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

Vikas Agarwal, Stefan Ruenzi, and Florian Weigert*

This Version: August 10, 2016

Abstract

We develop a new systematic tail risk measure for equity-oriented 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, leverage and exposure to funding liquidity shocks are important determinants of tail risk. We find evidence of some funds being able to time tail risk exposure prior to the recent financial crisis.

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

JEL Classification Numbers: G11, G23

* Vikas Agarwal is from Georgia State University, J. Mack Robinson College of Business, 35 Broad Street, Suite 1234, Atlanta GA 30303, USA. Email: vagarwal@gsu.edu.Tel: +1-404-413-7326. Fax: +1-404-413-7312. Vikas Agarwal is also a Research Fellow at the Centre for Financial Research (CFR), University of Cologne. Stefan Ruenzi is from the University of Mannheim, L9, 1-2, 68161 Mannheim, Germany. Email: ruenzi@bwl.uni-mannheim.de. Tel: +49-621-181-1646. Florian Weigert is from the University of St. Gallen, Swiss Institute of Banking and Finance, Rosenbergstrasse 52, 9000 St. Gallen, Switzerland. Email: florian.weigert@unisg.ch. Tel: +41-71-224-7014. We thank Bill Schwert (editor) and the referee for helpful comments. We thank George Aragon, Turan Bali, Martin Brown, Stephen Brown, John Cochrane, Yong Chen, Teodor Dyakov, Rene Garcia, Andre Güttler, Olga Kolokolova, Jens Jackwerth, Juha Joenväärä, Petri Jylha, Marie Lambert, Tao Li, Bing Liang, Gunter Löffler, Scott Murray, George Panayotov, Liang Peng, Lubomir Petrasek, Alberto Plazzi, Paul Söderlind, Fabio Trojani, and Pradeep K. Yadav for their helpful comments and constructive suggestions. We benefited from the comments received at presentations at the 6th Annual Conference on Hedge Funds 2014 in Paris, the 9th Imperial College Conference on Advances in the Analysis of Hedge Fund Strategies 2014, the Berlin Asset Management Conference 2015, the CFEA 2015 Conference, the Annual Meeting of the German Finance Association 2015, the FMA 2015 conference, the FMA Consortium on Activist Investors, Corporate Governance and Hedge Funds 2015, the Luxembourg Asset Management Summit 2015, the 15th Colloquium on Financial Markets 2016 in Cologne, the 8th Conference on Professional Asset Management 2016 in Rotterdam, the EDHEC Risk Institute Singapore, the National Taiwan University, the Purdue University, the University of Mannheim, the University of St. Gallen, and the University of Ulm. We would also like to thank Kevin Mullally and Honglin Ren for excellent research assistance.

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

This Version: August 10, 2016

Abstract

We develop a new systematic tail risk measure for equity-oriented 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, leverage and exposure to funding liquidity shocks are important determinants of tail risk. We find evidence of some funds being able to time tail risk exposure prior to the recent financial crisis.

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

JEL Classification Numbers: G11, G23

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

1. Introduction

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 systematic tail risk, i.e., they can incur substantial losses in times of market downturns when investors' marginal utility is very high.[1] 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 equity-oriented 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.[2] In particular, we ask the following questions. First, does tail risk explain the cross-sectional and time-series variation in equity-oriented 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

[1]As an illustration, Fig. A.1 in the Appendix plots monthly returns for the HFR Equal-Weighted Hedge Fund Strategy Index in the period from 1998 to 2012. The two worst return realizations occur in August 1998 and October 2008 which coincide with periods of severe equity market downturns (i.e., the Russian Financial Crisis in 1998 and the bankruptcy of Lehman Brothers in 2008, respectively).
[2]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).

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 non-parametric estimate for hedge funds' systematic 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 equity 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 equity-oriented hedge fund strategies.[3] We find that the return spread between the portfolios of hedge funds with the highest and the lowest past tail risk amounts to 4.68% per annum after controlling for the risk factors in the widely used Fung and Hsieh (2004) 7-factor model. 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), volatility risk (Bondarenko, 2004; Agarwal, Bakshi, and Huij, 2009), and rare disaster concerns (Gao, Gao, and Song, 2014). 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, standard deviation, delta, past yearly excess return, management and incentive fees, minimum investment, lockup and restriction period, and indicator variables for offshore

[3]In principle, our investigation can be extended to non-equity hedge funds too, but we restrict ourselves to equity funds to link tail risk with the underlying holdings that are available only for equity positions in the Thomson Reuters database.

domicile, leverage, high watermark, and hurdle rate, as well as univariate risk measures such as skewness, kurtosis, value-at-risk (*VaR*), and market beta. The predictability of future returns extends as far as six months into the future.

In addition to explaining the cross-sectional variation in fund performance, tail risk explains the time-series variation in aggregate fund performance. In particular, the return of a portfolio that is long in funds with high tail risk and short in funds with low tail risk explains a significant fraction of the time-series variation in aggregate equity hedge fund performance. We observe that accounting for tail risk in fund-level time-series regressions attenuates fund alphas and improves the explanatory power compared to the Fung and Hsieh (2004) model.

We conduct a number of robustness checks to show that our 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 computing tail risk, change the weighting procedure in portfolio sorts from equal-weighting to value-weighting, and account for delisting returns of funds that leave the database. Our results also remain stable when we compute tail risk with daily instead of monthly returns using data for a subsample of funds that report daily data to Bloomberg, use returns reported after the listing date of a subsample of funds from the Lipper TASS database, and unsmooth fund returns using the Getmansky, Lo, and Makarov (2004) procedure.

Next, we investigate the determinants of tail risk of 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 prior 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 can 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 that led to an exogenous shock to the funding of hedge funds by prime brokers. This event 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 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 funds' tail risk, we first regress 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 funds' overall tail risk can be explained by their 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 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 a fund's tail risk and return exposure to the equity tail risk factor, we directly analyze fund's investments in common stocks. For this purpose, we merge the fund returns reported in the commercial 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 firm. This effect is even more pronounced for levered funds. The 13F filings available from the Securities and Exchange Commission (SEC) 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. 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). Taken together, these findings show that tail risk of funds is (at least partially) driven by the nature of 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 funds' returns. The idea is to capture how much the funds actively change their tail risk relative to the scenario in which 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 pre-crisis buy-and-hold equity portfolio. This finding 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' systematic tail risk and show that it explains the cross-sectional and time-series 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 2 reviews the related literature. Section 3 describes the data. Section 4 presents results on the impact of tail risk on the cross-section of fund returns. Section 5 sheds light on the relation between funds' characteristics and tail risk. Section 6 explicitly studies if tail risk is induced by portfolio holdings of funds. Section 7 investigates funds' ability to time tail risk and Section 8 concludes.

2. 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. Such strategies can eventually expose funds to significant tail risk, which is difficult to diversify (Brown and Spitzer, 2006; Brown, Gregoriou, and Pascalau, 2012). Bali, Gokcan, and Liang (2007) show that surviving funds with high *VaR* outperform those with low *VaR*. 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 correlation risk has an impact on the cross-section of hedge fund returns. Agarwal, Arisoy, and Naik (2016) find that uncertainty about equity market volatility, as measured by volatility of aggregate volatility, can explain hedge fund performance both in cross section and over time. We contribute to this strand of literature by not only proposing a new systematic 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 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 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 funds' contractual features and their 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. These studies generally measure a fund's risk based on its return volatility, while we focus on tail risk. Aragon (2007) and Agarwal, Daniel, and Naik (2009) show that funds with greater redemption restrictions (longer lockup and redemption periods) perform better due to their ability to make long-term and illiquid investments. We build on this literature by showing that funds' tail risk is driven both by managerial incentives and redemption restrictions.

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 are also able to time tail risk by reducing their tail risk exposure prior to the financial crisis.

3. Data and variable construction

3.1. Data

Our hedge fund data come 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.[4] Individual stock data come from the CRSP database.

The Union Hedge Fund Database merges four different major commercial databases: Eureka, Hedge Fund Research (HFR), Morningstar, and Lipper TASS, and includes data for 25,732 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 only 22% unique funds). A Venn diagram in Fig. A.2 in the Appendix shows the overlap across the four databases.

To mitigate survivorship bias we start our sample period in 1994, the year in which commercial hedge fund databases started to track defunct hedge funds. Further, we use

[4]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.

multiple standard filters for our sample selection. First, since we measure a fund's tail risk with regard to the equity market return, we only include funds with an equity-oriented focus, i.e., those whose investment strategy is either 'Emerging Markets', 'Event Driven', 'Equity Long-Short', 'Equity Long Only', 'Equity Market Neutral', 'Short Bias' or 'Sector'.[5] Second, we require a fund to have at least 24 monthly return observations. Third, we filter out funds denoted in a currency other than US dollars. Fourth, we follow Kosowski, Naik, and Teo (2007) and eliminate the first 12 months of each fund's return series to avoid backfilling bias. Finally, we estimate *TailRisk* (our main independent variable in the empirical analysis, as explained in Section 3.2) based on a rolling window of 24 monthly return observations which uses the first two years of our sample. This filtering process leaves us with a final sample of 6,281 equity-oriented funds in the sample period from January 1996 to December 2012.

We report the summary statistics of 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. Summary statistics are computed over all funds and months in our sample period. All variable definitions are contained in Table A.1 of the Appendix.

[Insert Table 1 around here]

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 start) to 2012. Since hedge fund firms are not separately identified in this database, 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

[5]The selection of equity-oriented fund styles follows Agarwal and Naik (2004). We also classifiy 'Emerging Markets' and 'Sector' funds as equity-oriented since these two fund styles are associated with the stock market.

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 sample of 1,694 unique hedge fund firms among the 13F filing institutions.[6] Next, we merge these firms from the 13F filings to the hedge fund firms listed in the Union Database following Agarwal, Fos, and Jiang (2013). Our merging procedure applied at the firm level 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 in which 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 funds during the period from 1996 to 2012. Since our focus in this analysis is on equity-related 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 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.,

[6]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).[7] 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. Out of the 793 firms that appear both in the 13F database and the Union database, 406 firms file at least one long option position during our sample period. We use this sample in Sections 6 and 7 to study the relation between a firm's returns-based tail risk and tail risk induced from long positions in equities and options.

3.2 Tail risk measure

To evaluate an individual fund's systematic 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

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

where F_i (F_m) denotes the cumulative marginal distribution function of the returns of a 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.[8] However, this measure does not take into

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

[8]Longin and Solnik (2001) and Rodriguez (2007) apply the lower tail dependence coefficient to analyze financial contagion between different international equity markets. Boyson, Stahel, and Stulz (2010) use a similar technique to study contagion across different hedge fund styles. 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.

account how bad the worst return realization of a fund really is. Thus, in a second step, to account for the severity of poor fund returns, we define a hedge fund's tail risk (*TailRisk*) as

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

where ES_{r_i} and ES_{r_m} denote the expected shortfall (also sometimes referred to as conditional *VaR*) of the 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.[9]

We estimate *TailRisk* for hedge fund *i* in month *t* based on a rolling window of 24 monthly returns. We perform the estimation non-parametrically purely based on the empirical return distribution function of 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}.[10] 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 that occurred in September 2008 (–9.24%) and October 2008 (–17.23%). To compute *TailSens* for fund *i* during January 2007 to December 2008, we analyze whether the two worst return realizations of fund *i* occur at the same time as these market crashes, i.e.,

[9]This ratio is reminiscent of market beta, 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.

[10]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 report these results later in Table 3.

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 fund *i* in the period from January 2007 to December 2008 as zero, 0.5, or 1, respectively. *TailRisk* for 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 fund *i*'s *ES* and the market return's *ES* during the same 24-month period. We report summary statistics of our *TailRisk* measure in Panel C of Table 1. Average *TailRisk* is 0.38 across all funds and months in the sample. Among the different strategies, *TailRisk* is lowest for Short Bias, Equity Market Neutral, and Event Driven funds and highest for Emerging Markets, Equity Long Only, and Sector funds. Correlations between *TailRisk* and other fund characteristics are reported in Panel D of Table 1. We find that *TailRisk* is positively related to a fund's standard deviation, delta, leverage, the lockup period and age as well as negatively related to fund size. We will look more closely at the relation between fund characteristics and *TailRisk* in Section 5.1.

We now inspect the behavior of aggregate *TailRisk* over time. We compute aggregate *TailRisk* as the monthly cross-sectional average of *TailRisk* across all funds. Fig. 1 plots the time series of aggregate *TailRisk* on an equal-weighted and value-weighted basis.

[Insert Fig. 1 here]

Visual inspection shows that the time-series variation in our tail risk measure (both for equal-weighted and value-weighted schemes) corresponds well with 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 Russian financial crisis along with the collapse of Long Term Capital Management in August 1998.

We look at the correlations between aggregate equal-weighted *TailRisk* and fund specific risk factors (see Panel E in Table 1). Aggregate *TailRisk* is positively related to the correlation risk factor of Buraschi, Kosowski, and Trojani (2014), the Chicago Board Options Exchange (CBOE) volatility index (*VIX*), and the Gao, Gao, and Song (2014) *RIX* factor as well as 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 high correlations of 0.52 with the funding liquidity measure of Fontaine and Garcia (2012) and 0.47 with 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 and funding liquidity are strongly interconnected. Later in the paper, we will try and establish a causal relation between *TailRisk* and funding liquidity in Section 5. 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 funds that had a prime brokerage relation with Lehman.

4. Tail risk and hedge fund performance

4.1. Does tail risk have an impact on the cross-section and time-series of future fund returns?

To evaluate the predictive power of differences in fund's tail risk on the cross-section of future fund returns, we relate fund returns in month *t+1* to fund's *TailRisk* in month *t*. We first look at equal-weighted univariate portfolio sorts. For each month *t*, we include all funds with *TailRisk* of zero in portfolio 0. All other funds are sorted into quintile portfolios based on their *TailRisk* in increasing order. We then compute equally-weighted monthly average excess returns of these portfolios in month *t+1*. 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 zero in the lowest *TailRisk* portfolio up to 1.66 in the highest *TailRisk* portfolio. The second column shows that 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 0.49% (1.17%). The return spread between portfolios 0 and 5 is 0.68% per month, which is statistically significant at the 5% level with a *t*-statistic of 2.16. We also estimate alphas for each of the portfolios and for the difference (5−0) portfolio using the Carhart (1997) four-factor model and the Fung and Hsieh (2004) seven-factor model. We find that the spread between portfolios 5 and 0 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 amount to 0.50% and 0.39% per month, respectively. These spreads translate into an economically large return premium of 6.00% and 4.68% per annum, respectively, that investors earn for investing in funds exposed to greater tail risk.

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 (5−0) *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 (4) in Panel A). In the second column, we 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 funds, we include the Pástor and Stambaugh (2003) traded liquidity factor in the fifth column. In columns six to nine, we control for the exposures to the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Buraschi, Kosowski, and Trojani (2014) correlation risk factor, the *VIX* (as in Agarwal, Bakshi, and Huij, 2009), and the Gao, Gao, and Song (2014) *RIX* factor, respectively. In each case, we continue to observe a significant positive alpha for (5–0) *TailRisk* return portfolio ranging from 0.30% to 0.51% per month. These findings further corroborate the importance of tail risk in explaining the cross section of hedge fund returns.

Panel C reports the results of regression of excess fund returns in month *t+1* on *TailRisk* and fund characteristics in month *t* using Fama and MacBeth (1973) approach:

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

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. As fund characteristics, we include all variables defined in Table A.1 of the Appendix. To distinguish the impact of *TailRisk* from other measures of risk, we also include a fund's return skewness, kurtosis, *VaR*, and market beta (all computed based on estimation windows of 24 months) in the regression.[11] Hence, our results indicate that it is the systematic tail risk (with the market) that drives fund returns rather than the tail risk of the funds.[12]

Controlling for both fund characteristics and other risk measures, we find a positive impact of *TailRisk* on future fund returns. Depending on the specification, the coefficient

[11]Our results are robust if we use *ES* instead of *VaR* as an additional control variable.

[12]This finding is in accordance with Bali, Brown, and Caglayan (2012) that systematic risk drives hedge fund returns, not idiosyncratic risk.

estimate for *TailRisk* ranges from 0.227 to 0.451 with *t*-statistics ranging from 2.01 to 3.16. These results confirm that the relation between future fund returns and tail risk is not subsumed by fund characteristics and other fund risk measures.

In models (1) – (6) of Panel D, we investigate the returns associated with *TailRisk* in different states of the world. We use a specification identical to that in model (4) of Panel C, but only show the coefficients of *TailRisk*. All control variables are included but suppressed for the sake of brevity. As expected, we find that the impact of *TailRisk* on future returns is strongly positive in periods of positive market returns, while it is negative when the market returns are negative (models (1) – (2)). These results are in line with the following economic intuition. When market returns are positive, tail risk does not realize, and therefore the returns associated with tail risk are positive. When market returns are negative, tail risk does realize and funds with greater tail risk perform worse. As an example, the quintile portfolio of funds with the highest *TailRisk* underperforms the portfolio of funds with zero *TailRisk* by –16.81% during the October 2008 crisis. However, these drawdowns are more than compensated during non-crisis periods. So we observe an unconditional premium for *TailRisk*.

The returns associated with tail risk are positive during periods of both low and high market volatility (models (3) – (4)), with the returns being double during high-volatility periods. Moreover, positive returns associated with tail risk exist in each subperiod when we evenly split our sample period to 1996–2003 and 2004–2012 (models (5) – (6)).[13]

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 persists. Panel E reports the results of

[13]We compute market volatility as the standard deviation of the CRSP value-weighted market return over the past 24 months. We classify month *t* as a high (low) market volatility period if the standard deviation is above (below) the median standard deviation over the whole sample period from 1996 to 2012.

regressions of future excess returns over different horizons (2-month returns, 3-month returns, 6-month returns, and 12-month returns) on *TailRisk* after controlling for various fund characteristics measured in month *t*. Again, we use a specification identical to model (4) of Panel C, but only report the coefficient estimate of *TailRisk* for the sake of brevity. We find that *TailRisk* can significantly predict future fund returns up to six months into the future.

Finally, we conduct time-series analysis of the effect of tail risk on aggregate hedge fund returns. Panel F presents the results of time-series regressions. Each month, we regress the average monthly excess return of all equity-related funds in month *t+1* on the returns of difference (5–0) portfolio and the seven factors in the Fung and Hsieh (2004) model. We find that the *TailRisk* factor has a positive coefficient of 0.241 with a *t*-statistic of 7.79. When investigating different fund styles, our results show that *TailRisk* is positive and significant for all styles with the exceptions of the Equity Market Neutral and the Short Bias strategy. The negative sign of the Short Bias strategy can be explained by the fact that these funds display net-short exposure to the market and do particularly well when equity market returns are negative. Thus, they are well-suited to hedge against market downturns and tail events. Including the *TailRisk* factor in time-series regressions reduces the monthly average alpha for equity-related funds by 0.083% and increases the adjusted R-squared by 6.68% in comparison to the Fung and Hsieh (2004) seven-factor model. Note, however, that the *TailRisk* factor is not practically feasible, since it is not possible to short hedge funds.

In summary, *TailRisk* has strong predictive power to explain the cross-sectional and time-series variation in fund returns. Funds with high tail risk outperform their counterparts by more than 4.5% p.a. after adjusting for the Fung and Hsieh (2004) factors. This premium persists even after controlling for additional factors (e.g., liquidity, macroeconomic uncertainty, correlation risk, volatility risk, and rare disaster risk) and fund characteristics.

4.2. Robustness checks

To further corroborate our results in Table 2, we conduct a battery of robustness checks on the relation between *TailRisk* of 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 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 procedure, and (v) assigning a delisting return of –1.61% to those funds that leave the database, following Hodder, Jackworth, and Kolokolova (2014).[14] Models (1) – (8) of Panel A in Table 3 report the results from univariate portfolio sorts using these alternative specifications. We only report returns of the (5 – 0) difference portfolio between funds with the highest *TailRisk* and funds with the lowest *TailRisk*, after adjusting for the risk factors in the seven-factor model.

In model (9), we use daily returns instead of monthly returns to estimate tail risk for a subsample of 444 hedge funds that report daily returns to Bloomberg in the time period from 2003 and 2012. In the spirit of Kolokolova and Mattes (2014), we use two filters: (i) restrict

[14] A large literature on the delisting bias suggests different signs and/or estimates for the bias. Ackermann, McEnally, and Ravenscraft (1999) point out that returns of missing funds can be greater than those of the funds included in the commercial databases as successful funds could stop reporting. In contrast, Posthuma and Van der Sluis (2003) and Malkiel and Saha (2005) suggest that funds could stop reporting as they may realize or anticipate worse performance. Therefore, the poor returns for funds in the final months of their existence could be missing in the databases. More recently, using long equity positions of hedge funds in the 13F data and hedge fund holdings of funds of hedge funds respectively, Agarwal, Fos, and Jiang (2013) and Aiken, Clifford, and Ellis (2013) find that fund performance declines after delisting. However, Edelman, Fung, and Hsieh (2013) use a private database of very large hedge fund firms and find a statistically insignificant delisting bias.

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 mitigate the effect of outliers, we winsorize daily returns that exceed 100%. We require an overall number of at least 30 funds per month which excludes the months before 2003 in our empirical analysis. Due to the smaller sample size of funds that report daily returns to Bloomberg, we report results of the (3–0) difference portfolio instead of the (5–0) difference portfolio.

In our main data set, we drop the first 12 months of each fund's return series. This procedure helps to mitigate the likelihood that our analysis is affected by the backfilling bias. As a robustness test, we redo the baseline analysis with Lipper TASS funds. The Lipper TASS database displays the exact listing date of each hedge fund, so we can exclusively use returns that are reported after the listing date. Model (10) reports the results.

Returns for many individual funds display substantial serial correlation. Getmanky, Lo, and Makarov (2004) show that such serial correlation results from infrequent trading and return smoothing of funds which makes their returns appear less volatile. To address the concern that return smoothing could potentially bias the results of our asset pricing tests, we use the correction method of Getmansky, Lo, and Makarov (2004) to unsmooth fund returns and subsequently run asset pricing tests in model (11).[15]

[Insert Table 3 here]

Panel B reports the results of Fama and MacBeth (1973) regressions (as in model (4) of Panel C in Table 2) of future excess returns in month *t+1* on *TailRisk* and different fund

[15] As in Getmansky, Lo, and Makarov (2004), we estimate the return smoothing model using maximum likelihood and constrain the estimators to yield invertible MA(2) processes.

characteristics measured in month t using the same stability checks as above. We only report the coefficient estimate for *TailRisk*. Other control variables 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.

5. Determinants and sources of tail risk

5.1. Tail risk and fund characteristics

Section 4 documents that tail risk is an important factor to explain the cross-sectional variation in 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, both of 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 the following regression 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:

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

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 included in Eq. (3). To adjust the standard errors for serial correlation, we use the Newey and West (1987) adjustment with 24 lags.[16] Table 4 reports the results.

[Insert Table 4 here]

[16]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.

In model (1), we include fund characteristics such as size, fund age, standard deviation, as well as delta and past yearly return as independent variables. We observe a significantly positive relation between *TailRisk* and fund age, standard deviation of returns, and delta, 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 fund's management and incentive fee, minimum investment, lockup and restriction period, as well as indicator variables for offshore domicile, leverage, high watermark, and hurdle rate. Consistent with the notion that managers of 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. 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 fee does not capture managerial incentives as two managers charging the same incentive fee can face different dollar incentives depending on the timing and magnitude of investors' flows, funds' return history, and other contractual features.

Finally, model (3) includes all 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 the 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 a 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).

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

Panel E of Table 1 shows that aggregate *TailRisk* is strongly correlated to the two proxies of funding liquidity risk: the TED spread (e.g., Teo, 2011) and the Fontaine and Garcia (2012) measure extracted from US Treasury security pairs across different maturities. However, the correlation by itself does not imply a causal relation between funding liquidity risk and tail risk. Thus, we assess the impact of a funding liquidity shock due to the Lehman Brothers bankruptcy in September 2008 on the tail risk of funds that had a prime brokerage relation with Lehman during this month as compared to the funds without such a relation.

To identify the funds that had Lehman Brothers as their prime broker, we use a snapshot of the Lipper TASS database in 2007.[17] Lipper TASS data contain information on the prime broker, along with other affiliated companies (e.g., custodian bank) for each fund.

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

We can identify 60 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.[18] 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. This setup allows us to control for observable fund characteristics explaining heterogeneity between the Lehman and non-Lehman funds.

We estimate a logistic regression of an indicator variable that is equal to one if a fund is Lehman-connected on different fund characteristics (same as in Table 4), and zero otherwise. We then match each Lehman-connected fund with its closest neighbor based on the estimated propensity score. As an additional robustness check, we create a second control group based on a 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 into decile portfolios based on *TailRisk*, size, and returns in August 2007. We match each Lehman-connected fund with a non-connected fund of the identical investment strategy in the same *TailRisk*, size and return decile. In the case that this matching procedure does not yield one-to-one matches, we randomly assign a non-connected fund out of the possible matches to a Lehman-connected fund.

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

Fig. 2 displays the evolution of *TailRisk* for Lehman-connected funds and the two matched control samples of non-Lehman funds between September 2007 and August 2010.

[Insert Fig. 2 around here]

Fig. 2 shows that, although both types of 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 Lehman 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 funds display an aggregate *TailRisk* of 0.82 (0.82) whereas the propensity-score-matched (style-, *TailRisk*-, size-, and returns-matched) non-Lehman funds display *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 two groups of funds are statistically indistinguishable from each other. 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 if 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 funds and the respective matched samples (based on the same criteria as above) of non-connected Lehman funds:

$$\begin{aligned}\Delta TailRisk_{i,t} &= \alpha + \beta_1 \Delta_{Postcrisis-Crisis} + \beta_2 \Delta_{Crisis\text{-}Precrisis} \times Lehman + \beta_3 \Delta_{Postcrisis-Crisis} \times Lehman \\ &\quad + \kappa X_{i,t-1} + \varepsilon_{i,t}\end{aligned} \tag{5}$$

where $\Delta TailRisk_{i,t}$ denotes the change in tail risk for 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 the crisis and pre-crisis, and post-crisis and crisis, respectively.[19] *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 used earlier in Table 4, all measured at time *t*–1. As expected, the coefficient estimate for the interaction term between *Lehman* and $\Delta_{Crisis\text{-}Precrisis}$ is significantly positive. This result indicates that 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 relation with Lehman we use and whether we include additional controls or not. The significantly

[19]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.

negative coefficient estimate for the interaction of $\Delta_{Postcrisis-Crisis}$ with *Lehman* suggests that this effect is (at least partially) subsequently reversed.

5.3. Sources of tail risk

So far we have investigated which fund characteristics are associated with funds' tail risk. In this section, we take a closer look at and examine the channels through which funds can 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.[20] Second, *explicit investments* in tail-sensitive stocks can be another source of tail risk in 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 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).[21] 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,

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

[21]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.

the Fung and Hsieh (2004) trend-following factors,[22] the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Buraschi, Kosowski, and Trojani (2014) correlation risk factor, the *VIX*, and the Gao, Gao, and Song (2014) *RIX* factor.

We estimate a 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 fund level of tail risk in month *t* (as defined in Section 3) 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*:

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

where $TailRisk_{i,t}$ is a 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]

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

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

is positively related to a trading strategy of writing out-of-the-money put options on the equity market index.[23] 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. Given an average tail risk of our sample funds of 0.38, this means 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.

6. Tail risk and portfolio holdings

6.1. Tail risk induced from equity holdings of hedge funds

[23]This result also suggests that tail risk can be reduced by a trading strategy of holding long put options. Later in Section 6, we investigate the relation between actual long put option positions of hedge funds and their tail risk.

Our results hitherto suggest that a 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 long equity holdings of 1,694 manually classified hedge fund firms. We merge the Union Hedge Fund Database and the 13F portfolio holdings as in Agarwal, Fos, and Jiang (2013). Our final sample consists of 793 hedge fund firms managing 2,720 distinct funds during the period from 1996 to 2012.

Since portfolio holdings are reported at the hedge fund firm level, we first compute excess return of firm i in month t as the value-weighted excess returns of the firm's individual funds. We then compute a firm i's tail risk in month t based on its reported excess returns and the market using an estimation horizon of 24 months. Second, using the 13F equity holdings, we compute the excess equity portfolio return of a firm as the value-weighted excess returns of the firm's disclosed equity positions. Specifically, to obtain a return series of monthly observations, we use a firm i's 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 a firm 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 use the disclosed positions at the end of March 2012, and so on. We calculate a 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 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). 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 its 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:

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

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 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 (coeff. = 0.145) and is highly statistically significant at the 1% level. This finding provides direct evidence of a strong positive relation between a fund's tail risk and tail risk induced by its equity holdings. In models (2) to (5), we expand our specification to control for portfolio characteristics. In model (2), we add return standard deviation, skewness, kurtosis, *ES*, and market beta (all based on disclosed holdings). Our results reveal that fund's tail risk is also positively related to market beta but shows no 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 drives this finding. These results also hold in model (4), in which we include liquidity, size, book-to-market, and past yearly returns (again all based on equity holdings) as additional controls. More importantly, in all regressions, equity tail risk is significantly positively related to tail risk estimated from fund returns.

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 finding implies a relative increase of almost 20% as the tail risk for funds is 0.38 (see Panel C of Table 1), which 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's leverage in the relation between equity tail risk and fund tail risk. Intuitively, equity tail risk should matter more if the firm employs a higher level of equity leverage. We follow Farnsworth (2014) and compute a 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.[24] 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 the interaction term to be positive and 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, with a more pronounced effect in case of funds employing greater leverage.

6.2. Tail risk and option holdings of hedge funds

[24]To reduce the impact of outliers, we winsorize our measure of long-only leverage at the 1% level.

In addition to tail risk induced from long equity holdings, we had earlier found that a fund's sensitivity to an out-of-the-money put option factor was one of the main factors to explain fund's tail risk in Table 7. Since 13F filings only include long positions in options, we cannot observe if 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 in the SEC EDGAR database. Specifically, we analyze long call and put option holdings of the 793 hedge fund firms in our sample from the first quarter of 1999 to the last quarter of 2012. We find that during this period 51.2% of 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 tail risk estimates of firms, 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's tail risk, we compute for 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).[25] Since the data does not contain information that would allow us to calculate the actual value of the option positions, we rely on these coarser 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

[25] 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.

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.[26]

We regress tail risk of hedge fund firm *i* in month *t* on its 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 firms' tail risk. There is never any significant impact of the call option positions. In model (4), we estimate a regression of firms' tail risk jointly on all variables regarding 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.

7. Tail risk timing: Evidence from the financial crisis in 2008

In the last part, we investigate whether funds possess tail risk timing ability. Although funds with high tail risk on average outperform funds with low tail risk, they earn very low

---

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

returns during market downturns. As an example, we observe that funds with the highest tail risk (measured in September 2008 based on the prior 24 months) underperforms the portfolio of funds with tail risk of zero by –16.81% during October 2008, which is the worst financial crisis during our sample period with a CRSP value-weighted market return of –17.23%.[27] 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 hedge fund firms during October 2008 crisis.[28] To estimate hypothetical equity tail risk for a 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 the 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 based on actual portfolio holdings information updated over time. Fig. 3 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.[29]

---

[27]Considering all months in our sample period with a market return of smaller than –10% (six months in total), we find that the portfolio of funds with the highest tail risk underperforms the portfolio with tail risk of zero by –8.80%. This spread is statistically significant at the 1% level (with a *t*-statistic of –5.20).
[28]Given the relatively short sample period, we choose this approach instead of using the timing factor in a multifactor model that has been used in the literature (e.g., Chen, 2007; Chen and Liang, 2007).
[29]Note that Fig. 3 plots the development of aggregate equity tail risk. Aggregate equity tail risk is generally higher than fund tail risk (which is displayed, e.g., in Fig. 2).

[Insert Fig. 3 here]

Fig. 3 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]

Our results indicate that in October 2008, the aggregate hypothetical equity tail risk of 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 by investing less in long stock positions that have high tail risk exposure prior to the crisis (i.e., between March and September 2008).

In the next step, we analyze whether 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 funds during the period from March 2008 to March 2009 in Fig. 4.

[Insert Fig. 4 here]

We find that funds increase 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 by 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.[30]

Next, we investigate whether 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 funds that hold put positions on this stock, (b) the overall number of equity shares held by different funds underlying the put positions (in millions) on this stock, and (c) the overall value of equity shares held by different funds underlying the put positions (in $ millions) on this stock. Then, we regress these stock-level put option holdings 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 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 (a) the size of the respective stock (as larger stocks might be simply more likely to appear in fund portfolios) or (b) funds' preferences for

[30]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 funds is $872.55 million in March 2008, which reduces to $715.67 million in October 2008.

certain stock characteristics. Therefore, in models (4) through (6), we control for firm size and additional firm and return characteristics of the stocks. After 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 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). We report results in Panel D. We find that the good timers' portfolios 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 are consistent with 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. If funds did so to a larger extent, this is also reflected in significantly better performance as compared to other funds.[31]

8. 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 tail risk is important to explain the cross-section and time-series of equity-oriented hedge funds. 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 for funds that used Lehman Brothers as their prime broker compared to other funds, indicating that funding liquidity shocks can enhance tail risk.

[31]Considering the evidence of hedge funds' timing tail risk prior to the financial crisis, we repeat the cross-sectional and time-series regressions of Tables 2, 4, 6, 7, and 8 for the two sub-periods from 1996 to 2008 and 2009 to 2012. Allowing for changes in the exposure to tail risk before and after the financial crisis, our results (not tabulated for the sake of brevity) continue to hold in both subsamples.

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 managed to reduce their exposure to tail risk prior to the onset of the crisis and indicates that funds seem to possess some tail risk timing skills.

Appendix

Figure A.1: HRF Hedge Fund Index over Time

This figure displays the monthly returns of the HFR Equal-Weighted Hedge Fund Strategy Index during the period from 1998 to 2012.

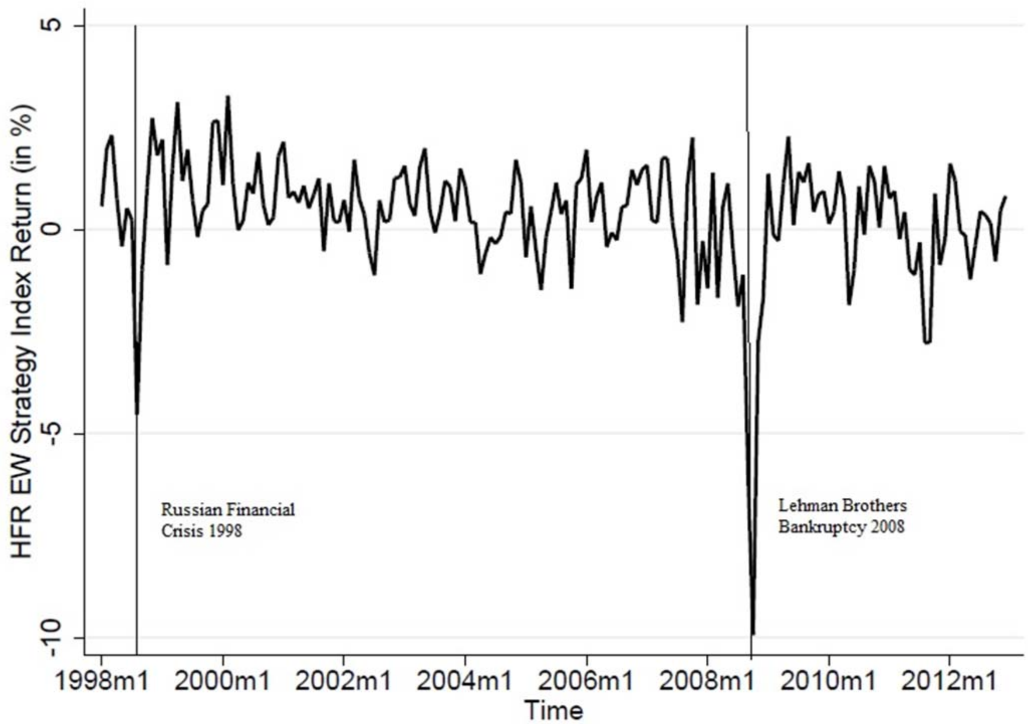

Figure A.2: Venn Diagram of the Union Hedge Fund Database

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.

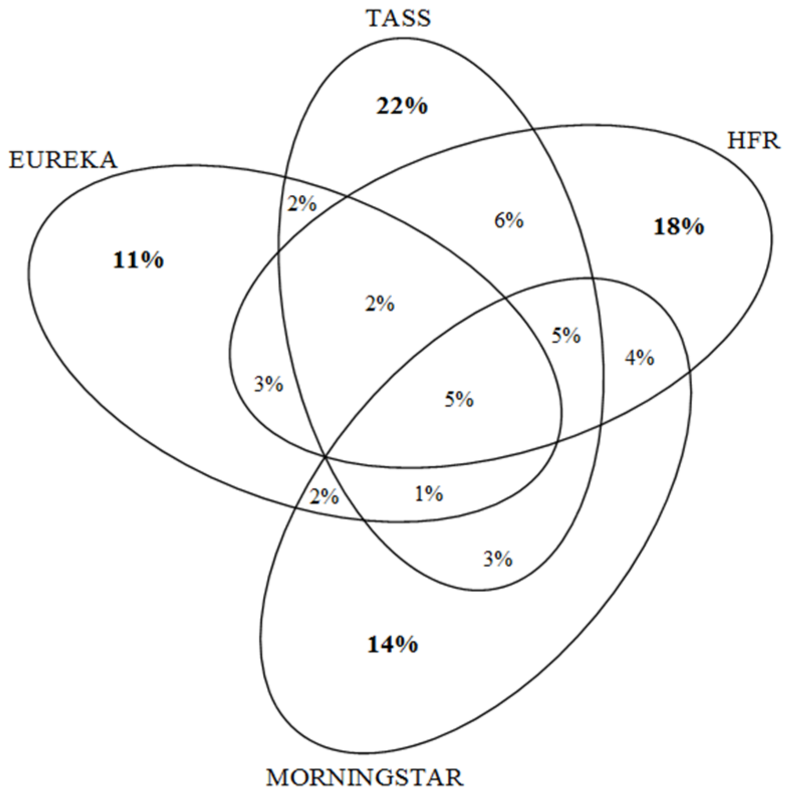

Table A.1: Definitions and Data Sources of Main Variables

This table briefly defines the main variables used in the empirical analysis. The data sources are; (i) UNION: Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases, (ii) KF: Kenneth French Data Library, (iii) DH: David A. Hsieh's webpage, (iv) FRS: Data library of the Federal Reserve System, (v) FED: Data library of the Federal Reserve Bank of St.Louis. EST indicates that the variable is estimated or computed based on original variables from the respective data sources.

Panel A: Tail Risk, Excess Returns, and Fund Characteristics

Variable Name	Description	Source
TailSens	Tail sensitivity of a hedge fund. Estimated based on monthly fund returns over the past 24 months as detailed in Section 3.2.	UNION, EST
TailRisk	Tail risk of a hedge fund. Estimated based on monthly fund returns over the past 24 months as detailed in Section 3.2.	UNION, EST
Excess Return	Monthly raw excess return of a hedge fund over the risk-free rate. As risk-free rate, the 1-month T-Bill rate is used.	UNION, KF, EST
Size	Natural logarithm of the hedge fund's asset under management (in million USD).	UNION
Age	The age of a hedge fund since its inception (in months).	UNION
Standard Deviation	Standard Deviation of a hedge fund's reported excess returns over the past 24 months	UNION, EST
Delta	Hedge fund manager's delta computed as the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value (in \$100 thousands)	Agarwal, Daniel, and Naik (2009)
Management Fee	The annual hedge fund management fee (in percentage).	UNION
Incentive Fee	The annual hedge fund incentive fee (in percentage).	UNION
Min Investment	Hedge fund's minimum investment amount (in \$100 thousands).	UNION
Lockup Period	The lockup period of a hedge fund, defined as the minimum amount of time that an investor is required to keep his money invested in the fund (in years).	UNION
Restriction Period	The restriction period of a hedge fund, computed as the sum of its notice period and redemption period (in years).	UNION
Offshore	Indicator variable that takes the value of one if the hedge fund is located outside of the USA and zero otherwise.	UNION
Leverage	Indicator variable that takes the value of one if the hedge fund uses leverage and zero otherwise.	UNION
HWM	Indicator variable that takes the value of one if the hedge fund uses a high-watermark and zero otherwise.	UNION
Hurdle Rate	Indicator variable that takes the value of one if the hedge fund uses a hurdle rate and zero otherwise.	UNION

Panel B: Hedge Fund Risk Factors

Variable Name	Description	Source
Market	The CRSP US value-weighted monthly market return,	KF
S&P	The S&P 500 index monthly total return.	DH
SCMLC	The size spread factor, computed as the difference between the Russell 2000 index monthly return and the S&P 500 monthly return.	DH
BD10RET	The bond market factor, computed as the monthly change in the 10-year treasury maturity yield.	FRS
BAAMTSY	The credit spread factor, computed as the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield.	FRS
PTFSBD	Monthly return on trend-following risk factor in bonds.	DH
PTFSFX	Monthly return on trend-following risk factor in currencies.	DH
PTFSCOM	Monthly return on trend-following risk factor in commodities.	DH
MSCI EM	The MSCI Emerging Market index monthly total return.	DH
SMB	Monthly return on Fama and French (1993) small-minus-big size factor.	KF
HML	Monthly return on Fama and French (1993) high-minus-low value factor.	KF
UMD	Monthly return on Carhart (1997) momentum factor.	KF
PS Liquidity	Monthly return on Pástor and Stambaugh (2003) liquidity risk factor.	Pástor and Stambaugh (2003)
TED Spread	The TED spread, computed as the difference between the interest rates on interbank loans and on short-term US Government debt.	FED
Funding Liquidity	Funding liquidity measure extracted from a panel of US Treasury security pairs across different maturities.	Fontaine and Garcia (2012)
Macro Uncertainty	Monthly return on Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor.	Bali, Brown, and Caglayan (2014)
Correlation Risk	Monthly return on Buraschi, Kosowski, and Trojani (2014) correlation risk factor.	Buraschi, Kosowski, and Trojani (2014)
VIX	Monthly relative changes in the CBOE volatility index (VIX).	FED
RIX	Monthly return on Gao, Gao, and Song (2014) RIX factor.	Gao, Gao, and Song (2014)

References

Ackermann, C., McEnally, R., Ravenscraft, D., 1999. The performance of hedge funds: risk, return, and incentives. Journal of Finance 54, 833–874.

Agarwal, V., Arisoy, Y.E., Naik, N.Y., 2016. Volatility of aggregate volatility and hedge fund returns. Journal of Financial Economics, forthcoming.

Agarwal, V., Naik, N.Y., 2004. Risks and portfolio decisions involving hedge funds. Review of Financial Studies 17, 63–98.

Agarwal, V., Bakshi, G., Huij, J., 2009. Do higher-moment equity risks explain hedge fund returns? Unpublished working paper. Erasmus University, Georgia State University, and University of Maryland.

Agarwal, V., Daniel, N.D., Naik, N.Y., 2003. Flows, performance, and managerial incentives in the hedge fund industry. Unpublished working paper. Georgia State University and London Business School.

Agarwal, V., Daniel, N.D., Narayan, N.Y., 2009. Role of managerial incentives and discretion in hedge fund performance. Journal of Finance 64, 2221−2256.

Agarwal, V., Fos, V., Jiang, W., 2013. Inferring reporting-related biases in hedge fund databases from hedge fund equity holdings. Management Science 59, 1271−1289.

Agarwal, V., Jiang, W., Tang, Y., Yang, B., 2013. Uncovering hedge fund skill from the portfolios they hide. Journal of Finance 68, 739−783.

Aiken, A.L., Clifford, C.P., Ellis, J., 2013. Out of the dark: Hedge fund reporting biases and commercial databases. Review of Financial Studies 26, 208−243.

Ang, A., Chen, J., Xing, Y., 2006. Downside risk. Review of Financial Studies 19, 1191−1239.

Aragon, G.O., 2007. Share restrictions and asset pricing: Evidence from the hedge fund industry. Journal of Financial Economics 83, 33–58.

Aragon, G.O., Martin, J.S., 2012. A unique view of hedge fund derivatives usage: Safeguard or speculation? Journal of Financial Economics 105, 436–456.

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

Aragon, G.O., Strahan, P.E., 2012. Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy. Journal of Financial Economics 103, 570−587.

Bali, T.G., Brown, S.J., Caglayan, M.O., 2012. Systematic risk and the cross-section of hedge fund returns. Journal of Financial Economics 106, 114−131.

Bali, T.G., Brown, S.J., Caglayan, M.O., 2014. Macroeconomic risk and hedge fund returns. Journal of Financial Economics 114, 1−19.

Bali, T.G., Gokcan, S., Liang, B., 2007. Value at risk and the cross-section of hedge fund returns. Journal of Banking and Finance 31, 1135−1166.

Bondarenko, O., 2004. Market price of variance risk and performance of hedge funds. Unpublished working paper. University of Illinois.

Boyson, N.M., Stahel, C.W., Stulz, R.M., 2010. Hedge fund contagion and liquidity shocks. Journal of Finance 65, 1789−1816.

Brown, S.J., Goetzmann, W.N., Park, J., 2001. Careers and survival: competition and risk in the hedge fund and CTA industry. Journal of Finance 56, 1869−1886.

Brown, S.J., Gregoriou, G.N., Pascalau, R., 2012. Is it possible to overdiversify? The case of funds of hedge funds. Review of Asset Pricing Studies 2, 89−110.

Brown, S.J., Spitzer, J.F., 2006. Caught by the tail: Tail risk neutrality and hedge fund returns. Unpublished working paper. New York University.

Buraschi, A., Kosowski, R., Trojani, F., 2014. When there is no place to hide: correlation risk and the cross-section of hedge fund returns. Review of Financial Studies 27, 581–616.

Cao, C., Chen, Y., Liang, B., Lo, A.W., 2013. Can hedge funds fund time market liquidity? Journal of Financial Economics 109, 493–516.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Chabi-Yo, F., Ruenzi, S., Weigert, F., 2015. Crash sensitivity and the cross-section of expected stock returns. Unpublished working paper. Ohio State University, University of Mannheim, and University of St. Gallen.

Chen, Y., 2007. Timing ability in the focus market of hedge funds. Journal of Investment Management 5, 66–98.

Chen, Y., Liang, B., 2007. Do market timing hedge funds time the market? Journal of Financial and Quantitative Analysis 42, 827–856.

Duarte, J., Longstaff, F., Yu, F., 2007. Risk and return in fixed income arbitrage: Nickels in front of a steamroller? Review of Financial Studies 20, 769−811.

Edelman, D., Fung, W., Hsieh, D.A., 2013. Exploring uncharted territories of the hedge fund industry: Empirical characteristics of mega hedge fund firms. Journal of Financial Economics 109, 734−758.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3−56.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 607−636.

Farnsworth, G., 2014. Strategic hedge fund leverage and investor welfare: A holdings-based approach. Unpublished working paper. Penn State University.

Fontaine, J.-S., Garcia, R., 2012. Bond Liquidity Premia. Review of Financial Studies 25, 1207–1254.

Fung, W., Hsieh, D.A., 1997. Empirical characteristics of dynamic trading strategies: The case of hedge funds. Review of Financial Studies 10, 275–302.

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

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

Gao, G.P., Gao, P, Song, Z., 2014. Do hedge funds exploit rare disaster concerns? Unpublished working paper. Cornell University and the University of Notre Dame.

Getmansky, M., Lo, A.W., Makarov, I., 2004. An econometric model of serial correlation and illiquidity in hedge fund returns. Journal of Financial Economics 74, 319−352.

Goetzmann, W.N., Ingersoll, J.E., Ross, S.A., 2003. High-water marks and hedge fund management contracts. Journal of Finance 58, 1685−1717.

Graham, J.R., Harvey, C.R., 1996. Market timing ability and volatility implied in investment newsletters’ asset allocation recommendations. Journal of Financial Economics 42, 397–422.

Graham, J.R., Harvey, C.R., 1997. Grading the performance of market-timing newsletters. Financial Analysts Journal 53, 54–66.

Griffin, J.M., Xu, J., 2009. How smart are the smart guys? A unique view from hedge fund stock holdings. Review of Financial Studies 22, 2331–2370.

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

Hodder, J.E., Jackwerth, J.C., Kolokolova, O., 2014. Recovering Delisting Returns of Hedge Funds. Journal of Financial and Quantitative Analysis 49, 797–815.

Jiang, H., Kelly, B., 2012. Tail risk and hedge fund returns. Unpublished working paper. Erasmus University Rotterdam and University of Chicago Booth School of Business.

Kelly, B., Jiang, H. 2014. Tail risk and asset prices. Review of Financial Studies 27, 2841–2871.

Kolokolova, O., Mattes, A., 2014. Recovering managerial risk taking from daily hedge fund returns: Incentives at work? Unpublished working paper. University of Manchester and University of Konstanz.

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

Liang, B., Park, H., 2007. Risk measures for hedge funds: a cross-sectional approach. European Financial Management 13, 333–370.

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

Longin, F., Solnik, B., 2001. Extreme correlation of international equity markets. Journal of Finance 56, 649–676.

Malkiel, B., Saha, A., 2005. Hedge funds: risk and return. Financial Analysts Journal 61, 80–88.

Mitchell, M., Pulvino, T., 2001. Characteristics of risk and return in risk arbitrage. Journal of Finance 56, 2135–2175.

Modigliani, F., Modigliani, L., 1997. Risk-adjusted performance. Journal of Portfolio Management 23, 45–54.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.

Ozik, G., Sadka, R., 2015. Skin in the game versus skimming the game: governance, share restrictions, and insider flow. Journal of Financial and Quantitative Analysis 50, 1293–1319.

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

Pástor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Posthuma, N., Sluis, P.N., 2003. A reality check on hedge fund returns. Unpublished working paper, ABP Investments.

Rodriguez, J.C., 2007. Measuring financial contagion: A copula approach. Journal of Empirical Finance 14, 401−423.

Sadka, R., 2010. Liquidity risk and the cross-section of hedge fund returns. Journal of Financial Economics 98, 54–71.

Shanken, J., 1992. On the estimation of beta-pricing models. Review of Financial Studies 5, 1–33.

Stulz, R., 2007. Hedge funds: past, present, and future. Journal of Economic Perspectives 21, 175–194.

Teo, M., 2011. The liquidity risk of liquid hedge funds. Journal of Financial Economics 100, 24–44.

Figure 1: 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 average of the individual *TailRisk* measures over all hedge funds in our sample. We compute aggregate *TailRisk* both on an equal-weighted and value-weighted basis. Our sample covers equity-oriented hedge funds from the Union Hedge Fund Database constructed from combining Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1996 to December 2012.

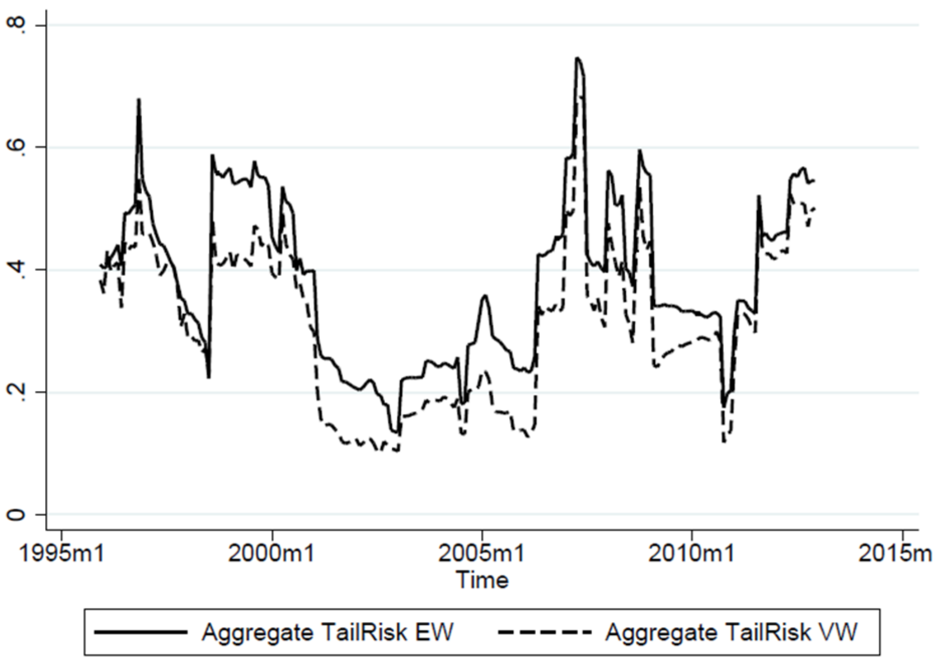

Figure 2: Tail Risk and Funding Liquidity: Evidence from Lehman Brothers connected Hedge Funds

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.

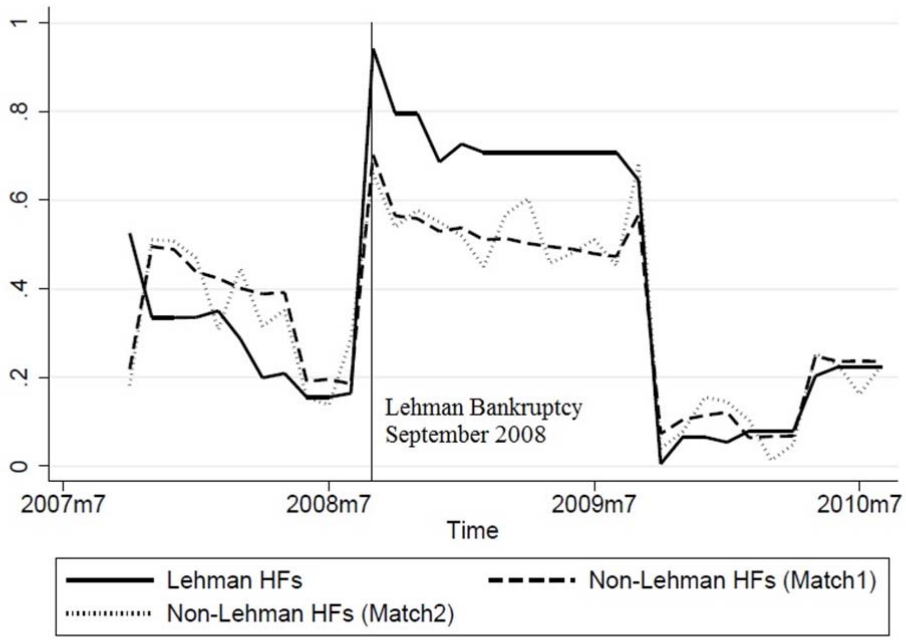

Figure 3: Tail Risk Timing: Evidence From Equity Holdings in the Financial Crisis 2008

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.

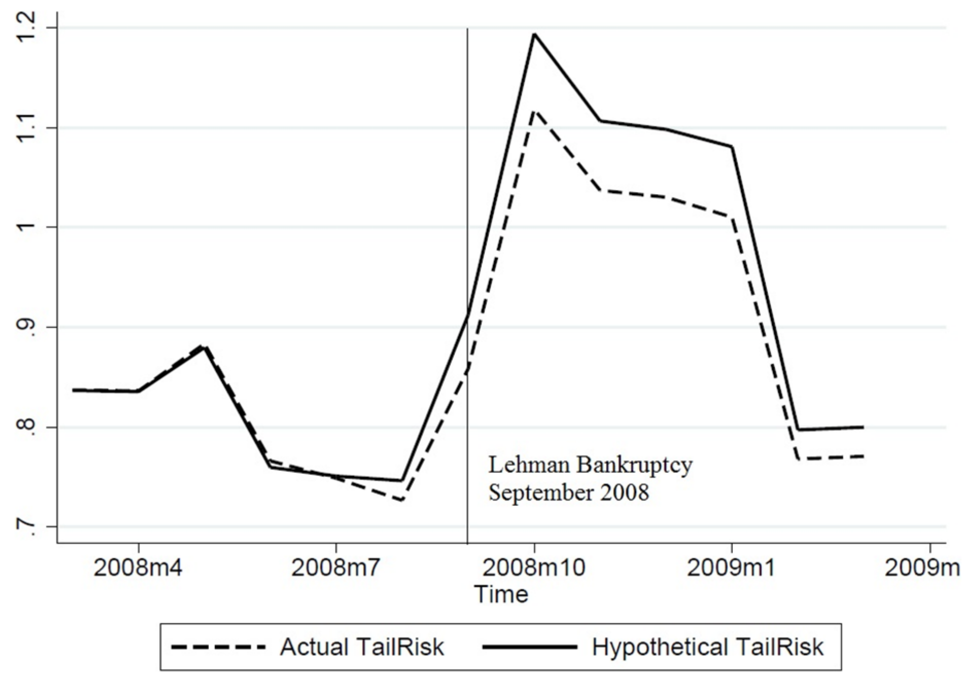

Figure 4: Tail Risk Timing: Evidence From Derivative Holdings in the Financial Crisis 2008

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.

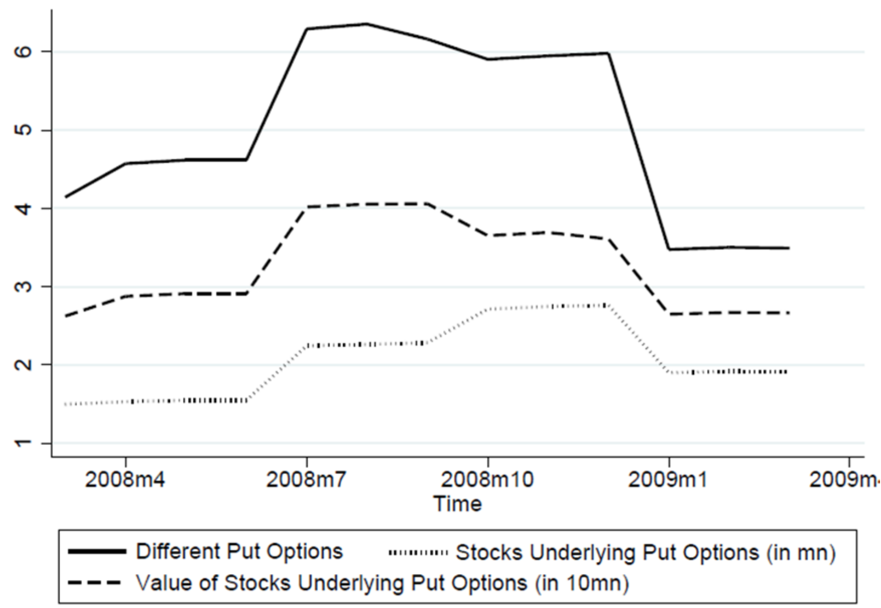

Table 1: Summary Statistics

This table provides summary statistics for the monthly excess returns (over the risk-free rate) of hedge funds (Panel A), fund characteristics (Panel B), and the *TailRisk* measure as defined in Eq. (2) in the main text (Panel C). Summary statistics are calculated over all hedge funds and months in our sample period. As the risk-free rate we use the one-month T-bill rate. We also display correlations between *TailRisk* and fund characteristics in Panel D. Finally, we provide 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 E. 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 1996 to December 2012. All variables are defined in Table A.1.

Panel A: Excess Returns

Sample	Mean	25%	Median	75%	StdDev
All	0.52%	–0.98%	0.42%	1.89%	5.23

Panel B: Fund Characteristics

Variable	Mean	25%	Median	75%	StdDev
Size	3.35	2.19	3.40	4.56	1.83
Age (in months)	63.85	22.00	48.00	90.00	55.86
Standard Deviation	4.54	2.09	3.53	5.81	3.81
Delta (in $100 thousands)	1.83	0.07	0.37	1.46	4.16
Management Fee (in %)	1.41	1.00	1.50	1.75	0.53
Incentive Fee (in %)	18.13	20.00	20.00	20.00	5.56
Min Investment (in $100 thousands)	10.90	1.50	5.00	10.00	92.81
Lockup Period (in years)	0.41	0.00	0.00	1.00	0.61
Restriction Period (in years)	0.34	0.16	0.33	0.38	0.30
Offshore	0.51	0.00	1.00	1.00	0.50
Leverage	0.60	0.00	1.00	1.00	0.49
HWM	0.80	1.00	1.00	1.00	0.40
Hurdle Rate	0.27	0.00	0.00	1.00	0.44

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
All	6,281	0.38	0.00	0.00	0.12	0.58	1.06	0.58

Panel D: Correlation between TailRisk and Fund Characteristics

	TailRisk	Size	Age	Standard Deviation	Delta	Management Fee	Incentive Fee	Min Investment	Lockup Period	Restriction Period	Offshore	Leverage	HWM	Hurdle Rate
TailRisk	1.00													
Size	–0.09	1.00												
Age	0.05	0.26	1.00											
Std. Dev.	0.29	–0.22	–0.03	1.00										
Delta	0.08	0.49	0.28	–0.09	1.00									
Mgmt. Fee	–0.00	0.07	–0.07	0.03	0.05	1.00								
Inc. Fee	–0.02	0.00	–0.09	–0.02	0.10	–0.03	1.00							
Min Inv	–0.05	0.26	0.06	–0.09	0.27	–0.03	0.01	1.00						
Lockup	0.07	0.00	0.01	0.05	–0.00	–0.04	0.13	0.05	1.00					
Restriction	–0.00	0.10	0.08	–0.02	0.12	–0.11	0.14	0.07	0.30	1.00				
Offshore	–0.01	0.15	–0.09	–0.00	0.08	0.22	–0.04	–0.08	–0.24	–0.30	1.00			
Leverage	0.09	0.03	–0.01	0.02	0.03	0.03	0.14	–0.03	0.04	0.03	0.03	1.00		
HWM	0.00	0.05	–0.06	–0.01	0.07	0.07	0.30	0.02	0.14	0.07	–0.04	0.09	1.00	
Hurdle Rate	–0.01	–0.05	0.11	–0.01	–0.03	–0.13	0.02	0.03	0.11	0.17	–0.47	0.03	–0.09	1.00

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

	TailRisk	Market	TED Spread	Funding Liquidity	PS Liquidity	Macro Uncertainty	Correlation Risk	VIX	RIX
TailRisk	1.00								
Market	–0.02	1.00							
TED Spread	0.47	–0.18	1.00						
Funding Liquidity	0.52	0.03	0.47	1.00					
PS Liquidity	–0.04	0.25	–0.18	-0.05	1.00				
Macro Uncertainty	–0.19	–0.00	0.01	-0.02	–0.07	1.00			
Correlation Risk	0.03	–0.48	0.13	-0.00	–0.16	–0.06	1.00		
VIX	0.09	–0.39	0.44	0.16	–0.25	0.52	0.12	1.00	
RIX	0.14	–0.10	0.49	0.24	–0.19	0.55	–0.00	0.72	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 future monthly excess returns. 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 *t*, we sort all hedge funds with *TailRisk* of zero into portfolio 0. All other hedge funds are sorted into quintile portfolios based on their *TailRisk* estimate in increasing order. We then compute equally-weighted monthly average excess returns of these portfolios in month *t+1*. 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 0 with the lowest tail risk subtracted from the returns of the funds in portfolio 5 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), the VIX (Return VIX), and the Gao, Gao, and Song (2014) RIX factor (Return RIX). 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*. In Panel D, we report the results of Fama and MacBeth (1973) regressions of excess returns in month *t+1* on *TailRisk* and different fund characteristics (as in model (4) of Panel C) in times of positive (negative) market returns, high (low) market volatility, and in subsamples in the period from 1996 – 2003 and 2004 – 2012. We compute market volatility as the standard deviation of the CRSP value-weighted market return over the past 24 months. We classify *t* as a high (low) market volatility period if the standard deviation is above (below) the median standard deviation over the whole sample period from 1996 - 2012. 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*. Finally, Panel E reports the results of time-series regerssions of the average monthly excess return of all equity-related hedge funds in month *t+1* on the difference (5-0) *TailRisk* portfolio and the seven factors in the Fung and Hsieh (2004) model. 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 1996 to December 2012. All variables are defined in Table A.1. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Table 2: (Continued)

Panel A: Univariate Portfolio Sorts

Portfolio	(1) TailRisk	(2) Excess Return	(3) Car-4-Factor	(4) FH-7-Factor
0 (Lowest)	0.00	0.49%	0.28%	0.34%
1	0.17	0.40%	0.25%	0.27%
2	0.39	0.47%	0.22%	0.22%
3	0.58	0.54%	0.30%	0.33%
4	0.86	0.61%	0.40%	0.42%
5 (Highest)	1.66	1.17%	0.78%	0.73%
5-0	1.66	0.68%**	0.50%***	0.39%**
		(2.16)	(3.20)	(2.12)

Table 2: (Continued)

Panel B: Additional Factors

	(1) PF 5–0	(2) PF 5–0	(3) PF 5–0	(4) PF 5–0	(5) PF 5–0	(6) PF 5–0	(7) PF 5–0	(8) PF 5–0	(9) PF 5–0
S&P	0.765***	0.588***	0.543***	0.530***	0.551***	0.548***	0.173***	0.101*	0.530***
	(18.62)	(9.64)	(10.15)	(9.26)	(9.49)	(9.46)	(2.74)	(1.76)	(9.21)
SCMLC	0.256***	0.180***	0.146***	0.201***	0.178***	0.181***	0.0630	–0.115**	0.145***
	(4.95)	(3.50)	(3.04)	(3.96)	(3.45)	(3.51)	(1.40)	(–2.52)	(2.78)
BD10RET	–0.110	–0.103	–0.0771	–0.0973	–0.101	–0.134	–0.0248	0.00518	–0.0664
	(–1.09)	(–1.07)	(–0.87)	(–1.04)	(–1.05)	(–1.39)	(–0.31)	(0.07)	(–0.70)
BAAMTSY	0.377***	0.304***	0.374***	0.291***	0.322***	0.265***	0.101	0.162**	0.365***
	(3.72)	(3.13)	(4.14)	(3.06)	(3.27)	(2.68)	(1.21)	(2.19)	(3.74)
PTFSBD	0.0466***	0.0515***	0.0414***	0.0474***	0.0521***	0.0476***	0.0389***	0.0395***	0.0436***
	(3.60)	(4.19)	(3.61)	(3.92)	(4.23)	(3.79)	(3.75)	(4.23)	(3.51)
PTFSFX	–0.00267	–0.00360	-0.000704	–0.00315	–0.00441	–0.00175	–0.0134	–0.00740	–0.00267
	(–0.24)	(–0.35)	(-0.07)	(–0.31)	(–0.42)	(–0.17)	(–1.53)	(–0.94)	(–0.26)
PTFSCOM	–0.0154	–0.0142	–0.0174	–0.00678	–0.0148	–0.0160	–0.00408	–0.000124	–0.0155
	(–1.10)	(–1.07)	(–1.43)	(–0.52)	(–1.12)	(–1.21)	(–0.37)	(–0.01)	(–1.20)
MSCI EM		0.189***	0.163***	0.179***	0.197***	0.195***	0.0366	–0.0522	0.213***
		(4.86)	(4.49)	(4.68)	(4.98)	(5.00)	(1.01)	(–1.48)	(5.46)
HML			–0.276***						
			(–5.90)						
UMD				–0.100***					
				(–3.16)					
Traded PS Liquidity					–0.0472				
					(–1.11)				
Return Macro						–0.0833*			
						(–1.97)			
Return CORR							0.632***		
							(9.44)		
Return VIX								0.718***	
								(12.35)	
Return RIX									0.132***
									(3.15)
Alpha	0.391**	0.390**	0.452**	0.443**	0.419**	0.486***	0.329**	0.514***	0.300*
	(2.12)	(2.24)	(2.87)	(2.59)	(2.38)	(2.71)	(2.25)	(3.89)	(1.71)
Observations	204	204	204	204	204	204	204	204	204
Adjusted R^2	0.707	0.737	0.776	0.749	0.738	0.742	0.820	0.853	0.750

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**	0.306**	0.240***	0.227***
	(2.01)	(2.34)	(2.60)	(3.16)
Size		–0.0906***		–0.0848***
		(–3.16)		(–3.28)
Age		–0.000107		–0.000203
		(–0.26)		(–0.50)
Delta		0.0190***		0.0168***
		(2.86)		(3.12)
Management Fee		0.0488		0.0403
		(1.28)		(1.05)
Incentive Fee		–0.000903		–0.0000219
		(–0.30)		(–0.01)
Min Investment		0.00233**		0.00207***
		(2.54)		(2.97)
Lockup Period		0.0490		0.0556*
		(1.49)		(1.73)
Restriction Period		0.0721*		0.0456
		(1.91)		(1.24)
Offshore		0.0350		0.0308
		(0.47)		(0.43)
Leverage		0.0268		0.0277
		(0.64)		(0.71)
HWM		0.125**		0.103**
		(2.50)		(2.21)
Hurdle Rate		0.108***		0.102***
		(3.99)		(4.50)
Past Yearly Return		0.0221***		0.0229***
		(7.36)		(9.42)
Standard Deviation		0.0182		0.0361
		(0.54)		(0.98)
Skewness			0.154**	0.0379
			(2.54)	(1.04)
Kurtosis			–0.0126	–0.0178
			(–0.62)	(–1.44)
VaR			0.00130	0.0150
			(0.06)	(1.13)
Beta			0.262	0.112
			(1.07)	(0.48)
Constant	0.426***	0.272**	0.509***	0.352***
	(3.08)	(2.11)	(4.18)	(2.61)
Observations	420,329	195,170	420,329	195,170
Adjusted R^2	0.058	0.165	0.160	0.230

Table 2: (Continued)

Panel D: Returns associated with TailRisk in Different States of the World

	(1) Market Return > 0	(2) Market Return < 0	(3) High Market Volatility	(4) Low Market Volatility	(5) Subsample: 1996 – 2003	(6) Subsample: 2004 – 2012
TailRisk	1.202***	–0.893***	0.441**	0.220*	0.301**	0.242*
	(8.35)	(–5.89)	(2.54)	(1.76)	(2.43)	(1.79)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	115,196	79,974	98,658	96,185	77,967	116,876
Adjusted R^2	0.222	0.243	0.232	0.229	0.252	0.212

Panel E: 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	0.227***	0.319**	0.327**	0.516*	0.613
	(3.16)	(2.42)	(2.10)	(1.85)	(1.10)
Control Variables	Yes	Yes	Yes	Yes	Yes
Observations	195,170	194,401	190,953	189,598	186,512
Adjusted R^2	0.230	0.241	0.252	0.246	0.251

Table 2: (Continued)

Panel F: Time Series Regressions

	Fung and Hsieh (2004) Model	Equity-Related	Emerging Markets	Event Driven	Equity Long-Short	Equity Long Only	Equity Market Neutral	Short Bias	Sector
S&P	0.432***	0.241***	0.212***	0.174***	0.288***	0.318***	0.079***	–0.471***	0.254***
	(21.55)	(7.79)	(2.63)	(7.55)	(8.57)	(5.79)	(4.10)	(–7.36)	(3.90)
SMB	0.275***	0.205***	0.124*	0.140***	0.255***	0.177***	0.028*	–0.372***	0.385***
	(10.91)	(8.25)	(1.92)	(7.57)	(9.46)	(4.01)	(1.79)	(–7.25)	(7.38)
Term	–0.082*	–0.076*	–0.102	–0.069**	–0.0894*	–0.084	0.005	–0.022	–0.069
	(–1.73)	(–1.66)	(–0.85)	(–2.00)	(–1.80)	(–1.02)	(0.17)	(–0.24)	(–0.71)
Credit	0.206***	0.120**	0.309**	0.268***	0.054	0.245***	0.077***	0.220**	–0.089
	(4.12)	(2.52)	(2.50)	(7.58)	(1.05)	(2.91)	(2.61)	(2.24)	(–0.88)
PTFSBD	–0.007	–0.019***	–0.054***	–0.021***	–0.015**	–0.013	–0.007*	–0.008	–0.010
	(–1.13)	(–3.10)	(–3.45)	(–4.67)	(–2.24)	(–1.20)	(–1.97)	(–0.67)	(–0.77)
PTFSFX	0.008*	0.010**	0.021	0.007*	0.010*	0.004	0.005*	0.002	0.012
	(1.68)	(2.01)	(1.61)	(1.81)	(1.92)	(0.47)	(1.66)	(0.23)	(1.13)
PTFSCOM	0.000	0.003	0.003	–0.004	0.004	0.002	0.000	–0.004	0.012
	(0.04)	(0.45)	(0.20)	(–0.74)	(0.62)	(0.17)	(0.05)	(-0.28)	(0.87)
TailRisk 5 – 0		0.244***	0.486***	0.083***	0.259***	0.313***	–0.007	–0.234***	0.501***
		(7.56)	(5.77)	(3.46)	(7.38)	(5.45)	(–0.35)	(–3.50)	(7.37)
Constant	0.436***	0.353***	0.275	0.395***	0.366***	0.331**	0.355***	0.295*	0.347*
	(5.04)	(4.18)	(1.25)	(6.29)	(4.01)	(2.21)	(6.81)	(1.70)	(1.95)
Difference to Constant in FH-7-Factor Model	–	–0.083	–0.104	–0.032	–0.090	–0.045	+0.007	+0.015	–0.260
Adjusted R2	0.778	0.830	0.599	0.796	0.834	0.712	0.263	0.669	0.713
Improvement in Adjusted R2 in Comparison to FH-7-Factor Model	–	0.052	0.100	0.031	0.047	0.057	–0.006	0.037	0.086
		(6.68%)	(20.04%)	(4.05%)	(5.97%)	(8.70%)	(–2.22%)	(5.85%)	(13.72%)

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) assign a delisting return of –1.61% to those hedge funds that leave the database. Moreover, we check the robustness if we (vi) use returns reported after the listing date for funds in the Lipper TASS database and (vii) use the correction method of Getmansky, Lo, and Makarov (2004) to unsmooth hedge fund returns and subsequently run asset pricing tests. Panel A displays the results of from the same univariate portfolio sorts as in Column 4, Panel A, Table 2 using these alternative definitions of *TailRisk*. Panel B reports the results of Fama and MacBeth (1973) regression (4) of Panel C 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 1996 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: Portfolio Sorts

	(1) Baseline	(2) Horizon 3y	(3) Horizon 4y	(4) Cut-Off 10%	(5) Cut-Off 20%	(6) VaR	(7) Value-Weighted	(8) Delisting Return	(9) Bloomberg Returns	(10) TASS	(11) Return Smoothing
TailRisk 5–0	0.39%**	0.34%**	0.32%**	0.36%**	0.30%*	0.31%*	0.34%**	0.37%**	0.40%***	0.34%**	0.40%**
	(2.12)	(2.10)	(2.05)	(2.25)	(1.74)	(1.82)	(2.31)	(2.03)	(3.79)	(2.07)	(2.06)

Panel B: Fama-MacBeth Regressions

	(1) Baseline	(2) Horizon 3y	(3) Horizon 4y	(4) Cut-Off 10%	(5) Cut-Off 20%	(6) VaR	(7) Value-Weighted	(8) Delisting Return	(9) Bloomberg Returns	(10) TASS	(11) Return Smoothing
Tail Risk	0.227***	0.202***	0.165*	0.211***	0.155*	0.201**	0.189*	0.222***	0.341***	0.245***	0.241***
	(3.16)	(2.81)	(1.84)	(2.78)	(1.71)	(2.14)	(1.78)	(3.1)	(4.31)	(3.28)	(3.42)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.230	0.226	0.223	0.227	0.220	0.226	0.219	0.229	0.301	0.267	0.229

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 1996 to December 2012. We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation. All variables are defined in Table A.1. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) TailRisk	(2) TailRisk	(3) TailRisk
Size	–0.000282		–0.000951
	(–0.11)		(–0.26)
Age	0.000336**		0.000168
	(2.60)		(1.12)
Standard Deviation	0.0809***		0.0788***
	(8.96)		(8.33)
Delta	0.00280**		0.00619**
	(2.04)		(2.60)
Past Yearly Return	–0.00333***		–0.00310***
	(–3.17)		(–2.82)
Management Fee		–0.00394	–0.0101
		(–0.55)	(–1.14)
Incentive Fee		–0.00477***	–0.00407
		(–3.50)	(–1.38)
Min Investment		–0.00219	–0.000923
		(–1.44)	(–1.23)
Lockup Period		0.0410***	0.0131**
		(5.17)	(2.01)
Restriction Period		–0.0000101	–0.0000101
		(–0.00)	(–0.00)
Offshore		–0.0286	–0.0308
		(–1.15)	(–1.30)
Leverage		0.0187	0.0287**
		(1.45)	(2.45)
HWM		0.0185	0.0142
		(1.39)	(1.28)
Hurdle Rate		–0.0211	–0.0267
		(–1.63)	(–1.08)
Constant	–0.00197	0.485***	0.137***
	(–0.11)	(9.49)	(4.40)
Observations	287,301	265,145	195,108
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. All variables are defined in Table A.1. ***, **, 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)
$\Delta_{Crisis\text{-}Precrisis} \times Lehman$	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	2,627	2,049	2,627	2,049
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*), to the CBOE VIX index (*VIX*), and to the Gao, Gao, and Song (2014) RIX factor *(RIX)*. 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 1996 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. All variables are defined in Table A.1. ***, **, and * denotes statistical significance at the 1%, 5%, and 10% level.

	(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)
β_{RIX}				0.164 (1.24)
Constant	0.0644*** (3.98)	0.134*** (4.86)	0.0579*** (4.46)	0.0559*** (6.11)
Observations	424,334	422,734	422,734	422,712
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, down beta, up beta, 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 model (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 1996 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	42,353	41,896	41,896	39,708	39,695
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.

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	44,702	44,702	44,702	44,702
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	4,211	4,211	4,211	3,801	3,801	3,801
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)