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

Supplementary result appendix

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This appendix presents several additional results discussed in "A time to scatter stones, and a time to gather them: the annual cycle in hedge fund risk taking".

A Controlling for possible multiple share classes

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

Table 1: Piecewise regressions of residual hedge fund risk excluding potential multiple fund share classes

The table reports estimation results for piecewise linear regressions of residual fund RISK with 207 hedge funds exhibiting return correlations above 98% with other funds within the same investment company excluded from the sample. κ stands for the constant terms, δ is the slope coefficient on $Value_{t\_}$. The subscripts *low*, *mid*, and *high* capture fund values below 0.6, between 0.6 and 1, and above 1 respectively. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Q1		Q2		Q3		Q4	
κ_{low}	-0.02	(-0.51)	+0.01	(+0.18)	+0.04	(+1.08)	-0.04	(-0.73)
δ_{low}	+0.10	(+0.95)	+0.07	(+0.61)	+0.02	(+0.23)	+0.34 **	(+2.18)
κ_{mid}	-0.01	(-0.09)	-0.34 **	(-2.35)	+0.02	(+0.11)	+0.55 ***	(+3.32)
δ_{mid}	-0.01	(-0.04)	+0.38 **	(+2.44)	-0.00	(-0.02)	-0.58 ***	(-3.23)
κ_{high}	-0.71	(-1.62)	+0.31	(+1.08)	+0.14	(+0.53)	-0.02	(-0.13)
δ_{high}	+0.72 *	(+1.68)	-0.31	(-1.12)	-0.15	(-0.59)	+0.01	(+0.03)

B Comparison of risk factor loadings

We aggregate daily returns of the hedge funds in our sample to a monthly frequency and estimate the Fung and Hsieh (2004) seven factor model for each fund over its entire life. We repeat the estimation using a merged database of hedge funds reporting on a monthly basis. The database comprises five commercial databases (BarclayHedge, Eurekahedge, Morningstar, HFR, and TASS) over the same time period as the daily reporting hedge funds in our sample. Table 2 reports the estimated mean factor loadings and their differences across two data sources. Overall, the hedge funds reporting daily have significantly smaller average alphas, which are also often negative. Emerging markets and managed futures are the two styles that exhibit the most pronounced difference in their risk profile, with most of the loadings being statistically significantly different across the data bases. Other styles have more comparable average factor loadings, which are often not significantly different across the two data sets.

Table 2: Factor loadings of daily and monthly reporting hedge funds

The table reports the average loadings on the Fung and Hsieh (2004) seven factors across different hedge fund styles. The model is estimated based on monthly returns of the funds in our sample (initially reporting daily) as well as for funds reporting monthly to commercial databases, between October 2001 and April 2011. The abbreviations stand for: EqDirec – directional equity; EqMktNeut – equity market neutral; EmgMkt – emerging markets; EvDriv – event driven; FixedInc – fixed income; GlobMac – global macro; MgtFut – managed futures; MultiStrat – multi strategy. *Alpha* is a constant term in the regression; $Mkr - Rf$ is the excess return of the S&P500 index; SMB is the size factor, the difference between monthly total returns on the Russell 2000 and S&P500 indices; $BOND$ is the bond factor, the monthly change in the 10-year Treasury constant maturity yield; $CREDIT$ is the credit factor, the monthly change in the difference between the Moody's Baa yield and the 10-year Treasury constant maturity yield; $PTFSBD$, $PTFSFX$, and $PTFSCOM$ are bond, currency, and commodity trend-following factors, respectively, as downloaded from the David A. Hsieh web page https://faculty.fuqua.duke.edu/˜dah7/HFData.htm. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

		$Alpha$	$Mrk - Rf$	SMB	$BOND$	$CREDIT$	$PTFSBD$	$PTFSFX$	$PTFSCOM$
EqDirec	Daily	-0.18	+30.41	-3.54	+111.04	-135.49	-3.91	+3.05	-0.97
	Monthly	+0.46	+36.24	-12.60	+153.94	-207.05	-1.12	+0.27	-0.31
	Diff	-0.64**	-5.83	+9.06	-42.91	+71.56	-2.79**	+2.78*	-0.67
EqMktNeut	Daily	-0.18	+14.42	+3.28	-39.42	-130.47	-0.95	-1.05	+0.06
	Monthly	+0.42	+31.73	-9.72	+73.78	-255.79	-0.88	-0.12	+0.31
	Diff	-0.60**	-17.32***	+13.00	-113.20*	+125.31	-0.07	-0.92	-0.26
EmgMkt	Daily	-0.69	+13.49	-17.35	+175.58	-187.10	-12.27	+8.24	-5.09
	Monthly	+0.79	+46.30	+13.15	-27.34	-489.82	-0.46	-1.49	+0.23
	Diff	-1.49***	-32.81***	-30.49***	+202.92*	+302.71*	-11.81***	+9.74***	-5.32***
EvDriv	Daily	+0.03	+28.95	-6.77	+102.28	-146.33	+0.36	-0.29	-2.23
	Monthly	+0.55	+24.75	-5.82	+26.52	-311.09	-1.49	+0.54	-0.29
	Diff	-0.51**	+4.21	-0.95	+75.76	+164.77	+1.85	-0.83	-1.94
FixedInc	Daily	+0.42	+6.66	+2.54	+19.87	-87.58	-0.56	-0.59	-1.00
	Monthly	+0.41	+10.51	+3.82	-62.22	-369.75	-1.42	-0.82	-0.67
	Diff	+0.01	-3.86	-1.28	+82.09	+282.16**	+0.86	+0.24	-0.33
GlobMac	Daily	-0.17	+24.24	+8.95	+39.44	-216.20	-0.19	-2.88	+3.60
	Monthly	+0.54	+13.92	+4.55	+53.12	-44.59	+1.21	+0.94	+3.41
	Diff	-0.71	+10.32	+4.40	-13.68	-171.62	-1.41	-3.82*	+0.20
MgtFut	Daily	-0.32	+48.16	+26.36	-514.80	-865.95	+7.85	-7.98	+14.70
	Monthly	+0.78	+11.02	+1.84	+104.27	-30.23	+3.62	+0.72	+6.31
	Diff	-1.09***	+37.14***	+24.52***	-619.07**	-835.71***	+4.23	-8.70***	+8.40**
MultiStrat	Daily	-0.45	+29.33	+6.24	-60.96	-15.79	-0.12	-2.62	+3.38
	Monthly	+0.60	+13.18	+2.25	-0.49	-245.66	-1.11	+0.24	-0.80
	Diff	-1.05***	+16.15**	+3.99	-60.47	+229.88	+1.00	-2.86*	+4.19**

C Alternative risk measures

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

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

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

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

$$RISK_{i,t}^{M} = ln\left(\frac{STD_{i,t}}{STD(Market)_t}\right). \quad (1)$$

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

D Alternative specifications of the high-water mark

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

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

E Piecewise continuous linear specification for managerial risk taking

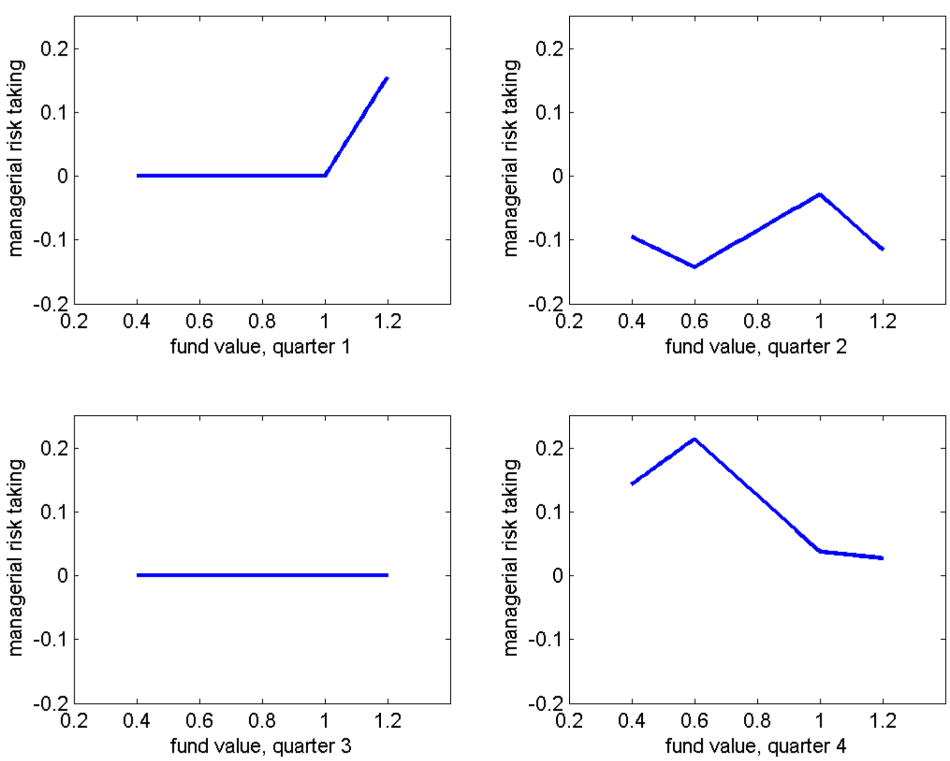
We re-estimate a piecewise linear specification of the model given in Equation (4) of the main paper, but this time we require that the resulting regression line is piecewise continuous. We impose continuity restrictions at the breakpoints, and obtain the following regression for each quarter of a year:

$$\hat{e}_{i,t} = \kappa + \delta_{low} Value_{i,t_-} + \delta_{mid}(Value_{i,t_-} - \bar{V})^+ + \delta_{high}(Value_{i,t_-} - 1)^+ + \eta_{i,t}. \qquad (2)$$

Figure 1 depicts the resulting regression lines, where we set insignificant regression coefficients to zero. The results support the main findings from the kernel regression and the unrestricted version of the piecewise linear specification. We see a risk decline for poorly performing funds during the second quarter and a risk increase during the fourth quarter of a year.

Figure 1: Managerial risk taking: piecewise continuous linear specification

The figure plots the regression results for managerial risk taking on the fund value relative to the HWM as specified in the piecewise continuous panel regression in Equation (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.



F Hedge fund style

This section analyzes variations in the seasonal risk-taking pattern with respect to fund style. We augment Equation (8) of the main paper and use dummy variables for each of the reported styles, one at a time. As the data requirements are substantial (we need to make sure that in each quarter for each fund value band we have enough observations in each style) we are not able to single out all the reported styles. We are able to estimate the regression for the three largest styles: directional equity, equity market neutral, and managed futures. All these styles belong to the capacity unconstrained hedge fund styles (Ding et al. 2009). Whenever one of those styles is singled out, the average risk-shifting pattern among all other funds constitutes the reference case. Table 3 reports the results.

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

Table 3: Determinants of residual hedge fund risk: fund style

The table reports estimation results for piecewise linear regressions of residual fund RISK. κ stands for the constant term, δ is the slope coefficient on $Value_{t\_}$. The subscript mid captures fund values between 0.6 and 1. In Panel A, γ is the estimate of the dummy variable indicating directional equity funds. In Panel B, γ indicates equity market neutral funds. In Panel C, it represents managed futures funds, as specified in Equation (8) of the main paper. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

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

G Excluding the crisis period

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

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

H Linear specification for the fund value relative to the high-water mark

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

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

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

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

Table 4: 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 the fund value relative to the HWM, a set of dynamic explanatory variables and controls. The regression includes fund and time fixed effects. Compared to the main panel regression in Equation (3), the fund value variable has a linear relation to managerial risk taking. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, 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	

When we run the linear regression in Equation (3) for the non-crisis period only, the coefficient estimate for the value variable becomes insignificant, while the truly nonlinear managerial risk taking is still present (Appendix G). This means that besides hiding the truly nonlinear nature of the managerial risk taking, a linear specification can fail to identify managerial risk taking altogether, which could explain the insignificant results in some earlier papers (e.g., Brown et al. 2001, Agarwal et al. 2002). This problem seems to be more pronounced for samples that lack a significant fraction of poorly performing funds, that is, sample periods that are characterized by bullish markets.

We then include the relative fund performance with respect to peers into the regression. Similar to our previous findings, both the fund value relative to the HWM and the short-term performance relative to the industry are negatively related to fund risk. The coefficients of –0.17 and –0.19 are significant at the 1% and 10% levels, respectively (Column (II), Table 4).

We now analyze the impact of hedge fund fixed characteristics, such as fees, size, and notice period prior to redemption. We re-estimate the panel regression specified in Equation (3) and include interaction terms between the fund value variable and (1) a dummy for the use of a HWM; (2) a dummy for the incentive fee being above the median; (3) a dummy for the management fee being above the median; and (4) a dummy for the notice period being above the median. The results are reported in Table 5.

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

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

Table 5: 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 the fund value relative to the HWM, a set of dynamic explanatory variables and controls. The regressions include fund and time fixed effects. Additional interaction terms between the fund value variable and several fund characteristics are included. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, 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)		
$Value_{t\_} \times NoticeLarge$							-0.20 **	(-2.23)
R-sqr.	0.90		0.90		0.90		0.90	
Rbar-sqr.	0.89		0.89		0.89		0.89	
Nobs	10,141		10,141		10,141		10,141	

I Alternative model specifications for systematic risk

In Section 4.4 of the main paper, we fit a Carhart (1997) four factor model to the daily return of hedge funds in our sample, allowing the loadings to vary each quarter. Now, we repeat the analysis allowing the loadings to change every month. We next use the Fung and Hsieh (2004) model instead of the Carhart (1997) model. As the trend-following factors are available only on monthly frequency, we follow Patton and Ramadorai (2013) and use the first four factors of the model only. Both models provide a comparable fit to the data in terms of adjusted R-square. The Carhart (1997) model fits equity-related styles better: the mean adjusted R-squares for equity directional, equity market neutral, and emerging markets styles are 0.26, 0.12, and 0.13, compared to 0.24, 0.08, and 0.10 for the reduced Fung and Hsieh (2004) model. The latter model provides, however, a better fit for fixed income funds, with the adjusted R-square being 0.11, compared to 0.05 of the Carhart (1997) model. Table 6 reports the estimation results of the piecewise liner specification based on fitted return values (Panels A1 and B1) and residuals (Panels A2 and B2) of the two models. Overall, similar to the previously discussed results, we find seasonality in RISK of both fitted values and residuals, with the RISK increase at the end of the year being significantly stronger in fitted values than in residuals.

Table 6: Market vs. idiosyncratic risk taking: alternative models

The table reports estimation results for piecewise linear regressions of residual fund RISK based on fitted returns from the Carhart (1997) regression (Panel A1), the corresponding residuals (Panel A2), and fitted and residual returns from the reduced Fung and Hsieh (2004) regression (Panel B1 and B2) respectively. κ stands for the constant term, δ is the slope coefficient on $Value_{t\_}$. The subscript mid captures fund values between 0.6 and 1. The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

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

J Scalability of the Investment Strategy

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

Table 7: Determinants of residual hedge fund risk: market correlation

The table reports estimation results for piecewise linear regressions of residual fund RISK. κ stands for the constant term, δ is the slope coefficient on $Value_{t\_}$. The subscript mid captures fund values between 0.6 and 1. γ is the estimate of the dummy variables indicating funds that exhibit higher than median return correlation with the market (MSCI World Index). The t-statistics from panel robust bootstrapped standard errors are given in parenthesis. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

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

with a higher return correlation with the market will exhibit a stronger risk increase at the end of a year.

We estimate Equation (8) of the main paper using an indicator variable taking a value of 1 if the fund's returns have higher than median correlation with the market returns. The results reported in Table 7 suggest that such hedge funds do indeed exhibit a stronger risk increase during the last quarter of a year. The corresponding coefficient of +0.05 is significant at the 5% level. Interestingly, the risk shifting during the third quarter is reduced by the same magnitude. Those funds that can easily level up their risk do not need to adjust it early. Instead, they can scale the risk up right when they need it – at the end of a year.

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