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Tail risk in hedge funds: A unique view from portfolio holdings

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Tail risk in hedge funds: A unique view from portfolio holdings

Vikas Agarwal, Stefan Ruenzi, and Florian Weigert*

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Abstract

We develop a new tail risk measure for hedge funds to examine the impact of tail risk on fund performance and to identify the sources of tail risk. We find that tail risk affects the cross-sectional variation in fund returns, and investments in both, tail-sensitive stocks as well as options, drive tail risk. Moreover, managerial incentives and discretion as well as exposure to funding liquidity shocks are important determinants of tail risk. We find evidence that is consistent with funds being able to time tail risk exposure prior to the recent financial crisis.

Keywords: Hedge Funds, Tail Risk, Portfolio Holdings, Funding Liquidity Risk

JEL Classification Numbers: G11, G23

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Tail risk in hedge funds: A unique view from portfolio holdings

Hedge funds are often described as pursuing trading strategies that generate small positive returns most of the time before incurring a substantial loss akin to "picking up pennies in front of a steam roller" or "selling earthquake insurance" (Duarte, Longstaff, and Yu, 2007; Stulz, 2007). Hedge funds are therefore likely to be exposed to substantial tail risk, i.e., they can incur substantial losses in times when investors' marginal utility is very high. However, there is limited research on whether hedge funds are exposed to tail risk, and if so, how hedge funds' investments and trading strategies contribute to tail risk and how it affects hedge fund performance. Our paper fills this void in the literature by using hedge fund return data as well as the mandatorily reported 13F quarterly equity and option holdings of hedge fund firms to examine the sources and performance implications of tail risk.[1] In particular, we ask the following questions. First, does tail risk explain the cross-sectional variation in hedge fund performance? Second, is tail risk related to certain observable fund characteristics and funds' exposure to funding liquidity shocks? Third, does tail risk in hedge funds arise from their dynamic trading strategies and/or their investments in stocks that are sensitive to equity market crashes? Finally, can hedge funds time tail risk by altering their positions in equities and options before market crashes?

We address these questions by first deriving a new non-parametric estimate for hedge funds' tail risk based on their reported returns. This tail risk measure is defined as the lower tail dependence of hedge funds' returns and the market return, scaled by the ratio of the absolute value of their respective expected shortfalls (*ES*). The lower tail dependence is defined as the conditional probability that an individual hedge fund has its worst individual return realizations exactly at the same time when the market also has its worst return realizations in a given time span. We show that this tail risk measure has significant predictive power for the cross-section of hedge fund returns. We find that the return spread between the portfolios of hedge funds with the highest and the lowest past tail risk amounts to

[1]Institutional investors including hedge funds that exercise investment discretion over $100 million of assets in 13F securities are required to disclose their *long* positions in 13F securities (common stocks, convertible bonds, and options) on a quarterly basis. They are not required to report any short positions (see Griffin and Xu, 2009; Aragon and Martin, 2012; Agarwal, Fos, and Jiang, 2013; and Agarwal, Jiang, Yang, and Tang, 2013).

4.8% per annum after controlling for the risk factors in the widely used Fung and Hsieh (2004) 7-factor model. The spread in risk-adjusted returns is even more pronounced (5.3% per annum) for equity-oriented hedge fund styles. These spreads are robust to controlling for other risks that have been shown to influence hedge fund returns including correlation risk (Buraschi, Kosowski, and Trojani, 2014), liquidity risk (Aragon, 2007; Sadka, 2010; Teo, 2011), macroeconomic uncertainty (Bali, Brown, and Caglayan, 2014), and volatility risk (Bondarenko, 2004; Agarwal, Bakshi, and Huij, 2009). In addition, results from multivariate regressions confirm that tail risk predicts future fund returns even after controlling for various fund characteristics such as fund size, age, past yearly excess return, standard deviation, skewness, kurtosis, value-at-risk (*VaR*), *ES*, market beta, delta, lockup period, restriction period, minimum investment, management and incentive fees, and indicator variables for leverage, offshore domicile, hurdle rate, and high watermark. The predictability of future returns extends as far as six months into the future.

We conduct a number of robustness checks to show that these results are not sensitive to several choices that we make in our empirical analysis. Our results are stable when we change the estimation horizon of tail risk, compute tail risk using different cut-off values, use *VaR* instead of *ES* in the computation of tail risk, change the weighting procedure in portfolio sorts from equal-weighting to value-weighting, and compute tail risk with daily instead of monthly returns using data for a subsample of hedge funds that report daily data to Bloomberg.

Next, we investigate the determinants of tail risk of hedge funds, i.e., why some funds are more exposed to tail risk than others and which fund characteristics are associated with high tail risk. We document several findings that are consistent with the earlier theoretical and empirical literature on the relation between risk-taking behavior and contractual features of hedge funds. First, we find that the managerial incentives stemming from the incentive fee call option are positively related to funds' tail risk. This result is consistent with the risk-inducing behavior associated with the call option feature of incentive fee contracts (Brown, Goetzmann, and Park, 2001; Goetzmann, Ingersoll, and Ross, 2003; Hodder and Jackwerth, 2007). Second, we observe that tail risk is negatively associated with past performance, i.e., worse performing fund managers engage in greater risk-taking behavior. This finding is

similar to the increase in propensity to take risk following poor performance as documented in Aragon and Nanda (2012). Finally, both the lockup period and leverage exhibit a significant positive relation with tail risk. Since funds with longer lockup period are likely to invest in more illiquid securities (Aragon, 2007), this finding suggests that funds that make such illiquid investments are more likely to be exposed to higher tail risk. Levered funds may use derivatives and short selling techniques to take state-contingent bets that can exacerbate tail risk in such funds.

We also use the bankruptcy of Lehman Brothers in September 2008 as a quasi-natural experiment leading to an exogenous shock to the funding of hedge funds by prime brokers. This allows us to examine a causal relation between funding liquidity risk and tail risk. We find evidence of a greater increase in tail risk of funds that used Lehman Brothers as their prime broker as compared to other funds, indicating that funding liquidity shocks can enhance tail risk.

We next investigate different trading strategies that can induce tail risk in hedge funds to shed light on the sources of tail risk. In particular, we consider (i) dynamic trading strategies captured by exposures to a factor that mimics the return of short out-of-the-money put options on the equity market of Agarwal and Naik (2004) as well as (ii) an investment strategy involving long positions in high tail risk stocks and short positions in low tail risk stocks, i.e., exposure to an equity tail risk factor (Chabi-Yo, Ruenzi, and Weigert, 2015; Kelly and Jiang, 2014). To understand which of these strategies explain the tail risk of hedge funds, we first regress individual hedge funds' returns on the S&P 500 index put option factor as in Agarwal and Naik (2004) and on the Chabi-Yo, Ruenzi, and Weigert (2015) equity tail risk factor. We then analyze how the cross-sectional differences in hedge funds' overall tail risk can be explained by the funds' exposures to these factors. We find that funds' tail risk is negatively related to the Agarwal and Naik (2004) out-of-the-money put option factor and positively related to the Chabi-Yo, Ruenzi, and Weigert (2015) equity tail risk factor. Ceteris paribus, a one standard deviation decrease (increase) in the put option beta (equity tail risk beta) is associated with an increase of overall tail risk by 0.26 (0.13). Given an average tail risk of equity-related funds of 0.38, this translates into an increase of 68% and 34% in the tail

risk for a one standard deviation increase in the sensitivities to the put option factor and the equity tail risk factor, respectively.

Motivated by the positive relation between hedge fund tail risk and return exposure to the equity tail risk factor, we directly analyze hedge fund's investments in common stocks. For this purpose, we merge the fund returns reported in the commercial hedge fund databases to the reported 13F equity portfolio holdings of hedge fund firms. We find that there is a positive and highly significant relation between the returns-based tail risk of hedge fund firms and the tail risk of the individual long equity positions of the funds that belong to the respective hedge fund firm. This effect is even more pronounced for levered funds. As mentioned before, the 13F filings also consist of long positions in equity options. We analyze these option holdings to corroborate our earlier finding of tail risk being related to a negative exposure to the out-of-the-money put option factor. Furthermore, we generally find a negative relation between returns-based tail risk and the number of different stocks on which put positions are held by funds (as well as the equivalent number and value of equity shares underlying these put positions) in their 13F filings. Taken together, these findings show that tail risk of hedge funds is (at least partially) driven by the nature of hedge funds' investments in tail-sensitive stocks and put options.

Finally, we examine if hedge funds can time tail risk. We start by comparing the tail risk imputed from a hypothetical buy-and-hold portfolio of funds' long positions in equities with the actual tail risk estimated from hedge funds' returns. The idea is to capture how much the funds actively change their tail risk relative to the scenario where they passively hold their equity portfolio. We find that during the recent financial crisis in October 2008, the actual tail risk is significantly lower than the tail risk imputed from the precrisis buy-and-hold equity portfolio. This is consistent with hedge funds reducing their exposure to tail risk prior to the crisis by decreasing their positions in more tail-sensitive stocks. Complementing this finding, we observe that funds increase the number of different stocks on which they hold long put option positions as well as the number and value of the equity shares underlying these put positions before the onset of the crisis. Furthermore, we find that the hedge funds' long put positions are concentrated in stocks with high tail risk.

We make several contributions to the literature. First, we derive a new measure for hedge funds' tail risk and show that it explains the cross-sectional variation in fund returns. Second, we link tail risk exposures to fund characteristics. Third, we utilize an exogenous shock to the funding of hedge funds through prime broker connections to examine the relation between funding liquidity shocks and tail risk. Fourth, we use the mandatory 13F portfolio disclosures of hedge fund firms to uncover the sources of tail risk by examining funds' investments in equities and options. Finally, we analyze hedge funds' changes in equity and put option holdings to shed light on their ability to time tail risk.

The structure of this paper is as follows. Section 1 reviews the related literature. Section 2 describes the data used in this study. Section 3 presents results on the impact of tail risk on the cross-section of average hedge fund returns. Section 4 sheds light on the relation between hedge funds' characteristics and tail risk. Section 5 explicitly studies if the tail risk is induced by portfolio holdings of hedge funds. Section 6 investigates hedge funds' ability to time tail risk and Section 7 concludes.

1. Literature Review

Our study relates to the substantial literature studying the risk-return characteristics of hedge funds. A number of studies including Fung and Hsieh (1997, 2001, 2004), Mitchell and Pulvino (2001), and Agarwal and Naik (2004) show that hedge fund returns exhibit a nonlinear relation with the market return due to their use of dynamic trading strategies. This in turn can expose hedge funds to significant tail risk, which is difficult to diversify (Brown and Spitzer, 2006; Brown, Gregoriou, and Pascalau, 2012). Agarwal, Bakshi, and Huij (2009) document that hedge funds are exposed to higher moments of equity market returns, i.e., volatility, skewness, and kurtosis. Jiang and Kelly (2012) find that hedge fund returns are exposed to extreme event risk. Gao, Gao, and Song (2014) present a different view where hedge funds benefit from exploiting disaster concerns in the market instead of being themselves exposed to the disaster risk. Buraschi, Kosowski, and Trojani (2014) show that hedge fund returns are associated with exposure to correlation risk and that correlation risk has an impact on the cross-section of average hedge fund returns. We contribute to this strand of literature by not only proposing a tail risk measure but also identifying the channels through which hedge funds are exposed to tail risk and the tools they use to manage tail risk.

Our findings show that in addition to the dynamic trading strategies of hedge funds, investments in more tail-sensitive stocks expose funds to tail risk and taking long positions in put options help funds mitigate tail risk. We also find evidence of hedge funds timing tail risk by reducing their exposure to tail risk by decreasing their positions in tail-sensitive stocks and increasing their positions in put options prior to the recent financial crisis.

Another strand of literature examines the link between the contractual features of hedge funds and funds' performance and risk-taking behavior. Agarwal, Daniel, and Naik (2009) and Aragon and Nanda (2012) show that the managerial incentives from the hedge fund compensation contracts significantly influence funds' performance and risk taking, respectively. However, these studies generally measure hedge fund risk based on hedge fund return volatility, while we focus on tail risk. Aragon (2007) and Agarwal, Daniel, and Naik (2009) show that funds with longer lockup and redemption periods perform better due to their ability to make long-term and illiquid investments. We build on this literature by providing evidence on tail risk in hedge funds being driven both by managerial incentives and redemption restrictions placed on investors.

Our paper also contributes to the literature on the factor timing ability of hedge funds. Chen (2007) and Chen and Liang (2007) study the market timing and volatility timing ability of hedge funds. They find evidence in favor of funds timing both market returns and volatility, especially during periods of market downturns and high volatility. In contrast, Griffin and Xu (2009) do not find evidence that hedge funds show market timing abilities. Cao, Chen, Liang, and Lo (2013) investigate if hedge funds selectively adjust their exposures to liquidity risk, i.e., time market liquidity. They find that many fund managers systematically reduce their exposure in times of low market liquidity, especially during severe liquidity crises. We extend this literature to show that hedge funds on aggregate are also able to time their exposure to tail risk by reducing their exposure prior to the financial crisis.

2. Data and Variable Construction

2.1 Data

Our hedge fund data comes from three distinct sources. Our first source of self-reported hedge fund returns is created by merging four commercial databases. We refer to the

merged database as "Union Hedge Fund Database." The second source is the 13F equity portfolio holdings database from Thomson Reuters (formerly the CDA/Spectrum database). Our third data source consists of hedge funds' long positions in call and put options extracted from the 13F filings from the SEC EDGAR (Electronic Data Gathering, Analysis, and Retrieval) database.[2] Individual stock data comes from the CRSP database.

The Union Hedge Fund Database consists of a merge of four different major commercial databases: Eureka, Hedge Fund Research (HFR), Morningstar, and Lipper TASS and includes data for 25,732 hedge funds from 1994 to 2012. The use of multiple databases to achieve a comprehensive coverage is important since 65% of the funds only report to one database (e.g., Lipper TASS has 22% unique funds).[3] A Venn diagram in Figure 1 shows the overlap across the four databases.

[Insert Figure 1 here]

To eliminate survivorship bias we start our sample period in 1994, the year in which commercial hedge fund databases started to also track defunct hedge funds. Further, we use multiple standard filters for our sample selection. First, we require a fund to have at least 24 monthly return observations. Second, we filter out funds denoted in a currency other than US dollars. Third, we eliminate the first 12 months of each fund's return series to avoid backfilling bias. Finally, we exclude all funds of hedge funds from our sample. This filtering process leaves us with a final sample of 10,834 hedge funds out of which 6,281 are equity-oriented funds. We classify a hedge fund as equity-oriented when its investment strategy is either 'Emerging Markets', 'Event Driven', 'Equity Long-Short', 'Equity Long Only', 'Equity Market Neutral', 'Short Bias' or 'Sector'. Hedge funds employing an investment strategy of 'CTA / Trend-Following', 'Global Macro', 'Multi-Strategy', 'Relative Value', or 'Others' are classified as non-equity oriented funds.

We report the summary statistics of hedge funds' excess returns (i.e., returns in excess of the risk free rate) in Panel A and fund characteristics in Panel B of Table 1, respectively.

[Insert Table 1 around here]

[2] In principle, it is possible to also use the long equity positions reported to the SEC and stored in the EDGAR database. However, due to the non-standardized format of 13F filings, it is challenging to extract this data. Therefore, we rely on the Thomson Reuters database for the long equity positions.

[3] Agarwal, Daniel, and Naik (2009) show a similar limited overlap between different commercial databases.

The 13F Thomson Reuters Ownership database consists of quarterly equity holdings of 5,536 institutional investors during the period from 1980 (when Thomson Reuters data starts) to 2012. Unfortunately, hedge fund firms are not separately identified in this database. Hence, we follow Agarwal, Fos, and Jiang (2013) to manually classify a 13F filing institution as a hedge fund firm if it satisfies at least one of the following five criteria: (i) it matches the name of one or multiple funds from the Union Hedge Fund Database, (ii) it is listed by industry publications (e.g., Hedge Fund Group, Barron's, Alpha Magazine) as one of the top hedge funds, (iii) on the firm's website, hedge fund management is identified as a major line of business, (iv) Factiva lists the firm as a hedge fund firm, and (v) if the 13F filer name is one of an individual, we classify this case as a hedge fund firm if the person is the founder, partner, chairman, or other leading personnel of a hedge fund firm.

Applying these criteria provides us with a dataset of 1,694 unique hedge fund firms among the 13F filing institutions.[4] Next, we merge these firms from the 13F filings to the hedge fund firms listed in the Union Hedge Fund Database following Agarwal, Fos, and Jiang (2013). The merging procedure is applied at the hedge fund firm level and entails two steps. First, we match institutions by name allowing for minor variations. Second, we compute the correlation between returns imputed from the 13F quarterly holdings and returns reported in the Union Database. We eliminate all pairs where the correlation is either negative or not defined due to lack of overlapping periods of data from both data sources. We end up with 793 hedge fund firms managing 2,720 distinct hedge funds during the period from 1994 to 2012. Since our main focus in this analysis is on equity-related hedge funds, it is comforting to notice that 70.4% of 13F filing hedge fund firms are classified as equity-related fund firms in the Union Database.

Finally, we merge our sample with the quarterly 13F filings of long option positions of these hedge fund firms in the period from the first quarter of 1999 (when electronic filings became available from the SEC EDGAR database) to the last quarter of 2012. The 13F filing institutions have to report holdings of long option positions on individual 13F securities (i.e.,

[4] This number might appear low at first glance but is significant when considered in the context of the size of the industry. The total value of equity positions held by 13F hedge funds is $2.52 trillion which is equivalent to 88% of the size of the hedge fund industry in 2012 according to HFR.

stocks, convertible bonds, and options).[5] Institutions are required to provide information whether the options are calls or puts and what the underlying security is, but do not have to report an option's exercise price or maturity date. We find that out of the 793 hedge fund firms (which appear both in the 13F equity portfolio database and the Union database), 406 firms file at least one long option position during our sample period. We use this sample in Sections 5 and 6 to investigate the relation between a fund firm's returns-based tail risk and tail risk induced from long positions in equities and options.

2.2 Tail Risk Measure

To evaluate an individual fund's tail risk, we measure the extreme dependence between a fund's self-reported return and the value-weighted CRSP equity market return. In particular, we first define a fund's tail sensitivity (*TailSens*) via the *lower tail dependence* of its return r_i and the CRSP value-weighted market r_m return using

$$TailSens = \lim_{q \to 0} P\left(r_i \le F_i^{-1}(q) \middle| r_m \le F_m^{-1}(q)\right), \qquad (1)$$

where F_i (F_m) denotes the marginal distribution function of the returns of hedge fund *i*, r_i (the market return r_m) in a given period and $q \in (0,1)$ is the argument of the distribution function. According to this measure, funds with high $TailSens$ are likely to have their lowest return realization at the same time when the equity market realizes its lowest return, i.e., these funds are particularly sensitive to market crashes.[6] However, this measure does not take into account how bad the worst return realization of the hedge fund really is. Thus, in a second step, to account for the severity of poor hedge fund returns, we define a hedge fund's tail risk (*TailRisk*) as

[5] See https://www.sec.gov/divisions/investment/13ffaq.htm for more details.

[6] Longin and Solnik (2001) and Rodriguez (2007) apply the lower tail dependence coefficient to analyze financial contagion between different international equity markets. Chabi-Yo, Ruenzi, and Weigert (2015) use lower tail dependence to analyze asset pricing implications of extreme dependence structures in the bivariate distribution of a single stock return and the market return. Our focus in this paper is on the equity tail risk in hedge funds but in priniciple, our approach can be extended to other asset markets such as bonds, currencies, and commodities. However, due to the lack of data on hedge funds' holdings in these other assets, it is not possible to analyze the nature of holdings as a potential channel for tail risk, which is one of the key contributions of our study.

$$TailRisk = TailSens \cdot \frac{|ES_{r_i}|}{|ES_{r_m}|} \quad (2)$$

where ES_{r_i} and ES_{r_m} denote the expected shortfall (also sometimes referred to as conditional *VaR*) of the hedge fund return and the market return, respectively. *ES* has been used in several hedge fund studies as a univariate risk measure to account for downside risk (see, e.g., Agarwal and Naik (2004) and Liang and Park (2007, 2010) for a discussion of the superiority of *ES* over *VaR*). Taking the ratio of *ES* of individual funds with respect to the *ES* of the market allows us to measure a fund's tail risk *relative* to that of the market.[7]

We estimate *TailRisk* for hedge fund *i* in month *t* based on a rolling window of 24 monthly returns. The estimation is performed non-parametrically purely based on the empirical return distribution function of hedge fund r_i and the value-weighted CRSP equity market r_m with a cut-off of q = 0.05. We also use a cut-off of q = 0.05 for the computation of ES_{r_i} and ES_{r_m}.[8] As an example of our estimation procedure, consider the time period from January 2007 to December 2008. The fifth percentile of the market return distribution consists of the two worst realizations which occurred in September 2008 (–9.24%) and October 2008 (–17.23%). To compute *TailSens* for hedge fund *i* during January 2007 to December 2008, we analyze whether the two worst return realizations of hedge fund *i* occur at the same time as these market crashes, i.e., in September 2008 and October 2008. If none, one, or both of the fund's two worst return realizations occur in September 2008 and/or October 2008, we compute *TailSens* for hedge fund *i* in the period from January 2007 to December 2008 as zero, 0.5, or 1, respectively. *TailRisk* for hedge fund *i* in the period from January 2007 to December 2008 is then subsequently defined as the product of *TailSens* and the absolute value of the fraction between hedge fund *i*'s *ES* and the market return's *ES*

[7] This ratio is reminiscent of market beta in the context of the CAPM, the M-squared measure (Modigliani and Modigliani, 1997) and the Graham and Harvey's GH1 and GH2 (1996, 1997) measures often used for performance evaluation.

[8] The specific choice of an estimation horizon of 24 months and a cut-off of q=0.05 does not influence our results. We obtain similar results when we apply different estimation horizons of 36 months and 48 months as well as cut-off points of q=0.10 and q=0.20, respectively. We later report these results in Table 3.

during the same 24-month period. We report summary statistics of our *TailRisk* measure in Panel C of Table 1.

Panel C of Table 1 shows that average *TailRisk* is 0.30 across all hedge funds in the sample. Among the different hedge fund strategies, *TailRisk* is lowest for Short Bias, Equity Market Neutral, and Relative Value hedge funds and highest for Emerging Markets, Equity Long Only, and Sector hedge funds. Moreover, *TailRisk* is twice as high for equity-related hedge funds (0.38) compared to non-equity related funds (0.19).

We now inspect the behavior of aggregate *TailRisk* over time. Aggregate *TailRisk* is computed as the monthly cross-sectional, equally-weighted average of *TailRisk* across all hedge funds in the sample. Figure 2 plots the time series of aggregate *TailRisk* together with aggregate *TailRisk* of equity-related and non-equity related hedge funds.

[Insert Figure 2 here]

Visual inspection shows that the time-series variation in our tail risk measure corresponds well with known crisis events in financial markets. The highest spike in aggregate *TailRisk* occurs in October 2008, one month after the bankruptcy of Lehman Brothers and the beginning of a worldwide recession. Additional spikes correspond to the beginning of the Asian financial crisis in autumn 1996 and the Russian financial crisis along with the collapse of Long Term Capital Management (LTCM) in August 1998.

We also look at the correlations between aggregate *TailRisk* and hedge fund specific risk factors (see Panel D in Table 1). Aggregate *TailRisk* is moderately positively related to the correlation swap factor of Buraschi, Kosowski, and Trojani (2014) and the Chicago Board Options Exchange (CBOE) volatility index (VIX) as well as moderately negatively related to the market return, the Pástor and Stambaugh (2003) aggregate liquidity risk factor, and the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor. Interestingly, we find a high correlation of 0.49 between aggregate *TailRisk* and the TED Spread (i.e., the difference between the interest rates for three-month U.S. Treasury and three-month Eurodollar contracts) indicating that tail risk of hedge funds and funding liquidity are strongly interconnected. Later in the paper, we will take a closer look at the relationship between *TailRisk* and funding liquidity in Section 4. In particular, we will assess the impact of a

funding liquidity shock due to the Lehman Brothers bankruptcy in September 2008 on tail risk of hedge funds that had a prime brokerage relation with Lehman.

3. Tail risk and hedge fund performance

3.1 Does tail risk have an impact on the cross-section of future hedge fund returns?

Tail risk induced by nonlinearities in hedge fund returns can contribute to fund returns.[9] To evaluate the predictive power of differences in hedge fund's tail risk on the cross-section of average future hedge fund returns, we relate hedge fund returns in month *t+1* to hedge fund *TailRisk* in month *t*. We first look at equal-weighted univariate portfolio sorts. For each month *t*, we sort hedge funds into decile portfolios based on *TailRisk*. We then compute monthly average excess returns of these portfolios at time *t+1*. We also repeat this analysis separately for the subsample of equity-related hedge funds and non-equity related hedge funds. Panel A of Table 2 reports the results.

[Insert Table 2 here]

The numbers in the first column show considerable cross-sectional variation in *TailRisk* across funds. Average *TailRisk* ranges from virtually zero in the lowest decile up to above 2 in the highest decile. The second column shows that hedge funds with high *TailRisk* have significantly higher future returns than those with low *TailRisk*. Hedge funds in the portfolio with the lowest (highest) *TailRisk* earn a monthly excess return (in excess of the risk-free rate) of 0.45% (1.01%). The return spread between portfolios 1 and 10 is 0.56% per month, which is statistically significant at the 5% level with a *t*-statistic of 2.02. We also estimate alphas for each of the decile portfolios and the difference (10−1) portfolio using the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model. We find that the spread between portfolios 10 and 1 remains significantly positive after controlling for other risk factors in these models, and are of similar order of magnitude as the excess returns with 4-factor and 7-factor alphas amounting to 0.53% and 0.40% per month, respectively. These spreads translate into an economically large return premium of 6.36% and 4.80% per annum, respectively.

[9] The underlying intuition is that strategies with a payoff concave to the benchmark (i.e., the market return) earn stable premiums in normal times but lose money during bad times. Goetzmann, Ingersoll, Spiegel, and Welch (2007) demonstrate that such strategies can reduce the utility of standard performance measures such as Sharpe ratios.

Repeating the portfolio sorts for the subsamples of equity-related and non-equity related hedge funds, our results indicate that the premium for *TailRisk* is driven by the equity-related funds. For example, controlling for the seven factors in the Fung and Hsieh (2004) model, for the equity-related hedge funds, we obtain a return spread between portfolios 10 and 1 of 0.44% per month which is statistically significant at the 5% level with a *t*-statistic of 2.00. In contrast, we do not find a statistically significant return spread for the non-equity related hedge funds (spread of 0.07% per month with a *t*-statistic of 0.35). This makes sense as our tail risk measure is based on the worst returns in the equity market. Therefore, in the rest of the paper we focus on the subsample of equity-related hedge funds.

In Panel B, we explore the robustness of our results after controlling for other risk factors that have been shown to be important in explaining hedge fund performance. To do so, we regress the 10–1 *TailRisk* return portfolio on various extensions of the Fung and Hsieh (2004) model. For the sake of comparison, we report the results of the Fung and Hsieh (2004) seven-factor model as our baseline model in the first column (which corresponds to the results from Column (7) in Panel A). In the second column, we then include the MSCI Emerging Markets return as an additional risk factor. In columns three and four, we add the HML and UMD factors from the Carhart (1997) model to control for book-to-market and momentum. To control for liquidity exposure of hedge funds, we include the Pástor and Stambaugh (2003) traded liquidity factor in the fifth column. In columns six to eight, we control for the exposures to the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Buraschi, Kosowski, and Trojani (2014) correlation risk factor, and the VIX (as in Agarwal, Bakshi, and Huij, 2009), respectively. In each case, we continue to observe a significant positive alpha of our 10–1 *TailRisk* return portfolio ranging from 0.36% to 0.54% per month. These findings further corroborate the importance of tail risk in explaining the cross-section of hedge fund returns.

In Panel C, we report the results of regressions of excess fund returns in month *t+1* on *TailRisk* and other fund characteristics measured in month *t* using the Fama and MacBeth (1973) methodology. We specify:

$$r_{i,t+1} = \alpha + \beta_1 TailRisk_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t}, \qquad (3)$$

where $r_{i,t+1}$ denotes fund *i*'s excess return in month *t+1* , $TailRisk_{i,t}$ a fund's tail risk, and $X_{i,t}$ is a vector of fund characteristics. We use the Newey and West (1987) adjustment with 24 lags to adjust standard errors for serial correlation. Fund characteristics include fund size (computed as a fund's natural logarithm of assets under management), age (in months), past yearly excess return, standard deviation, skewness, kurtosis, *VaR*, *ES*, market beta (all computed over the past 24 months), delta, lockup period (in months), restriction period (computed as the sum of a fund's notice period and redemption period), minimum investment, management and incentive fees, and indicator variables for leverage, offshore domicile, hurdle rate, and high watermark. Controlling for these fund characteristics, we find a positive impact of *TailRisk* on future hedge fund returns. Depending on the regression specification, the coefficient estimate for *TailRisk* ranges from 0.217 to 0.451 with *t*-statistics ranging from 1.85 to 3.37. These results confirm that the relation between future fund returns and tail risk is not subsumed by fund characteristics and other risk measures including higher moments of fund returns and fund's systematic risk.

So far we have examined the ability of tail risk to predict next month's fund returns. A natural question is how far this predictability goes. Panel D reports the results of regressions of future excess returns over different horizons on *TailRisk* after controlling for various fund characteristics measured in month *t*. We find that *TailRisk* can significantly predict future fund returns up to six months into the future.

In summary, we find that *TailRisk* has strong predictive power to explain the cross-sectional variation in hedge fund returns. Hedge funds with high tail risk outperform their counterparts by around 5% per annum after adjusting for risk factors from the Fung and Hsieh (2004) seven-factor model. We show that this premium persists even after controlling for additional recently proposed risk factors (such as liquidity risk, macroeconomic uncertainty, correlation risk, and volatility risk) and fund characteristics.

3.2 Robustness checks

To further corroborate our results in Table 2, we now briefly report results from additional robustness checks on the relation between *TailRisk* of hedge funds in month *t* and average fund returns in month *t+1*. Specifically, we investigate the stability of our results by

(i) changing the estimation horizon of the *TailRisk* measure from 2 years to either 3 years or 4 years, (ii) computing *TailRisk* using different cut-off values (10% or 20% instead of 5%) to define the worst returns, (iii) using *VaR* instead of *ES* in the computation of *TailRisk*, (iv) applying a value-weighted sorting procedure instead of an equal-weighted sorting procedure, and (v) using daily returns instead of monthly returns to estimate tail risk for a subsample of funds that report daily returns to Bloomberg.[10] Panel A in Table 3 reports the results from univariate portfolio sorts using these alternative specifications. We only report returns of the (10 – 1) difference portfolio between hedge funds with the highest *TailRisk* and hedge funds with the lowest *TailRisk*, after adjusting for the risk factors in the Fung and Hsieh (2004) seven-factor model.

[Insert Table 3 here]

In specifications (1) through (6), we look at the results of equal-weighted portfolio sorts when we change the estimation horizon of the *TailRisk* measure, compute *TailRisk* using different cut-off values, and use *VaR* instead of *ES* in the computation of *TailRisk*. In specification (7) we show the findings for the value-weighted portfolio sorts and specification (8) reports the results when daily returns instead of monthly returns are used to estimate *TailRisk*.[11] Panel B reports the results of Fama and MacBeth (1973) regression (similar to those from Panel D in Table 2) of future excess returns in month *t+1* on *TailRisk* and different fund characteristics measured in month *t* using the same alternatve specifications as above. We only report the coefficient estimate for the impact of *TailRisk*. The other controls are included in the regressions, but supressed in the table. For ease of comparison, we report the baseline results from Table 2 in the first column of Panels A and B of Table 3. Across all robustness checks, we continue to observe a positive and statistically significant impact of *TailRisk* on future fund returns.

[10] For this purpose, we use a subsample of 444 hedge funds that report daily returns to Bloomberg between 2003 and 2012. In the spirit of Kolokolva and Mattes (2014), we use two filters: (i) restrict our sample to funds with an average daily reporting difference smaller or equal than two days and a maximum gap of seven days, and (ii) require at least 15 daily return observations per month and at least two years of return data per fund. To prevent that our results are driven by outliers, we winsorize daily returns that exceed 100%. Further, we require an overall number of at least 30 hedge funds per month which excludes the months before 2003 in our empirical analysis.

[11] Due to the lower sample size of hedge funds that report daily returns to Bloomberg, we report results of the (3–1) tercile difference portfolio instead of the (10–1) decile difference portfolio.

4. Determinants and Sources of Tail Risk

4.1 Tail Risk and Fund Characteristics

Section 3 documents that tail risk is an important factor to explain the cross-sectional variation in hedge fund returns. We now investigate which fund characteristics are associated with high tail risk. Besides fund characteristics like size, age, and domicile, we mainly focus on a fund manager's incentives and discretion which have been shown to be related to the risk-taking behavior of fund managers (Brown, Goetzmann, and Park, 2001; Goetzmann, Ingersoll, and Ross, 2003; Hodder and Jackwerth, 2007; Aragon and Nanda, 2012). We estimate regressions of *TailRisk* of hedge fund *i* in month *t+1* on fund *i*'s characteristics measured in month *t* again using the Fama and MacBeth (1973) methodology. Specifically, we estimate:

$$TailRisk_{i,t+1} = \alpha + \beta_1 X_{i,t} + \varepsilon_{i,t}, \qquad (4)$$

where $TailRisk_{i,t+1}$ denotes fund *i*'s tail risk in month *t+1*, and $X_{i,t}$ is a vector of fund characteristics including the same variables as those from regression equation (3). To adjust the standard errors for serial correlation, we use the Newey and West (1987) adjustment with 24 lags.[12] Table 5 reports the results.

[Insert Table 4 here]

In model (1), we include fund characteristics such as fund age, size, delta, as well as past yearly return and standard deviation as independent variables. We observe a significantly positive relation between *TailRisk* and fund age, delta, and standard deviation of returns, and a significantly negative relation with past yearly returns. These findings are consistent with risk-inducing behavior associated with the call option feature of the incentive fee contract (Goetzmann, Ingersoll, and Ross, 2003; Hodder and Jackwerth, 2007; Aragon and Nanda, 2012; Agarwal, Daniel, and Naik, 2009). Moreover, managers seem to respond to poor recent performance by increasing tail risk (Brown, Goetzmann, and Park, 2001).

In model (2), we include fund characteristics such as a hedge fund's lockup and restriction period, minimum investment, management and incentive fee, as well as indicator variables for leverage, offshore domicile, hurdle rate, and high watermark. Consistent with

[12] We obtain similar results if we use non-overlapping data and apply standard OLS regressions with monthly time dummies and standard errors clustered by funds. Results are available upon request.

the notion that funds with longer lockup period have greater discretion in managing their portfolios, we observe a positive relation between *TailRisk* and a fund's lockup period. In addition, we find a negative relation between *TailRisk* and a fund's incentive fee. Although surprising at first sight, this result is consistent with Agarwal, Daniel, and Naik (2009) who find that incentive fees by themselves do not capture managerial incentives as two different managers that change the same incentive fee rate could be facing different dollar incentives depending on the timing and magnitude of investors' capital flows, funds' return history, and other contractual features.

Finally, in model (3), we include all the fund characteristics together. We continue to observe that *TailRisk* exhibits a significant positive relation with delta, return standard deviation, and lockup period, as well as a negative relation with past yearly returns. In presence of delta, the coefficient on incentive fee is not significant anymore, consistent with the findings in Agarwal, Daniel, and Naik (2009). In this specification, we also document a positive association between a fund's leverage and *TailRisk.* This finding is intuitive since leveraged funds are likely to be particularly vulnerable when faced with funding liquidity shocks and systemic crises that force them to deleverage at the worst time. In the next subsection, we formally test this possibility using the quasi-natural experiment of Lehman's bankruptcy.

Our findings are also meaningful based on economic significance. For example, we find that one standard deviation change in a fund's delta is associated with an increase of 0.046 in *TailRisk*. In contrast, a one standard deviation increase in past yearly returns decreases *TailRisk* by 0.076. These figures are economically significant considering that the average tail risk for equity-related hedge funds is 0.38 (see Panel C of Table 1).

4.2 Tail risk and funding liquidity: Evidence from Lehman-connected hedge funds

Panel D of Table 1 shows that aggregate *TailRisk* is strongly correlated to the TED spread which has been previously used as a proxy for aggregate funding liquidity (e.g., Teo, 2011). However, the correlation by itself does not shed light on the causal relation between funding liquidity risk and tail risk. For this purpose, we assess the impact of a funding liquidity shock due to the Lehman Brothers bankruptcy in September 2008 on the tail risk of

hedge funds that had a prime brokerage relation with Lehman during this month as compared to the hedge funds without such a relation.

To identify the hedge funds that had Lehman Brothers as their prime broker, we use a snapshot of the Lipper TASS database in 2007.[13] Lipper TASS data contains information on the prime broker, along with other affiliated companies (e.g., custodian bank) for each hedge fund. We can identify 60 hedge funds that report Lehman Brothers as their prime broker in 2007 and report monthly returns during the financial crisis in 2008–2009.

We compute *TailRisk* for the 39 equity-related funds out of the 60 Lehman-connected funds and 1,516 equity-related non-Lehman funds from the TASS database in the period from September 2007 to August 2010. We emphasize the impact of the Lehman Brothers bankruptcy in September 2008 by estimating *TailRisk* based on a shorter horizon of 12 months.[14] To test if *TailRisk* of Lehman-connected funds display a larger spike than *TailRisk* of their counterparts, we construct a matched sample of non-Lehman funds using the propensity score from a logistic model. We estimate a logistic regression of an indicator variable that is equal to one if a hedge fund is Lehman-connected on different fund characteristics (the same fund characteristics as in Table 5), and zero otherwise. We then match each Lehman-connected hedge fund with its closest neighbour based on the estimated propensity score. As an additional robustness check we create a second control group based on a hedge fund's style as well as *TailRisk*, size, and monthly excess return in August 2007. To do so, we independently sort all funds within their investment strategy based on *TailRisk*, size, and returns in August 2007 into decile portfolios. We then match each Lehman-connected hedge fund with a non-connected fund of the identical investment style in the same *TailRisk*, size and return decile.[15]

Figure 3 displays the evolution of aggregate *TailRisk* for Lehman-connected equity-related hedge funds and the two matched control samples of non-Lehman funds during the period from September 2007 to August 2010.

[13] A similar setting is used by Aragon and Strahan (2012). They find that stocks held by Lehman-connected hedge funds experienced greater declines in market liquidity following the bankruptcy as compared to other stocks.

[14] We obtain similar results when we use our usual estimation horizon of 24 months to estimate *TailRisk*.

[15] In the case that this matching procedure does not yield one-to-one matches, we randomly assign a non-connected hedge fund out of the possible matches to a Lehman-connected fund.

[Insert Figure 3 around here]

Figure 3 shows that, although both Lehman-connected and non-Lehman funds experience a spike in *TailRisk* in September 2008, the spike is much more pronounced for the Lehman-connected funds.

We then compare the averages of *TailRisk* of Lehman-connected funds and the two matched samples of non-Lehman funds in the pre-Lehman crisis period (September 2007 to August 2008), the crisis period (September 2008 to August 2009), and the post-crisis period (September 2009 to August 2010). Panel A of Table 5 reports the results.

[Insert Table 5 around here]

If our matching between Lehman-connected funds and non-Lehman funds is close enough, we should not observe any difference in the tail risk between these funds prior to the bankruptcy. Panel A confirms that this is indeed the case for the pre-bankruptcy period (*Precrisis*). However, we find a significant difference in *TailRisk* in the period directly after the Lehman bankruptcy from September 2008 to August 2009 (*Crisis*). Lehman-connected hedge funds display an aggregate *TailRisk* of 0.82 whereas the propensity-score-matched (style-, *TailRisk*-, size-, and returns-matched) non-Lehman funds display an aggregate *TailRisk* of 0.57 (0.55). The difference in aggregate *TailRisk* of 0.25 (0.27) is economically large and statistically significant at the 5% level with a *t*-statistic of 2.01 (2.25). Finally, in Period 3 from September 2009 to August 2010, we observe that the tail risk averages of the different groups of funds are statistically indistinguishable from each other again. Together, these results show that the exogenous shock to the funding liquidity due to Lehman's bankruptcy leads to a sharp jump in the tail risk of funds that had a prime brokerage relation with Lehman.

To test whether these univariate findings hold in a multivariate setting after controlling for fund characteristics, we also conduct a difference-in-differences analysis by estimating the following regression for the sample covering the Lehman hedge funds and the respective matched samples (based on the same criteria as above) of non-connected Lehman funds:

$$\Delta TailRisk_{i,t} = \alpha + \beta_1 \Delta_{Postcrisis-Crisis} + \beta_2 \Delta_{Crisis-Precrisis} \times Lehman + \beta_3 \Delta_{Postcrisis-Crisis} \times Lehman + \kappa X_{i,t-1} + \varepsilon_{i,t} \quad (5)$$

where $\Delta TailRisk_{i,t}$ denotes the change in tail risk for hedge fund *i* between the pre-Lehman crisis and the crisis period, or between the crisis and the post-crisis period, respectively. $\Delta_{Crisis-Precrisis}$ and $\Delta_{Postcrisis-Crisis}$ are indicator variables for the period between the crisis and pre-crisis, and post-crisis and crisis, respectively.[16] *Lehman* is an indicator variable to identify funds that have a prime brokerage relation with Lehman Brothers. $X_{i,t-1}$ is a vector of fund-specific control variables including the fund characteristics also used above in Table 4, all measured at time *t*–1. As expected, the coefficient estimate for the interaction term between *Lehman* and $\Delta_{Crisis-Precrisis}$ is significantly positive. This indicates that hedge funds with a prime brokerage relation with Lehman experience a significantly more pronounced increase in tail risk in the crisis period as compared to the funds from the matched sample. We obtain this finding irrespective of which matched sample of funds without a prime brokearge relationship with Lehman we use and whether we include additional controls or not. The significantly negative coefficient estimate for the interaction of $\Delta_{Postcrisis-Crisis}$ with *Lehman* suggests that this effect is (at least partially) subsequently reversed.

4.3 Sources of Tail Risk

So far we have investigated which fund characteristics are associated with hedge funds' tail risk. In this section, we take a closer look and examine the channels through which hedge funds may be exposed to tail risk. In particular, we consider two channels. First, as shown in Agarwal and Naik (2004), *dynamic trading* by hedge funds can contribute to tail risk.[17] Second, *explicit investments* in tail-sensitive stocks can be another source of tail risk in hedge funds. To capture the impact of the first channel, we estimate funds' exposure to the out-of-the-money (OTM) put option factor. We follow Agarwal and Naik (2004) to compute

[16] We do not include an un-interacted indicator variable for the Precrisis-Crisis period as the constant already reflects the base case of the *TailRisk* change of between these two periods for funds from the matched sample without a prime brokerage relation with Lehman.

[17] Specifically, they show that it is the nature of funds' dynamic trading corresponding to their investment styles, rather than direct positions in options, that contributes to the tail risk that they capture by an OTM put option factor.

the return of a strategy that involves buying OTM put options on the S&P composite index with two months to maturity at the beginning of each month and selling them at the beginning of the next month. For the second channel, we use the Chabi-Yo, Ruenzi, and Weigert (2015) high minus low lower tail dependence (LTD)-risk factor as a proxy for tail risk induced by equity holdings. The LTD-risk factor is constructed as the return of a trading strategy going long in stocks with high tail risk exposure (i.e., stocks in the top quintile of crash sensitivity) and going short in stocks with low tail risk exposure (i.e., stocks in the bottom quintile of crash sensitivity).[18] To control for tail risk potentially induced by other trading strategies of funds, we also compute funds' exposures to the Agarwal and Naik (2004) OTM call option factor, the Fung and Hsieh (2004) trend-following factors,[19] the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Buraschi, Kosowski, and Trojani (2014) correlation risk factor, and the VIX.

We estimate hedge fund *i*'s univariate exposures to different risk factors for month *t* based on a rolling window of 24 monthly returns. In a second step, we estimate Fama and MacBeth (1973) regressions at the individual hedge fund level of tail risk in month *t* (as defined in Section 2) on the exposures to the Agarwal and Naik (2004) put option factor and the Chabi-Yo, Ruenzi, and Weigert (2015) LTD-risk factor in month *t*:

$$TailRisk_{i,t} = \alpha + \lambda_1 \beta_{OTMPut,i,t} + \lambda_2 \beta_{LTD-Risk,i,t} + \lambda_3 \beta_{X,i,t} + \varepsilon_{i,t}, \qquad (6)$$

where $TailRisk_{i,t}$ is fund *i*'s tail risk, $\beta_{OTM\ Put}$ ($\beta_{LTD-Risk}$) denotes the univariate exposure to the Agarwal and Naik (2004) out-of-the-money (OTM) put option factor (the Chabi-Yo, Ruenzi, and Weigert (2015) equity tail risk factor) and β_X is a vector of exposures to the other risk factors described above. To adjust the standard errors for serial correlation, we use the Newey and West (1987) adjustment with 24 lags. Since we perform a two-step estimation procedure, we correct the standard errors for the errors-in-variables problem using the Shanken (1992) correction. Table 6 reports the results of this regression.

[Insert Table 6 here]

[18] Chabi-Yo, Ruenzi, and Weigert (2015) compute the tail risk of individual stocks based on the lower tail dependence of an individual stock return and the market return.

[19] Fung and Hsieh (2001, 2004) construct the trend-following factors as the returns on lookback straddles on bonds, currencies, commodities, interest rate, and equities.

In model (1), we regress tail risk on funds' exposure to the Agarwal and Naik (2004) out-of-the-money (OTM) put option factor ($\beta_{OTM\ Put}$). We find that tail risk is strongly negatively related to $\beta_{OTM\ Put}$ with a slope coefficient of –12.46, which indicates that tail risk is positively related to a trading strategy of writing out-of-the-money put options on the equity market index.[20] This relation is statistically significant at the 1% level with a *t*-statistic of –3.63. Model 2 investigates the relation of tail risk and $\beta_{LTD\ Risk}$, the sensitivity to the Chabi-Yo, Ruenzi, and Weigert (2015) high minus low LTD-Risk factor. We find a highly significant positive relation between tail risk and $\beta_{LTD\ Risk}$ (coefficient of 0.630; *t*-statistic = 10.31), which indicates that tail risk is related to a trading strategy of buying stocks with high tail risk and selling stocks with low tail risk. In model 3, we regress *TailRisk* on funds' sensitivites to both, the OTM put option factor and the equity tail risk factor. We continue to find that tail risk is positively related to $\beta_{LTD\ Risk}$ and negatively related to $\beta_{OTM\ Put}$. Finally, in model (4), we regress *TailRisk* on the complete set of hedge fund return sensitivites. Our main results remain unchanged: We still observe that tail risk is driven by a fund's sensitivity to the OTM put option factor and the equity tail risk factor. A one standard deviation increase in $\beta_{LTD\ Risk}$ increases a fund's tail risk by 0.13, while a one standard deviation decrease in $\beta_{OTM\ Put}$ increases a fund's tail risk by 0.26.

5. Tail Risk and Portfolio Holdings

5.1 Tail risk induced from equity holdings of hedge funds

Our results hitherto suggest that a hedge fund's tail risk is induced by both dynamic trading as well as by portfolio holdings of stocks with high equity tail risk. We now dig deeper and investigate whether we can find direct evidence of the sources of funds' tail risk using their disclosed 13F portfolio holdings that include long positions in equities. To establish direct evidence between tail risk induced by equity holdings and tail risk estimated from hedge fund returns, we use the Thomson Reuters 13F database that provides common stock holdings of more than 5,000 institutional managers with 100 million or more in 13F

[20] This result also suggests that tail risk can be reduced by a trading strategy of holding long put options. Later in Section 5 of the paper, we investigate the relation between actual long put option positions of hedge funds and their tail risk.

securities (i.e., equities, convertible bonds, and options). The database provides long equity holdings of 1,694 manually classified hedge fund firms. The merge between the Union Hedge Fund Database and the 13F portfolio holdings follows Agarwal, Fos, and Jiang (2013) as explained earlier in Section 2. Our final sample consists of 793 hedge fund firms managing 2,720 distinct hedge funds during the period from 1994 to 2012.

Since portfolio holdings are reported at the hedge fund firm level, we first compute excess return of hedge fund firm *i* in month *t* as the value-weighted reported excess returns of the firm's individual hedge funds. We then compute a hedge fund firm *i*'s tail risk in month *t* based on the firm's reported excess returns and the market using an estimation horizon of 24 months. Second, using the 13F equity portfolio holdings, we compute the excess equity portfolio return of a hedge fund firm as the value-weighted excess returns of the firm's disclosed stock positions. Specifically, to obtain a return series of monthly observations, we use hedge fund firm *i'*s disclosed equity positions in month *t* to compute the equity portfolio return over months *t+1* to *t+3*. As an example, we use the disclosed portfolio positions of hedge fund *i* at the end of December 2011 to compute the equity portfolio return for the months from January 2012 to March 2012. To compute the equity portfolio return for the months from April 2012 to June 2012, we then use the disclosed positions at the end of March 2012, and so on. Finally, we calculate a hedge fund firm *i*'s equity tail risk in month *t* based on the firm's equity portfolio returns and the market using an estimation horizon of 24 months. We also estimate different risk characteristics from a firm's equity portfolio returns such as the standard deviation, skewness, kurtosis, *ES*, market beta, as well as upside and downside beta (defined as market beta when the market is above and below, respectively, its median return realization; see Ang, Chen, and Xing, 2006). In addition, we compute different portfolio firm characteristics using the value-weighted average of liquidity, size, book-to-market, and past yearly return of the underlying stocks.

To analyze the relation between hedge funds' tail risk from reported returns and equity tail risk estimated from disclosed equity positions, we estimate Fama and MacBeth (1973) regressions. We regress tail risk of hedge fund firm *i* in month *t* on hedge fund firm *i*'s holdings-based portfolio equity tail risk in month *t* controlling for different equity portfolio risk and firm characteristics using the Newey and West (1987) adjustment with 24 lags:

$$TailRisk_{i,t} = \alpha + \beta_1 Equity\ TailRisk_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t}, \quad (7)$$

where $TailRisk_{i,t}$ denotes fund *i*'s tail risk in month *t*, $Equity\ TailRisk_{i,t}$ is tail risk based on equity portfolio holdings as described above and $X_{i,t}$ is a vector of equity portfolio risk and fund characteristics. Table 7 reports the results.

[Insert Table 7 here]

In model (1), we use equity tail risk as the only explanatory variable. It has a positive impact and is highly statistically significant at the 1% level. This finding provides direct evidence of a strong positive relation between a hedge fund's tail risk and tail risk induced by its equity holdings. In models (2) to (5), we expand our specification to control for various portfolio characteristics. In model (2), we add return standard deviation, skewness, kurtosis, *ES*, market beta (all based on disclosed holdings). Our results reveal that fund tail risk is also positively related to market beta but shows no statistically significant relation to any of the other controls. When we split market beta into upside beta and downside beta in model (3), we find the intuitive result that downside beta is driving this finding. These results also hold in model (4), where we include , liquidity, size, book-to-market, and past yearly returns (again all based on disclosed equity holdings) as additional controls. More importantly, in all regressions, equity tail risk is significantly positively related to tail risk estimated from fund returns at the 1% level.

The impact of equity tail risk is also economically important. We find that a one standard deviation increase of equity tail risk increases fund tail risk by 0.07. This implies a relative increase of almost 20% as the tail risk for equity-related funds is 0.38 (see Panel C of Table 1). This is the largest effect in terms of economic magnitude of all variables included in model (4).

Models (1) to (4) ignore the possible impact of fund firm leverage in the relation between equity tail risk and fund tail risk. Intuitively, equity tail risk should matter more if the hedge fund firm employs a higher level of equity leverage. To account for this issue, we follow Farnsworth (2014) and compute a hedge fund firm *i*'s long-only leverage in month *t* as the market capitalization of equity portfolio positions divided by firm *i*'s assets under

management.[21] In model (5), we add the interaction of equity tail risk with this long-only leverage measure as an additional independent variable. As expected, we find this interaction term to be positive and statistically significant.

In summary, this section shows that tail risk of hedge funds is to a significant extent directly induced by tail risk of their long equity positions.

5.2 Tail risk and option holdings of hedge funds

In addition to tail risk induced from long equity holdings, we had earlier found that a hedge fund's sensitivity to an out-of-the-money put option factor was one of the main factors to explain fund tail risk in Table 7. Since 13F filings only include long positions in options, we cannot observe if hedge funds explicitly write out-of-the-money put options that would exacerbate their tail risk. However, we can investigate whether some hedge fund firms reduce their tail risk by holding long positions in put options.

To test this hypothesis we use option holdings data from 13F filings from the SEC EDGAR database. Specifically, we analyze long call and put option holdings of the 793 hedge fund firms in our sample during the period from the first quarter of 1999 to the last quarter of 2012. We find that during this period 51.2% of hedge fund firms in our sample (i.e., 406 of 793 firms) file at least one long option position. To merge fund firms that disclose their option positions quarterly with monthly fund firm tail risk estimates, we again use the convention that disclosed positions in month *t* are carried forward for the subsequent months *t+1* to *t+3*.

To investigate if holding long put options reduces fund tail risk, we compute for hedge fund firm *i* in month *t*, (a) the number of different stocks on which funds hold put positions, (b) the equivalent *number* of equity shares underlying these put positions (in millions), and (c) the equivalent *value* of equity shares underlying these put positions (in millions). [22] Unfortunately, the data does not contain information that would allow us to calculate the actual value of the option positions, which is why we rely on these coarser

[21] In order to reduce the impact of outliers, we winsorize our measure of long-only leverage at the 1% level.

[22] We illustrate these measures with an example: Assume that a fund holds put options on 10,000 shares of stock A that trades at $30 and 5,000 shares of stock B that trade at $20. Then, (i) the number of stocks on which put options are held is 2, (ii) the equivalent number of equity shares underlying the put positions is 15,000, and (iii) the equivalent value of equity shares underlying these put positions is $400,000.

measures of option use. We winsorize the number and the value of equity shares at the 1% level to mitigate the influence of outliers.

In our sample, the average number of different stocks on which put (call) positions are held is 3.54 (3.55), the number of equity shares underlying the put (call) positions is 1.59 (1.61) million, and the value of equity shares underlying the put (call) positions is $18.13 ($17.89) million.[23]

We regress tail risk of hedge fund firm *i* in month *t* on fund firm *i*'s option holdings in month *t* using the Newey and West (1987) adjustment with 24 lags. Table 8 reports the results.

[Insert Table 8 here]

In models (1) through (3), we regress tail risk on the number of different call and put options, the number of shares underlying these call and put options, and the value of shares underlying these call and put options, respectively. We find that the number of shares underlying the put options and the value of shares underlying the put options significantly reduce fund firms' tail risk. There is never any significant impact of the call option positions. In model (4), we estimate a regression of fund firms' tail risk jointly on all variables regarding hedge funds' derivative exposure. We find that both the number of put options and the value of shares underlying the put options significantly reduce a hedge fund firm's tail risk. A one standard deviation increase in the number of put options (value of shares underlying the put options) reduces fund tail risk by an economically significant value of 0.13 (0.08). Again, none of the call option variables has a significant impact. Overall, these results provide at least some suggestive evidence that hedge fund firms can reduce tail risk by taking long positions in put options.

6. Tail Risk Timing: Evidence from the Financial Crisis in 2008

In the last part, we now investigate whether hedge funds possess tail risk timing ability. Although hedge funds with high tail risk on average outperform funds with low tail risk, they earn very low returns during market downturns. As an example, we observe that the

[23] Please note that in our empirical analysis we retain all fund firms in the sample that do not disclose long option holdings at all. This reduces the average number and value of equity shares underlying the option positions considerably. Our main results regarding the relation between tail risk and long put holdings remain unaffected whether we include or exclude these firms.

decile of hedge funds with the highest tail risk (measured in September 2008 based on the previous 24 months) underperforms the decile of hedge funds with the lowest tail risk by –20.82% during October 2008, which is the worst financial crisis during our sample period with a CRSP value-weighted market return of –17.23%.[24] Hence, being able to reduce tail risk before severe market crises would be particularly beneficial.

To examine whether funds exhibit tail risk timing ability, we examine their equity and option positions shortly before and during October 2008. We first study funds' timing ability with regard to their equity positions. To do so, we look at funds' equity portfolio holdings and compare differences between actual equity tail risk and *hypothetical* equity tail risk for the sample of equity-related hedge fund firms during the financial crisis of October 2008.[25] To estimate hypothetical equity tail risk for hedge fund firm *i*, we look at its portfolio disclosures six months before the worst market crash happened, in March 2008. We then compute hypothetical tail risk for hedge fund firm *i* over the following year under the assumption that the fund manager did not change the fund's portfolio composition and continued to hold the same portfolio as in March 2008. In contrast, actual tail risk is computed as before based on actual portfolio holdings information updated over time. Figure 4 plots the development of aggregate actual equity tail risk (taken over all equity-related hedge fund firms in our sample) and aggregate hypothetical equity tail risk during the period from March 2008 to March 2009.

[Insert Figure 4 here]

Figure 4 shows that actual aggregate actual equity tail risk is lower than aggregate hypothetical equity tail risk beginning from August 2008 onwards and remains so until March 2009. We also perform a mean comparison test between hedge fund firms' actual tail risk and hypothetical tail risk in October 2008 in Panel A of Table 9.

[Insert Table 9 here]

[24] Looking at all months in our sample period with a market return of smaller than –10% (six months in total), we find that the decile portfolio of hedge funds with the highest tail risk underperforms the decile portfolio with the lowest tail by –10.41%. This spread is statistically significant at the 5% level (with a *t*-statistic of –3.14).

[25] Given the relatively short sample period, we choose this approach rather than using the timing factor in a multifactor model that has also been used in the literature (e.g., Chen, 2007; Chen and Liang, 2007; and Cao, Chen, Liang, and Lo, 2013).

Our results indicate that in October 2008, the aggregate hypothetical equity tail risk of hedge funds was 1.19 while aggregate actual equity tail risk of funds was 1.11. The difference of 0.08 is statistically significant at the one percent level with a *t*-statistic of 3.60. These findings show that the average fund did reduce its tail risk exposure by investing less in stock long positions that have high tail exposure prior to the crisis (i.e. between March and September 2008).

In the next step, we analyze whether hedge funds also used options to time tail risk, i.e. whether they increased their long positions in put options before October 2008. We plot the number of different stocks in which funds hold put options and the number and value of equity shares underlying the put positions of hedge funds during the period from March 2008 to March 2009 in Figure 5.

[Insert Figure 5 here]

We find that hedge funds increase both the number of different stocks on which funds hold put options as well as the number and value of equity shares underlying the put positions substantially from March 2008 to December 2008. Subsequently, they reduce these positions again. Panel B of Table 9 formalizes these observations in performing a mean comparison test between the number of different stocks in which funds hold put options (the number of equity shares underlying the put positions, the value of equity shares underlying the put positions) in March 2008 and October 2008. Our results reveal that the number of different stocks with put positions (the number of equity shares underlying the put positions, the value of equity shares underlying the put positions) in March 2008 was 4.14 (1.51 million, $26.25 million), whereas this number amounts to 5.90 (2.71 million, $36.53 million) in October 2008. The difference amounts to 1.76 (1.20 million, $10.28 million) and is statistically significant at the five percent level or better with a *t*-statistic of 2.03 (3.14, 4.51), showing that hedge funds on average increased their long positions in puts.[26]

Next, we investigate whether hedge funds hold put options on exactly those stocks that have higher tail risk. For this purpose, we compute for each stock *i* in October 2008, (a) the number of different hedge funds that hold put positions on this stock, (b) the overall

[26] The increasing number of put option positions of hedge funds between March 2008 and October 2008 is not driven by increases in funds' size. Actually, the average assets under management of hedge funds is $872.55 million in March 2008, which reduces to $715.67 million in October 2008.

number of equity shares held by different hedge funds underlying the put positions (in millions) on this stock, and (c) the overall value of equity shares held by different hedge funds underlying the put positions (in $ millions) on this stock. Then, we regress these stock-level put option measures on tail risk and different stock characteristics measured in September 2008.

Panel C of Table 9 reports the regression results using standard errors clustered by stock. Models (1) through (3) show the results of univariate regressions. We find that the higher the tail risk of a stock, the higher the number of different hedge funds holdings put positions on this stock and the higher is the overall number and value of equity shares underlying these put positions.

These effects could also be driven by the size of the respective stock (as larger stocks might be simply more likely to appear in hedge fund portfolios) or by hedge fund preferences for certain stock characteristics. Thus, in models (4) through (6), we additionally control for firm size and additional firm and return characteristics of the stocks. When controlling for these characteristics, we do not find a significant impact of equity tail risk on the number of equity shares underlying the put positions anymore. However, the impact remains statistically significant at the 1% and 10% level, respectively, for the number of different funds holding put positions on this stock and the overall value of equity shares underlying the put positions.

Finally, we examine whether differences in timing abilities across hedge fund firms are also reflected in cross-sectional performance differences. To address this issue, we sort hedge fund firms into tercile portfolios based on their tail risk timing ability. In particular, we use four different metrics for these sorts, which we also used in our previous analysis on aggregate timing ability. First, we take the difference of actual equity tail risk and hypothetical equity tail risk timing in October 2008. Second, we take the difference in the number of different stocks in which funds hold put options as well as the number and value of equity shares underlying the put positions between October 2008 and March 2008. We then compute the excess returns of these portfolios in October 2008 and assess return differences between portfolio 3 (good timers) and portfolio 1 (bad timers). Results are reported in Panel D. We find that the good timers' portfolios indeed outperform the bad

timers' portfolios using all four metrics of tail risk timing ability with statistically significant spreads ranging from 3.61% to 5.06%.

To summarize, our results in this section are consistent with hedge funds reducing tail risk before the market crash of September 2008 by either reducing equity tail risk or increasing their positions in put options, particularly on stocks with high tail risk. Furthermore, if funds did so to a larger extent, this is also reflected in significantly better performance as compared to other funds.

7. Conclusion

It has been well documented that hedge funds use dynamic trading strategies and take state-contingent bets that can expose them to tail risk. In this paper, we propose a non-parametric measure of tail risk to show that equity-related hedge funds with high tail risk outperform equity-related funds with low tail risk by 5.3% per annum even after controlling for various risk factors in the Fung and Hsieh (2004) 7-factor model. Moreover, we find that tail risk can predict future hedge fund returns up to a horizon of six months. We then dig deeper to uncover the sources of tail risk and find it to be strongly related to a fund's exposure to a put writing strategy on the equity market as well as to an equity-based tail risk factor. Using hedge funds' mandatory disclosure of long equity positions, we provide evidence on a strong direct link between funds' tail risk and their investments in tail-sensitive stocks. We also show that funds that take more long positions in equity put options exhibit lower tail risk. Our results therefore suggest that both, funds' investments in stocks with high tail risk as well as their dynamic trading strategies, contribute to the tail risk.

We show that certain hedge fund characteristics are related to funds' tail risk. Specifically, tail risk is positively related to the delta, lockup period, and leverage of a fund. We also find evidence of a greater increase in tail risk during the 2008 financial crisis of funds that used Lehman Brothers as their prime broker compared to other funds, indicating that funding liquidity shocks can enhance tail risk.

Finally, we find that during the recent financial crisis in October 2008, the actual tail risk of hedge funds is significantly lower than the tail risk imputed from a hypothetical buy-and-hold equity portfolio based on their disclosed positions prior to the onset of the crisis. Moreover, we observe an increase in the long positions in put options of hedge funds prior to

October 2008. These findings suggests that hedge funds on average successfully reduced their exposure to tail risk prior to the onset of the crisis and indicates that hedge funds seem to possess some tail risk timing skills.

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Figure 1: Venn Diagram of the Union Hedge Fund Database

The Union Hedge Fund Database contains a sample of 25,732 hedge funds created by merging four commercial databases: Eureka, HFR, Morningstar, and Lipper TASS. This figure shows the percentage of funds covered by each database individually and by all possible combinations of multiple databases.

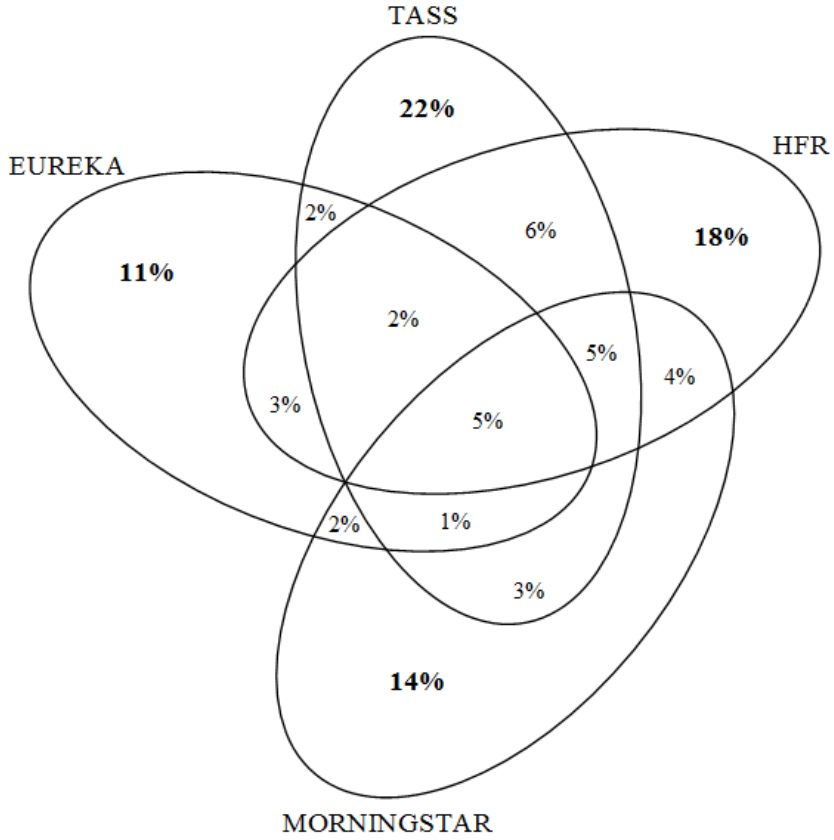

Figure 2: Aggregate Hedge Fund Tail Risk over Time

This figure displays the evolution of aggregate *TailRisk* over time. Aggregate *TailRisk* is defined as the monthly cross-sectional, equally-weighted average of the individual *TailRisk* measures over all hedge funds in our sample. We also show aggregate *TailRisk* separately for all equity-related and non-equity related hedge funds. Our sample covers hedge funds from the Union Hedge Fund Database constructed from combining Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1994 to December 2012.

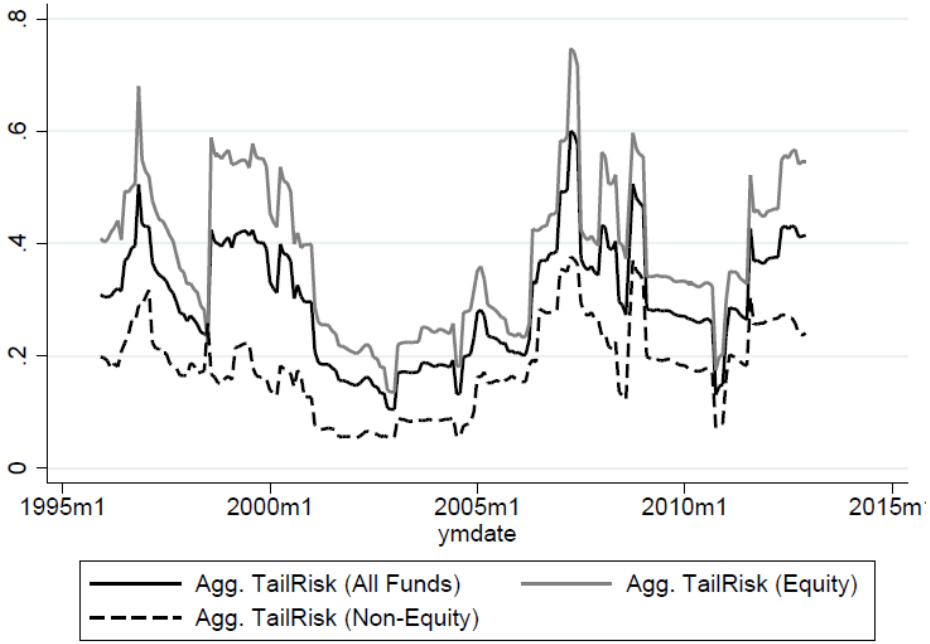

Figure 3: Tail Risk and Funding Liquidity: Evidence From Lehman Brothers connected Hedge Funds

This figure displays the evolution of aggregate *TailRisk* for equity-related hedge funds that had Lehman Brothers as a prime broker until September 2008 (solid line) and two matched samples of non-Lehman funds (dotted and dashed lines) from the Lipper TASS database during the period from September 2007 to August 2010. The dashed line corresponds to the first matched sample (Match1) using the propensity score from a model determining the choice of Lehman as a prime broker while the dotted line relates to the second matched sample (Match2) based on the same style and the same *TailRisk*, size, and past monthly excess return decile in August 2007. We estimate *TailRisk* each month based using prior 12 months of fund returns.

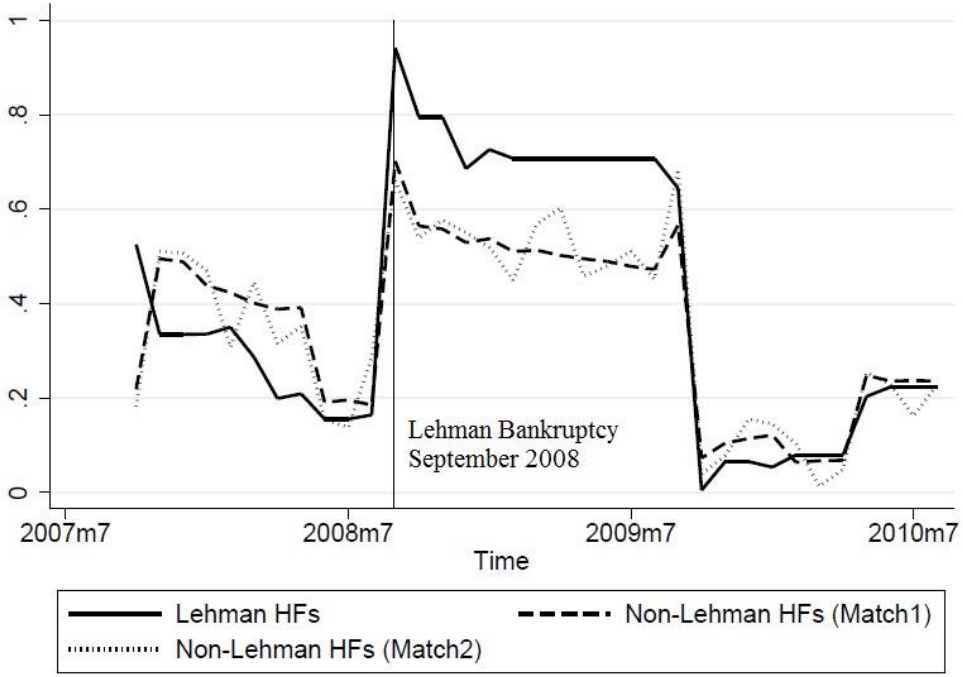

Figure 4: Tail Risk Timing: Evidence From Equity Holdings in the Financial Crisis 2008

This figure displays the evolution of aggregate actual *TailRisk* of hedge fund firms' disclosed long equity holdings (dashed line) and the evolution of aggregate hypothetical *TailRisk* based on hedge funds firms' disclosed long equity holdings from March 2008 (solid line) during the period from March 2008 to March 2009. We estimate *TailRisk* each month based using prior 24 months of returns. Our sample covers hedge fund firms from the Union Hedge Fund Database constructed from combining Eureka, HFR, Morningstar, and Lipper TASS databases who report 13F long equity holdings to the SEC.

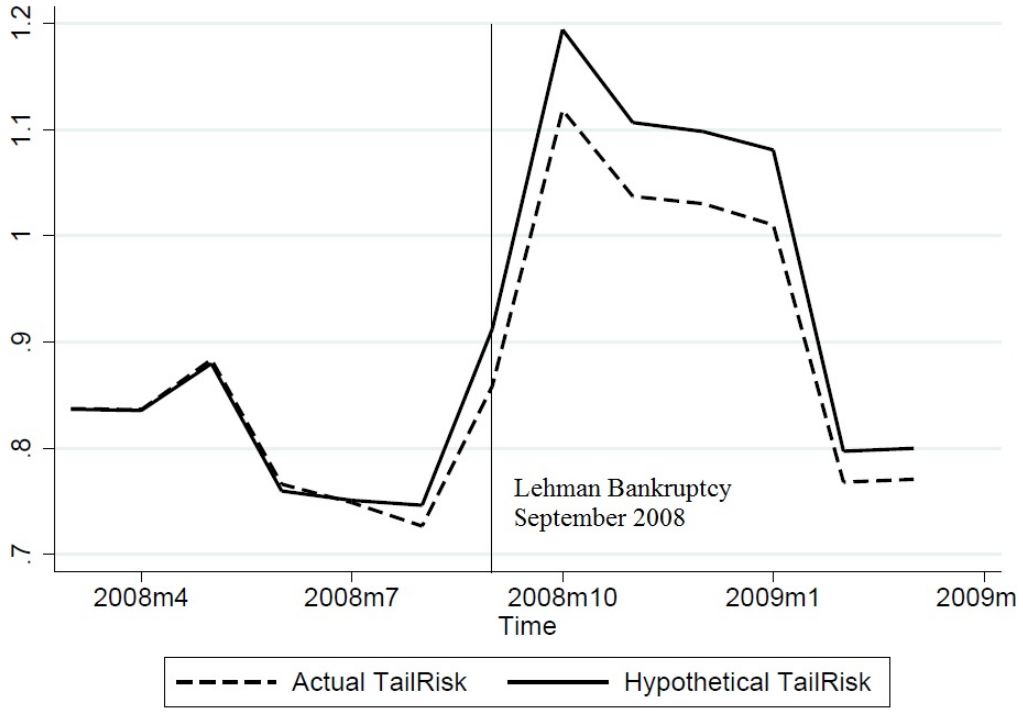

Figure 5: Tail Risk Timing: Evidence From Derivative Holdings in the Financial Crisis 2008

This figure displays the evolution of the average number of different stocks on which hedge funds hold put positions (*Different Put Options*, solid line) per hedge fund firm, the average number of equity shares (in millions) underlying the put positions of hedge funds (*Stocks Underlying Put Options*, dotted line) per hedge fund firm, and the average value of equity shares (in ten-millions) underlying the put positions of hedge funds (*Value of Stocks Underlying Put Options*, dashed line) per hedge fund firm during the period from March 2008 to March 2009. Our sample covers hedge fund firms from the Union Hedge Fund Database constructed from combining Eureka, HFR, Morningstar, and Lipper TASS databases who report 13F long derivative holdings to the SEC.

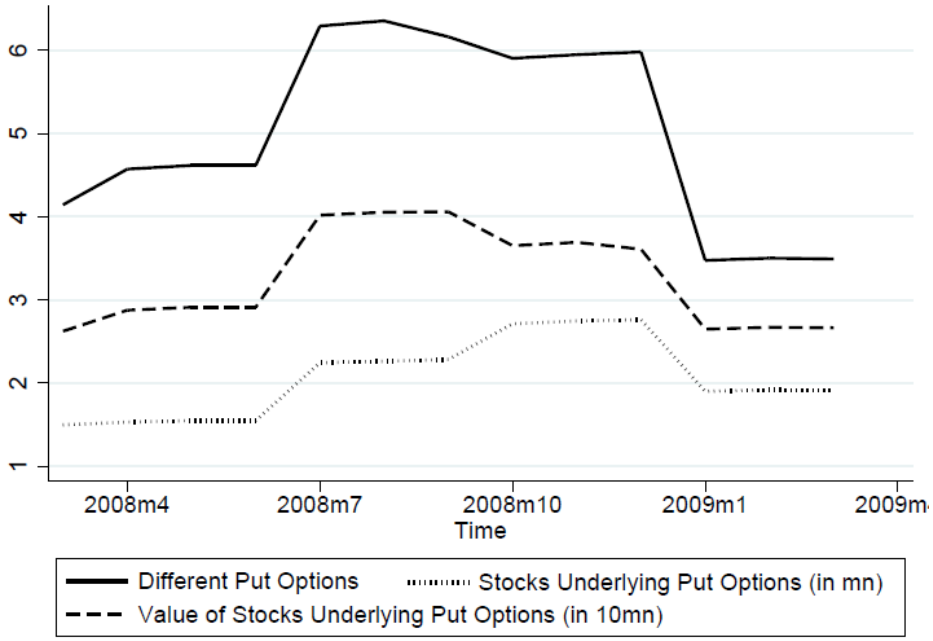

Table 1: Summary Statistics

This table provides summary statistics for excess returns of hedge funds over the risk-free rate (Panel A), fund characteristics (Panel B), and the *TailRisk* measure as defined in equation (2) in the main text (Panel C). Summary statistics for the *TailRisk* measure are calculated as the averages across all funds and across all 24-month periods over which the two measures are estimated. As the risk-free rate we use the one-month T-bill rate. We also display correlations between the aggregate *TailRisk* measure (computed as the equal-weighted average over all hedge funds) with various risk factors (as defined in the paper) in Panel D. Our sample covers hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1994 to December 2012.

Panel A: Excess Returns

Sample	Mean	25%	Median	75%	StdDev	Skew	Kurt
All	0.58%	–1.22%	0.47%	2.31%	5.76	2.13	83.12
Equity Related	0.52%	–0.98%	0.42%	1.89%	5.23	2.86	117.44
Non–Equity Related	0.62%	–1.40%	0.52%	2.64%	6.11	1.78	68.74

Panel B: Fund Characteristics

Variable	Mean	25%	Median	75%	StdDev	Skew	Kurt
AUM (in mio)	125.63	8.00	30.00	104.00	280.75	4.32	24.12
Market Beta	0.35	0.03	0.24	0.61	0.54	0.34	23.41
Delta (in 100 thousands)	1.97	0.06	0.37	1.59	4.38	3.77	18.27
Offshore Dummy	0.53	0.00	1.00	1.00	0.49	–0.13	1.02
Management Fee (in %)	1.51	1.00	1.50	2.00	0.68	2.70	27.68
Incentive Fee (in %)	18.10	20.00	20.00	20.00	6.07	–1.49	8.39
Min Investment (in 100T)	11.61	1.00	5.00	10.00	76.48	56.52	3636.99
Leverage Dummy	0.63	0.00	1.00	1.00	0.48	–0.55	1.31
Lockup Period (in years)	0.33	0.00	0.00	1.00	0.57	2.63	18.25
Restriction Period (in years)	0.29	0.13	0.21	0.38	0.28	2.51	12.20
HWM Dummy	0.78	1.00	1.00	1.00	0.42	–1.34	2.80
Hurdle Rate Dummy	0.25	0.00	0.00	1.00	0.43	1.14	2.31
Age (in months)	63.15	22.00	47.00	89.00	55.92	1.52	5.92

Panel C: TailRisk

Strategy	Number of Funds	Avg TailRisk	10%	25%	Median	75%	90%	Std Dev
Emerging Markets	531	0.51	0.00	0.00	0.26	0.81	1.36	0.71
Event Driven	852	0.25	0.00	0.00	0.04	0.35	0.66	0.42
Equity Long-Short	3736	0.41	0.00	0.00	0.21	0.64	1.10	0.58
Equity Long Only	331	0.49	0.00	0.00	0.30	0.76	1.24	0.68
Equity Market Neutral	1,265	0.12	0.00	0.00	0.00	0.10	0.39	0.29
Short Bias	66	0.07	0.00	0.00	0.00	0.00	0.12	0.27
Sector	250	0.49	0.00	0.00	0.26	0.75	1.30	0.70
Equity Related	6,281	0.38	0.00	0.00	0.12	0.58	1.06	0.58
CTA	1,094	0.17	0.00	0.00	0.00	0.00	0.65	0.50
Global Macro	599	0.23	0.00	0.00	0.00	0.29	0.77	0.49
Multi-Strategy	1,265	0.19	0.00	0.00	0.00	0.21	0.61	0.41
Relative Value	1,142	0.16	0.00	0.00	0.00	0.17	0.48	0.35
Others	453	0.23	0.00	0.00	0.09	0.33	0.61	0.35
Non-Equity Related	4,553	0.19	0.00	0.00	0.00	0.20	0.61	0.43
All	10,834	0.30	0.00	0.00	0.00	0.45	0.92	0.53

Panel D: Correlation between Aggregate TailRisk and Hedge Fund Risk Factors

	TailRisk	Market	TED Spread	PS Liquidity	Macro Uncertainty	Correlation Risk	VIX
TailRisk	1.00						
Market	–0.03	1.00					
TED Spread	0.49	–0.18	1.00				
PS Liquidity	–0.04	0.25	–0.18	1.00			
Macro Uncertainty	–0.16	0.00	0.01	–0.06	1.00		
Correlation Swap	0.07	–0.48	0.13	–0.16	–0.06	1.00	
VIX	0.09	–0.39	0.44	–0.25	0.52	0.12	1.00

Table 2: Tail Risk and Hedge Fund Performance

This table reports the results from the analysis of the relation between *TailRisk* of hedge funds in month *t* and their monthly excess returns in month *t+1*. Panel A reports the results from equal-weighted univariate portfolio sorts based on *TailRisk* in month *t* and risk-adjusted returns in month *t*+1. In each month, we rank funds into portfolios based on their lagged realized *TailRisk* and form equally-weighted portfolios at the beginning of each month. The column "Excess Return" reports the average portfolio return in excess of the one-month T-bill rate in the following month. The columns labeled "Car-4-Factor" and "FH-7-Factor" report the monthly alpha using the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model. In Panel B, we regress the return of a portfolio consisting funds in portfolio 1 with the lowest tail risk subtracted from the returns of the funds in portfolio 10 with the highest tail risk, on different risk factors. As risk factors, we use in addition to the factors in the Fung and Hsieh (2004) seven-factor model presented in the first column, the MSCI Emerging Markets factor (MSCI EM), the Pástor and Stambaugh (2003) traded liquidity factor (Traded PS Liquidity), the Fama and French (1993) value factor (HML), Carhart (1997) momentum factor (UMD), and the returns of a long-short hedge funds portfolio with regard to the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor (Return Macro), the Buraschi, Kosowski, and Trojani (2014) correlation risk factor (Return CORR), and the VIX (Return VIX). The seven factors in Fung and Hsieh (2004) model include the three trend-following risk factors constructed using portfolios of lookback straddle options on currencies (PTFSFX), commodities (PTFSCOM), and bonds (PTFSBD); two equity-oriented risk factors constructed using excess S&P 500 index returns (S&P), and the return difference of Russell 2000 index and S&P 500 index (SCMLC); two bond-oriented risk factors constructed using 10-year Treasury constant maturity bond yields (BD10RET), and the difference in yields of Moody's Baa bonds and 10-year Treasury constant maturity bonds (BAAMTSY), all yields adjusted for the duration to convert them into returns. Panel C reports the results of Fama and MacBeth (1973) regressions of excess returns in month *t+1* on *TailRisk* and different fund characteristics (as defined in the main text) measured in month *t.* Finally, Panel D shows the results of Fama and MacBeth (1973) regressions of future excess returns with different horizons on *TailRisk* and different fund characteristics measured in month *t.* We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation in all Fama and MacBeth (1973) regressions. Our sample covers hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1994 to December 2012. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Univariate Portfolio Sorts

		All Funds			Equity-Related Hedge Funds			Non-Equity Related Hedge Funds		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Portfolio	TailRisk	Excess Return	Car-4-Factor	FH-7-Factor	Excess Return	Car-4-Factor	FH-7-Factor	Excess Return	Car-4-Factor	FH-7-Factor
1 (Lowest)	0.00	0.45%	0.33%	0.36%	0.49%	0.28%	0.34%	0.47%	0.42%	0.42%
2	0.11	0.42%	0.33%	0.34%	0.45%	0.31%	0.36%	0.38%	0.33%	0.32%
3	0.25	0.38%	0.27%	0.28%	0.36%	0.23%	0.28%	0.41%	0.29%	0.28%
4	0.37	0.47%	0.30%	0.31%	0.49%	0.27%	0.31%	0.41%	0.30%	0.30%
5	0.46	0.50%	0.31%	0.31%	0.49%	0.28%	0.30%	0.53%	0.37%	0.37%
6	0.57	0.63%	0.36%	0.39%	0.61%	0.31%	0.35%	0.61%	0.41%	0.42%
7	0.70	0.60%	0.38%	0.40%	0.60%	0.36%	0.39%	0.49%	0.37%	0.36%
8	0.88	0.66%	0.40%	0.43%	0.65%	0.41%	0.42%	0.75%	0.49%	0.53%
9	1.15	0.80%	0.59%	0.59%	0.87%	0.53%	0.52%	0.64%	0.47%	0.48%
10 (Highest)	2.01	1.01%	0.86%	0.76%	1.13%	0.83%	0.78%	0.64%	0.52%	0.49%
10-1	2.01	0.56%**	0.53%**	0.40%*	0.64%**	0.55%***	0.44%**	0.17%	0.10%	0.07%
		(2.02)	(2.18)	(1.87)	(2.25)	(3.21)	(2.00)	(0.50)	(0.26)	(0.35)

Table 2: (Continued)

Panel B: Equity-Related Hedge Funds: Additional Factors

	(1) PF 10–1	(2) PF 10–1	(3) PF 10–1	(4) PF 10–1	(5) PF 10–1	(6) PF 10–1	(7) PF 10–1	(8) PF 10–1
S&P	0.860***	0.624***	0.607***	0.592***	0.614***	0.621***	0.278***	0.172**
	(17.35)	(8.88)	(9.28)	(8.50)	(8.73)	(8.81)	(3.49)	(2.22)
SCMLC	0.282***	0.196***	0.156***	0.220***	0.192***	0.195***	0.0944	–0.0524
	(4.52)	(3.13)	(2.66)	(3.56)	(3.08)	(3.09)	(1.63)	(–0.88)
BD10RET	–0.203*	–0.194*	–0.164	–0.188	–0.191	–0.213*	–0.0623	–0.0226
	(–1.66)	(–1.67)	(–1.52)	(–1.65)	(–1.65)	(–1.81)	(–0.59)	(–0.23)
BAAMTSY	0.366***	0.283**	0.364***	0.268**	0.311***	0.256**	0.0782	0.102
	(2.99)	(2.40)	(3.29)	(2.31)	(2.61)	(2.13)	(0.72)	(1.01)
PTFSBD	0.0514***	0.0570***	0.0453***	0.0522***	0.0580***	0.0557***	0.0448***	0.0533***
	(3.29)	(3.82)	(3.22)	(3.55)	(3.89)	(3.65)	(3.30)	(4.21)
PTFSFX	–0.00178	–0.00283	0.000530	–0.00232	–0.00413	–0.00311	–0.00442	0.00288
	(–0.13)	(–0.22)	(0.05)	(–0.19)	(–0.33)	(–0.24)	(–0.39)	(0.27)
PTFSCOM	–0.0162	–0.0149	–0.0187	–0.00630	–0.0160	–0.0149	–0.0185	–0.00686
	(–0.97)	(–0.93)	(–1.25)	(–0.39)	(–1.00)	(–0.92)	(–1.29)	(–0.51)
MSCI EM		0.215***	0.184***	0.203***	0.227***	0.217***	0.104**	0.0101
		(4.54)	(4.15)	(4.36)	(4.73)	(4.56)	(2.29)	(0.22)
HML			–0.321***					
			(–5.60)					
UMD				–0.116***				
				(–3.01)				
Traded PS Liquidity					–0.0756			
					(–1.47)			
Return Macro						–0.0571		
						(–1.03)		
Return CORR							0.610***	
							(7.11)	
Return VIX								0.737***
								(9.01)
Alpha	0.437**	0.436**	0.508**	0.498**	0.483**	0.518**	0.356*	0.543***
	(2.00)	(2.06)	(2.57)	(2.39)	(2.26)	(2.35)	(1.86)	(3.02)
Observations	204	204	204	204	204	204	204	204
Adjusted R^2	0.673	0.703	0.743	0.715	0.705	0.705	0.765	0.791

Table 2: (Continued)

Panel C: Fama and MacBeth Regressions

	(1) Future Excess Return	(2) Future Excess Return	(3) Future Excess Return	(4) Future Excess Return
TailRisk	0.451**	0.226***	0.425*	0.217***
	(2.01)	(3.37)	(1.85)	(3.20)
Size		–0.0857***		–0.0847***
		(–3.39)		(–3.30)
Age		–0.000620		–0.000192
		(–1.52)		(–0.47)
Past Yearly Return		0.0240***		0.0233***
		(6.10)		(9.37)
Standard Deviation		0.0370*		0.0395*
		(1.95)		(1.94)
Skewness		0.0336		0.0261
		(0.81)		(0.68)
Kurtosis		–0.00934		–0.0149
		(–0.73)		(–1.21)
VaR		0.0110		0.00959
		(0.66)		(0.55)
ES		0.00284		0.00567
		(0.15)		(0.25)
Beta		0.105		0.0995
		(0.46)		(0.43)
Delta		0.0191***		0.0166***
		(4.04)		(3.16)
Lockup Period			0.0885**	0.0559*
			(2.06)	(1.75)
Restriction Period			0.0225	0.0592
			(0.41)	(1.58)
Min Investment			0.00161	0.00199***
			(1.44)	(2.80)
Leverage			0.00617	0.0255
			(0.13)	(0.66)
Offshore			–0.0135	0.0253
			(–0.14)	(0.35)
Management Fee			0.0718	0.0393
			(1.39)	(1.01)
Incentive Fee			0.00167	–0.000103
			(0.47)	(–0.04)
Hurdle Rate			0.141***	0.0961***
			(5.28)	(4.47)
HWM			0.120**	0.0968**
			(2.09)	(2.14)
Constant	0.426***	0.615***	0.108	0.360***
	(3.08)	(4.56)	(0.82)	(2.72)
Observations	420,329	287,383	261,478	195,170
Adjusted R^2	0.058	0.212	0.080	0.236

Table 2: (Continued)

Panel D: Predictability of TailRisk on Longer-Term Returns

	(1) Baseline Holding Period: 1 month	(2) Excess Return Holding Period: 2 months	(3) Excess Return Holding Period: 3 months	(4) Excess Return Holding Period: 6 months	(5) Excess Return Holding Period: 12 months
TailRisk	0.217***	0.316**	0.387**	0.545*	0.617
	(3.20)	(2.40)	(2.20)	(1.87)	(1.20)
Size	–0.0847***	–0.270***	–0.251***	–0.488***	–0.843***
	(–3.30)	(–3.82)	(–3.67)	(–3.73)	(–3.39)
Age	–0.000192	0.000866	–0.000343	–0.000944	–0.00128
	(–0.47)	(0.79)	(–0.33)	(–0.45)	(–0.32)
Past Yearly Return	0.0233***	0.0435***	0.0633***	0.0976***	0.134***
	(9.37)	(8.57)	(8.37)	(7.89)	(8.61)
Standard Deviation	0.0395*	0.0612**	0.0842*	0.104**	0.142**
	(1.94)	(2.14)	(1.91)	(2.13)	(2.12)
Skewness	0.0261	0.0953**	0.224*	0.241*	0.331
	(0.68)	(1.12)	(1.84)	(1.21)	(1.11)
Kurtosis	–0.0149	0.00557	–0.0207	–0.0364	–0.149
	(–1.21)	(0.16)	(–0.60)	(–0.55)	(–0.84)
VaR	0.00959	–0.0202	0.0150	0.0542	0.106
	(0.55)	(–0.53)	(0.45)	(0.80)	(1.02)
ES	0.00567	0.00362	–0.0481	–0.135*	–0.176
	(0.25)	(0.07)	(–1.27)	(–1.66)	(–1.05)
Beta	0.0995	0.619	0.626	1.410	2.548
	(0.43)	(0.69)	(0.95)	(1.11)	(1.10)
Delta	0.0166***	0.0798***	0.0482***	0.0993***	0.194***
	(3.16)	(3.40)	(3.64)	(3.51)	(2.84)
Lockup Period	0.0559*	0.208***	0.200**	0.442**	1.085***
	(1.75)	(2.63)	(2.30)	(2.29)	(2.80)
Restriction Period	0.0592	0.159	0.151	0.332	0.645
	(1.58)	(1.33)	(1.08)	(1.15)	(1.09)
Min Investment	0.00199***	0.00285	0.00493**	0.0113***	0.0257***
	(2.80)	(1.29)	(2.51)	(2.74)	(2.83)
Leverage	0.0255	0.0578	0.132	0.162	0.218
	(0.66)	(0.57)	(1.14)	(0.68)	(0.43)
Offshore	0.0253	0.0592	0.0318	0.223	0.668
	(0.35)	(0.31)	(0.15)	(0.50)	(0.78)
Management Fee	0.0393	0.103	0.146	0.315	0.469
	(1.01)	(1.02)	(1.36)	(1.44)	(1.09)
Incentive Fee	–0.000103	–0.00663	0.000613	–0.00181	–0.0179
	(–0.04)	(–1.35)	(0.07)	(–0.10)	(–0.84)
Hurdle Rate	0.0961***	0.174*	0.276***	0.676***	1.432***
	(4.47)	(1.69)	(4.71)	(4.37)	(3.05)
HWM	0.0968**	0.202	0.252*	0.568*	1.407**
	(2.14)	(1.46)	(1.78)	(1.89)	(2.03)
Constant	0.360***	1.090***	1.173***	2.097***	3.868**
	(2.72)	(2.71)	(3.03)	(2.76)	(2.26)
Observations	195,170	194401	190953	189598	186512
Adjusted R^2	0.236	0.256	0.257	0.251	0.255

Table 3: Tail Risk and Hedge Fund Performance: Robustness Checks

This table reports the results from robustness checks of the relation between *TailRisk* of hedge funds in month *t* and their monthly excess returns in month *t+1*. We investigate the robustness if we (i) change the estimation horizon of the *TailRisk measure* to 3 and 4 years, respectively, (ii) compute *TailRisk* using different cut-off values of 10% and 20% to define worst returns, (iii) use VaR instead of ES in the computation of *TailRisk*, (iv) apply a value-weighted sorting procedure instead of an equal-weighted sorting procedure, and (v) use daily returns instead of monthly returns to estimate *TailRisk* for a subsample of funds that report daily returns to Bloomberg. Panel A displays the results of from the same univariate portfolio sorts as in Column 7, Panel A, Table 2 using these alternative definitions of *TailRisk*. Panel B reports the results of Fama and MacBeth (1973) regression (4) of Panel D in Table 2 of future excess returns in month *t+1* on the same alternative *TailRisk* definitions and different fund characteristics measured in month *t*. The baseline specification in Column (1) is to estimate *TailRisk* as in Table 2 with two years of monthly returns with a cut-off percentile of 5% of the return observations. Our sample covers hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1994 to December 2012. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively. We only display the results of the relation between *TailRisk* and future excess returns (control variables are included but suppressed in the table).

Panel A: Equity-Related Hedge Funds: Portfolio Sorts

	(1) Equity-Related Baseline	(2) Equity-Related Horizon 3y	(3) Equity-Related Horizon 4y	(4) Equity-Related Cut-Off 10%	(5) Equity-Related Cut-Off 20%	(6) Equity-Related VaR	(7) Equity-Related Value-Weighted	(8) Bloomberg Daily Returns
TailRisk 10–1	0.44%**	0.38%**	0.34%*	0.40%**	0.35%*	0.36%*	0.30%*	0.43%**
	(2.00)	(2.06)	(1.81)	(1.98)	(1.83)	(1.83)	(1.82)	(2.32)

Panel B: Fama-MacBeth Regressions

	(1) Equity-Related Baseline	(2) Equity-Related Horizon 3y	(3) Equity-Related Horizon 4y	(4) Equity-Related Cut-Off 10%	(5) Equity-Related Cut-Off 20%	(6) Equity-Related VaR
TailRisk	0.217***	0.202***	0.156**	0.187***	0.167**	0.201**
	(3.20)	(2.97)	(2.31)	(3.01)	(2.21)	(2.43)
Adjusted R^2	0.236	0.234	0.233	0.234	0.234	0.235

Table 4: Tail Risk and Fund Characteristics

This table reports the results of Fama and MacBeth (1973) regressions of *TailRisk* in month *t+1* on fund characteristics in month *t*. For fund characteristics, we include a fund's age, size, delta of the incentive fee contract, past yearly return, standard deviation (estimated over the previous 24 months), the length of a fund's lockup and restriction period (in months), minimum investment amount (in 100 thousands), indicator variables that equal one if the fund employs leverage and is an offshore fund, respectively, and zero otherwise, a fund's management and incentive fee (in %), and indicator variables that equal one if the fund has a hurdle rate and a high water mark, respectively, and zero otherwise. Our sample covers hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1994 to December 2012. We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) TailRisk	(2) TailRisk	(3) TailRisk
Age	0.000336**		0.000168
	(2.60)		(1.12)
Size	–0.000282		–0.000951
	(–0.11)		(–0.26)
Delta	0.00280**		0.00619**
	(2.04)		(2.60)
Past Yearly Return	–0.00333***		–0.00310***
	(–3.17)		(–2.82)
Standard Deviation	0.0809***		0.0788***
	(8.96)		(8.33)
Lockup Period		0.0410***	0.0131**
		(5.17)	(2.01)
Restriction Period		–0.0000101	–0.0000101
		(–0.00)	(–0.00)
Min Investment		–0.00219	–0.000923
		(–1.44)	(–1.23)
Leverage		0.0187	0.0287**
		(1.45)	(2.45)
Offshore		–0.0286	–0.0308
		(–1.15)	(–1.30)
Management Fee		–0.00394	–0.0101
		(–0.55)	(–1.14)
Incentive Fee		–0.00477***	–0.00407
		(–3.50)	(–1.38)
Hurdle Rate		–0.0211	–0.0267
		(–1.63)	(–1.08)
HWM		0.0185	0.0142
		(1.39)	(1.28)
Constant	–0.00197	0.485***	0.137***
	(–0.11)	(9.49)	(4.40)
Observations	287301	265145	195108
Adjusted R^2	0.302	0.023	0.312

Table 5: Tail Risk and Funding Liquidity: Evidence from Lehman Brothers connected Hedge Funds

Panel A of this table reports the results of a mean comparison test between the *TailRisk* for equity-related hedge funds with Lehman Brothers as a prime broker and *TailRisk* for a matched sample (matched both on propensity scores as well as based on the requirement that matched funds belong to the same hedge fund style category as well as the same *TailRisk*, size, and monthly excess returns decile in August 2007) in the periods from September 2007 to August 2008 (*Pre-Crisis*), September 2008 to August 2009 (*Crisis*), and September 2009 to August 2010 (*Post-Crisis*). Panel B present the results from the following diff-in-diff regression:

$$\Delta TailRisk_{i,t} = \alpha + \beta_1 \Delta_{Postcrisis-Crisis} + \beta_2 \Delta_{Crisis\text{-}Precrisis} \times Lehman + \beta_3 \Delta_{Postcrisis-Crisis} \times Lehman + \kappa X_{i,t-1} + \varepsilon_{i,t}$$

where $\Delta TailRisk_{i,t}$ denotes the change in tail risk for hedge fund *i* between the pre-Lehman crisis and the crisis period, or between the crisis and the post-crisis period, respectively. $\Delta_{Crisis\text{-}Precrisis}$ and $\Delta_{Postcrisis-Crisis}$ are indicator variables for the period between Crisis and Pre-Crisis, and Post-Crisis and Crisis, respectively, where the respective periods are defined as in Panel A. *Lehman* is an indicator variable that takes on the value one if a fund has a prime brokerage relation with Lehman Brothers, and zero otherwise. $X_{i,t-1}$ is a vector of fund-specific control variables that includes age, size, delta, returns over the last one year, standard deviation estimated over the previous year, lockup period, restriction period, minimum investment, management fee, incentive fee, and indicator variables whether the fund employs leverage, is an offshore fund, uses a hurdle rate, and uses a high water mark, all measured at time *t*–1. We estimate *TailRisk* based on an estimation period of 12 months and cluster standard errors by fund. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: TailRisk: Mean Comparison Tests

Period 1: September 2007 - August 2008			Period 2: September 2008 - August 2009			Period 3: September 2009 - August 2010		
Lehman Hedge Funds	Matched Sample Non-connected	Difference	Lehman Hedge Funds	Matched Sample Non-connected	Difference	Lehman Hedge Funds	Matched Sample Non-connected	Difference
Match: Propensity Score Model								
0.39	0.45	–0.06 (–0.56)	0.82	0.57	0.25** (2.01)	0.13	0.16	–0.03 (–0.48)
Match: Style, *TailRisk*, Size, and Returns in August 2007								
0.39	0.44	–0.05 (–0.39)	0.82	0.55	0.27** (2.25)	0.13	0.15	–0.02 (–0.39)

Table 5: (Continued)

Panel B: Diff-in-Diff Analysis

	Match: Propensity Score Model		Match: Style, *TailRisk*, Size, and Returns	
	(1) TailRisk Change	(2) TailRisk Change	(3) TailRisk Change	(4) TailRisk Change
$\Delta_{Postcrisis-Crisis}$	–0.553***	–0.516***	–0.575***	–0.586***
	(–5.71)	(–4.11)	(–6.10)	(–5.78)
$\Delta_{Crisis-Precrisis} \times Lehman$	0.321**	0.272*	0.351**	0.252*
	(2.20)	(1.85)	(2.26)	(1.90)
$\Delta_{Postcrisis-Crisis} \times Lehman$	–0.253**	–0.228*	–0.281**	–0.221*
	(–2.02)	(–1.81)	(–2.22)	(–1.85)
Age		–0.003		–0.000
		(–1.15)		(–0.11)
Size		0.006		0.013
		(1.04)		(1.21)
Delta		–0.211		–0.149
		(–1.31)		(–1.21)
Past Yearly Return		–0.034		–0.091**
		(–1.13)		(–2.13)
Standard Deviation		0.076		–0.036
		(0.32)		(–0.05)
Lockup Period		–0.0004		–0.0024
		(–0.02)		(–0.71)
Restriction Period		–0.048		–0.093
		(–0.34)		(–0.93)
Min Investment		0.023		0.099*
		(0.89)		(1.89)
Leverage		0.077**		0.078**
		(2.15)		(2.00)
Offshore		–0.021		0.052
		(–0.56)		(1.46)
Management Fee		0.003		0.007
		(0.14)		(0.64)
Incentive Fee		0.008		0.034*
		(1.12)		(1.88)
Hurdle Rate		0.098		0.018
		(1.24)		(0.83)
HWM		–0.099		–0.059
		(–1.56)		(–0.96)
Constant	0.210***	0.415***	0.214***	0.447***
	(8.45)	(3.26)	(7.75)	(3.51)
Observations	2627	2049	2627	2049
Adjusted R^2	0.180	0.312	0.180	0.312

Table 6: Tail Risk and Portfolio Strategies

This table reports the results of Fama and MacBeth (1973) regressions of *TailRisk* in month *t* on a hedge fund's sensitivity, β , to different risk factors. As risk factors, we use the Agarwal and Naik (2004) out-of-the-money (OTM) put and call option factors (*OTM Put* and *OTM Call*), the Chabi-Yo, Ruenzi, and Weigert (2015) high minus low equity LTD-risk factor (*LTD-RISK*), the Fung and Hsieh (2004) trend-following factors for bonds, currencies, commodities, interest rates, and equities (*PTFSB*, *PTFSFX*, *PTFSCOM*, *PTFSIR*, and *PTFSSTK*), the Pástor and Stambaugh (2003) liquidity risk factor (*Liquidity*), and returns of a long-short hedge fund portfolio with regard to the Bali, Brown and Caglayan (2014) macroeconomic uncertainty factor (*Macro*), to the Buraschi, Kosowski, and Trojani (2014) correlation risk factor (*Correlation*), and to the CBOE VIX index (*VIX*). We estimate a fund's sensitivity to the respective factor based on a rolling window of 24 monthly returns. Our sample covers hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1994 to December 2012. We use the Newey-West (1987) adjustment with 24 lags and the Shanken (1992) correction to adjust the standard errors for serial correlation and the errors-in-variables problem, respectively. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) TailRisk	(2) TailRisk	(3) TailRisk	(4) TailRisk
$\beta_{OTM\ Put}$	–12.46*** (–3.63)		–11.85*** (–4.76)	–9.895** (–2.50)
$\beta_{LTD-RISK}$		0.630*** (10.31)	0.204*** (2.68)	0.178** (2.21)
$\beta_{OTM\ Call}$				–2.318 (–1.34)
β_{PTFSB}				0.397 (1.11)
β_{PTFSFX}				–0.233 (–0.42)
$\beta_{PTFSCOM}$				–0.114 (–0.54)
β_{PTFSIR}				–0.0447 (–0.16)
$\beta_{PTFSSTK}$				–0.467 (–1.53)
$\beta_{Liquidity}$				–0.0483 (–0.58)
β_{Macro}				–0.000230 (–0.02)
$\beta_{Correlation}$				0.569** (2.15)
β_{VIX}				0.284 (1.54)
Constant	0.0644*** (3.98)	0.134*** (4.86)	0.0579*** (4.46)	0.0559*** (6.11)
Observations	424334	422734	422734	422712
Adjusted R^2	0.411	0.357	0.446	0.582

Table 7: Returns-based Tail risk versus Stock-Holdings-based tail risk

This table reports the results of Fama and MacBeth (1973) regressions of returns-based *TailRisk* of hedge fund firm *i* in month *t* on hedge fund firm *i*'s Equity Tail Risk in month *t* controlling for different risk and firm characteristics. As control variables, we include a hedge fund firm's return standard deviation, skewness, kurtosis, *ES*, beta, downbeta, upbeta, liquidity (as proxied by the Amihud illiquidity ratio), size, book-to-market, and past yearly return. All firm characteristics except liquidity, size, book-to-market, and past yearly return (which are measured at the end of last month) are estimated based on a rolling window of 24 monthly returns of fund firm *i*. In regression (5), we interact Equity Tail Risk with (long-only) leverage defined as a hedge fund firm *i*'s market capitalization of long equity holdings divided by hedge fund firm *i*'s total assets under management. Our sample covers hedge fund firms from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases who report 13F long equity holdings to the SEC. The sample period is from January 1994 to December 2012. We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Stock Holdings-Based Variables	(1) TailRisk (Firm Level)	(2) TailRisk (Firm Level)	(3) TailRisk (Firm Level)	(4) TailRisk (Firm Level)	(5) TailRisk (Firm Level)
Equity Tail Risk	0.145***	0.0923***	0.0918***	0.0793***	0.0590***
	(14.97)	(5.03)	(4.91)	(3.69)	(2.93)
Equity Tail Risk x Leverage					0.0127**
					(2.02)
Standard Deviation		–0.0000680	–0.00133	–0.00624	–0.00939
		(–0.01)	(–0.10)	(–0.38)	(–0.57)
Skewness		0.00969	0.0105	0.00563	0.0136
		(0.47)	(0.48)	(0.28)	(0.73)
Kurtosis		–0.00411	–0.00517	–0.00699	–0.00613
		(–0.54)	(–0.69)	(–0.78)	(–0.66)
ES		–0.0123	–0.0135	–0.0169	–0.0190
		(–1.48)	(–1.48)	(–1.45)	(–1.61)
Beta		0.157***			
		(3.02)			
Up Beta			0.0113	–0.00915	0.00637
			(0.25)	(–0.15)	(0.12)
Down Beta			0.122*	0.108*	0.0821
			(1.86)	(1.94)	(1.29)
Liquidity				–0.0391	–0.0288
				(–0.88)	(–0.70)
Size				0.00439	0.00297
				(0.64)	(0.49)
Book–to–market				–0.373	–0.347
				(–1.56)	(–1.62)
Past Yearly Return				–0.00279	–0.00264
				(–1.42)	(–1.36)
Constant	0.206***	0.00190	0.0270	0.0293	0.0468
	(7.67)	(0.03)	(0.45)	(0.31)	(0.56)
Observations	42353	41896	41896	39708	39695
Adjusted R^2	0.051	0.114	0.121	0.153	0.169

Table 8: Returns-based Tail risk and Option Holdings

This table reports the results of Fama and MacBeth (1973) regressions of returns-based *TailRisk* of hedge fund firm *i* in month *t* on hedge fund firm *i*'s long positions in call and put options in month *t*. We compute a hedge fund firm *i*'s number of different stocks on which call positions are held (*Number of different call positions*), number of different stocks on which put positions are held (*Number of different put positions*), the number of equity shares underlying the call positions (*Number of equity shares underlying the call positions*, in millions), the number of equity shares underlying the put positions (*Number of equity shares underlying the put positions*, in millions), the value of equity shares underlying the call positions (*Value of equity shares underlying the call positions*, in $ millions), and the value of equity shares underlying the put positions (*Value of equity shares underlying the put positions*, in millions) Our sample covers hedge fund firms from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases who report long call and put positions to the SEC in their 13F filings. The sample period is from April 1999 to December 2012. We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Derivatives Holdings–Based Variables	(1) TailRisk (Firm Level)	(2) TailRisk (Firm Level)	(3) TailRisk (Firm Level)	(4) TailRisk (Firm Level)
Number of different call positions	0.000184			0.000654
	(0.21)			(0.40)
Number of different put positions	–0.000988			–0.00586**
	(–1.33)			(–2.32)
Number of equity shares underlying the call positions		0.00282		0.00405
		(0.52)		(1.12)
Number of equity shares underlying the put positions		–0.00801*		–0.00437
		(–1.89)		(–1.16)
Value of equity shares underlying the call positions			0.0000202	0.000726
			(0.02)	(1.04)
Value of equity shares underlying the put positions			–0.00101**	–0.00134*
			(–2.02)	(–1.90)
Constant	0.286***	0.286***	0.286***	0.288***
	(10.26)	(10.25)	(10.30)	(10.32)
Observations	44702	44702	44702	44702
Adjusted R^2	0.006	0.007	0.008	0.020

Table 9: Tail Risk Timing: Evidence From the Financial Crisis in 2008

This table reports the results on tail risk timing during the financial crisis in 2008. Panel A shows differences between aggregate hypothetical *TailRisk* and aggregate actual *TailRisk* of hedge funds' disclosed long equity holdings in March 2008 and in October 2008. Panel B compares hedge funds' number of different stocks on which put positions are held and the equivalent number and value of equity shares underlying the put positions (in millions) between March 2008 and October 2008. In Panel C, for each stock we compute (i) the number of different hedge funds that hold put positions, (ii) the overall number of equity shares held by different hedge funds underlying the put positions (in millions), and (iii) the overall value of equity shares held by different hedge funds underlying the put positions (in $ millions) on this stock in October 2008 and regress these measures on tail risk and different stock characteristics. Finally, Panel D reports the results of univariate portfolio sorts in October 2008. We sort individual hedge funds into tercile portfolios according to (i) equity *TailRisk* timing ability (i.e., the difference between hypothetical *TailRisk* and actual *TailRisk)*, (ii) the number of different stocks on which funds hold put positions, (iii) the equivalent number of equity shares underlying the put positions (in millions), and (iv) the equivalent value of equity shares underlying the put positions (in $ millions). We compute the average excess fund returns for these portfolios as well as the (3-1) difference portfolio in October 2008. Our sample covers hedge fund firms from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases who report long equity and option positions to the SEC in their 13F filings. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: TailRisk from Equity Holdings

	Pre-Crisis March 2008	Crisis October 2008
Hypothetical Equity TailRisk	0.83	1.19
Actual Equity TailRisk	0.83	1.11
Difference	0.00	0.08*** (3.60)

Panel B: Long Put Positions

	Number of different put positions	Number of equity shares underlying the put positions (in million)	Value of equity shares underlying the put positions (in million)
Pre-Crisis March 2008	4.14	1.51	26.25
Crisis October 2008	5.90	2.71	36.53
Difference	1.76** (2.03)	1.20*** (3.14)	10.28*** (4.51)

Table 9: (Continued)

Panel C: Put Options and Stock Characteristics

Stock Holdings-Based Variables	(1) Number of Hedge Funds with Puts	(2) Number of Equity Shares Held by Hedge Funds	(3) Value of Equity Shares Held by Hedge Funds	(4) Number of Hedge Funds with Puts	(5) Number of Equity Shares Held by Hedge Funds	(6) Value of Equity Shares Held by Hedge Funds
Equity Tail Risk	1.726***	0.537**	10.33**	0.709***	0.112	5.535*
	(7.21)	(2.11)	(2.34)	(3.37)	(0.38)	(1.83)
Standard Deviation				0.541***	0.428***	7.462***
				(13.09)	(7.71)	(8.45)
Skewness				0.237***	0.307***	5.819***
				(5.30)	(5.40)	(5.96)
Kurtosis				0.00769**	0.0128*	0.0682
				(2.05)	(1.68)	(0.85)
Beta				–0.0616	–0.280	–11.80***
				(–0.51)	(–1.64)	(–4.07)
Liquidity				0.0769***	0.0600***	1.290***
				(15.26)	(8.42)	(9.70)
Size				1.393***	0.970***	20.60***
				(26.65)	(10.95)	(11.64)
Book–to–market				0.0752*	0.114*	2.643***
				(1.92)	(1.70)	(2.82)
Past Yearly Return				–2.768***	–2.143***	–37.66***
				(–13.01)	(–8.28)	(–8.82)
Constant	1.114***	0.580***	9.764***	–17.25***	–12.33***	–257.9***
	(12.48)	(5.92)	(5.77)	(–24.32)	(–10.37)	(–11.22)
Observations	4211	4211	4211	3801	3801	3801
Adjusted R^2	0.019	0.002	0.002	0.472	0.204	0.239

Panel D: Fund Firm Performance Differences in October 2008

	Equity TailRisk Timing	Number of different put positions	Number of equity shares underlying the put positions (in million)	Value of equity shares underlying the put positions (in million)
PF 1	–9.57%	–10.06%	–9.11%	–8.88%
PF 2	–8.14%	–6.96%	–7.50%	–6.90%
PF 3	–5.34%	–5.00%	–5.05%	–5.27%
PF3 – PF1	4.23%***	5.06%***	4.06%***	3.61%*
	(2.95)	(3.69)	(3.01)	(1.82)

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