estimates (Table 3) enable us to address the time variation in hedge fund risk.

[Insert Table 3 around here]

3.2 Time Series Properties of Hedge Fund Risk

Figure 4 plots the time series of the cross-sectional means of RISK for EUR and USD funds, as well as the corresponding time series for the MSCI-World index. The standard deviation of both EUR and USD hedge funds are smaller than that of the MSCI-World index. Despite living on different levels, all series seem to share the same dynamics. The correlation coefficients between all plotted series are very high, ranging from from 0.80 for MSCI-World and EUR funds to 0.84 for MSCI-World and USD funds. When analyzing the hedge funds' risk taking and the associated managerial decisions on the desirable level of risk, we will, therefore, condition on the overall market risk.

[Insert Figure 4 around here]

Generally, return volatility is found to be rather persistent. In equity markets, for example, mixed evidence on the predictability of the first moments of stock returns coexists with strong evidence on the predictability of second moments (see Christoffersen and Diebold (2006) and Christoffersen, Diebold, Mariano, Tay, and Tse (2007)). There exists some evidence on hedge fund return predictability (Avramov, Kosowski, Naik, and Teo (2011) and Wegener, von Nitzsch, and Cengiz (2010)), which suggests an even stronger predictability in the second moments of hedge fund returns. Also, hedge fund managers are known to specialize in particular investment strategies. Following one or several related strategies consistently could result in rather stable levels of fund risk, even if the underlying securities in the portfolio often change. There exists some empirical evidence supporting this view. Teo (2010), for instance, finds that the liquidity risk exposure of hedge fund portfolios is rather persistent. Ang, Gorovyy, and van Inwegen (2011) document high stability of hedge fund leverage. Additionally, the transaction costs that especially high-risk funds are facing can be substantial. Persistent leverage and the potentially costly closure of risky and illiquid positions point towards overall stability of hedge fund risk, too.

At the same time, hedge funds are perceived as very dynamic investment vehicles, which frequently alter their exposures to different risk factors (Fung and Hsieh (2001); Billio, Getmansky, and Pelizzon (2012)). This could lead to considerable volatility of hedge fund risk, i.e. low risk persistence. To quantify the actual persistence in hedge fund risk, we estimate the serial correlation at the first 5 lags of RISK for each hedge fund separately and report the results in Table 4.

[Insert Table 4 around here]

Hedge fund RISK appears to be rather persistent. The average first order serial correlation is 36%. For 91% of hedge funds, the first order serial correlation is positive;

it is significant for 51% of all hedge funds. We find negative estimates for the first order serial correlation for 9% of the hedge funds. These correlations are all small in absolute terms (with an average of -0.12) and we do not document a single case of a statistically significant negative autocorrelation coefficient of the first order and only few such correlations at the lags of higher order. The average correlation coefficients decrease substantially to levels below 0.10 after the third lag, namely to 0.07 at lag 4 and 0.02 at lag 5. Still, the coefficients at lag 5 are positive and significant for 11% of the hedge funds.[10]

To understand the structure of the underlying data generating process and determine the optimal number of lags that should be used in the panel analysis, we compute the partial autocorrelations of RISK. Partial autocorrelations capture the relation between the values at lag zero and higher order lags in isolation of the lags in between. The fractions of negative and significant partial serial correlations are, again, negligible and the fractions of significantly positive coefficients drop after the third lag to only 3% at lag 4. Hence, we will include three lags of RISK for the later analysis.

So far, we focused on the short-term persistence in the riskiness of hedge funds. Investors, however, are often subject to notice periods prior to the redemption. Our database contains relatively liquid funds and the average notice period prior to the redemption is only 20 days. But the maximum is 93 days, which means there can be a substantial lag between an investor's decision to exit the fund and the actual time of redemption. From an investor perspective it is, thus, important to understand the longer-term persistence in hedge fund risk, too. To address this issue, for every month, we sort the hedge funds into a high-risk and a low-risk group according to their RISK being above or below the median, and estimate the probabilities of transition across the groups for different horizons.

[10] This pattern is very stable across EUR and USD hedge funds. The EUR funds exhibit only slightly higher persistence in RISK, with 55% (45%) of the EUR (USD) funds having significantly positive first order coefficients.

Table 5 reports the transition probability matrix. The probability to stay in the same risk category over the following month is much higher than the probability to move to the other category, where the difference is highly statistically significant. The persistence is common for both high- and low-risk funds. We gradually increase the horizon with an increment of one month. The probability to stay in the current risk category is significantly higher than the probability to leave it at all horizons until 18 month, where we cannot reject the hypothesis of zero difference between the probabilities anymore for the first time. We repeat the analysis for high-risk and low-risk funds separately, for USD and EUR funds separately, as well as for changes in risk from December (one year) to January (the next year) only. The results remain virtually unchanged.

[Insert Table 5 around here]

Overall, we document that the level of risk taken by hedge funds is rather persistent. To what extent trading cost and other frictions truly limit the ability of managers to alter fund risk rapidly, and to what extent risk persistence follows simply from general style constancy remains an open question, and we will revisit this issue when analyzing the impact of incentives on risk taking later. The overall stickiness of hedge fund risk levels suggests that while our focus is on time-varying drivers of hedge fund risk (e.g. fund value relative to the HWM), general cross-sectional differences, which potentially arise from differential managerial risk appetites and investment strategies, should not be ignored. Therefore, we will control for fund fixed effects in the panel analysis. Also, we supplement a cross-sectional analysis of an average hedge fund risk in Appendix B.1.

4 Methodology

We employ a semi-parametric panel regression approach to analyze the managerial risk taking in response to incentives. Here RISK (the natural logarithm of the monthly standard deviation of daily hedge fund returns) serves as the dependent variable. The time-series properties of RISK analyzed in Section 3.2 suggest that RISK follows an AR(3) process and we specify a panel regression that includes 3 lags of the dependent variable as regressors. 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 interested reader finds a detailed cross-sectional analysis of the average fund risk in Appendix B.1. As hedge fund risk is related to market risk (Figure 4), we include fixed effects in the time dimension, too, 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 of the AuM of fund i at the beginning of month t ($ln(AuM_{i,t_-})$) in the regression, where the minus sign as sub-index in t_- indicates the beginning of month t. The variable

[11]There are different potential reasons for a change in the serial correlation. A variation in the true underlying return generating process due to a deliberate change in the fund strategy by the managers can cause such a change. However, a change in the estimated correlation coefficient can be also artificially caused by not equally spaced observations of daily returns within consecutive months. The estimated correlation based on 15 returns per month can be different from that estimated on 22 returns, even though the underlying return process does not change. 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.

captures potential changes in the risk-taking pattern that result from fund size variations over time.

We recognize that the second moments of hedge fund returns can be influenced by fund flows. Particularly, the effect of large outflows on fund risk could be pronounced even without any deliberate managerial change to the investment strategy. 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

$$Flow_{i,t-1} = \frac{AuM_{i,t_-} - AuM_{i,t-1_-} CR_{i,t-1}}{AuM_{i,t-1_-}} \ , \tag{4.1}$$

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 ($OutflowLarge_{i,t}$).[12]

To identify risk shifting caused by the convex compensation contract, we include the value of the fund relative to its HWM at the beginning of a month, which is the variable of our main interest. 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.[13] The fund value relative to the HWM is then the ratio of the total cumulative return of the hedge

[12] Alternative potential relations of fund risk to fund flows are considered in Section 7.6.

[13] In Section 7.5 we employ several other specifications for the HWM and find that the results remain virtually unchanged.

fund (that would correspond to the net asset value of 1 dollar or Euro invested in the fund at origination) over the corresponding HWM. Formally,

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

The relationship between fund value relative to the HWM and managerial risk taking is expected to be nonlinear and to vary during a year (*Hypotheses A* and *B*). We capture it by introducing a non-parametric relation between fund risk and value. The relation is allowed to vary over K periods of a year, with I_k indicating either the different quarters ($K = 4$) or months ($K = 12$) of a year.

Our final semi-parametric model is given as

$$\begin{aligned} RISK_{i,t} &= \alpha_i + \alpha_t + \sum_{j=1}^{3} \beta_j RISK_{i,t-j} + \gamma DeltaCorr_{i,t} + \zeta ln(AuM_{i,t_-}) \\ &+ \theta OutflowLarge_{i,t-1} + \sum_{k=1}^{K} f_k(Value_{i,t_-}) I_k + \varepsilon_{i,t} \quad , \end{aligned} \tag{4.3}$$

where α_i and α_t are the fund and time fixed effects, respectively.

The regression in Equation 4.3 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 non-parametric kernel regression of the residuals on the corresponding fund value is estimated. Formally,

$$\hat{e}_{i,t} I_k = f_k(Value_{i,t_-}) I_k + \eta_{i,t,k} \quad . \tag{4.4}$$

For the kernel regression, we use a Gaussian kernel with a fixed bandwidth of 0.07.[14] 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 4.3, 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.[15]

The analysis above allows us to capture potential nonlinearities in the relationship of fund risk and value and motivates the choice of breakpoints (if any) in this relationship.

[14] Cross-validations conducted separately for different quarters yield optimal bandwidths ranging from 0.01 to 0.10 and from 0.01 to 0.11 for month-wise regressions. To make sure that our results for different periods are not driven by differential smoothing, we keep the bandwidth fixed for all kernel regressions. From manually comparing regression results and trading-off smoothness and variance for all bandwidths within the range suggested by cross-validation, we chose 0.07 as our fixed bandwidth. As a robustness check, we re-estimate the regressions with different bandwidths in Section 7.4 and our findings remain qualitatively the same.

[15] 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)).

In order to give a more precise quantification of the strength of risk shifting, we repeat the analysis using a piecewise liner specification for the residuals instead of a kernel regression. We analyze the residuals from the linear part of Equation 4.3 for the different quarters of a year and allow the estimated coefficients on the value variable to vary within three intervals: (1) fund value lower than $\bar{V}$ (expressed in percent relative to the HWM); (2) fund value between $\bar{V}$ and the HWM; and (3) fund value above the HWM. The choice of a breakpoint value $\bar{V}$ will be motivated by the results from the kernel regressions (Equation 4.4).

For each quarter of a year we estimate the following regression:

$$\hat{e}_{i,t} = \begin{cases} \alpha_{low} + \delta_{low} Value_{i,t_-} + \eta_{i,t} & \text{if } Value_{i,t_-} < \bar{V} \\ \alpha_{mid} + \delta_{mid} Value_{i,t_-} + \eta_{i,t} & \text{if } \bar{V} < Value_{i,t_-} < 1 \\ \alpha_{high} + \delta_{high} Value_{i,t_-} + \eta_{i,t} & \text{if } Value_{i,t_-} > 1 \ . \end{cases} \tag{4.5}$$

The standard errors are obtained via bootstrap. Here α-s indicate the average incremental risk taking in a given interval of fund values, whereas δ-s indicate the slope of fund-risk – value relation within this interval.[16]

5 Empirical Results

5.1 Managerial Risk-Taking: Quarter-Wise

Column (I) in Table 6 reports the estimation results based on the linear part of Equation 4.3. Consistent with the time-series analysis of hedge fund risk in Section 3.2, past values of RISK are important predictors of the current risk level. As expected, the

[16] In the robustness Section 7.2 we further require the estimated relation to be piecewise continuous and find qualitatively similar results.

explanatory power is decreasing in the lag length, where the first lag obtains the highest loading of 0.50 with a corresponding t-statistic of above 50, and the coefficient estimates for the two- and three-month lags decrease to 0.09 and 0.07, respectively. 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. We also include in the regression the fund flow directly as defined in Equation 4.1 at times $(t-1)$ and $(t-2)$, as well as an indicator function, which takes a value of one, if the corresponding flow is negative. In unreported results, none of these variables obtains a significant coefficient estimate.[17]

[Insert Table 6 around here]

Let us turn to analyzing the relation between fund value relative to the HWM and fund risk. Figure 5 plots the estimated kernel regression lines based on residuals from the linear part of Equation 4.3. 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.

[Insert Figure 5 around here]

[17] In Section 7.6 we will also see, that 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 as depicted in Figure 5 (a) 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. Thus, if a fund has been loosing money previously and by the beginning of the second quarter is substantially under water, managers reduce the fund risk. 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*. Below the HWM the risk shifting does not increase monotonically, instead it is bell-shaped as suggested by *Hypothesis A(1)*. The substantial risk increase at low fund values displayed in Figure 5 (d) and its reversal after fund value further drops below some 60% of the HWM is consistent with the predictions of Buraschi, Kosowski, and Sritrakul (2012): managerial incentive option induces risk-taking whereas investor redemptions and brokerage restrictions limit the risk shifting.

We do not document significant managerial risk changes around the HWM itself ($Value = 1$) in any quarter. The existence of the incentive option does not seem to induce an average manager to either increase the risk just below the HWM in order to push their incentive option into the money, or to decrease the risk right above the HWM to lock in the incentive pay. Significant alternations of fund risk seem to take place only when funds are substantially underperforming and their very existence is under question. This finding is consistent with the theoretical predictions in multi-period settings and reveals that managers are not myopic but seem to have longer, albeit finite, valuation horizons, instead.

Hodder and Jackwerth (2007) explicitly consider the time dimension in their model, but predict a rather uniform risk increase at the liquidation boundary across all months of a year[18]. Our empirical findings indicate, however, that the risk increase is pronounced only towards the end of a year. The risk does not increase during the first half year, to the contrary, it seems to decline for poorly performing funds.

The results obtained using the piecewise linear specification confirm the documented pattern. We choose as a breakpoint $\bar{V} = 0.60$ of the HWM. The estimated coefficients are reported in Table 7 and Figure 7 depicts the resulting regression lines, where we set insignificant regression coefficients to zero. The results replicate our main findings. No significant change in risk can be documented for the first quarter of a year for fund values below the HWM. During the second quarter, the incremental hedge fund risk decreases, if the fund value drops below the HWM, whereas in the same situation during the fourth quarter, fund risk increases.

Overall, the documented seasonality in risk taking 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 longer-term projects, by the end of the year poorly performing fund might be treated more like short term projects for the managers. We will address other possible determinants for the seasonality in Section 6 in more detail.

5.2 Managerial Risk-Taking: Month-Wise Refinement

We shaw that managers significantly decrease fund risk during the second quarter and increase the risk during the fourth quarter when 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 6 reports the estimated regression lines together with 1%, 5%, and 10% confidence bounds. As we keep the requirement

[18]See Figure 3 in Hodder and Jackwerth (2007)

of a minimum of five observations per window, the support of the month-wise estimates shrinks compared to the quarter-wise results.

[Insert Figure 6 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 a 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 managerial risk taking which is 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.

These results suggest that fund managers 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 (or increase the leverage) only in December. The time may be too short for the realized returns to cover past losses. Managers also seem to take persistent risk levels into account when adjusting the strategy.Given that risk is sticky, 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.

5.3 Economic Significance of Managerial Risk Taking

Having discussed the qualitative impact and statistical significance of managerial risk taking, we now briefly illustrate the economic significance of the documented risk shifts by a simplified example.

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 result in a 25% increase in the risk during the following month ($e^{0.50 \cdot ln((0.74+0.42)/0.74)} = 1.25$).

The results reported in Table 7 suggest, 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 α of -0.45 and γ of +0.49 suggest that the impact on risk is 14% decline relative to its current level ($e^{-0.45+0.49 \cdot 0.60} = 0.86$). Similarly, maximum risk increase achieved in the fourth quarter is 20% of the current level of risk ($e^{+0.48-0.50 \cdot 0.50} = 1.20$).

Hence, although the changes in the riskiness of hedge funds induced by the managerial response to poor fund performance can be rather substantial (from 14% decrease to 20% increase), they are slightly smaller than a shift induced by one cross-sectional standard deviation in the past level of risk (25%). Still, investors should be aware of managerial risk taking as it is strongly pronounced even on average. This can imply extremely high risk taking for certain funds that can relatively easy alter their risk levels. 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

6.1 Management Fees and Survival Probability

The documented risk reduction by poorly performing hedge funds at the beginning of a year is, to the best of our knowledge, a novel empirical result. In this section we take a closer look at the determinants of such reduction.

As Lan, Wang, and Yang (2013) point out, poorly performing hedge fund managers with very long (infinite) investment horizon optimally reduce leverage in order to avoid liquidation. 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.

Hypothesis C: Below the HWM, hedge funds with higher management fees are more prone to risk reduction during the second quarter.

Similarly, those funds that face higher liquidation probability at the beginning of a year should have more incentives to reduce risk. By reducing risk taking during earlier months of a year, poorly performing managers can improve the chances of survival of their fund as there exists a well documented positive relation between fund liquidation probability and its risk (see, e.g. Liang and Park (2010) among others). We compare the attrition rates of hedge funds in our sample between the first and the last six months and find that indeed 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 inception and fund flows.

Directly relating managerial decision to alter fund risk to estimated liquidation probability in a regression framework might be inaccurate because of endogeneity. Actual fund survival depends on fund risk, which is, in its turn, an optimal managerial response to fund liquidation probability. We suggest to use three instruments that are related to 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.[19]

The length of notice period prior to redemption, fund recent performance, and age are negatively related to liquidation probability (see Liang and Park (2010) and Aragon and Nanda (2012) among others). Funds having longer notice period, exhibiting positive returns over a previous quarter, and being of older age have lower liquidation probability and, thus, they should have less incentives to reduce risk taking.

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

In order to test *Hypotheses C* and *D*, we use the piecewise linear specification as in Equation 4.5. For each fund value range we introduce four indicator variables in turn (denoted by γ-s) and estimate Equation 6.1 below. The indicator variables represent funds with (1) higher than median management fee ($MgtFeeLarge$, to test *Hypothesis C*), (2) higher than median notice period prior to redemption ($NoticeLarge$), (3) positive cumulative return over the preceding quarter (equivalent to increasing fund value relative to the HWM $\Delta Value_{t^-} > 0$), and (4) larger than median age($AgeLarge$) to test *Hypothesis D*.

[19]There are other potential instruments linked to liquidation probability including managerial personal investment and characteristics of fund family (Kolokolova (2011) and Aragon and Nanda (2012)), they are, however, not available for our sample of hedge funds.

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

If, for instance, $MgtFeeLarge$ is used, a negative and significant γ_{mid} in the second quarter would imply that hedge funds with higher management fees reduce risk more strongly during the second quarter if their value is bellow the HWM but above 60% of the HWM.

The estimation results are reported in Tables 8 and 9. Consistent with the developed hypotheses, hedge funds charging higher than median management fees have 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 lower liquidation probability because of longer notice period prior to redemption, positive cumulative returns over a preceding quarter, and older age have a less pronounced risk decline during the second quarter of a year. The coefficients of $+0.15$, $+0.07$, and $+0.07$ in Table 9 respectively are highly significant.

Remarkably, we do not detect any significant impact of these factors on risk shifting behavior at the end of a year. This finding contributes 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 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 additional risk reduction during earlier months by funds with higher liquidation probability.

The empirical results shed some light into the managerial risk-taking behavior if fund is above its HWM. Both theoretical models of Hodder and Jackwerth (2007) and Buraschi, Kosowski, and Sritrakul (2012) suggest that at fund values above the HWM managers will take upon lower risks than would be desired by an investor with a CRRA utility function. Hodder and Jackwerth (2007) argue that by doing so managers lock in the incentive fees earned so far.[20] In all our previously discussed results, however, we did not detect any significant risk variations for fund values above the HWM. Panel 2 of Table 9 presents a notable exception. Those hedge funds, that end up above the HWM at the middle of a year and came "from below" – the cumulative return over the preceding quarter was positive pushing the managerial inventive option in-the-money – significantly reduce their risk during the third quarter. The highly significant coefficient of -0.11 supports the proposition of "locking in" fund performance.

6.2 High-Water Mark and Incentive Fees

We now turn our attention to the impact of a HWM on the risk taking. As Panageas and Westerfield (2009) suggest, managers of funds with a HMW provision possess not a single incentive option, but a sequence of multiple future incentive options. They avoid excess risks 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 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: Poorly preforming hedge funds with a high-water mark provision are less prone to 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 10. The estimated coefficients remain virtually unchanged as compared to the main results

[20] In personal discussions with fund managers we confirmed that practice of "going flat" after a certain level of returns is achieved is indeed used by some hedge fund managers.

in Table 7. This suggests that overall hedge funds that have and do not have a HWM provision adjust their risk taking in a similar way depending on their performance and 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 the HWM provision in the fund.

In Panel B of Table 10 we perform similar analysis but using a dummy variable indicating existence of a positive incentive fee ($HaveIveFee$) instead of the HWM. In our main 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. Such funds may or may not charge an incentive fee. 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 risk increase at the end of a year.

The findings above suggest that the risk taking increase at the end of a year may not be solely driven by the incentives provide by managerial option-like compensation contract. In order 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 estimation of the parameters of the linear part of the panel regression.

The regression lines depicted in Figure 8 indicate that the exclusion of funds without a reported incentive fee does not affect our main findings. The general risk taking pattern remains, and only the positive relationship for very low fund values in the last quarter is no longer significant, resulting in a flat rather than upward sloping line in that area. In the underlying (untabulated) regression results the corresponding coefficient estimates have the same signs and orders of magnitude as in the main run; only their significance vanishes, which can result from having fewer observations. Generally, all the coefficients are marginally larger, pointing towards stronger risk taking, but the differences are far from being statistically and economically significant. 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. Again, we see only marginal changes to the risk taking, which in this case point to slightly milder risk shifts, and do not depict the regression lines for the sake of space.

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 than 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 flow-performance relationship even without an explicit incentive fee. At the same time, managers may face pure "reporting" incentives. Majority of hedge funds provide their current (and potentially, perspective) clients end-of-year reports. Reporting better figures may lead to improvement of managerial reputation, what in its turn could, for example, make launching of consecutive funds easier. The existence of reporting-induced behaviour was documented also by Agarwal, Daniel, and Naik (2011) and Ben-David, Franzoni, Landier, and Moussawi (2013). Agarwal, Daniel, and Naik (2011) show that hedge fund managers tend to inflate their reported December returns by "borrowing" from the previous months' returns.[21] Ben-David, Franzoni, Landier, and Moussawi (2013) argue that large hedge funds that have to file end-of-quarter long equity holdings with SEC through 13F reports seem to manipulate prices of stocks that they hold by excessively buying the stocks during the last trading day of the quarter and unwinding the positions during the first trading day following the quarter end. We contribute to this line of evidence that end-of-year

[21] We find that in our sample of hedge funds the reported average returns in December are also significantly higher than during any other months. This again indicates that the funds in our sample exhibit general patterns common to the funds reporting on monthly bases. Inflated returns reported in December do not influence our risk-related results. The return STD is computed every month and takes into consideration mean differences. The monthwise results in Figure 6 also indicate that there is no significant risk alteration in December.

reporting seems to also induce excessive risk taking several month before the report date.

6.3 Hedge Fund Style

The overall portfolio risk can be changed through two distinct channels: adjusting the leverage while keeping the core investment strategy unchanged or changing the core investment strategy itself by moving towards riskier assets. For most of funds, the first option may seem preferable: it does not require additional research on new core assets, associated transaction costs are likely to be lower, and such decisions are easier to revert. 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 portions as compared to event driven funds that bet on special corporate events. We expect that risk increase toward a 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 are easier to scale.

Hypothesis F: Below the HWM, hedge funds with higher return correlation with the market are more prone to 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 11 suggest that indeed such hedge funds increase risk stronger during the last quarter of a year. The corresponding coefficient of +0.05 is significant at the 5% level. Interestingly, the risk stifling during third quarter is reduced by the same magnitude. The result may suggest that those funds that can easily level up their risk through leverage has less incentive to adjust it early. Instead, they can scale the risk up right when they need it – at the end of a year.

The cross-sectional results reported in Appendix B.1 indicate that hedge funds declaring different investment styles do have significantly different *average* levels of risk. We take now a closer look on variation in the changes in risk with respect to fund style. In the Equation 6.1 we use dummy variables (γ-s) for each of the reported styles in turn. 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 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 a reference case.

Directional Equity funds (Panel A of Table 12) behave differently than other funds in the area above the HWM. Profitable funds have higher risk taking during the first quarter (+0.10), but then reduce it in the second and the third quarters of a year (-0.09 and -0.11 respectively). All these changes are significant at the 1% level. There is no significant risk changes of well performing funds during the last quarter of a year. In terms of risk variation in case of poor performance, we do not detect any significant difference with respect to other funds. For Directional Equity funds below the HWM, the risk declines earlier in a year and then increases toward the end of a year at the same magnitude as for an average fund following other styles.

Poorly performing Equity Market Neutral funds (Panel B of Table 12) are somewhat less prone to risk increase during the fourth quarter of a year (with the loading of -0.07 significant at the 5% level). Despite being slightly milder, the overall risk increase in this region is still pronounced.

Managed Futures funds (Panel C of Table 12) do not exhibit any significant difference relative to other funds in terms of risk shifting at the end of a year. However, they seem to 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.

Overall, the results from Table 12 indicate that despite some statistically significant differences in risk-shifting magnitude across different hedge fund styles, these differences cannot drive away the main seasonal pattern of risk taking.

7 Robustness Checks

In this section we perform multiple robustness checks with respect to methodology and sample filtering. The results are predominantly inline with the main conclusions. We briefly discuss all the robustness checks performed, but we tabulate or depict only those results that substantially differ from the main runs.

7.1 Managerial Competition

Our findings show that hedge fund risk clearly depends on the fund value relative to the HWM, which is determined by the past hedge fund performance. However, not only the absolute fund performance over a potentially extended period, but the performance relative to the industry peers might play an important role, too. As hedge funds compete for investors and investor flows chase past performance (Agarwal, Daniel, and Naik (2004)), fund managers may try to enhance the realized performance by taking excessive risks, if they underperform relative to their peers. Investigating changes in hedge fund risk from the first to the second half of a year, Aragon and Nanda (2012) indeed find that funds, which are poorly ranked relative to their peers, tend to engage in tournament behavior and increase the risk. Brown, Goetzmann, and Park (2001) also show that fund survival depends on the fund performance relative to other funds within the industry.

The question arises, whether short term hedge fund underperformance relative to the competitors leads to an average increase in risk taking in our sample. And if it does, how such risk shifting relates to the risk shifting induced by the fund being below or above the HWM as analyzed earlier. To address these questions, we measure short-term fund performance relative to the peers as the cumulative return earned by fund i over month t ($CR_{i,t}$) in excess of the average cumulative industry return over the same month. We define,

$$ExcessPerf_{i,t} = CR_{i,t} - \frac{1}{N_t}\sum_{i=1}^{N_t} CR_{i,t} \ , \tag{7.1}$$

where N_t is the total number of hedge funds in our sample in the corresponding month. We add the lagged value of this variable to Equation 4.3 and re-run the regression.

The estimation results in Column (II) of Table 6 reveal that short-term underperformance relative to the competitors indeed leads to increased fund risk. The estimated loading of –0.27 is highly significant.[22] The long-term absolute fund performance will be still captured by the fund value relative to the HWM ($Value_{i,t_-}$). We re-run the kernel regressions using the residuals from the panel regression given in Column (II) of Table 6. The resulting regression lines remain qualitatively unchanged as compared to our main results. Hence, while we observe some short-term tournament behavior, the nonlinear and time varying managerial response to absolute performance remains pronounced as we control for the short-term tournament. This finding complements Aragon and Nanda (2012). The authors document tournament behavior of hedge fund managers on the half-year horizon. We show now that this 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).

[22]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. The latter observation points to a truly short-term effect.

7.2 Piecewise Continuous Linear Specification for Managerial Risk Taking

We re-estimate a piecewise linear specification of the model as in Equitation 4.5, but this time we require that the resulting regression line is piecewise continuous, by imposing continuity restrictions at the breakpoints, and obtain the following regression for each quarter of a year:

$$\hat{e}_{i,t} = \alpha + \delta_{low} Value_{i,t_-} + \delta_{mid}(Value_{i,t_-} - 0.6)^+ + \delta_{high}(Value_{i,t_-} - 1)^+ + \eta_{i,t} \quad . \quad (7.2)$$

Figure 9 depicts the resulting regression lines, where we set insignificant regression coefficients to zero. The results support the main findings from Section 5 of the kernel regression and the unrestricted version of the piecewise linear specification. Risk decline is pronounced for poorly performing funds during the second quarter and risk increases during the fourth quarter of a year.

7.3 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 are generally consistent with the ones reported in Table 6, 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 4.5, 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 in Figure 10. It shows that the risk decline is shifted forward and is now pronounced during the first quarter of a year and not during the second quarter, whereas risk increase is still strongly pronounced during the fourth quarter.

7.4 Kernel Regression with Different Bandwidths

In order to make sure that our results are not influenced by a particular bandwidth choice, we re-estimate the kernel regressions for managerial risk taking using alternative bandwidths. First, we use a smaller bandwidth of 0.05 (compared to 0.07 used in the main specification), and then we use a larger bandwidth of 0.09. Naturally, the regression line is less (more) smooth with a smaller (larger) bandwidth, but the results do not qualitatively change from the ones reported in the body of the paper.

7.5 Alternative Specifications of the High-Water Mark

In the main specification used in the paper, 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 the current value of the 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.[23]

7.6 Fund Outflows: An Alternative Explanation

In Section 5, we show that large fund outflows over the previous month exceeding 5% of the assets ($OutflowLarge_{i,t-1}$) lead to increased hedge fund risk. We attributed the finding to the forced liquidation of more liquid and less risky assets upon massive fund outflows, which leaves a riskier portfolio behind.

Now, we test an alternative explanation of the observed relation between, which suggests a more active role of the fund management. If an outflow is triggered by bad past performance, a hedge fund manager could deliberately increase the fund risk in an attempt to boost performance. We add as an additional term to Equation 4.3 the product of $OutflowLarge_{i,t-1}$ and a dummy variable, which takes a value of one, whenever the cumulative return over the preceding month was below the industry mean ($ExcessPerf_{i,t-2} < 0$). A positive and significant loading on this interaction term would indicate that the increase in fund risk is (partly) explained by the managerial response to large outflows following poor performance. We do not find any significant loading on the interaction term in unreported estimates of various model specifications.

[23] 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.

For mutual funds, flows tend to be sticky, which gives some prediction power to fund managers (e.g. Warther (1995)). We also include the cumulative flows over several preceding months into the regression and do not find any significant results. In line with our explanation in the main section, the outflows driving the risk changes seem to come unexpected and they should be large in magnitude.

7.7 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 signs of the other significant coefficients flip, as now higher risk corresponds to lower values of $VaR_{10\%}$. 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 (decrease in $VaR_{10\%}$) in the last quarter of a year a the significant risk decline (increase in $VaR_{10\%}$) during the second quarter.

7.8 Hedge Fund Risk Relative to Market Risk

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

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

The unreported results remain virtually unchanged as compared to the main results in Table 6, which indicates that the time dummies fully capture the impact of changing market risk over time.

We also try to adjust 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 risk taking remain largely unchanged, which is partly due to the poor explanatory power of the Carhart (1997) model (the median adjusted R-squared is about 5%).

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 recovered risk taking surface reveals that hedge fund managers significantly change the fund risk in response to the incentives provided by their complex compensation contracts. The risk taking is highly nonlinear and exhibits strong seasonal pattern.

At the beginning of a year, poorly performing hedge fund managers tend to reduce the risk taking. The risk reduction is especially pronounced at fund values between 50% and 75% of the high-water mark. This result may suggest that earlier in the year managers perceive their valuation horizon as very long and behave in a more risk averse way as discussed in Lan, Wang, and Yang (2013). Early liquidation is more costly for managers charging higher management fees. Such managers exhibit an even stronger risk reduction. Managers that are less threatened by the risk of immediate liquidation because of longer notice period prior to redemption, positive recent performance, and older age, on the contrary, exhibit a milder risk reduction.

Towards the end of a year, poorly performing managers considerably increase fund risk at low fund values relative to the high-water mark. This gamble for resurrection is in line with the existing models of risk taking by risk-averse hedge fund managers with finite valuation horizon. The bell-shaped relationship between the risk taking and fund value below the high-water mark is consistent with the existence of exogenous brokerage restrictions and investors' redemptions as suggested by Buraschi, Kosowski, and Sritrakul (2012). Importantly, the gamble for resurrection is not purely driven by the existence of incentive fees and high-water mark provisions. In facts, it is also strongly pronounced for funds not charging incentive fees at all. It suggests that there exist other, not directly link to incentive fees, incentives to report better performance at the end of a year. They may be linked to managerial reputation concerns as majority of funds issue detailed end-of-year reports to their clients and perspective investors. Such risk shifting is pronounced for hedge funds in all investment styles; and it is even stronger for funds that follow strategies closer linked to the equity market which are easier to scale though leverage.

These finding contributes to our understanding of the economics behind previously documented negative association between changes in risk from the first to the second half year and fund performance (Aragon and Nanda (2012)). It seems to be driven not only by the excessive risk taking during later month of a year, but also by additional risk reduction earlier in a year.

Our results show that hedge fund risk is persistent and managers do take it into account when adjusting risk taking. For example, higher risk at the end of a year is due to positive risk adjustment in October and November, and not in December.

The estimated maximum average risk shifts are economically significant and span 14% decrease to 20% increase of the risk levels. They are, however, slightly smaller than a risk shift of 25% induced by one cross-sectional standard deviation in the past level of risk. In the presence of significant managerial risk taking, standard hedge fund performance measures can be misleading and should be adjusted, as Buraschi, Kosowski, and Sritrakul (2012) argue. Investors should be aware of dynamic managerial risk taking and assess its implications for their portfolios and for standard compensation practices. 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 obligatory reporting and disclosure by hedge funds. It seems that scheduled reporting dates (although seeking to achieve transparency) might induce (unwanted) changes in investment behaviour of hedge 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 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.

A 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 (2009). Role of managerial incentives and discretion in hedge fund performance. *Journal of Finance 64*(5), 2221–2256.

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.

Aggarwal, R. K. and P. Jorion (2010). The performance of emerging hedge funds and managers. *Journal of Financial Economics 96*(2), 238–256.

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.

Avramov, D., R. Kosowski, N. Y. Naik, and M. Teo (2011). Hedge funds, managerial skill, and macroeconomic variables. *Journal of Financial Economics 99*(3), 672–692.

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 (2012). Incentives and endogenous risk taking: A structural view of hedge funds alphas. Working Paper, Imperial College.

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

Cassar, G. and J. Gerakos (2010). Determinants of hedge fund internal controls and fees. *The Accounting Review 85*(6), 1887–1919.

Chan, N., M. Getmansky, S. M. Haas, and A. W. Lo (2007). Systemic risk and hedge funds. In M. Carey and R. M. Stulz (Eds.), *The Risks of Financial Institutions*, pp. 235–338. Chicago: University of Chicago Press.

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.

Fung, W. and D. A. Hsieh (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal 60*(5), 65–80.

Getmansky, M., A. W. Lo, and I. Makarov (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics 74*(3), 529–610.

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.

Gibson, R. and S. Gyger (2007). The style consistency of hedge funds. *European Financial Management 13*(2), 287–308.

Goetzmann, W. N., J. Ingersoll, Jonathan E., and S. A. Ross (2003). High-water marks and hedge fund management contracts. *Journal of Finance 58*(4), 1685–1717.

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. (2013). The cross-section of mangerial ability, incentives, and risk preferences. *Journal of Finance Forthcoming*.

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

Kosowski, R., N. Y. Naik, and M. Teo (2007). Do hedge funds deliver alpha? A bayesian and bootstrap analysis. *Journal of Financial Economics 84*(1), 229–264.

Kouwenberg, R. and W. T. Ziemba (2007). Incentives and risk taking in hedge funds. *Journal of Banking & Finance 31*(11), 3291–3310.

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

Li, Y. and J. Mehran (2009). Risk-taking and managerial incentives: Seasoned versus new funds of funds. *Journal of Alternative Investments 11*(3), 100–108.

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.

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

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.

Wegener, C., R. von Nitzsch, and C. Cengiz (2010). An advanced perspective on the predictability in hedge fund returns. *Journal of Banking and Finance 34*(11), 2694–2708.

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

B Appendix

B.1 Cross-Sectional Analysis of Hedge Fund Risk

This paper finds that hedge fund risk is rather persistent. Here, we investigate its cross-sectional determinants. We also compare our results to earlier cross-sectional studies of hedge fund risk, and show, that hedge funds in our sample generally behave much like hedge funds that report returns on a monthly basis. We run cross-sectional regressions, in which the dependent variable measures the average level of risk for each hedge fund. It is calculated as the natural logarithm of the average intra-month standard deviation of daily hedge fund returns ($ln\left(\overline{STD}_i\right)$). The set of explanatory variables includes hedge fund characteristics potentially influencing the overall fund risk (X_i) and several control variables (Z_i). The regression equation is given as

$$ln(\overline{STD}_i) = \alpha + X_i'\beta + Z_i'\gamma + \epsilon_i \ . \tag{B.1}$$

The cross-sectional analysis is structured as follows: We first discuss potential determinants of hedge fund risk and introduce some control variables. Then, we present the estimation results and continue with some robustness checks similar to the ones conducted for the panel analysis earlier.

B.1.1 Managerial Incentives and Flexibility

Managerial incentives and flexibility can affect the average level of risk-taking by hedge funds. The general consensus in the literature is that the existence of a HWM provision, the levels of incentive and management fees, as well as the length of lock-up and notice periods have a substantial impact on the managerial risk taking. The empirical as well as the theoretical evidence on the directions of the relationships between these factors and the level of risk is, however, mixed.

Hedge fund managers (especially those with a short investment horizon) increase the risk of their investments, if their compensation contract is convex, that is, if there exists a HWM and managers receive an incentive fee, once the fund value is above the HWM by the end of a year (Hodder and Jackwerth (2007)). At the same time, as the investment horizon increases, the existence of a HWM can limit the risk taking, as in this case the manager possesses sequential options (Panageas and Westerfield (2009)). This observation is in line with the theoretical finding by Ross (2004), that a convex compensation contract does not necessarily lead to increased risk taking. Aragon and Nanda (2012) report supporting empirical evidence that managers of hedge funds with a HWM provision are less prone to risk-shifting, when their fund is below water. To the contrary, Kouwenberg and Ziemba (2007) argue, that loss averse managers with higher incentive fees tend to increase the risk of their investments. They find supporting empirical evidence using the Zurich hedge fund universe for both hedge funds and funds of funds.

The managerial option is more valuable, if hedge fund performance fees are high. The performance fees, however, are set by managers at their own discretion. Possibly, only well performing and highly skilled managers with a well established reputation are able to set high performance fees. Cassar and Gerakos (2010) also show that manages of hedge funds with better internal controls charge higher fees. The riskiness of the investment strategies of reputable and well controlled managers might be different from that of an average manager.

To analyze the impact of a convex compensation contract on the average level of fund risk, we consider two regression specifications using the information on the HWM and the incentive fee. First, we include as a proxy for managerial incentives the level of the incentive fee ($IncFee_i$). Second, we use a dummy variable for an incentive fee being above the median ($IncFeeLarge_i$) instead. In both specifications, we use a dummy variable indicating funds with a HWM. It allows us to disentangle the pure effect of the existence of a HWM from a high incentive fee.

While the managerial compensation resulting from the existence of a performance fee is convex in fund profitability, the compensation generated by the management fee is linear in hedge fund size, as it pays a fixed percentage of the assets under management (AuM). Other things being equal, hedge fund managers would prefer to increase the size of their funds to boost their fee income. There is much evidence in the literature on the convexity of the relationship between fund performance and consecutive fund flows for mutual funds (see Chevalier and Ellison (1997)). Clients tend to invest after superior fund performance more actively, as compared to divestiture as a response to poor fund performance. The findings for hedge funds are mixed. Agarwal, Daniel, and Naik (2004) find a convex relationship, whereas Goetzmann, Ingersoll, and Ross (2003) document a concave flow-performance relationship. Ding, Getmansky, Liang, and Wermers (2009) reconcile this issue, and show that the flow-performance relationship is more complex, changing from convex to concave, if a hedge fund imposes share restrictions including longer lock-up and notice periods and has illiquid securities in the portfolio. The higher the management fee, the larger is the share of managerial compensation, which is generated by the part of the compensation contract, that is linear in fund size, and, thus, works just like the mutual fund type of contract. If hedge fund managers themselves perceive the flow-performance relationship as convex, increasing fund risk would be a beneficial strategy. The expected gains in case of investment success are larger than the expected losses in case of investment failure. The hedge funds in our sample are rather liquid, with relatively loose share restrictions. Most of the funds in our sample, for example, do not impose any lock-up period. In fact, only seven funds report a non-zero period. According to Ding, Getmansky, Liang, and Wermers (2009), one could indeed expect a convex flow-performance relationship for such funds. Thus, we expect hedge funds with high management fees to be characterized by a higher level of average fund risk.

In order to empirically capture this relationship, we, first, include the level of the management fee as reported to the database ($MmtFee_i$) in the regression. Second, we use a dummy variable taking a value of one, if the management fee is above the median level ($MmtFeeLarge_i$). Third, we recognize that the management fee effect can be more pronounced for large funds. In addition to the management fee dummy, we include the product of the dummy variable indicating a management fee above the median and a dummy indicating an average fund size above the industry median.[24]

Lock-up and redemption periods imposed by hedge funds on their investors assure that hedge fund managers are more flexible in their investment strategies, as the investors cannot demand immediate redemption of their shares. Using monthly data, Agarwal, Daniel, and Naik (2009) find that funds with higher managerial flexibility tend to outperform their peers. More managerial flexibility also makes excessive risk taking easier. Thus, we expect funds with greater managerial flexibility to exhibit higher risk levels. We measure managerial flexibility by the length of the redemption period expressed in months as reported to the database.[25] Again, we include the level ($Redem_i$) and a dummy variable indicating a value above the industry median ($RedemLarge_i$) into the regression.

B.1.2 Other Determinants of Hedge Fund Risk and Control Variables

The hedge funds in our sample report their returns in different currencies with 56% (44%) of all funds reporting in EUR (USD). The average fund return standard deviations are different between EUR and USD funds (see Table 1) and this difference is highly statistically significant. We pool the estimated return standard deviations of EUR and USD funds together, but include a dummy variable for funds reporting in EUR as a

[24]There are 61 hedge funds that do not report a management fee and we set the fee to zero here. The results do not change, if we exclude the funds from the analysis.

[25]We do not consider lock-up periods because only 7 of our 714 funds report a non-zero period.

control (EUR_i). Eighteen hedge funds (2.52% of our sample) report their returns in EUR but are domiciled in the U.S. We include the product of the dummy variable for funds reporting in EUR, and another dummy variable indicating U.S. domicile, as an additional control ($EUR - US_i$).

As long as hedge fund managers do not switch between completely orthogonal strategies frequently and major alternations in the management teams are rare, the fund risk should be largely determined by the implemented strategy together with the unobserved managerial risk preferences. Hedge funds following different styles, therefore, are likely to exhibit different levels of risk. For example, the average return standard deviation for Emerging Market funds is likely to be higher than for Equity Market Neutral funds, as found by Chan, Getmansky, Haas, and Lo (2007, Table 6.4, p.255). To capture style variations in the average hedge fund risk, we include eight style dummies in the regression, one for each hedge fund style excluding the largest style (Directional Equity), which serves as the reference category.

The hedge fund styles are self reported and style drifts might affect their information content.[26] We introduce two additional controls to better capture the nature of the hedge fund strategies. The first is the correlation coefficient between the hedge fund returns and the returns on the MSCI World Index over the entire life time of the hedge fund ($MarketCorr_i$). It proxies for the average exposure of a hedge fund to global equity markets. Given the distribution of funds over the different styles in our sample, the vast majority of all funds can be expected to exhibit a positive correlation with the global equity market, and we expect to find a positive coefficient for this control variable. Second, we include the standard deviation of the monthly estimates of RISK over a fund's life time ($STD(RISK_i)$). It captures the likelihood of style drifts and considerable risk shifting by the hedge fund managers. The cross-sectional correlation coefficient between the standard deviation of RISK and average RISK is -0.13 and significant at the 5% level. Funds that

[26] Gibson and Gyger (2007) provide a detailed discussion on hedge fund style classification.

take higher risks on average, alter their risk levels less and stick more firmly to their risky strategies. Thus, we expect to find a negative coefficient on the standard deviation of risk.

The life times of the hedge funds in our sample span different time periods. The riskiness of funds operating predominantly during the economic boom in 2005-2006 can substantially differ from the riskiness of funds operating during the sub-prime mortgage crisis of 2007 and the following financial crisis. To control for these differences, the natural logarithm of the average intra-month standard deviation of the daily returns on the MSCI World Index over the life time of a hedge fund ($ln(\overline{STD(Market)_i})$) is included in the regression.

Return serial correlation proxies for investment illiquidity and deliberate return smoothing by fund managers (Getmansky, Lo, and Makarov (2004)). Although return smoothing is less likely to be a problem for more transparent hedge funds reporting on a daily basis, if it does take place, the estimated return standard deviation will be biased downwards relative to its true value. At the same time, technically, if daily returns follow an AR(1) process, their total variance increases in the level of the autocorrelation keeping the variance of innovations constant. Hence, we include the first order return serial correlation for each fund ($ReturnCorr_i$) as an additional control.

In order to control for possible differences in risk levels between live and defunct funds, we include a dummy variable ($Dead_i$), which takes a value of one for hedge funds that stop reporting their performance prior to the final date of the sample.

Hedge fund managers often start their career operating small funds and being rather aggressive in terms of their investment strategy and associated risk taking. However, as funds grow older and larger, they tend to become more conservative. Their outstanding performance tends to deteriorate (e.g. Aggarwal and Jorion (2010)) and the riskiness of their investments can decline. This is largely due to two factors. First, there are diseconomies of scale (Goetzmann, Ingersoll, and Ross (2003)). The scope for truly alternative strategies and arbitrage opportunities is limited. As hedge funds grow larger, the profitable opportunities targeted by the management are getting exploited and exhausted. The new capital has to be allocated to more conventional and liquid investments, which are typically less risky. Second, managers of the established larger and older funds have more to lose in terms of reputation and fee income in the case of fund failure. Thus, the risk taking of larger and older funds is expected to be lower relative to younger and smaller funds. There is, however, contrasting evidence for funds of hedge funds by Li and Mehran (2009), who show that younger funds of funds exhibit less total and less systemic risk taking.

Similar to the previously discussed factors, we, first, include the average AuM across the life of a hedge fund converted to millions USD ($ln(\overline{AuM_i})$) as a measure of size, and the age of a fund expressed in years at the last available return date ($LifeTime_i$) in the regression. Second, we use two indicator variables: a dummy for fund being larger than the median ($ln(\overline{AuM})Large_i$) and a dummy for fund being older that the median ($LifeTimeLarge_i$).

B.1.3 Main Cross-Sectional Regression Results

Table 13 reports the estimation results with bootstrapped standard errors for different specifications of Equation B.1.

[Insert Table 13 around here]

We find considerable variation in fund risk taking with respect to fund style. The Managed Futures funds are the riskiest in our sample with the corresponding loading of +0.46 being highly significant and the Fixed Income funds exhibit the lowest overall risk with a highly significant coefficient of -0.88. The summary statistics in Section 3 already revealed that EUR funds are less risky, which results in a negative and significant loading on the corresponding dummy, but a U.S. domicile for EUR funds does not have a significant impact.

The two further factors included to control for hedge fund style are both highly statistically significant and show the expected signs. Funds having a higher return correlation with the market tent to be riskier, whereas funds with volatile risk levels take lower risk on average.

A positive and significant coefficient on the mean market risk over the fund life corresponds to hedge fund risk moving in line with market risk, as documented in Figure 4. Our control variable for illiquidity and return smoothing concerns is not significantly different from zero, and the control for dead funds is significant at the 10% level only in one regression specification.

With regard to the relationship between the existence of the HWM provision and the average risk taking, we cannot find any significant results. The indicator variable for the existence of the HWM is not significant in any of our specifications. There are several reasons that can explain the lack of significance. First, there is still no consensus in the theoretical literature on whether the existence of a HWM should induce higher or lower risk taking. Theoretically, it depends on the type of the utility function of the manager and, thus, there might not be any significant effect on average. Second, the relationship between the existence of a HWM and the level of risk is not static and it depends on other time-varying fund characteristics, such as the current position of the fund value relative to the HWM. In this case, on the aggregate level there can be no clear result. Also, the information content of the HMW provision can be covered by the level of the performance fee, also included in the regression.

The level of the incentive fee does not seem to be a valuable determinant of the average level of risk due to its low cross-sectional variation. At the same time, the coefficient on the dummy variable indicating a fee above the median level is negative and highly significant. Hence, the result suggests that there is a negative relationship between the level of the incentive fee and hedge fund risk taking, however, it is driven only by funds charging a fee above the median of 20%.

The empirical results strongly support a positive relationship between the level of the management fee and average fund risk taking. The loadings on both corresponding variables are positive and highly significant. Hedge funds charging higher management fee tend to take higher risks, which is consistent with managerial incentives to exploit the convex flow-performance relationship and increase the fund size.

Managerial discretion as measured by the length of the notice period is positively related to fund risk. On the aggregate level, funds imposing longer notice periods do take higher risks. The corresponding loadings are +0.08 for the length of the notice period prior to redemption and +0.12 for the long-redemption-period dummy, significant at the 5% and 10% levels, respectively.

Fund size is negatively related to the risk taking. The loading on the natural logarithm of the average AuM converted to USD is -0.07 and significant at the 1% level and the loading on the corresponding large-fund dummy is -0.10 and it is no longer significant indicating that the relation is not only driven by some large funds. Including an interaction term between the high management fee dummy and the large fund size dummy does not reveal any significnt difference between the partial and the average effects and is dropped from the regression and the reported results.

There is some evidence on a positive relation between fund life time and fund risk. The dummy variable for life times above the median is positive and significant at the 5% level.

Overall, the cross-sectional analysis suggests that hedge fund risk taking does vary considerably across hedge fund strategies. Larger funds as well as funds charging above median incentive fees tend to be less risky, whereas funds with longer notice periods prior to the redemption can implement riskier investment strategies. The strongest effect by any means is documented for management fees. Higher management fees induce higher risk taking by hedge funds' managers. The impact of a HWM is not strongly pronounced in cross-sectional regressions.

B.1.4 Cross-Sectional Regression Without Control Variables

In Section B.1, we included two control variables into the regression equation. The correlation between the returns of hedge fund i and the market returns ($MarketCorr_i$) served as a data driven proxy for investment style, and the standard deviation of RISK over the fund life time ($STD(RISK_i)$) controled for unstable risk taking potentially resulting from style drifts. Together with the included dummy variables for self reported styles, these two controls capture the part of the overall fund risk, related to fund investment strategy.

In order to assess the stability of our results, we systematically drop these control variables from our regression. The corresponding estimation results in Table 14 show, that the key cross-sectional differences in the average levels of hedge fund risk remain highly significant. Hedge fund risk increases in the level of the management fee as well as the length of the notice period, and it decreases with fund size. We conclude that our main findings are robust to variations in the control variables capturing investment style.

[Insert Table 14 around here]

Considering the actual controls, we see that the return correlation with the market indeed partially captures style effects. The exclusion of this variable changes the estimated loadings on the style dummies. The most pronounced effect is documented for the Equity Market Neutral funds. In Table 13, the loadings on the style dummy are not significant. As Equity Market Neutral funds exhibit little correlation with the market, they were unaffected by the large positive loading on $MarketCorr$ in Table 13, in contrast to other styles. Thus, other things being equal, Equity Market Neutral funds exhibit lower levels of fund risk than their peers having higher return correlation with the market. This effect translates into a negative and significant loading on the Equity Market Neutral style dummy in Table 14, when $MarketCorr$ is excluded. The loading is significant at the 5% level and its estimated value varies from -0.21 to -0.26 depending on the regression specification. Comparing the loadings with and without $STD(RISK)$ (Table 13 vs. Columns (III) and (IV) in Table 14), we do not find evidence of any significant changes. Although the coefficient on the $STD(RISK)$ is highly significant in Table 13, the R^2 drops only slightly when this variable is dropped from the regression.

B.1.5 Cross-Sectional Regression With a Relative Measure of Risk

In this subsection, we define hedge fund risk not in absolute terms, but relative to market risk. We now measure risk as the natural logarithm of the average ratio of the funds' intra-month return standard deviation over the intra-month standard deviation of returns on the MSCI-world index over the same month

$$RISK_i = ln\left(\overline{\frac{STD_{i,t}}{STD(Market)_t}}\right) .$$

The key difference with respect to the results reported in Table 13 is that the market risk variable $ln\left(\overline{STD\left(Market\right)_i}\right)$ is no longer significant in this regression. It is not surprising, as market risk is taken out from the dependent variable straight away. The remaining results remain stable.

B.1.6 Cross-Sectional Regression Excluding Funds without Incentive Fee

We repeated the cross-sectional analysis excluding 30% of hedge funds that do not report incentive fee. The results remain very similar to the ones for the compete sample reported in Table 13. The largest change is in the loading on the dummy variable $IveFeeLarge$, which increases in absolute value from -0.48 to -0.55, and remains highly significant.

B.1.7 Cross-Sectional Regression Excluding the Crisis Period

In this subsection, the cross-sectional analysis is repeated on a pre-crisis subsample, excluding data after July 2007. The results reported in Table 15 are consistent with the ones from Table 13 and seem to be even more pronounced. Most of the significant coefficients increase in absolute values. The main difference is that the interaction dummy variable for funds reporting their performance in EUR while being domiciled in the U.S. gains statistical significance and is positively related to hedge fund risk. Fund size is now significant only at the 10% level.

To summarize the results, besides the hedge fund style, also the management and incentive fees, the fund size, and the length of the notice period prior to redemption are important drivers of the cross-sectional variation in the average levels of hedge fund risk. Funds with higher than the median incentive fee take lower risk, whereas smaller funds, funds having longer notice periods, and funds with higher management fees tend to be riskier. The level of the management fee has by far the strongest effect on fund risk. It is linked to the incentives of hedge fund managers to increase the fund size by exploiting the convex flow-performance relationship. Investors should therefore be aware that a high management fee does not only, ceteris paribus, decrease their post-fee return, and must be offset by the performance of the manager, but can also induce increased risk taking.

B.2 Linear Specification for the Fund Value Relative to the HWM

Our main analysis differs from earlier empirical research with respect to data and methodology. The sample of hedge funds used in the paper consists of rather liquid funds that report their returns on a daily basis and have generally slightly lower and less volatile returns than funds that report on a monthly basis (see Section 3). In terms of methodology, we employ a semi-parametric approach that enables us to reveal a nonlinear and time-varying relation of fund value relative to the HWM to fund risk. In this section, we use a linear specification of this relation instead. It allows us to directly compare our findings to earlier papers and analyze the drivers of differential results.

We modify Equation 4.3 to include a linear specification for the relationship between fund value and the managerial risk taking to the following form

$$\begin{aligned} RISK_{i,t} &= \alpha_i + \alpha_t + \sum_{j=1}^{3} \beta_j RISK_{i,t-j} + \gamma DeltaCorr_{i,t} + \zeta ln(AuM_{i,t_-}) \\ &+ \theta OutflowLarge_{i,t-1} + \kappa Value_{i,t_-} + \varepsilon_{i,t} \ . \end{aligned} \tag{B.2}$$

The estimation results reported in Column (I) of Table 16 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 recent 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 6.

In Section 7.3 of the main paper, we exclude the crisis period from the sample, and saw that the number of observations associated with low fund values drops more than proportionally. When we run the linear regression B.2 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 (Figure 10). 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 7.1 into the regression. Similar to our findings in Section 7.1, 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 16).

B.2.1 Hedge Fund Fixed Characteristics and Their Impact on Risk Shifting

The cross-sectional results suggest that the average level of risk depends on a fund's fixed characteristics, such as fees, size, and redemption period. We now test, if the risk shifting pattern at low fund values is influenced by these characteristics. To capture the effects of the factors, we re-estimate the panel regression specified in Equation B.2 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 redemption period being above the median. The results are reported in Table 17.

Consistent with Aragon and Nanda (2012), the existence of the HWM does mitigate the risk shifting incentives of hedge fund managers (Column (I) of Table 17). The corresponding loading on the interaction term is positive (+0.15) and 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 redemption 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 liner specification does not allow to capture trully nonlinear risk taking and seassonality in the impact of various fixed hedge fund characteristics. It seams that the interpretaion of the economic mechanism of risk shifting might be missleading if the true seasonlity is not taken into account.

C Tables

Table 1: **Descriptive Statistics**

Panel A reports the general characteristics of the hedge funds in our sample, including the average fund size, life in years, usage of a HWM and an incentive fee, working under UCITS regulation or being a SICAV, etc. Panel B reports the descriptive statistics of daily hedge fund returns. Panel C reports the descriptive statistics of the corresponding monthly returns. Returns are expresses in percent per day and month, respectively.

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

Table 2: **Descriptive Statistics Across Hedge Fund Styles**

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

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

Table 3: **Descriptive Statistics for Hedge Fund Risk**

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

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

Table 4: **Autocorrelation in Hedge Fund Risk**

The table reports the descriptive statistics of autocorrelation coefficients estimated for different lags of the hedge fund's individual time series of RISK (the natural logarithm of the intra-month standard deviation of daily hedge fund returns). The last two rows of the table report the shares of significantly positive and significantly negative coefficient estimates among all hedge funds.

	lag1	**lag2**	**lag3**	**lag4**	**lag5**
Mean	0.36	0.17	0.12	0.07	0.02
Median	0.38	0.18	0.14	0.06	0.01
STD	0.26	0.25	0.23	0.20	0.20
Min	-0.34	-0.55	-0.53	-0.40	-0.45
Max	0.85	0.76	0.76	0.60	0.56
Fract. pos.	0.91	0.75	0.67	0.61	0.52
Fract. neg.	0.09	0.25	0.33	0.39	0.48
Mean pos.	0.41	0.28	0.25	0.20	0.18
Mean neg.	-0.12	-0.15	-0.13	-0.13	-0.15
Fract. pos. sign.	0.51	0.30	0.22	0.15	0.11
Fract. neg. sign.	0.00	0.01	0.01	0.00	0.00

Table 5: **Transition Probabilities for Hedge Fund Risk Categories**

The table reports the probabilities for hedge funds to move between high-risk and low-risk groups for different horizons from 1 up to 18 months. The funds are sorted into the two risk categories according to RISK (the natural logarithm of the intra-month standard deviation of daily hedge fund returns) being above or below the median of all hedge funds in a given month. The probabilities are expressed in percent. ***, **, and * indicate that a probability to stay in the current risk category is significantly different from the corresponding probability to leave the category at the 1%, 5%, and 10% significance level, respectively.

	Low	**High**	**Dead**
		1 Month	
Low	84.40***	13.18	2.42
High	13.27	84.41***	2.32
		6 Month	
Low	49.78***	36.67	13.56
High	36.91	49.82***	13.27
		12 Month	
Low	38.31***	36.52	25.17
High	36.76	38.35***	24.89
		18 Month	
Low	32.55	32.24	35.21
High	32.45	32.58	34.96

Table 6: **Panel Regressions of Hedge Fund Risk**

The table reports estimation results for panel regressions of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) on a set of dynamic explanatory variables and controls. The regressions include fund and time fixed effects. The regressions and the included variables are described in Sections 4 and 7.1. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

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

Table 7: **Piecewise Regressions of Residual Hedge Fund Risk**

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

	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)

Table 8: **Determinants of Residual Hedge Fund Risk: Manageent Fee**

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.

	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)

Table 9: **Determinants of Residual Hedge Fund Risk: Notice Period, Performance, Age**

The table reports estimation results for piecesise linear regressions of residual fund RISK as discussed in Section 6. In Panel A $RedemLarge$ 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 a 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.

	Q1		Q2		Q3		Q4	
Panel A: Redemption Period Effect								
$ConstLow$	+0.04	(+0.53)	+0.05	(+0.64)	+0.08	(+0.97)	-0.13	(-1.36)
$RedemLarge \cdot I_{Value_t\_Low}$	-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)
$RedemLarge \cdot I_{Value_t\_Middle}$	-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)
$RedemLarge \cdot I_{Value_t\_High}$	-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)

Table 10: **Determinants of Residual Hedge Fund Risk: HWM, Incentive Fees**

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.

	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)

Table 11: **Determinants of Residual Hedge Fund Risk: Market Correlation**

The table reports estimation results for piecesise linear regressions of residual fund RISK as discussed in Section 6. $CorrHigh$ indicates those funds which returns exhibit higher than median correlation with market teruns measured by the 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.

	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)

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

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 $EqMktNeu$ indicatses Euity 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.

	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)

Table 13: **Cross-Sectional Regressions of Hedge Fund Risk**

The table reports estimation results for cross-sectional regressions of the natural logarithm of the average intra-month standard deviation of daily hedge fund returns on a set of hedge fund characteristics and a set of controls. The regressions and the included variables are described in Section B.1. The t-statistics from bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(I)		(II)	
$Const$	-1.22 *	(-1.72)	-1.81 **	(-2.45)
EUR	-0.47 ***	(-6.78)	-0.46 ***	(-6.68)
$EUR-US$	+0.17	(+0.80)	+0.19	(+0.85)
$EqMktNeutral$	-0.10	(-0.98)	-0.12	(-1.16)
$EmergMkt$	-0.34 **	(-1.98)	-0.35 **	(-2.03)
$EventDriven$	-0.38 ***	(-2.68)	-0.35 **	(-2.31)
$FixedIncome$	-0.88 ***	(-6.93)	-0.89 ***	(-7.72)
$GlobalMacro$	-0.12	(-0.93)	-0.06	(-0.49)
$MgdFutures$	+0.46 ***	(+4.46)	+0.45 ***	(+4.31)
$MultiStrat$	-0.34 ***	(-3.00)	-0.31 ***	(-2.79)
$NotDefined$	-0.67 ***	(-2.78)	-0.62 **	(-2.57)
$MarketCorr$	+0.60 ***	(+5.73)	+0.64 ***	(+6.17)
$STD(RISK)$	-0.45 ***	(-3.41)	-0.35 ***	(-2.62)
$ln(\overline{STD(Market)})$	+0.80 ***	(+5.73)	+0.72 ***	(+4.81)
$ReturnCorr$	+0.01	(+0.04)	-0.07	(-0.32)
$Dead$	-0.15 *	(-1.90)	-0.07	(-0.96)
HWM	-0.05	(-0.58)	-0.01	(-0.15)
$IveFee$	-0.00	(-0.76)		
$IveFeeLarge$			-0.48 ***	(-3.86)
$MmtFee$	+0.26 ***	(+6.34)		
$MmtFeeLarge$			+0.30 ***	(+4.49)
$Redem$	+0.08 **	(+1.99)		
$RedemLarge$			+0.12 *	(+1.73)
$ln(\overline{AuM})$	-0.07 ***	(-3.56)		
$ln(\overline{AuM})Large$			-0.10	(-1.50)
$LifeTime$	+0.01	(+1.05)		
$LifeTimeLarge$			+0.14 **	(+1.97)
R-sqr.	0.45		0.44	
Rbar-sqr.	0.43		0.41	
Nobs	535		535	

Table 14: **Cross-Sectional Regressions of Hedge Fund Risk Excluding Controls**

The table reports estimation results for cross-sectional regressions of the natural logarithm of the average intra-month standard deviation of daily hedge fund returns on a set of hedge fund characteristics and a set of controls. The regressions and the included variables are described in Section B.1.4. Compared to the base line cross-sectional regression, two control variables that capture hedge fund style and style drift are systematically dropped from the regression. The t-statistics from bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(I)		(II)		(III)		(IV)		(V)		(VI)	
$Const$	-0.68	(-0.95)	-1.01	(-1.36)	-1.89 ***	(-2.82)	-2.17 ***	(-2.89)	-1.56 **	(-2.30)	-1.45 *	(-1.96)
EUR	-0.51 ***	(-7.05)	-0.52 ***	(-7.08)	-0.50 ***	(-6.86)	-0.49 ***	(-6.83)	-0.56 ***	(-7.47)	-0.56 ***	(-7.26)
$EUR-US$	+0.16	(+0.73)	+0.20	(+0.95)	+0.13	(+0.63)	+0.15	(+0.69)	+0.11	(+0.48)	+0.14	(+0.68)
$EqMktNeutral$	-0.24 **	(-2.38)	-0.26 **	(-2.58)	-0.06	(-0.62)	-0.08	(-0.81)	-0.21 **	(-2.10)	-0.22 **	(-2.09)
$EmergMkt$	-0.45 **	(-2.54)	-0.47 ***	(-2.62)	-0.36 **	(-2.04)	-0.37 **	(-2.14)	-0.50 ***	(-2.68)	-0.51 ***	(-2.70)
$EventDriven$	-0.28 *	(-1.89)	-0.26 *	(-1.80)	-0.42 ***	(-2.98)	-0.38 **	(-2.45)	-0.33 **	(-2.24)	-0.30 *	(-1.92)
$FixedIncome$	-1.00 ***	(-8.06)	-1.01 ***	(-8.81)	-0.88 ***	(-7.06)	-0.89 ***	(-7.43)	-1.02 ***	(-8.04)	-1.02 ***	(-8.04)
$GlobalMacro$	-0.15	(-1.22)	-0.10	(-0.76)	-0.11	(-0.85)	-0.05	(-0.43)	-0.15	(-1.12)	-0.09	(-0.72)
$MgdFutures$	+0.33 ***	(+3.07)	+0.34 ***	(+3.33)	+0.51 ***	(+4.72)	+0.50 ***	(+4.74)	+0.38 ***	(+3.63)	+0.40 ***	(+3.58)
$MultiStrat$	-0.47 ***	(-4.28)	-0.44 ***	(-4.09)	-0.34 ***	(-2.97)	-0.30 ***	(-2.80)	-0.49 ***	(-4.40)	-0.45 ***	(-3.95)
$NotDefined$	-0.79 ***	(-3.18)	-0.70 ***	(-2.73)	-0.55 **	(-2.25)	-0.52 **	(-2.14)	-0.65 ***	(-2.72)	-0.57 **	(-2.30)
$MarketCorr$					+0.68 ***	(+6.37)	+0.69 ***	(+6.50)				
$STD(RISK)$	-0.62 ***	(-4.61)	-0.51 ***	(-3.86)								
$ln(\overline{STD(Market)})$	+0.84 ***	(+5.88)	+0.81 ***	(+5.36)	+0.70 ***	(+5.15)	+0.67 ***	(+4.42)	+0.71 ***	(+5.09)	+0.76 ***	(+5.05)
$ReturnCorr$	+0.16	(+0.66)	+0.05	(+0.22)	-0.03	(-0.12)	-0.11	(-0.45)	+0.13	(+0.54)	+0.02	(+0.10)
$Dead$	-0.16 **	(-2.04)	-0.08	(-1.02)	-0.23 ***	(-3.14)	-0.14 **	(-1.98)	-0.28 ***	(-3.92)	-0.19 **	(-2.58)
HWM	-0.03	(-0.37)	+0.00	(+0.02)	-0.01	(-0.08)	+0.01	(+0.21)	+0.03	(+0.38)	+0.04	(+0.55)
$IveFee$	-0.00	(-0.79)			-0.00	(-0.90)			-0.00	(-1.04)		
$IveFeeLarge$			-0.47 ***	(-3.69)			-0.50 ***	(-4.03)			-0.50 ***	(-3.80)
$MmtFee$	+0.26 ***	(+5.97)			+0.25 ***	(+5.78)			+0.25 ***	(+5.71)		
$MmtFeeLarge$			+0.30 ***	(+4.31)			+0.29 ***	(+4.22)			+0.29 ***	(+4.20)
$Redem$	+0.08 **	(+2.22)			+0.07 *	(+1.82)			+0.07 *	(+1.90)		
$RedemLarge$			+0.15 **	(+2.15)			+0.13 *	(+1.83)			+0.17 **	(+2.37)
$ln(\overline{AuM})$	-0.07 ***	(-3.37)			-0.07 ***	(-3.31)			-0.07 ***	(-3.12)		
$ln(\overline{AuM})Large$			-0.05	(-0.73)			-0.10	(-1.43)			-0.04	(-0.59)
$LifeTime$	+0.00	(+0.16)			+0.01	(+0.86)			-0.00	(-0.25)		
$LifeTimeLarge$			+0.05	(+0.74)			+0.11	(+1.52)			-0.00	(-0.05)
R-sqr.	0.42		0.40		0.44		0.43		0.39		0.39	
Rbar-sqr.	0.39		0.38		0.42		0.41		0.37		0.36	
Nobs	535		535		535		535		535		535	

Table 15: **Cross-Sectional Regressions of Hedge Fund Risk Excluding the Crisis**

The table reports estimation results for cross-sectional regressions of the natural logarithm of the average intra-month standard deviation of daily hedge fund returns on a set of hedge fund characteristics and a set of controls. The regressions and the included variables are described in Section B.1.7. Compared to the base line cross-sectional regression, the financial crisis (starting from June 30th, 2007 onwards) is excluded from the sample period.The t-statistics from bootstrapped standard errors are given in parenthesis. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(I)		(II)	
$Const$	-6.94 ***	(-2.81)	-4.22 **	(-2.16)
EUR	-0.81 ***	(-6.24)	-0.68 ***	(-5.39)
$EUR-US$	+0.81 **	(+2.25)	+0.65 *	(+1.89)
$EqMktNeutral$	-0.12	(-0.50)	-0.28	(-1.15)
$EmergMkt$	-0.45	(-1.45)	-0.49	(-1.62)
$EventDriven$	-0.94 ***	(-2.61)	-0.81 **	(-2.27)
$FixedIncome$	-0.62 ***	(-2.70)	-0.63 ***	(-2.96)
$GlobalMacro$	+0.03	(+0.12)	+0.09	(+0.34)
$MgdFutures$	+0.55 ***	(+2.66)	+0.60 ***	(+2.97)
$MultiStrat$	-0.27	(-1.08)	-0.27	(-1.02)
$NotDefined$	-0.28	(-0.81)	-0.38	(-1.18)
$MarketCorr$	+0.33	(+1.37)	+0.31	(+1.25)
$STD(RISK)$	-0.82 ***	(-3.03)	-0.67 ***	(-2.68)
$ln(\overline{STD(Market)})$	-0.33	(-0.72)	+0.21	(+0.57)
$ReturnCorr$	+0.50	(+1.11)	+0.34	(+0.81)
$Dead$	-0.17	(-1.14)	-0.25 *	(-1.91)
HWM	+0.22	(+1.42)	+0.07	(+0.54)
$IveFee$	-0.01 *	(-1.82)		
$IveFeeLarge$			-0.59 **	(-2.57)
$MmtFee$	+0.33 ***	(+4.42)		
$MmtFeeLarge$			+0.58 ***	(+5.22)
$Redem$	+0.07	(+1.41)		
$RedemLarge$			+0.23 *	(+1.93)
$ln(\overline{AuM})$	-0.06 *	(-1.91)		
$ln(\overline{AuM})Large$			-0.18	(-1.33)
$LifeTime$	+0.04	(+1.64)		
$LifeTimeLarge$			+0.11	(+0.74)
R-sqr.	0.52		0.54	
Rbar-sqr.	0.47		0.49	
Nobs	201		201	

Table 16: **Panel Regression of Hedge Fund Risk with a Linear Specification for Fund Value**

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 regression includes fund and time fixed effects. The regressions and the included variables are described in Section B.2. Compared to the main panel regression in Equation B.2, the fund value variable is added to the regression as a linear specification of 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.

	(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	

Table 17: **Panel Regressions of Hedge Fund Risk with a Linear Specification for Fund Value and Interaction Terms**

The table reports estimation results for panel regressions of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) on a set of dynamic explanatory variables and controls. The regressions include fund and time fixed effects. The regressions and the included variables are described in Section B.2.1. Compared to the panel regression in Equation B.2, 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.

	(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)		
$Value_{t\_} \times RedemLarge$							-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	

D 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 of funds in our sample (reporting daily to Bloomberg) as well as funds reporting monthly to commertial databases between October 2001 and April 2011. The correlation between two series is 93%.

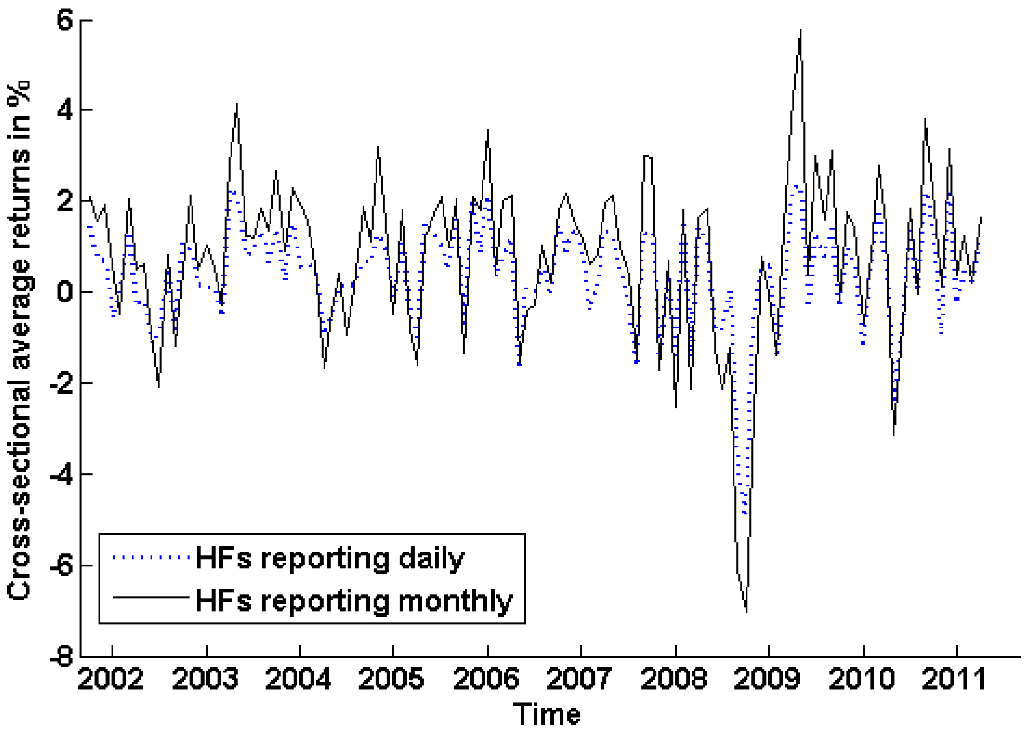


Figure 2: **Distribution of Styles of "Daily" and "Monthly" Hedge Funds**

The figure presents a hystogram of reported styles distributins of funds in our sample (reporting daily to Bloomberg) as well as funds reporting monthly to commertial databases between October 2001 and April 2011. EqDirec states for Directional Ewuity, 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".

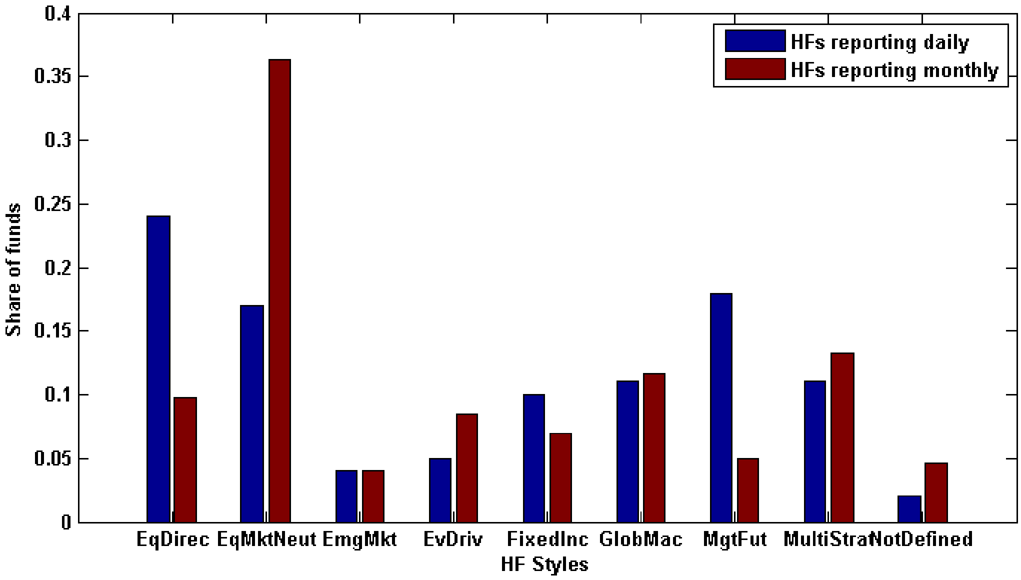


Figure 3: **Individual Time Series of Hedge Fund Risk**

The figure presents an envelop plot from the individual time series of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns) of all individual hedge funds in our sample. The sample is described in Section 3 and contains 714 hedge funds that report their returns on a daily basis between October 2001 and April 2011.

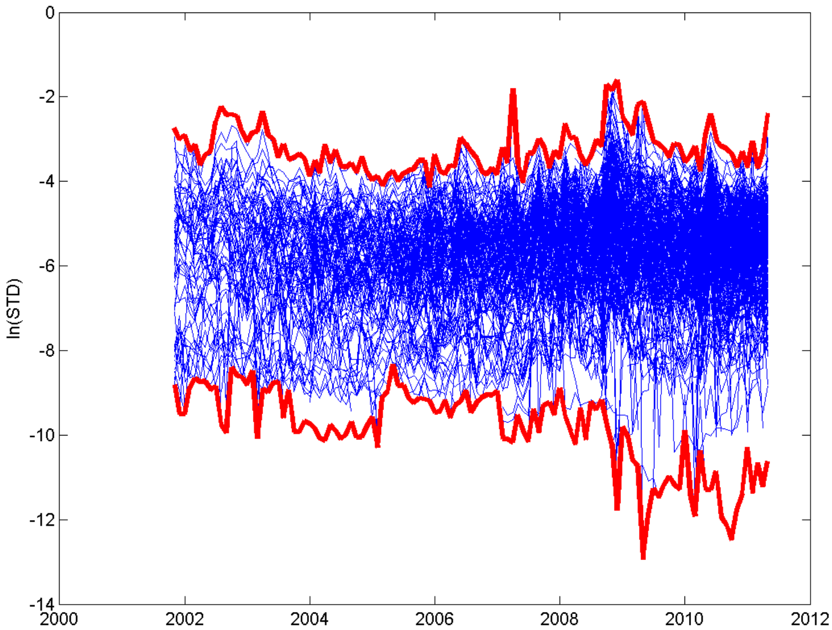


Figure 4: **Time Series of Aggregate Hedge Fund Risk and Market Risk**

The figure plots the time series of the cross-sectional averages of RISK (the natural logarithm of the intra-month standard deviations of daily hedge fund returns). It shows the time series of averages from all hedge funds, as well as from hedge funds reporting in USD and EUR separately. The sample of hedge funds is described in Section 3 and contains 714 hedge funds that report their returns on a daily basis between October 2001 and April 2011. The time series of market risk over the sample period is measured as the natural logarithm of the intra-month standard deviations of daily returns on the MSCI World Index.

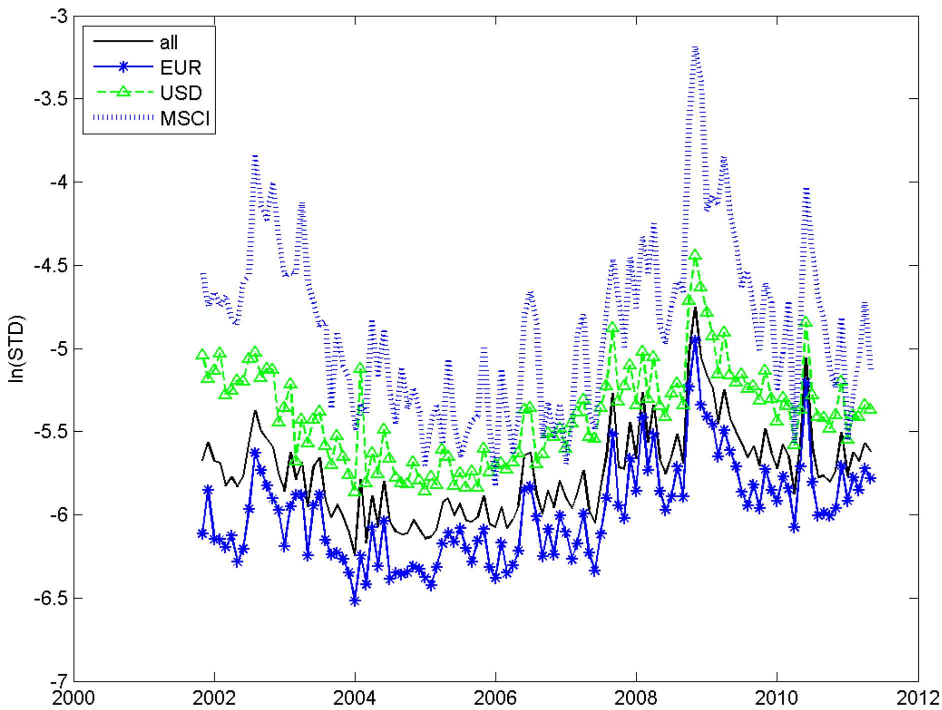
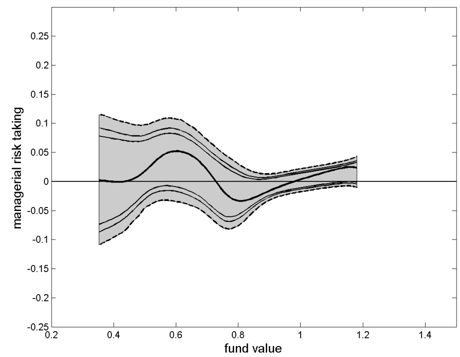
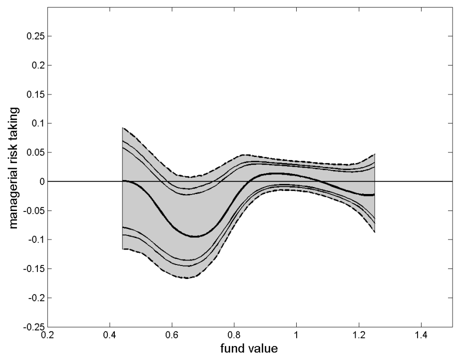


Figure 5: **Managerial Risk Taking: Quarter-Wise**

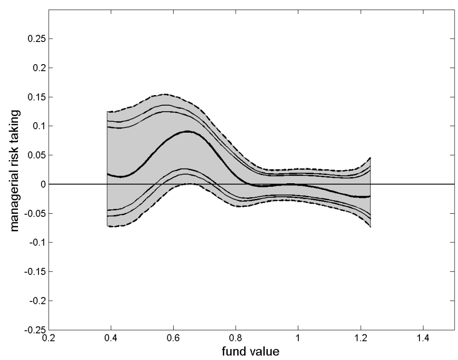
The figure plots the result of the kernel regression specified in Section 4 for the different quarters of a year. On the horizontal axis is the fund value relative to the HWM. On the vertical axis is the managerial risk taking contained in the residuals from a panel regression of RISK (the natural logarithm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



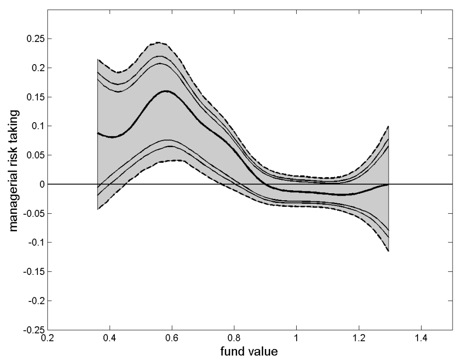
(a) Quarter 1



(b) Quarter 2



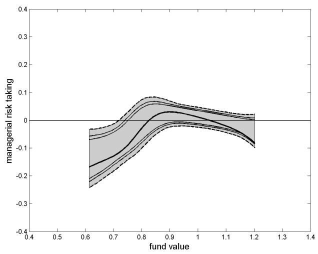
(c) Quarter 3



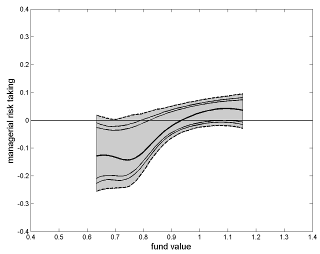
(d) Quarter 4

Figure 6: **Managerial Risk Taking: Month-Wise**

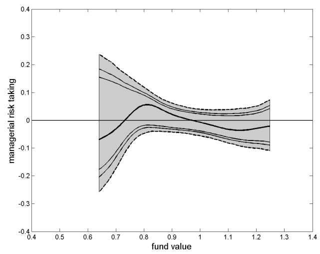
The figure plots the results of kernel regressions specified in Section 4 for each month in the second and the fourth quarter of a year. On the horizontal axis is the fund value relative to the HWM. On the vertical axis is the managerial risk taking contained in the residuals from a panel regression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



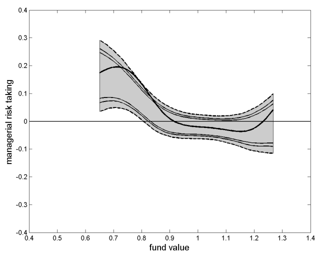
(a) April



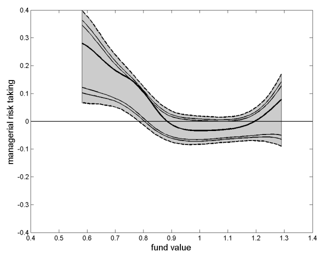
(b) May



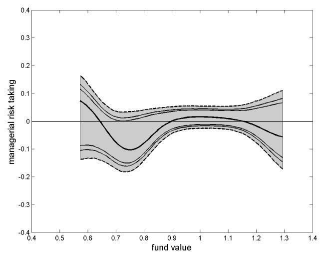
(c) June



(d) October



(e) November



(f) December

Figure 7: **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 4.5 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.

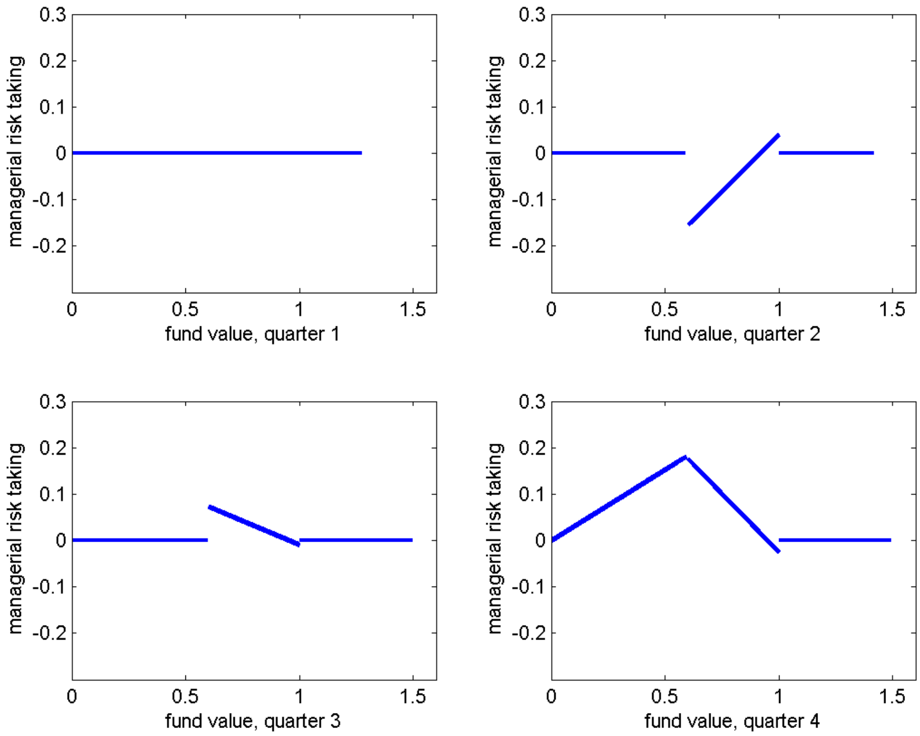


Figure 8: **Managerial Risk Taking: Piecewise Linear Specification Excluding Funds without Incentive Fee**

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 4.5 for four quarters of a year. Here, funds that do not explicitly report a positive incentive fee are excluded from the sample. 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 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.

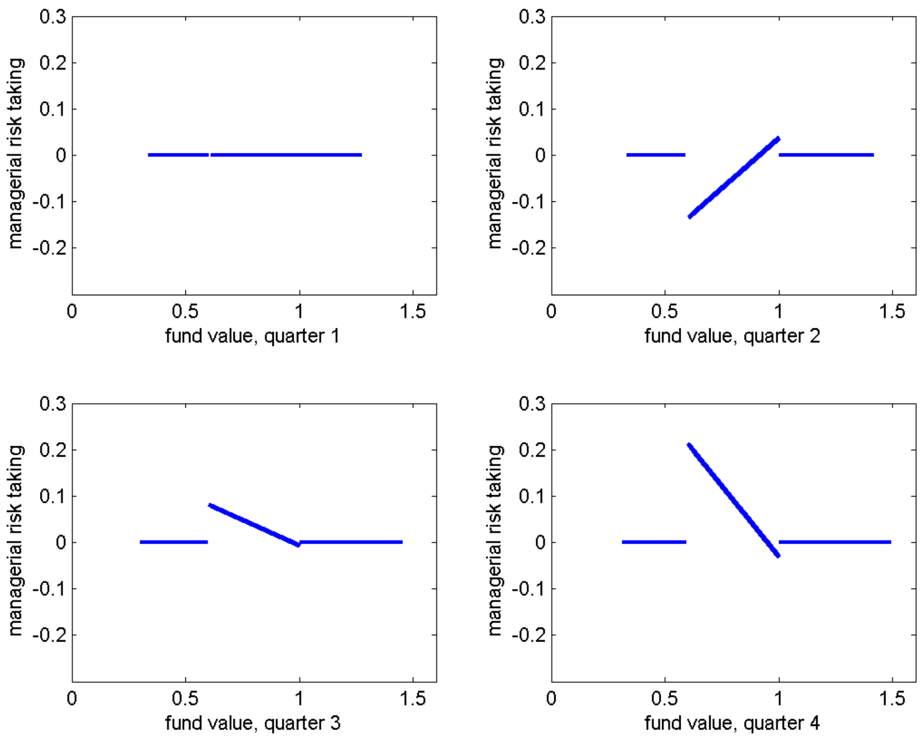


Figure 9: **Managerial Risk Taking: Piecewise Continuous Linear Specification**

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 7.2 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.

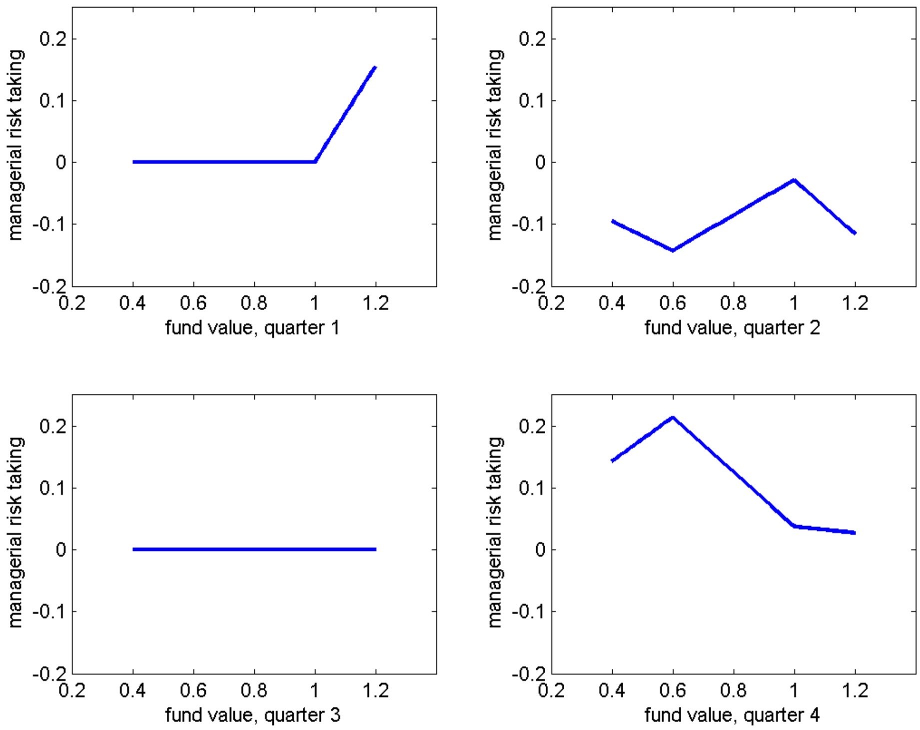


Figure 10: **Managerial Risk Taking: Piecewise Linear Specification Excluding the Crisis**

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 4.5 for four quarters of a year. Here, The financial crisis is excluded from the sample period, which now spans October 1st, 2001 only to June 30th, 2007. 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 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.