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Tail Risk and Hedge Fund Returns*

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Preliminary. Comments Welcome.

Abstract

We document large, persistent exposures of hedge funds to downside tail risk. For instance, the hardest hit hedge funds in the 1998 crisis also suffered predictably worse returns than their peers in 2007–2008. Using the conditional tail risk factor derived by Kelly (2012), we find that tail risk is a key driver of hedge fund returns in both the time-series and cross-section. A positive one standard deviation shock to tail risk is associated with a contemporaneous decline of 2.88% per year in the value of the aggregate hedge fund portfolio. In the cross-section, funds that lose value during high tail risk episodes earn average annual returns more than 6% higher than funds that are tail risk-hedged, controlling for commonly used hedge fund factors. These results are consistent with the notion that a significant component of hedge fund returns can be viewed as compensation for selling disaster insurance.

Keywords: Hedge fund, tail risk, performance evaluation

JEL Codes: G12, G20

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1 Introduction

Hedge fund managers are often characterized as pursuing strategies that generate small positive returns for a period of time before incurring a substantial loss. For instance, Stulz (2007) argues that,

Hedge funds may have strategies that yield payoffs similar to those of a company selling earthquake insurance; that is, most of the time the insurance company makes no payouts and has a nice profit, but from time to time disaster strikes and the insurance company makes large losses that may exceed its cumulative profits from good times.

Tail events represent states in which investors have extremely high marginal utility, thus investors are willing to pay large sums to insure such states. As a result, tail risks have large impacts on asset prices even if crashes are infrequently realized, an idea formalized in the rare disaster hypothesis of Rietz (1988) and Barro (2006). If hedge funds are the providers of crash insurance, they earn an attractive insurance premium in normal times, but suffer severe losses in a tail event. Leveraging this kind of strategy can further enhance its performance, as long as the hazard does not materialize. When a large enough disaster strikes, payouts on the crash insurance that it has written can quickly obliterate a fund's capital, especially when these positions have been levered-up, leaving the fund unable to meet margin requirements and driving fund value to zero.

Moreover, anecdotes such as the collapse of Long Term Capital Management (LTCM), the "quant" crisis of 2007, and the recent financial crisis demonstrate that infrequent but dramatic losses of large hedge funds can exert significant pressures on the stability of the financial system. Accordingly, both academics and practitioners have intensified their investigation of the risk and return characteristics of hedge funds.

In this paper, we investigate the exposure of hedge funds to extreme event risk. We quantify how tail risk exposure impacts average hedge fund returns both over time and in the cross section. Our analysis establishes that exposure to tail risk is a key determinant of hedge fund returns.

Persistence in Performance Across Crises

We begin by investigating hedge fund performance during two extreme episodes: the 1998 and 2007–2008 financial crises. The 1998 crisis was triggered by the Russian debt default in August 1998 and ultimately led to the demise of the star hedge fund, LTCM, and sent ripples of adverse returns through the hedge fund industry. Similarly, in the recent financial crisis many hedge funds incurred unprecedented losses over a short period of time resulting from pressure to unwind crowded, high risk trades (Khandani and Lo (2007)) and exposure to the subprime mortgage market (Hellwig (2009)).

Figure 1 plots monthly returns for the Hedge Fund Research (HFR) Fund Weighted Composite Index. Two hedge fund crashes in 1998 and 2008 stand out. The occurrence of these two crises provides a unique opportunity to ask the question: Did hedge funds that underperformed in the 1998 crisis also perform worse in the recent crisis? We find that a fund’s return during the 1998 disaster strongly predicts its performance during the 2007–2008 crisis. In particular, a 1% decline in a fund’s return during the 1998 crisis predicts a 0.56% drop in fund return in the 2007–2008 crisis. The data show that many of the worst performers during the 1998 episode were again the worst suffering funds in 2008. This predictability in hedge fund performance across the two crises is statistically significant, and robust to controlling for a variety of hedge fund characteristics. This result is a preliminary indication that hedge funds have persistent exposure to extreme downside risk. Fahlenbrach, Prilmeier and Stulz (2012) find a similar result for US banks in these two crisis episodes, and conclude that this is evidence that certain banks may operate in

a tail risky industry niche, and that this business model deliberately exposes the bank to extreme shocks. A similar view can be taken with respect to hedge funds' business models.

A Systematic Tail Risk Factor

To more deeply investigate the exposures of hedge funds to tail risk, we adopt a factor model approach that is motivated by asset pricing theory. Time-varying rare disaster models suggest that economy-wide variation in disaster risk generates differential pricing across assets depending on their crash risk exposure, and also produces predictable time variation in compensation that investors receive for bearing this risk. Examples of these models include Gabaix (forthcoming), Wachter (2011), Drechsler and Yaron (2011) and Kelly (2012).

We follow the approach of Kelly (2012) and construct an economy-wide tail risk factor from information in the cross section of individual firm extreme events. Kelly (2012) shows that this factor has strong cross section and time series explanatory power for US equity returns. In particular, he finds that stocks that serve as tail risk hedges (those that tend to appreciate during times of high tail risk) are relatively valuable and thus earn lower average returns than stocks that are adversely exposed to tail risk (those that depreciate in high tail risk episodes). He also shows that the tail risk factor positively forecasts returns on the aggregate US stock market due to the fact that investors demand more compensation for holding the market portfolio during times of heightened crash risk. Luo et al. (2012) show that this factor has similar explanatory for returns on a range of other asset classes and in international markets, while Allen et al. (2010) show that it captures banking sector systemic risk.

We first examine the covariation between aggregate hedge fund portfolio returns and Kelly's tail risk factor. Analyzing over 6,000 hedge funds from the Lipper/TASS database over the 1994–2009 period, we identify a robust link between tail risk and hedge fund

returns. A one standard deviation increase in aggregate tail risk is associated with a contemporaneous decline of 2.88% in the value of the aggregate hedge fund portfolio, after controlling for the loadings of hedge fund returns on the widely used Fung and Hsieh (2001) seven factor model. Furthermore, this negative exposure emerges across different investment styles, such as convertible arbitrage, emerging markets, equity market neutral, event driven, long-short equity, and multi-strategy. It is especially strong among funds that pursue strategies of emerging markets and long-short equity. A positive one standard deviation shock to tail risk is accompanied by a 7.20% and 4.44% drop in annual returns for these two styles, respectively. This large negative covariation of hedge fund returns with the tail factor captures the tendency of the hedge fund industry as a whole to lose value during times of high tail risk. It also naturally leads us to investigate whether the high average returns enjoyed by hedge funds arises as compensation for taking on tail-risky investments.

To this end, we document substantial heterogeneity in individual hedge fund exposures to the tail risk factor, and test whether differences in tail exposure are associated with differences in average returns across funds. We find that funds in the bottom tail exposure quintile (those that are most adversely affected in times of high tail risk) earn average annual returns approximately 6% higher than funds in the top tail exposure quintile (those that serve as relative hedges of tail risk). This large return spread remains near 6% per year after we adjust for the Fung-Hsieh factors, and is robust to various alternative performance evaluation models commonly used in the asset pricing literature. These results are consistent with high average returns of some funds being driven by their willingness to bear abnormally high crash risk, consistent with the prediction from the theory models cited above. Furthermore, these results highlight the need to account for tail risk exposure in evaluating fund manager performance. “Alpha” in excess of standard factors may

not represent managerial skill, but merely the willingness of managers to sell “earthquake insurance.”

We then relate estimates of funds’ tail risk betas to a range of observable fund characteristics. The funds that are most susceptible to tail risk are those that are younger, have a “high water mark” provision, have longer minimum investment horizons, do not employ leverage, and those in which managers do not risk their own capital. These results are intuitively consistent with risk taking behavior responses to incentives. For example, our findings support the idea that funds have an incentive to establish a track record of high returns early in their life cycle in order to attract fund flows. One way for young funds to establish “alpha” relative to standard benchmarks is to take on tail-risky investments which carry high risk compensation. Our results also suggest that when managers do not invest their own capital in the fund, a standard principal-agent problem arises in which the manager is willing to take on extremal risk in order to earn incentive fees and attract more fund inflows.

Related Literature

Our paper joins a growing literature that studies the exposures of hedge funds to systematic risk factors. Asness, Krail, and Liu (2001), Patton (2009), and Bali, Brown, and Caglayan (2011a) provide evidence that, despite the frequent claim that funds are market neutral, they often have significant exposures to market factors. Fung and Hsieh (1997, 2001), Mitchell and Pulvino (2001), Agarwal and Naik (2004), and Fung, Hsieh, and Ramadorai (2008) emphasize that dynamic trading and arbitrage strategies can lead hedge funds to exhibit option-like returns and suggest factors to adjust for this pattern. Agarwal, Bakshi, and Huij (2010) examine the exposures of hedge fund returns to volatility, skewness, and kurtosis risks derived from the S&P 500 index options as proxies higher order risks. They argue that strategies such as Managed Futures, Event Driven, and Long/Short Equity

show significant exposures to high-moment risks. Bali, Brown, and Caglayan (2011b) find that only market volatility, and not skewness or kurtosis, explains the cross-sectional variation in hedge fund returns. Sadka (2010) provides evidence of liquidity risk as a contributing factor for hedge fund returns. We establish that a conditional tail risk factor is an important determinant of hedge fund returns, even after controlling for previously studied factors, including the Fung and Hsieh factors, option-based risk measures as in Agarwal, Bakshi and Huij, and a liquidity risk factor as in Sadka.

This paper is also related to recent studies on hedge fund contagion. Boyson, Stahel, and Stulz (2008) find evidence of contagion across hedge fund styles. Chan, Getmansky, Haas, and Lo (2009) find that the correlation across hedge funds increased prior to the LTCM crisis and after 2003. Adrian (2007) argues that the increase in correlation across hedge funds since 2003 is driven by the reduction in volatility. Dudley and Nimalendran (2011) provide evidence for the liquidity spiral associated with margin increases in futures exchange. Adrian, Brunnermeier, and Nguyen (2011) find the increase in tail sensitivities between hedge funds in times of crisis with a quintile regression approach. We contribute to this literature by showing that common exposures to an economy-wide time-varying tail risk factor lead to comovement among hedge funds in times of distress.

The rest of the article is organized as follows: Section 2 introduces our methodology and sample construction and Section 3 provides evidence of predictability of hedge fund performance across the 1998 and 2007–2008 financial crises. In Section 4, we show that the tail risk factor is an important determinant of the time-series and cross-section variation in hedge fund returns, and consider a series of robustness checks. Section 5 concludes.

2 Methodology and Sample

2.1 Economic Framework

Recently, a range of theoretical papers have proposed links between dynamic tail risk and asset prices (Gabaix (forthcoming) and Wachter (2011)), though these are difficult to implement empirically due to inherent challenges of quantifying time-varying tail risk. To overcome this, we follow the approach of Kelly (2012), who proposes a measure of economy-wide, time-varying tail risk that is directly estimable from the cross section of returns. It exploits firm-level price crashes every month to identify common fluctuations in tail risk across stocks. Because individual returns contain information about the likelihood of market-wide extremes, the cross section of firms can be used to accurately measure prevailing tail risk in the economy. Therefore, in a sufficiently large cross section, enough stocks will experience individual tail events each period to provide accurate information about the prevailing level of tail risk.

In his appendix, Kelly shows that this measure arises naturally in an economic setting similar to variable rare disaster models, and captures the same intuition as those theories. First, he shows that tail risk positively forecasts excess returns. Because tail risk is utility decreasing, rises in tail risk increase the return required by investors to hold the market, thereby inducing a positive predictive relationship between tail risk and future returns. Second, the cross section of expected returns is in part determined by assets' differential tail risk exposure. High tail risk is associated with bad states of the world and high marginal utility. This implies that the price of tail risk is negative, hence assets that hedge tail risk (have high tail risk betas) are more valuable, and thus have lower expected returns than those with low tail risk betas.

Kelly shows that his tail risk measure is highly persistent (monthly AR(1) coefficient

of 0.948), is closely linked to measures of tail risk implied by S&P 500 index options, varies with business cycle variables including unemployment and the Chicago Fed National Activity Index, and is positively related to credit risk measures like the term spread and the default spread. Luo et al. (2012) show that Kelly’s tail factor has similar explanatory for returns on a range of other asset classes and in international markets.

2.2 Constructing the Tail Risk Factor

Our central statistical representation of economy-wide tail risk, as proposed by Kelly (2012), is the following equation. It states that, conditional upon exceeding some extreme “tail threshold,” u_t , and given information \mathcal{F}_t , an asset’s return obeys the tail probability distribution

$$P_t(-R_{i,t+1} > r \mid -R_{i,t+1} > u_t, \mathcal{F}_t) \sim \left(\frac{r}{u_t} \right)^{-a_i \zeta_t}.$$

The relation (\sim) describes tail equivalence at the upper support boundary of $-R_{i,t+1}$.¹ To operationalize this specification, asymptotic equivalence is treated as an exact relationship. The focus of this paper is the left tail of the return distribution. The convention in extreme value theory is to represent a tail distribution as the right, or upper, tail. This is without loss of generality since returns in the negative tail are simply transformed to an upper tail representation via a sign change.

Motivated by this specification, Kelly’s procedure applies Hill’s (1975) power law estimator to the pooled cross section of extreme daily return observations for all CRSP stocks in a given month t . The Hill estimator is a maximum likelihood estimator of power law

¹The relation $f \sim g$, read “ f is asymptotically equivalent (or tail equivalent) to g ,” denotes $\lim_{u \rightarrow \infty} f(u)/g(u) = 1$.

tail exponents.² Applied to the pooled cross section each month, it takes the form³

$$\frac{1}{\zeta_t^{Hill}} = \frac{1}{K_t} \sum_{k=1}^{K_t} \ln \frac{R_{k,t}}{u_t}$$

where $R_{k,t}$ is a daily return during month t , and K_t is the number of daily returns that exceed the extremal threshold u_t that month.⁴ The standard extreme value approach constructs the Hill measure using only those observations that exceed the tail threshold (observations such that $R_{i,t}/u_t > 1$, referred to as “ u -exceedences”) while non-exceedences are discarded. To understand why this is a sensible estimate of the exponent, first note that non-exceedences are part of the non-tail domain, thus are *not* assumed to obey a power law and are appropriately omitted from tail estimates.

By the properties of a power law variable, a more positive value of the power law exponent $-\zeta_t$ is associated with higher tail risk. Kelly (2011,2012) shows that $-\zeta_t^{Hill}$ is an asymptotically consistent estimator of the tail risk process in his model up to a scalar multiple. Since scaling is irrelevant for the purpose of the asset pricing tests that we conduct, our analyses use the following standardized measure that is increasing in tail risk:

$$Tail_t = -\frac{\left(\hat{\zeta}_t^{Hill} - \hat{E}\left[\hat{\zeta}_t^{Hill}\right]\right)}{\hat{\sigma}\left(\hat{\zeta}_t^{Hill}\right)}.$$

$Tail_t$ is the tail risk factor that we employ in our empirical analysis.

²Kelly (2011) specifies ζ_t to be an autoregressive process updated by recent extreme return observations and develops the properties of maximum likelihood estimation under this assumption. For purposes of the asset pricing tests presented in this paper, we use a simpler and more transparent estimation approach that produces the same qualitative results as the more complicated estimator.

³For simplicity, the Hill formula is written as though the cross-sectional u -exceedences are the first K_t elements of R_t . This is without loss of generality since the elements of R_t are exchangeable from the perspective of the estimator.

⁴ R may denote either an arithmetic or log return. At the daily frequency, this distinction is minor since extreme returns typically remain of small enough magnitude that the approximation $\ln(1+x) \approx x$ is highly accurate.

2.3 Hedge Fund Sample

We obtain data on hedge fund returns and characteristics from the Lipper/TASS database for the period 1994–2009. The sample includes both “live” funds that are in operation and “graveyard” funds that no longer report to TASS for reasons such as liquidation, fund merger, closure to new investments, or other reasons. To mitigate the impact of survivorship bias, we follow the literature and include graveyard funds that are available in the post-1994 period.

We use the following standard filters for our sample selection. First, we require that the funds report their net-of-fee returns at a monthly frequency. Second, we filter out funds denoted in a currency other than US dollars. To mitigate the effects of backfill bias, we exclude the first 18 months of returns for each fund. Finally, we exclude all funds-of-funds from our sample. This process leaves us with a final sample of 6,252 distinct hedge funds.

TASS classifies hedge funds into ten style categories: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long-short equity, managed futures, and multi-strategy. In terms of the number of funds, long-short equity is the largest strategy category, consisting of 2,342 distinct hedge funds, whereas dedicated short bias is the smallest strategy category, including only 45 distinct hedge funds. In our initial analysis, we group all hedge funds based on their exposures to the tail risk factor. Later, we repeat the analysis for hedge funds within each investment style category.

Panel A of Table I shows the summary statistics of monthly returns in excess of the one month Treasury bill rate for a single, equally-weighted aggregate portfolio of all individual hedge funds. We also report summary statistics for portfolios of funds formed on the basis of investment style. The equal-weight portfolio of all individual hedge funds yields an average monthly excess return of 0.63% over the sample period, with a standard deviation of 1.83%.

Among the ten style categories, an equal-weight portfolio of long-short equity funds yields the highest average excess return, 0.84% per month, while an equal-weight portfolio of dedicated short bias hedge funds realizes the lowest performance with an average monthly excess return of -0.05%. In terms of volatility, a portfolio of equity market neutral hedge funds has a standard deviation of only 0.89%, presumably due a strategy of neutralizing exposure to equity market fluctuations. In contrast, emerging market-oriented hedge funds and dedicated short bias funds have monthly return standard deviations of 4.34% and 5.15% respectively.

3 Did Funds That Underperformed in 1998 Also Perform Worse in 2007–2008?

The 1994–2009 period witnesses two market-wide tail events: one in 1998 that was triggered by the Russian debt default and notoriously brought about the downfall of star hedge fund Long-Term Capital Management, and the recent financial crisis during which hedge funds incurred unprecedented losses over a short period of time due to the “quant meltdown” in 2007 and the fall of subprime mortgage derivative markets. Figure 1 plots the monthly return in percent for the Hedge Fund Research (HFR) Fund Weighted Composite Index, which indicates these two crashes in hedge fund performance – centered around August 1998 and 2008.

We exploit this unique opportunity and directly investigate whether hedge funds possess persistent exposure to extreme events. Fahlenbrach, Prilmeier and Stulz (forthcoming) argue that these two episodes share close similarities. At the time each was taking place, they were each considered the worst financial crisis in fifty years. In both cases, investors experienced massive losses in securities that were designed to be nearly risk free. These

losses induced fire sales and liquidity spirals in other asset classes.

Our research question posits the existence of a crisis factor and examines how hedge fund returns respond to this factor over time. As a preliminary evaluation of this hypothesis, we adopt an approach used by Fahlenbrach, Prilmeier and Stulz (forthcoming) to evaluate how accurately a fund's performance in 1998 foreshadowed its performance during the arguably similar crisis of 2007–2008. If there is a strong positive correlation in crisis performance at the fund level, this is indicative of persistent, systematic exposure of hedge funds to tail events, and potentially consistent with our broader hypothesis that conditional tail risk helps explain hedge fund returns.

Our test uses 603 hedge funds that survived the 1998 crisis and stayed in operation at the end of June 2007. Admittedly, this test design introduces the potential for survivorship bias. However, in this case, it is unclear that this sample construction would unduly favor identification of time series correlation in funds' crisis returns.⁵ With this caveat in mind, we perform cross-sectional regressions of the cumulative return to individual funds from July 2007 to December 2008 on their performance in the 1998 crisis. We measure a fund's performance in the 1998 crisis using two metrics: the cumulative return to the fund from August 1998 to December 1998 and the worst month return to the fund in the period from August to December 1998.

Because our main analysis of the hedge fund tail risk hypothesis in Section 3 will rely on factor regression models for describing fund return behavior, it is useful to discuss the current correlation between funds' crises outcomes in a similar frame. In this section, rather than forming a tail factor, we select two particular tail shock realizations. In effect, this test defines the crisis factor to be an indicator variable taking the value of one during the 1998 and 2007–2008 crises and zero otherwise. Thus, a hedge fund's return during the

⁵We refer interested readers Fahlenbrach, Prilmeier and Stulz (forthcoming) for elaboration on this point.

1998 crisis is effectively an estimate of the fund's loading on the tail factor. We then test whether this estimated loading explains the fund's return during the 2008 crisis. One may think of this as a factor model case study of two particular factor realizations.

We present the test results in Table II, which unequivocally support the tail risk factor hypothesis. Specifically, Column 1 indicates that a 1% decline in fund return during the 1998 crisis (from August to December 1998) predicts a 0.56% drop in fund return in the 2008 crisis. In the cross-section of hedge funds, a one standard deviation lower return during the 1998 crisis associates with a 10% (0.560×0.187) lower return in the recent financial crisis. This effect is highly statistically significant. In Column 2, we include the fund performance in 2006 as a control variable. We find that a fund's performance in 2006 is negatively associated with its performance in the recent crisis. This mean-reversion in hedge fund returns could be driven by better performing funds in 2006 increasing their risk exposures or leverage and subsequently being more exposed to the crisis shock. But the inclusion of a fund's performance in 2006 leaves the persistence in underperformance of hedge funds across the two crises intact. The slope coefficient declines only slightly from 0.560 to 0.506 and the t -statistic remains above 4.0.

In Column 3, we include several additional fund characteristics that previous literature shows might relate to hedge fund performance. In particular, we include fund size measured as the natural log of total assets under management in millions of dollars, fund age measured as the number of years since fund inception, fund return volatility during 2006, percentage fund flow in 2006, personal capital, incentive fee, management fee, redemption notice period, lock-up period, a high water mark dummy variable, and a leverage dummy variable. These fund characteristics are measured at the end of 2006 and their inclusion reduces the sample size to 469 distinct hedge funds. Controlling for fund characteristics and fund return in 2006 to some extent attenuates the effect. The main message from

Column 3, however, is that the forecasting power of a fund's performance in the 1998 crisis for its performance in the recent crisis remains economically large with a slope coefficient of 0.367 that is statistically significant at the 1% level. In Columns 4 to 6, we use a fund's worst month performance in the 1998 crisis as the independent variable and uncover a similar relation between this variable and the fund's performance in the recent crisis.

In summary, we find that hedge funds who suffered poor returns during the 1998 crisis experienced predictably worse performance in the recent crisis as well. This evidence is consistent with the view that the choice of a hedge fund manager to pursue trading strategies that are vulnerable to extreme events is a persistent attribute of the fund's business model. The same managers that were most exposed to the tail shock in 1998 were again the most exposed to the 2007–2008 tail shock.

4 Tail Risk and Hedge Fund Returns

The preceding analysis is suggestive of an economy-wide tail risk factor that drives hedge fund performance. In this section, we examine in detail whether a recently developed tail risk factor (Kelly (2012)) helps to explain time-series and cross-sectional variation in hedge fund returns.

Before presenting results from the asset pricing tests, we provide additional details about the behavior of our tail risk factor. Panel B of Table I shows the correlation between our tail risk measure and various options-based measures of tail risk over the period 1996–2010. In particular, we compare our tail factor with the price of an option portfolio designed to pay off when the S&P 500 index experiences an extreme tail event. This portfolio, called the tail put spread, combines a long position in a deep out-of-the-money (delta = -20) S&P 500 put with an offsetting short position in a closer-to-the-money (delta = -25)

put.⁶ The put spread is constructed to be both delta and vega neutral.⁷ Since a put becomes relatively more sensitive to tail risk the deeper it is out-of-the money, the put spread portfolio should be more valuable at times when tail risk is high, all else equal. Furthermore, by subtracting the price of closer-to-the-money option, this portfolio adjusts for common price effects in options that are less sensitive to tail risks. Our return-based tail measure has a correlation of 58% with the cost of this put spread strategy, suggesting that our tail factor is closely associated with tail risks perceived by investors in equity index options.⁸ Similarly, tail risk has a correlation of 43% with an unhedged version of this strategy. We then calculate the tail put spread for the one hundred largest constituents of the S&P 500 each day (again delta and vega neutralized), and find that the average put spread for individual stocks has a 41% correlation with my measure of tail risk. It has a -10% correlation with risk-neutral skewness (Bakshi, Kapadia and Madan (2003)), suggesting that the risk-neutral distribution of the index is more left-skewed when tail risk is high. It is less correlated, only 5%, with the variance risk premium,⁹ though this is perhaps unsurprising given that many factors, such as a fluctuating price of variance risk, are likely to impact variation in this series more directly than tail risk. The tail put spread, which focuses on the most extreme portions of the risk neutral distribution, is more closely aligned with the description of tail risk that I pursue in this paper than are implied

⁶We use options with one year to maturity to capture tail risks facing investors over the medium-term. Results are nearly identical using shorter maturities.

⁷An options delta (vega) is the sensitivity of the option price to small changes in the price (volatility) of the underlying. Neutral portfolios set these derivatives to zero by construction. Since the value of an option position can be influenced by fluctuations in delta and vega, neutrality is an attractive feature when comparing option prices over time. I use Black-Scholes delta and vega when constructing put spread portfolios. Table 1 also reports “unhedged” put spreads, which combine a simple long out-of-money and short near-the-money position without imposing neutrality.

⁸We also consider a second put spread portfolio that again goes long a 20 delta put and short an at-the-money (delta = 45) put. Correlation of my series with this options-based tail measure is also over 50%.

⁹The variance risk premium is the difference between the squared VIX and S&P 500 realized variance, see Bollerslev, Tauchen and Zhou (2009). Data is from Hao Zhou's website.

skewness and volatility measures. This is analogous to the distinction between extreme value estimators and, say, volatility, skewness or kurtosis, when attempting to describe the physical tail distribution.

Panel C of Table 1 reports correlations between tail risk and macroeconomic variables. This table shows further evidence of moderate countercyclicality in tail risk, as it shares a monthly correlation of 44%, -8% and -11% with unemployment, inflation, and the Chicago Fed National Activity Index (CFNAI). Tail risk appears fairly closely associated with credit risk, having correlations of 39% and 15% with the term spread (the difference between yields on long and short term government bonds) and the default spread (the difference in yields on BAA and AAA corporate bonds). It is weakly correlated with stock market volatility (7%).¹⁰

4.1 Hedge Fund Tail Risk Exposure

We start with a time-series analysis that examines the exposures of hedge funds to the tail risk factor. We compute returns on an equally-weighted portfolio of all hedge funds, as well as equal-weight portfolios within each style category. We then examine the sensitivities of fund portfolio returns to the tail risk factor, after controlling for their loadings on the Fung and Hsieh seven factors. In another specification, we assess the relevance of the tail risk factor after including three high-moment risk proxies extracted from S&P 500 Index options: the change in the CBOE volatility index (ΔVIX), change in risk-neutral skewness ($\Delta RNSKEW$), and change in risk-neutral kurtosis ($\Delta RNKURT$). Risk neutral skewness and kurtosis are calculated according to Bakshi, Kapadia and Madan (2003). To facilitate interpretation, we standardize the tail factor and high-moment risk proxies to have means of zero and standard deviations of one. The sample period is from January

¹⁰Tail risk correlations reported in Table I are from Kelly (2012).

1994 to December 2009. For the regressions using the option data, the sample period is from February 1996 to December 2009.

Table III presents the results. For the aggregate hedge fund portfolio, a one-standard deviation increase in tail risk is associated with a decline in hedge fund returns of 0.24% per month, or 2.88% per year. The effect is statistically significant. When we further include changes in VIX and risk-neutral skewness and kurtosis, we find that they are insignificantly related to hedge fund returns. However, the association between innovations in the tail risk factor and hedge fund returns remains economically strong and statistically significant.

We next analyze investment style portfolios, and find that the average exposure of hedge funds to tail risk is statistically significant across most fund styles, including convertible arbitrage, emerging markets, equity market neutral, event driven, long-short equity, and multi-strategy. In terms of magnitudes, returns to hedge funds that invest in emerging markets and those that pursue long-short equity strategy are particularly sensitive to tail risk shocks. For example, a one-standard deviation increase in tail risk is associated with a drop in returns of 0.60% per month for hedge funds investing in emerging markets; and for hedge funds that engage in long-short equity investing, the corresponding number is 0.41% per month. For both of these style categories, changes in VIX, risk-neutral skewness and kurtosis are insignificantly related to hedge fund returns.

4.2 Tail Risk in the Cross Section of Hedge Fund Returns

The evidence that returns to a typical hedge fund are sensitive to tail risk after controlling for its exposures to commonly used hedge fund factors suggests that tail risk may be an important determinant of average return differences across hedge funds. In this subsection, we provide evidence that strongly supports this conjecture.

We construct hedge fund portfolios sorted on the basis of their exposures to tail risk.

Specifically, at the end of each month we run a time-series regression of individual fund excess returns on the market return and tail risk factor using the most recent two years of data (we require at least 18 months of data in the estimation window). We then sort funds into five quintile portfolios based on their tail risk factor betas. We track the performance of the quintile portfolios over various holding periods ranging from 1 month to 12 months, following the scheme of Jegadeesh and Titman (1993). For holding periods beyond one month, our tests use Newey and West (1987) standard error adjustments for serial correlation.

Table IV shows the performance of hedge fund tail beta quintile portfolios as well as a long-short portfolio that is long quintile five and short quintile one. Our results show substantial dispersion in hedge fund returns captured by their loadings on the tail risk factor.

Hedge funds in quintile one have negative tail betas. When tail risk is high, the returns of these funds tends to be negative; thus the funds in quintile 1 are especially susceptible to tail risk shocks. These funds may be interpreted as providers of crash insurance. This portfolio earns an average post-formation monthly return of 0.85%, representing large compensation for tail risk exposure. On the other hand, funds in quintile five have high, positive tail betas, and are thus effective tail risk hedges. These funds may be thought of as purchasers of crash insurance, and realize an average return of 0.36% in the post-formation month. The return spread between the two groups of funds is -0.49% per month with a t -statistic of -2.63. After adjusting for funds' differential exposures to the Fung and Hsieh seven factors, the tail risk spread (quintile five minus quintile one) widens slightly to -0.53% per month, with a t -statistic of -2.69.

The difference in performance between tail risk insurers and hedgers persists when we extend the holding period of tail beta quintile portfolios. For example, with a 6-month

holding horizon, the average return spread between hedge funds with positive exposures to tail risk and those with negative exposures to tail risk is -0.40% per month, with a t -statistic of -3.00. With a 12-month holding period, the average return difference remains as large as -0.33% per month, with a t -statistic of -2.50. As in the one-month holding period case, adjusting for the Fung and Hsieh seven factors renders the difference in performance even larger both in magnitudes and statistical significance.

If the exposures of individual hedge funds to tail risk arise primarily from features of the trading strategies pursued by their managers, we would expect a certain degree of persistence of the exposures. Table V presents evidence that is strongly consistent with this conjecture. On average, 87.26% of hedge funds in tail risk quintile 1 each month remain in quintile 1 the subsequent month, and 88.09% of funds in quintile 5 remain there the subsequent month.

4.3 Robustness Tests

In this section, we perform several robustness tests. We use alternative models for hedge fund performance evaluation, examine the influence of tail risk on hedge fund performance after taking into account liquidity risk and correlation risk, and examine the influence of tail risk on cross-sectional dispersion in hedge fund returns conditional upon their fund style.

4.3.1 Alternative Performance Evaluation Models

Our first robustness check explores alternative hedge fund performance evaluation models. In Table VI, we estimate alphas for tail beta quintile portfolios after extending the Fama-French and Fung-Hsieh models to include a richer set of risk factors. First, we consider the Carhart (1997) four factor model, which augments the Fama and French (1993) factors (the

market, size, and value factors) with the Jegadeesh and Titman (1993) momentum factor. This model is motivated by the observation that equity-oriented hedge funds dominate our sample, and momentum is one of the most common strategies pursued by equity funds. Next, we consider a five factor extension of the Carhart model that further includes the Pastor and Stambaugh (2003) traded liquidity risk factor. The third performance evaluation model in Table VI comes specifically from the hedge fund literature. It augments the Fung and Hsieh seven factors with two additional option return factors, namely the return on OTM put options on the S&P 500 Index and the return spread between OTM and ATM put options on the S&P 500 Index, following Agarwal and Naik (2004).

Table VI shows that the return spread between hedge funds with negative and positive exposures to tail risk remains economically large and statistically significant after adjusting for their loadings on the extended factor models. Controlling for momentum, liquidity, and options strategy returns has little effect on our findings. Alphas on a strategy that is long tail risk beta quintile 5 and short quintile 1 range from -0.33% to -0.53% per month, with t -statistics above 2.5 in absolute value in all cases.

Sadka (2010) emphasizes the contribution of liquidity risk to hedge fund performance. We provide a second robustness test with respect to liquidity in Table VII. In particular, we examine whether the time-series association between tail risk and hedge fund returns is influenced by liquidity risk. We also consider the influence of correlation risk on our results, motivated by the finding of Buraschi, Kosowski, and Trojani (2011) that correlation risk is important for hedge fund returns. Table VII reports that our tail risk factor remains an important contributor to hedge fund returns after controlling for liquidity risk proxied either by the Pastor and Stambaugh factor (column 1) or the Sadka permanent liquidity factor (column 2). Correlation risk appears to have little influence on fund return behavior after controlling for our tail factor (column 3).

Our findings are also robust to other traditional measures of performance evaluation such as Sharpe ratios. Hedge funds that behave as sellers of tail risk insurance (quintile 1) earn an average smoothing-adjusted monthly Sharpe ratio¹¹ of 0.22, twice as large as the 0.10 Sharpe ratio for their peers who hedge tail risk (quintile 5). Similarly, the appraisal ratio for low tail risk beta funds (the average Fung and Hsieh seven-factor monthly alpha divided by its standard deviation) is 0.40, which is three times as large as that for high tail risk beta funds (0.13).

4.3.2 Tail Risk and Fund Returns Conditional on Style

In Table VIII, we examine the influence of tail risk on the cross-sectional dispersion of hedge fund returns within each investment style category. One caveat is that certain strategy styles contain a relatively small number of hedge funds, in which case we may lack power to detect evidence of a significant influence of tail risk on hedge fund returns. For example, monthly quintile portfolios of funds in convertible arbitrage, dedicated short bias, equity market neutral, fixed income arbitrage, and global macro strategies contain below twenty funds on average. With this caveat in mind, we find broad support that tail risk exposure is an important determinant of fund performance even within styles. Within strategies such as emerging market, event driven, long-short equity, and multi-strategy, the tail risk factor captures particularly strong cross-sectional variation in returns across funds.

4.4 Fund Characteristics and Tail Risk

Why are some funds more susceptible to tail risk than others? To answer this question we examine the relationship between funds' tail risk betas and the characteristics of each

¹¹See Getmansky, Lo and Makarov (2004).

fund as reported in the TASS/Lipper database. In particular, Table IX reports Fama-MacBeth (1973) cross-sectional regression coefficients of monthly estimated tail risk betas on contemporaneous fund characteristics over the period December 1995 to November 2009. For ease of interpretation, we cross-sectionally standardize tail risk beta, size, age, fund return, return volatility and fund flow to have means of zero and standard deviations of one. Payout period, redemption notice period, and lock-up period are transformed using the natural log of one plus the number of days. Test statistics are based on Newey-West (1987) autocorrelation-consistent standard errors with a maximum lag of 24 months

We divide available fund characteristics into six groups: size/age, recent performance (returns and net fund flows over the previous 24 months and fund return volatility), incentive contracts (percentage management fee on assets under management, incentive fee as percentage of fund profits, and an indicator for whether the fund has a high water mark provision), minimum investment horizons¹² (length of lock-up, redemption notice and payout periods), manager “skin in the game” (indicators for whether the manager has personal capital invested in the fund or is an owner of the management company), and an indicator for whether a fund employs leverage. Columns 1 through 5 of Table IX consider various subsets of characteristics, while column 6 reports results controlling for all characteristics simultaneously.

Recall that funds with negative tail risk betas are those that are most susceptible to tail risk. When crash risk rises, these funds experience negative returns. Our estimates suggest that the funds whose investment strategies are most susceptible to tail risk are those funds that are younger and more volatile, have a “high water mark” provision, have longer minimum investment horizons, do not employ leverage, and those in which managers do

¹²Lock-up period is the length of the window over which newly purchased share of a fund cannot be sold or redeemed. Redemption notice period is the length of advanced notice that funds require from investors wishing to redeem their shares. Payout period is the time before investors receive cash back once sell orders are processed.

not risk their own capital. These characteristics explain as much as 11% of the variation in tail risk betas across funds, and are robust to alternative configurations of control variables.

Our results relating fund characteristics with tail risk exposure have intuitive interpretations. Funds have an incentive to establish a track record of high returns early in their life cycle in order to attract fund flows. One way for young funds to establish a track record of “alpha” relative to standard benchmarks is to take on tail-risky investments which carry high risk compensation, leading to the positive coefficient that we find. Funds that are below their high water mark may similarly reach for alpha by loading up on tail risky investments, producing the negative coefficient that we find on the high water mark dummy. When funds subject their investors to long lock-ups and redemption periods they have more flexibility to take on riskier, less liquid positions. Leverage may serve as a disciplining device, since a tail shock within a leverage fund can quickly wipe out all of the fund’s capital. Rather than jeopardizing a fund’s ongoing viability, levered funds may invest less in or even hedge against tail risk, leading to the large positive coefficient that we estimate. Finally, when managers do not invest their own capital in the fund, the standard principal-agent problem becomes exacerbated, and the manager may be more willing to take on extremal risk in order to earn incentive fees and attract more fund inflows, since they can do this without risking their own wealth.

5 Conclusion

We have shown that hedge funds exhibit persistent exposures to extreme downside risk. For instance, the very same hedge funds that underperformed in the 1998 crisis suffered predictably lower returns during the 2007–2008 crisis. Using an *ex ante* measure of conditional tail risk derived by Kelly (2012), we find that tail risk is an important determinant of the time-series and cross-section variation of hedge fund returns. A positive one standard

deviation shock to tail risk is associated with a contemporaneous decline of 2.88% per year in the aggregate hedge fund portfolio return. In the cross-section, hedge funds that covary negatively with tail risk earn average annual returns more than 6% higher than funds with positive tail risk covariation, controlling for commonly used hedge fund factors. These results are consistent with the notion that a significant component of hedge fund returns can be viewed as compensation for providing insurance against tail risk.

References

- [1] Adrian, T., 2007. Measuring Risk in the Hedge Fund Sector, *Current Issues in Economics and Finance by the Federal Reserve Bank of New York* 13(3), 1–7.
- [2] Adrian T., M. K. Brunnermeier, and H.L. Nguyen, 2011. Hedge Fund Tail Risk, Working Paper, Princeton University.
- [3] Agarwal, V., G. S. Bakshi, and J. Huij, 2010. Do higher-moment equity risks explain hedge fund returns?, Working Paper.
- [4] Agarwal, V. and N. Naik, 2004. Risks and Portfolio Decisions Involving Hedge Funds, *Review of Financial Studies* 17, 63–98.
- [5] Allen, L., T. Bali, and Y. Tang, 2010. Does Systemic Risk in the Financial Sector Predict Future Economic Downturns?, Working Paper.
- [6] Asness, Clifford, Robert Krail, and John Liew, 2001. Do hedge funds hedge, *Journal of Portfolio Management* 28, 6–19.
- [7] Bali, T.G., Brown, S.J., Caglayan, M. O., 2011. Do hedge funds' exposures to risk factors predict their future returns? *Journal of Financial Economics* 101, 36–68.

- [8] Bali, T.G., Brown, S.J., Caglayan, M. O., 2011. Systematic Risk and the Cross-section of Hedge Fund Returns, Working Paper.
- [9] Bakshi, G., N. Kapadia, and D. Madan, 2003. Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options, *Review of Financial Studies* 16, 101–143.
- [10] Barro, R. 2006, Rare disasters and asset markets in the twentieth century. *Quarterly Journal of Economics*, 121(3): 823–866.
- [11] Bollerslev, T. , G. Tauchen, and H. Zhou, 2009. Expected Stock Returns and Variance Risk Premia, *Review of Financial Studies* 22, 4463–4492.
- [12] Boyson, N. M., C. W. Stahel, and R. M. Stulz, 2008. Is there Hedge Fund Contagion, *Journal of Finance* 65, 1789–1816.
- [13] Buraschi, A., R. Kosowski, and F. Trojani, 2010, When There Is No Place to Hide: Correlation Risk and the Cross-Section of Hedge Fund Returns, Imperial College London Working Paper.
- [14] Carhart, M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance* 52, 57–82.
- [15] Chan, N., M. Getmansky, S. Haas, and A. W. Lo, 2006. Systemic Risk and Hedge Funds,.in *The Risks of Financial Institutions and the Financial Sector*, ed. by M. Carey, and R. M. Stulz. The University of Chicago Press: Chicago, IL.
- [16] Drechsler, I. and Yaron, A., 2011. What’s vol got to do with it, *Review of Financial Studies* 24.

- [17] Dudley, E., and M. Nimalendran, 2011. Margins and hedge fund contagion, *Journal of Financial and Quantitative Analysis* 46, 1227–1257.
- [18] Duffie, D., 2007. Innovations in Credit Risk Transfer: Implications for Financial Stability, Stanford University Working Paper.
- [19] Fahlenbrach, R., R. Prilmeier, and R.M. Stulz, forthcoming. This Time is the Same: Using Bank Performance in 1998 to Explain Bank Performance During the Recent Financial Crisis, *Journal of Finance*.
- [20] Fama, E., and K. French, 1993, Common Risk Factors in the Returns on Bonds and Stocks, *Journal of Financial Economics* 33, 3–53.
- [21] Fung, W. and D. Hsieh, 1997, Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds, *Review of Financial Studies* 10, 275–302.
- [22] Fung, W. and D. Hsieh, 2001, The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers, *Review of Financial Studies* 14, 313–341.
- [23] Fung, W. and D. Hsieh, 2004, Hedge Fund Benchmarks: A Risk Based Approach, *Financial Analysts Journal* 60, 65–80.
- [24] Fung, W., D. Hsieh, N. Naik, and T. Ramadorai, 2008. Hedge Funds: Performance, Risk, and Capital Formation, *Journal of Finance* 63, 1777–1803.
- [25] Gabaix, X. Forthcoming, Variable rare disasters: An exactly solved framework for ten puzzles in macro-nance. *Quarterly Journal of Economics*.
- [26] Getmansky, M., A. Lo and I. Makarov. 2004. An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics* 74, 529–609.

- [27] Hellwig, M. 2009. Systemic risk in the financial sector: an analysis of the subprime-mortgage financial crisis. *De Economist* 157, 129–207.
- [28] Hill, B. 1975. A simple general approach to inference about the tail of a distribution. *The Annals of Statistics* 3, 1163–1174.
- [29] Khandani, A.E., and A. W. Lo, 2007. What Happened to the Quants in August 2007?, *Journal of Investment Management* 5, 5–54.
- [30] Kelly, B., 2011. The Dynamic Power Law Model. University of Chicago Working Paper.
- [31] Kelly, B., 2012. Tail risk and asset prices. University of Chicago Working Paper.
- [32] Luo, Y., Wang, S. Cahan, R., Alvarez, M., Jussa, J., and Chen, Z. 2012. New insights in country rotation, *Deutsche Bank Quantitative Strategy*.
- [33] Pastor, L., and R. Stambaugh, 2003. Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642–685.
- [34] Patton, A.J., 2009. Are “market neutral” hedge funds really market neutral?, *Review of Financial Studies* 22, 2495–2530.
- [35] Rietz, T. 1988. The equity risk premium: A solution. *Journal of Monetary Economics* 22, 117–131.
- [36] Sadka, R., 2010. Liquidity risk and the cross-section of hedge fund returns. *Journal of Financial Economics* 98, 54–71.
- [37] Stulz, R., 2007. Hedge Funds: Past, Present and Future. *Journal of Economic Perspectives* 21, 175–194.
- [38] Wachter, J. 2011, Can time-varying risk of rare disasters explain aggregate stock market volatility? Wharton Working Paper.

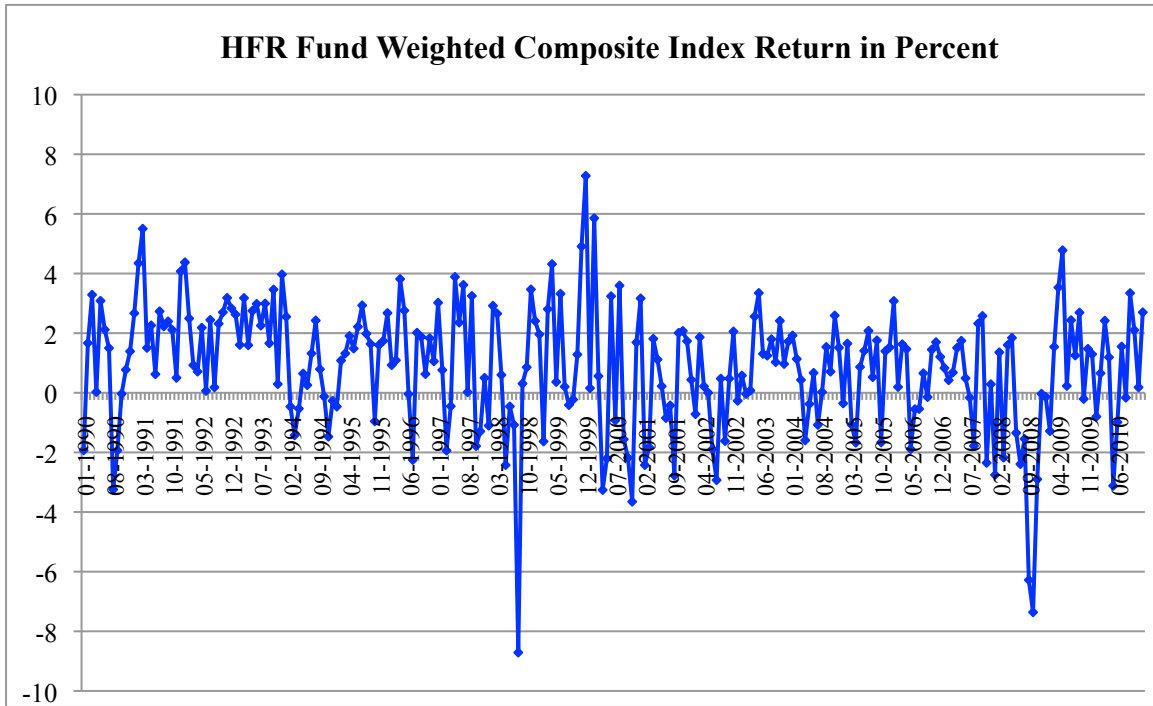


Figure 1 Hedge Fund Research (HFR) Fund Weighted Composite Index Return. This figure plots the time-series of the hedge fund research (HFR) fund weighted composite index return in per cent. It shows two large drops in hedge fund returns that occurred in 1998 and 2008.

Table I**Descriptive Statistics**

This table presents the descriptive statistics for hedge fund returns and risk factors used in our sample. Panel A shows the summary statistics of monthly excess returns on the equal-weighted portfolios of hedge funds in each style category and all hedge funds in our sample. Returns are in percent per month in excess of the one-month T-bill rate. N is the number of distinct hedge funds in each category. The sample period is from January 1994 to December 2009. The correlation matrix for the tail risk factor and S&P 500 option-based tail risk measures over 1996-2009 (Panel B) and macroeconomic variables over 1963-2009 (Panel C).

Panel A: Summary Statistics of Monthly Excess Hedge Fund Returns (%)

	N	Mean	Std Dev	Minimum	10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl	Maximum
Convertible Arbitrage	215	0.40	2.12	-16.02	-1.28	-0.26	0.62	1.24	1.83	7.46
Dedicated Short Bias	45	-0.05	5.15	-11.53	-6.02	-3.06	-0.63	2.84	6.60	22.96
Emerging Markets	701	0.81	4.34	-21.84	-4.36	-2.04	1.51	3.46	5.46	13.66
Equity Market Neutral	404	0.48	0.89	-3.24	-0.45	0.07	0.48	0.94	1.53	3.05
Event Driven	619	0.58	1.59	-7.86	-1.23	-0.18	0.86	1.50	2.26	4.13
Fixed Income Arbitrage	247	0.39	1.23	-7.59	-0.63	0.01	0.49	1.00	1.63	3.30
Global Macro	470	0.50	1.78	-4.20	-1.49	-0.66	0.46	1.29	2.82	7.10
Long/Short Equity	2342	0.84	2.77	-9.24	-2.40	-0.86	0.87	2.32	4.02	10.47
Managed Futures	670	0.49	2.90	-5.46	-3.07	-1.59	0.36	2.32	4.33	9.80
Multi-Strategy	539	0.53	1.42	-5.60	-1.28	-0.34	0.70	1.50	1.99	3.79
All Hedge Funds	6252	0.63	1.83	-5.83	-1.66	-0.53	0.68	1.67	2.71	6.22

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Panel B: Options-Based Tail Variables									
Tail	(1)	1.00							
S&P 500 Tail Put Spread	(2)	0.58	1.00						
S&P 500 Spread (Unhedged)	(3)	0.44	0.76	1.00					
Indiv. Tail Put Spread	(4)	0.39	0.50	0.53	1.00				
R.N. Skew	(5)	-0.10	0.02	0.47	-0.13	1.00			
Var. Risk Prem.	(6)	0.05	-0.04	-0.45	-0.09	-0.47	1.00		
Panel C: Macro Variables									
Tail	(1)	1.00							
Dividend-Price Ratio	(2)	0.04	1.00						
Unemployment	(3)	0.44	0.43	1.00					
Inflation	(4)	-0.08	0.35	0.01	1.00				
CFNAI	(5)	-0.11	-0.06	-0.19	0.05	1.00			
Market Volatility	(6)	0.07	-0.17	0.16	-0.07	-0.39	1.00		
Term Spread	(7)	0.39	-0.13	0.50	-0.31	0.02	0.12	1.00	
Default Spread	(8)	0.15	0.40	0.72	0.06	-0.45	0.43	0.25	1.00

Table II**Did Hedge Funds with Lower Performance in the 1998 Crisis Perform Worse in the Recent Crisis as well?**

This table analyzes the performance in the 2007-2008 financial crisis for 603 hedge funds that survived the 1998 crisis. To address whether funds with low performance in the 1998 crisis performed poorly as well in the 2007-2008 financial crisis, we run regressions using the cumulative hedge fund return from August 1998 to December 1998 or the worst month return in this period to predict the funds' cumulative return from July 2007 to December 2008. We control for the funds' return in 2006 and a battery of fund characteristics including Size (in million dollars), Age (years since their inception), Return Volatility and Fund Flow in 2006, Personal Capital, Incentive Fee, Management Fee, Redemption Notice Period, Lockup Period, High Water Mark, and a Leverage indicator. These fund characteristics are measured at the end of 2006 and their inclusion leaves us with 469 hedge funds. The *t*-statistics are based on heteroskedasticity-consistent standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
Ret1998	0.560 (5.42)	0.506 (4.83)	0.367 (3.23)			
Worst Month Return 1998				0.586 (5.07)	0.453 (3.66)	0.474 (3.31)
Ret2006		-0.251 (-2.60)	-0.332 (-2.17)		-0.278 (-2.25)	-0.359 (-2.33)
Size			-0.0206 (-2.18)			-0.0239 (-2.52)
Age			0.00833 (2.16)			0.00852 (2.17)
Return Volatility			0.810 (0.72)			1.446 (1.17)
Flow			-0.00436 (-0.78)			-0.00548 (-1.02)
Personal Capital			-0.00374 (-0.13)			-0.000424 (-0.01)
Incentive Fee			0.0107 (2.38)			0.0114 (2.55)
Management Fee			0.0435 (1.49)			0.0440 (1.53)
Redemption Notice Period			-0.00101 (-1.81)			-0.00141 (-2.52)
Lockup Period			-0.00259 (-1.24)			-0.00266 (-1.28)
High Water Mark			0.0397 (1.16)			0.0443 (1.24)
Leverage			0.0519 (1.97)			0.0655 (2.52)
Constant	-0.0908 (-6.83)	-0.0578 (-3.10)	-0.0671 (-0.36)	-0.0271 (-1.51)	-0.00386 (-0.18)	0.0154 (0.08)
Observations	603	603	469	603	603	469
Adj. R-squared	0.0881	0.110	0.192	0.0309	0.0568	0.180

Table III

Exposure of Hedge Funds to Tail Risk Factor

This table presents the results of time-series regressions of hedge fund portfolio returns on the Fung and Hsieh seven factors and the tail risk factor. We group hedge funds into 10 portfolios based on their investment styles and compute their monthly returns in excess of the one-month Treasury-bill rate. In another specification, we include three high-moment risk proxies extracted from S&P 500 Index options: change in the CBOE volatility index (ΔVIX), change in skewness ($\Delta RNSKEW$), and change in the kurtosis ($\Delta RNSKURT$). The tail factor and high-moment risk proxies are standardized to have a mean of zero and standard deviation of one. Our sample period is from January 1994 to December 2009. For the regressions using the option data, the sample period is from February 1996 to December 2009.

	Intercept	MKTRF	SMB	$\Delta TERM$	$\Delta CREDIT$	PTFSBD	PTFSFX	PTFSCOM	TAIL	ΔVIX	$\Delta RNSKEW$	$\Delta RNSKURT$	Adj-R2
All Hedge Funds	0.0048	0.2780	0.1243	-0.0095	-0.0182	-0.0035	0.0085	0.0160	-0.0024				0.702
	6.36	14.34	5.86	-3.00	-4.16	-0.65	2.01	2.74	-2.74				
	0.0048	0.2862	0.1201	-0.0090	-0.0155	-0.0036	0.0076	0.0156	-0.0027	0.0020	0.0010	-0.0022	0.731
	5.95	11.05	5.50	-2.57	-3.05	-0.59	1.54	2.54	-2.94	1.59	0.75	-1.44	
Convertible Arbitrage	0.0048	0.1307	0.0329	-0.0243	-0.0646	-0.0104	-0.0068	-0.0077	-0.0029				0.631
	6.37	5.23	1.20	-5.97	-11.44	-1.52	-1.25	-1.03	-2.60				
	0.0035	0.1311	0.0228	-0.0216	-0.0587	-0.0107	-0.0083	-0.0083	-0.0031	0.0008	-0.0022	-0.0045	0.661
	3.26	3.86	0.80	-4.70	-8.85	-1.33	-1.28	-1.03	-2.56	0.49	-1.23	-2.21	
Dedicated Short Bias	0.0045	-0.9325	-0.4359	-0.0103	-0.0312	0.0026	0.0041	0.0018	-0.0002				0.844
	2.95	-23.67	-10.11	-1.61	-3.50	0.24	0.47	0.15	-0.10				
	0.0037	-0.9115	-0.4233	-0.0118	-0.0312	-0.0025	0.0014	0.0034	0.0001	0.0004	-0.0009	0.0006	0.852
	2.16	-16.87	-9.29	-1.61	-2.95	-0.19	0.14	0.26	0.04	0.15	-0.31	0.19	
Emerging Markets	0.0050	0.5490	0.2029	-0.0078	-0.0371	-0.0268	-0.0008	0.0092	-0.0060				0.516
	2.21	9.37	3.16	-0.81	-2.80	-1.67	-0.06	0.52	-2.33				
	0.0058	0.4847	0.1689	-0.0083	-0.0295	-0.0368	0.0101	0.0076	-0.0072	0.0008	0.0062	-0.0049	0.596
	2.54	6.64	2.74	-0.84	-2.06	-2.13	0.72	0.44	-2.76	0.22	1.63	-1.11	

	Intercept	MKTRF	SMB	Δ TERM	Δ CREDIT	PTFSBD	PTFSFX	PTFSCOM	TAIL	Δ VIX	Δ RNSKEW	Δ RNSKURT	Adj-R2
Equity Market	0.0044	0.0758	0.0109	-0.0032	-0.0062	-0.0040	0.0016	0.0032	-0.0014				0.197
Neutral	7.34	4.91	0.65	-1.25	-1.77	-0.93	0.46	0.69	-2.10				
	0.0037	0.0855	0.0105	-0.0025	-0.0066	-0.0067	0.0026	0.0040	-0.0011	0.0017	-0.0004	-0.0010	0.227
	6.03	4.32	0.63	-0.95	-1.71	-1.44	0.69	0.84	-1.49	1.78	-0.37	-0.86	
Event Driven	0.0046	0.1959	0.0914	-0.0041	-0.0249	-0.0175	0.0018	-0.0007	-0.0025				0.725
	7.34	12.12	5.17	-1.56	-6.81	-3.95	0.52	-0.15	-3.50				
	0.0042	0.2114	0.0831	-0.0028	-0.0219	-0.0222	0.0037	0.0002	-0.0026	0.0028	-0.0006	-0.0038	0.771
	6.52	10.15	4.73	-1.01	-5.37	-4.53	0.94	0.05	-3.43	2.75	-0.54	-3.01	
Fixed Income	0.0036	0.0275	0.0118	-0.0180	-0.0361	-0.0144	-0.0087	0.0051	-0.0012				0.475
Arbitrage	5.33	1.59	0.62	-6.36	-9.22	-3.03	-2.30	0.97	-1.51				
	0.0034	0.0649	0.0049	-0.0151	-0.0381	-0.0125	-0.0071	0.0076	-0.0004	0.0042	-0.0008	-0.0018	0.543
	5.12	3.03	0.27	-5.18	-9.09	-2.46	-1.73	1.48	-0.50	3.98	-0.75	-1.38	
Global Macro	0.0039	0.1444	0.0575	-0.0194	-0.0166	-0.0132	0.0314	0.0164	-0.0009				0.371
	3.67	5.27	1.92	-4.34	-2.68	-1.75	5.23	1.99	-0.78				
	0.0039	0.1952	0.0561	-0.0195	-0.0149	-0.0054	0.0226	0.0170	-0.0009	0.0047	-0.0017	-0.0036	0.385
	3.65	5.70	1.94	-4.21	-2.23	-0.66	3.44	2.08	-0.74	2.81	-0.93	-1.74	
Long/Short	0.0058	0.4734	0.2479	-0.0041	-0.0045	-0.0023	0.0026	0.0154	-0.0037				0.774
Equity	5.87	18.55	8.87	-0.99	-0.78	-0.32	0.47	2.00	-3.23				
	0.0058	0.4701	0.2392	-0.0033	-0.0025	0.0008	0.0017	0.0164	-0.0041	0.0021	0.0017	-0.0023	0.781
	5.20	13.25	7.99	-0.69	-0.37	0.10	0.25	1.95	-3.24	1.22	0.93	-1.08	
Managed Futures	0.0053	-0.0146	0.0045	-0.0250	-0.0065	0.0293	0.0404	0.0554	0.0019				0.344
	3.00	-0.32	0.09	-3.36	-0.63	2.34	4.04	4.02	0.96				
	0.0052	-0.0047	0.0163	-0.0267	-0.0098	0.0330	0.0419	0.0533	0.0015	0.0007	0.0029	0.0025	0.349
	2.67	-0.07	0.31	-3.14	-0.80	2.24	3.50	3.59	0.65	0.22	0.90	0.66	
Multi-Strategy	0.0042	0.2082	0.0594	-0.0054	-0.0134	-0.0031	0.0009	0.0053	-0.0019				0.612
	6.37	12.16	3.17	-1.95	-3.46	-0.67	0.23	1.02	-2.46				
	0.0047	0.2107	0.0537	-0.0024	-0.0105	-0.0018	0.0009	0.0044	-0.0018	0.0013	-0.0001	-0.0020	0.666
	6.92	9.73	2.94	-0.82	-2.48	-0.36	0.22	0.85	-2.28	1.19	-0.05	-1.54	

Table IV**Tail Risk in the Cross-Section of Hedge Fund Returns**

This table presents the average excess returns and alphas for hedge fund portfolios formed on the basis of their exposures to the tail risk factor. In each month, we form five portfolios based on the funds' loadings on the tail risk factor in a regression of the funds' excess return on the market excess return and the tail factor in the past 24 months. We vary the holding periods of these portfolios for K months, with K ranging from 1 to 12. The Newey-West (1987) *t*-statistics are reported in parentheses.

	Low Tail Beta	2	3	4	High Tail Beta	High - Low
Average Tail Risk Beta	-0.10	-0.03	0.00	0.02	0.09	0.20 (29.34)
<i>Holding Period: One Month</i>						
Average Excess Return	0.85 (3.47)	0.53 (3.47)	0.46 (3.85)	0.39 (2.71)	0.36 (1.55)	-0.49*** (-2.63)
Fung-Hsieh 7-Factor α	0.78 (4.71)	0.46 (5.36)	0.41 (5.97)	0.31 (3.42)	0.25 (1.53)	-0.53*** (-2.69)
<i>Holding Period: Three Months (Overlapping)</i>						
Average Excess Return	0.82 (3.23)	0.53 (3.21)	0.44 (3.18)	0.39 (2.47)	0.39 (1.57)	-0.43*** (-2.72)
Fung-Hsieh 7-Factor α	0.75 (5.07)	0.47 (5.39)	0.39 (5.06)	0.31 (3.60)	0.28 (1.83)	-0.47*** (-2.82)
<i>Holding Period: Six Months (Overlapping)</i>						
Average Excess Return	0.80 (3.17)	0.52 (3.02)	0.44 (3.04)	0.40 (2.38)	0.40 (1.54)	-0.40*** (-3)
Fung-Hsieh 7-Factor α	0.73 (5.36)	0.45 (5.21)	0.39 (4.72)	0.32 (3.57)	0.29 (1.89)	-0.44*** (-3.2)
<i>Holding Period: Nine Months (Overlapping)</i>						
Average Excess Return	0.79 (3.21)	0.51 (2.98)	0.45 (2.95)	0.41 (2.37)	0.40 (1.49)	-0.39*** (-3.15)
Fung-Hsieh 7-Factor α	0.71 (5.44)	0.44 (5.06)	0.39 (4.48)	0.34 (3.53)	0.29 (1.93)	-0.42*** (-3.54)
<i>Holding Period: Twelve Months (Overlapping)</i>						
Average Excess Return	0.75 (3.18)	0.50 (2.99)	0.44 (2.81)	0.42 (2.42)	0.43 (1.65)	-0.33** (-2.5)
Fung-Hsieh 7-Factor α	0.67 (5.22)	0.43 (5.01)	0.38 (4.09)	0.35 (3.58)	0.33 (2.25)	-0.35*** (-3.05)

Table V**Transition Matrix for Fund Portfolios Sorted on Tail Risk Beta**

In this table, we show the transition matrix for hedge fund portfolios sorted on tail risk beta. Specifically, in each month, we form five portfolios based on the funds' loadings on the tail risk factor in a regression of the funds' excess return on the market excess return and the tail factor in the past 24 months. For each quintile, we compute the average fractions of funds that stay in the particular quintile and migrate to other quintiles in the next month. Panel A shows the results for fund portfolios sorted on tail risk beta and Panel B shows the results for fund portfolios sorted on beta with respect to out-of-the-money put option returns.

		Ranking of Tail Risk Beta in Month t				
Quintile (t)		1	2	3	4	5
Quintile (t+1)						
1		86.81%	10.06%	1.45%	0.87%	0.64%
2		10.43	72.00	13.96	2.73	0.89
3		1.39	14.29	69.00	14.01	1.46
4		0.78	2.81	14.12	71.79	10.59
5		0.59	0.84	1.47	10.60	86.42

Table VI

Alternative Performance Evaluation Models

This table presents the average excess returns and alphas for hedge fund portfolios formed on the basis of their exposures to the tail risk factor using two alternative performance evaluation models: a 4-factor model that augments the Fama and French (1993) three factors with a momentum factor; a 5-factor model that further includes the Pastor and Stambaugh (2003) factor; and a 9-factor model that augments the Fung and Hsieh 7 factors with returns to OTM put options on the S&P500 Index and returns to a long-short strategy that buys OTM and shorts ATM put options on the S&P500 Index. In each month, we form five portfolios based on the funds' loadings on the tail risk factor in a regression of the funds' excess return on the market excess return and the tail factor in the past 24 months. We vary the holding periods of these portfolios for K months, with K ranging from 1 to 12. The Newey-West (1987) *t*-statistics are reported in parentheses.

	Low Tail Beta	2	3	4	High Tail Beta	High - Low
Average Tail Risk Beta	-0.10	-0.03	0.00	0.02	0.09	0.20 29.34
<i>Holding Period: One Month</i>						
4-Factor α	0.60 (3.85)	0.36 (3.97)	0.32 (4.72)	0.24 (3.05)	0.17 (1.22)	-0.42*** (-2.61)
5-Factor α	0.55 (3.48)	0.32 (3.56)	0.30 (4.28)	0.22 (2.82)	0.20 (1.36)	-0.35** (-2.14)
9-Factor α	0.82 (4.48)	0.47 (4.35)	0.41 (4.55)	0.29 (2.35)	0.32 (1.56)	-0.50** (-1.98)
<i>Holding Period: Three Months (Overlapping)</i>						
4-Factor α	0.58 (3.95)	0.36 (3.88)	0.30 (3.73)	0.24 (2.88)	0.20 (1.37)	-0.38*** (-2.65)
5-Factor α	0.54 (3.66)	0.33 (3.51)	0.28 (3.31)	0.22 (2.62)	0.22 (1.44)	-0.32** (-2.26)
9-Factor α	0.81 (4.81)	0.48 (4.40)	0.40 (3.91)	0.29 (2.43)	0.34 (1.73)	-0.46** (-2.08)
<i>Holding Period: Six Months (Overlapping)</i>						
4-Factor α	0.57 (3.78)	0.35 (3.62)	0.31 (3.59)	0.25 (2.85)	0.21 (1.44)	-0.36*** (-2.91)
5-Factor α	0.53 (3.62)	0.31 (3.20)	0.29 (3.11)	0.23 (2.46)	0.22 (1.45)	-0.31** (-2.53)
9-Factor α	0.81 (5.14)	0.46 (4.20)	0.40 (3.75)	0.32 (2.69)	0.31 (1.66)	-0.51*** (-2.7)
<i>Holding Period: Nine Months (Overlapping)</i>						
4-Factor α	0.56 (3.83)	0.34 (3.69)	0.31 (3.59)	0.26 (3.07)	0.20 (1.45)	-0.36*** (-3.42)
5-Factor α	0.52 (3.66)	0.31 (3.14)	0.29 (2.99)	0.24 (2.56)	0.21 (1.40)	-0.31*** (-2.95)

9-Factor α	0.81 (5.28)	0.46 (4.18)	0.41 (3.52)	0.33 (2.75)	0.29 (1.69)	-0.52*** (-3.34)
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Holding Period: Twelve Months (Overlapping)

4-Factor α	0.53 (3.71)	0.34 (3.78)	0.29 (3.36)	0.27 (3.28)	0.22 (1.80)	-0.31*** (-3.17)
5-Factor α	0.49 (3.55)	0.31 (3.16)	0.27 (2.70)	0.25 (2.70)	0.23 (1.71)	-0.26*** (-2.68)
9-Factor α	0.76 (5.15)	0.46 (4.21)	0.39 (3.17)	0.36 (2.95)	0.32 (1.99)	-0.44*** (-2.99)

Table VII**Hedge Fund Exposures to Tail Risk Controlling for Liquidity and Correlation Risks**

This table presents the results of time-series regressions of hedge fund portfolio returns on the tail risk factor and the Fung and Hsieh seven factors after controlling for liquidity risk factors (the Pastor and Stambaugh 2003 liquidity risk factor and the Sadka 2006 permanent variable factor) and a correlation risk factor. We compute monthly returns on an equal-weight portfolio of all individual hedge funds in our sample in excess of the one-month Treasury-bill rate. The tail factor, liquidity risk factors, and the correlation risk factor are standardized to have a mean of zero and standard deviation of one. Our sample period is from January 1994 to December 2009. For the regressions using the Sadka factor, the sample period is from February 1994 to December 2008.

	(1)	(2)	(3)
Tail	-0.00241 (-2.84)	-0.00187 (-2.02)	-0.00218 (-2.48)
Pastor-Stambaugh	0.00184 (2.42)		
Sadka PV		0.00237 (2.83)	
Correlation Risk			-0.000758 (-0.97)
MKTRF	0.269 (13.77)	0.290 (13.93)	0.278 (14.32)
SMB	0.128 (6.09)	0.131 (6.19)	0.124 (5.84)
Δ TERM	-0.00983 (-3.14)	-0.00823 (-2.53)	-0.00898 (-2.80)
Δ CREDIT	-0.0178 (-4.11)	-0.0102 (-1.83)	-0.0171 (-3.78)
PTFSBD	-0.00350 (-0.67)	-0.00438 (-0.83)	-0.00312 (-0.59)
PTFSFX	0.00854 (2.04)	0.00788 (1.85)	0.00827 (1.94)
PTFSCOM	0.0168 (2.91)	0.0156 (2.68)	0.0158 (2.70)
Intercept	0.00478 (6.49)	0.00451 (5.91)	0.00476 (6.37)
Observations	192	180	192
R-squared	0.711	0.713	0.703

Table VIII

Tail Risk in the Cross-Section of Hedge Fund Returns for Each Style

This table presents the average excess returns and alphas for hedge fund portfolios formed on the basis of their exposures to the tail risk factor for each investment style of hedge funds. In each month for each of the 10 investment styles, we form five portfolios based on the funds' loadings on the tail risk factor in a regression of the funds' excess return on the market excess return and the tail factor in the past 24 months. We rebalance the portfolios each month and compute the monthly average returns for each of the portfolios. The Newey-West (1987) *t*-statistics are reported in parentheses.

	Low Tail Beta	2	3	4	High Tail Beta	High - Low
<i>Convertible Arbitrage</i>						
# of Funds	14	14	14	14	14	
Average Excess Return	0.57	0.32	0.22	0.37	0.31	-0.25
	(1.60)	(1.49)	(1.11)	(1.98)	(1.32)	(-1.08)
Fung-Hsieh 7-Factor α	0.53	0.28	0.19	0.34	0.24	-0.29
	(2.40)	(2.07)	(1.30)	(2.81)	(1.40)	(-1.28)
<i>Dedicated Short Bias</i>						
# of Funds	2	3	3	3	3	
Average Excess Return	-0.30	0.15	-0.18	-0.22	-0.49	-0.19
	(-0.44)	(0.29)	(-0.41)	(-0.51)	(-0.86)	(-0.34)
Fung-Hsieh 7-Factor α	0.03	0.40	-0.05	-0.06	-0.30	-0.33
	(0.05)	(1.25)	(-0.21)	(-0.22)	(-0.76)	(-0.56)
<i>Emerging Markets</i>						
# of Funds	33	34	34	34	33	
Average Excess Return	1.52	0.60	0.56	0.72	0.52	-1.00***
	(2.63)	(1.58)	(1.68)	(2.05)	(0.93)	(-2.75)
Fung-Hsieh 7-Factor α	1.30	0.43	0.41	0.51	0.18	-1.12***
	(3.10)	(1.64)	(1.69)	(1.86)	(0.36)	(-2.91)
<i>Equity Market Neutral</i>						
# of Funds	18	18	18	18	18	
Average Excess Return	0.45	0.32	0.29	0.24	0.41	-0.04
	(3.08)	(3.74)	(2.83)	(2.65)	(3.57)	(-0.25)
Fung-Hsieh 7-Factor α	0.43	0.29	0.26	0.20	0.40	-0.03
	(2.99)	(3.55)	(2.37)	(2.34)	(3.52)	(-0.16)
<i>Event Driven</i>						
# of Funds	40	40	40	40	40	
Average Excess Return	0.76	0.48	0.43	0.31	0.42	-0.35**
	(3.02)	(3.19)	(3.03)	(2.53)	(2.36)	(-2.18)
Fung-Hsieh 7-Factor α	0.65	0.43	0.36	0.26	0.35	-0.29**
	(4.53)	(4.84)	(4.07)	(3.24)	(3.08)	(-2.09)
<i>Fixed Income Arbitrage</i>						
# of Funds	13	14	14	14	14	

Average Excess Return	0.14	0.43	0.34	0.22	0.37	0.23
	(0.57)	(3.44)	(4.19)	(2.04)	(2.09)	(1.18)
Fung-Hsieh 7-Factor α	0.06	0.42	0.35	0.20	0.36	0.29*
	(0.37)	(4.38)	(5.09)	(1.93)	(2.47)	(1.66)
<i>Global Macro</i>						
# of Funds	17	17	17	17	17	
Average Excess Return	0.29	0.33	0.22	0.45	0.47	0.18
	(1.36)	(2.09)	(1.54)	(3.02)	(2.21)	(0.82)
Fung-Hsieh 7-Factor α	0.11	0.27	0.13	0.39	0.36	0.25
	(0.59)	(2.00)	(1.04)	(3.13)	(1.88)	(1.18)
<i>Long/Short Equity</i>						
# of Funds	132	132	132	132	132	
Average Excess Return	0.95	0.81	0.62	0.43	0.42	-0.53**
	(3.12)	(3.87)	(3.15)	(1.86)	(1.23)	(-2.17)
Fung-Hsieh 7-Factor α	0.87	0.73	0.54	0.34	0.30	-0.56**
	(4.26)	(5.62)	(5.08)	(2.63)	(1.55)	(-2.21)
<i>Managed Futures</i>						
# of Funds	36	37	37	37	36	
Average Excess Return	0.64	0.53	0.41	0.41	0.52	-0.12
	(2.51)	(2.58)	(2.04)	(1.63)	(1.37)	(-0.4)
Fung-Hsieh 7-Factor α	0.64	0.53	0.39	0.41	0.55	-0.08
	(2.73)	(2.78)	(2.33)	(1.80)	(1.65)	(-0.29)
<i>Multi-Strategy</i>						
# of Funds	24	24	24	24	24	
Average Excess Return	0.77	0.45	0.39	0.39	0.31	-0.45**
	(3.35)	(3.23)	(3.31)	(3.41)	(1.71)	(-2.54)
Fung-Hsieh 7-Factor α	0.67	0.42	0.35	0.37	0.19	-0.48**
	(4.03)	(4.89)	(4.10)	(4.18)	(1.19)	(-2.3)

Table IX**Tail Risk Betas and Hedge Fund Characteristics**

This table reports Fama-MacBeth (1973) cross-sectional regression coefficients of monthly estimated tail risk beta on contemporaneous fund characteristics over the period December 1995 to November 2009. For the ease of interpretation, we cross-sectionally standardize tail risk beta, size, age, fund return, return volatility and fund flow to have means of zero and standard deviations of one. The payout period, redemption notice period, and lockup period are transformed using the natural log of one plus the number of days. Variable descriptions are provided in the text. Test statistics are based on Newey-West (1987) autocorrelation-consistent standard errors with a maximum lag of 24 months.

	(1)	(2)	(3)	(4)	(5)	(6)
Size	-0.012 (-0.58)	0.034 (1.56)	0.047** (2.33)	-0.013 (-0.61)	-0.011 (-0.47)	0.01 (0.47)
Age	0.032*** (2.64)	0.019** (1.99)	0.01 (1.56)	0.025** (1.99)	0.033*** (2.68)	0.013 (1.31)
Ret24	-0.038 (-1.34)			-0.042 (-1.49)	-0.04 (-1.45)	-0.051* (-1.97)
Flow24	0.018 (1.51)			0.019 (1.61)	0.020* (1.68)	0.013 (1.34)
Volatility	-0.137*** (-4.41)			-0.140*** (-4.61)	-0.138*** (-4.38)	-0.150*** (-4.00)
Management Fee		4.068 (1.26)				2.543 (0.98)
Incentive Fee		0.658 (1.51)				0.58 (1.45)
High Water Mark		-0.131*** (-4.32)				-0.092*** (-2.74)
Log Payout Period			-0.008 (-1.10)			0.002 (0.27)
Log Redemption Period			-0.070* (-1.96)			-0.086** (-2.50)
Log Lock-up Period			-0.022** (-2.24)			-0.001 (-0.16)
Personal Capital				0.097*** (2.88)		0.097*** (3.24)
Manager Ownership				0.009 (0.09)		0.061 (0.66)
Leverage					0.071** (2.40)	0.046 (1.59)
Adj. R ²	0.078	0.019	0.026	0.083	0.079	0.112