Hedge fund performance and systemic risk*

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Abstract

Hedge funds exposed to systemic risk generate steady returns most of the time, but they underperform severely when a systemic event occurs. During the recent financial crisis the highest systemic risk decile portfolio underperformed the lowest by an annual -10.7 percent in risk-adjusted terms with respect to liquidity factor augmented Fung-Hsieh (2004) model. Large systemic risk exposure among hedge funds is associated with higher failure probability even after controlling for the role of other variables that are documented to explain fund failures. Systemic risk measures such as co-expected shortfall and marginal expected shortfall explain performance differences among hedge funds better than traditional risk measures like expected shortfall and market beta.

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1 Introduction

This paper analyses the relation between systemic risk and hedge fund performance. While, for instance, Brown, Kacperczek, Ljungqvist, Lynch, Pedersen, and Richardson (2009) suggest that there is very little evidence that hedge funds create systemic risk in the financial system, hedge funds have been associated with systemic risk during the collapse of LTCM in the fall of 1998 and the recent financial crisis in 2007-2009. It is also well-known (e.g. Boyson, Stahel, and Stulz (2010)) that hedge funds as a group tend to deliver extremely low returns when the aggregate level of funding and asset liquidity is low. The previous literature, however, does not examine the cross-sectional differences in hedge fund systemic risk and does not investigate how well systemic risk explains cross-sectional differences in hedge fund performance and failures.

The paper aims to contribute to the understanding of the determinants driving hedge fund systemic risk-taking and performance. This paper makes three contributions. First, it examines the determinants of systemic and traditional risk measures by showing that the properties of the systemic and traditional measures differ significantly from each other. Second, in the cross-section of hedge funds, the findings of the paper suggest that funds having high systemic risk exposure tend to outperform most of the time. However, during the financial stress, these funds face significant losses delivering significantly lower risk-adjusted returns than their peers. In other words, hedge funds' excess risk-taking generate superior short-term performance that seems to be associated with tail risks. Third, the paper finds that hedge fund systemic risk is an important determinant in explaining fund failures. Overall, the paper provides support for the recently proposed systemic risk measures, since they are better able to capture performance differences across funds compared to traditional risk measures, especially during the financial crises.

While traditional risk measures aim to assess the riskiness of a financial institution in isolation, systemic risk measures are measuring the riskiness of a financial institution conditional on the occurrence of a systemic event. In this paper, systemic risk is measured using Co-Expected Shortfall (*CoES*) and Marginal Expected Shortfall (*MES*) ratios, whereas Expected Shortfall (ES) is used as a traditional risk measure.[1] The definition and the estimation of systemic risk measures follow closely Adrian and Brunnermeier (2009) and Acharya, Pedersen, Philippon, and Richardson (2010), who originally proposed them.

The empirical analysis of the paper is performed using a comprehensive hedge fund data containing 10,026 funds obtained from BarcleyHedge, HFR, and TASS databases. To understand the properties of the hedge fund's risk measures, I conduct a pooled regression analysis in which different risk measures are explained by fund-specific characteristics. The overall results suggest that the determinants of the hedge fund's systemic and fund-level risk exposures differ significantly from each other.

Specifically, the results suggest that hedge fund systemic risk decrease with higher managerial incentives measured using manager's option delta and incentive fee.[2] It may be the case that funds with higher managerial incentives have a lower tendency to generate systemic risk in the financial system. On the other hand, unskilled managers may have incentives to take hidden tail risks, which generate steady returns during the "good" times, while during the "bad" times the tail risk realizes. Indeed, a very lucky unskilled manager can earn significant incentive and management fees with such risk-taking behavior. According to Weisman (2002), hedge funds commonly follow these informationless strategies in order to generate a "fake" alpha that does not require any true investment skills. To support this view, Titman and Tiu (2008) find that skilled hedge fund managers choose to hedge away common risk factors, since funds with low R-square of returns on a set of common risk factors deliver better performance than their peer.

Hence, it is interesting to address the main question of the paper, which investigates how hedge funds' systemic risk taking explains the cross-sectional differences in hedge fund performance. Using portfolio sorts and Fama-MacBeth regressions, I document a significant time-varying cross-sectional relation between systemic risk and hedge fund performance. The findings suggest that hedge funds with a high systemic risk exposure tend to deliver

[1] As a robustness check the role of market beta is controlled for.

[2] Agarwal, Daniel, and Naik (2009) propose the use of manager's delta, the expected dollar increase in the manager's compensation for one percent increase in the fund's net-asset-value, to measure the hedge fund's managerial incentives.

extremely low returns during the times of financial distress, whereas they seem to generate steady positive return most of the time. Specifically, I find that there a significantly negative mean spread between the top and bottom hedge fund systemic risk portfolios during the financial crisis 2007-2009. The mean spreads is -3.3% (-1.9%) per month when the systemic risk is measured using *MES* (*CoES*) ratio, being also economically important. In contrast, the respective mean spread is significantly positive being 1.8% (0.7%) per month during the steady normal times suggesting that hedge funds exposed to systemic risk outperform.

To confirm that the main results are not driven by the common systematic risk factors, I repeat Fama-MacBeth regressions and portfolio sorts using risk-adjusted returns obtained from the Fung-Hsieh (2004) model that includes the Pastor and Stambaugh (2003) liquidity factor. Indeed, I find a time-varying relation between systemic risk and risk-adjusted returns consistently with the results presented earlier. Specifically, during the recent financial crisis the highest systemic risk decile portfolio underperformed the lowest by an montly -0.89% when systemic risk is measured using *MES* ratio. Hence, during financial crises common risk factors can not explain the abnormally poor performance of hedge funds that are exposed to systemic risk.

Of course, the classification of "good" and "bad" times is arbitrary. Therefore, I conduct an additional test in which instead of the recent financial crisis 2007-2009, I use the failure of LTCM and the burst of technology stocks in 2001 as test periods. The working hypothesis is that the LTCM episode and the recent financial crisis have been associated with systemic risk, whereas the turndown related to technology stocks was not systemic. This idea is also supported by data, since I find that hedge funds with high systemic risk suffered during the LTCM case, but not during the 2001 recession. This analysis provides further evidence that the proposed systemic risk measures are capture what they are designed to do.

Importantly, the documented time-varying cross-sectional relation is captured better using systemic risk measures compared to traditional risk measures. Indeed, the coefficient for systemic risk measures remains economically and statistically significant even after the impact of both expected shortfall and market beta is explicitly controlled for in Fama-MacBeth regressions. In addition, the conducted portfolio sorts show that the mean spread between high and low expected shortfall hedge fund portfolios does not capture the cross-sectional relation as systemic risk measures do.

Finally, to understand the explanatory power of risk measures in predicting hedge fund failures, I conduct a survival analysis using a Cox semiparametric hazards model. The results of the analysis suggest that systemic risk is an important determinant of hedge fund failures even after explicitly controlling for the role of traditional risk measures and other fund-specific characteristics that are associated with fund failures. Specifically, I find that hedge fund failure probability increases significantly with higher systemic risk measured using *MES*, but the higher fund's *CoES* is not associated with a higher failure probability. However, the expected shortfall remains as an important variable in predicting fund failures along with the systemic risk.

This paper relates to literature that examines hedge fund contagion as well as liquidity, correlation and extreme risks. Using hedge fund index data, Boyson, Stahel, and Stulz (2010) examine hedge fund contagion based on Brunnermeier and Pedersen (2009) model's predictions. They provide clear evidence on hedge fund contagion that is magnified during the liquidity shocks. They explain hedge fund contagion using a set of aggregate funding and asset liquidity variables. In this paper, I use individual hedge funds with a rich set of fund characteristics. Hence, I can examine which individual hedge funds are associated with risk spillovers, and how they perform during the times of financial distress.

Recent papers (Sadka (2009) and Buraschi, Kosowski, and Trojani (2009)) show that liquidity and correlation risks explain cross-sectional variation in hedge fund returns. Bali, Gokcan, and Liang (2007) document a significant cross-sectional relation between hedge fund returns and financial risk measures such as value-at-risk. This paper differs from those by demonstrating that the fund's systemic risk is an important determinant in the cross-section of hedge fund returns, and that the relationship is magnified during the times of financial distress.

2 Measuring systemic risk

In this paper, hedge funds' systemic risk is measured using two slightly modified versions of recently proposed systemic risk measures. Traditional risk measures aim to assess the riskiness of a financial institution in isolation. In contrast, systemic risk measures attempt to capture the riskiness of a financial institution conditional on the occurrence of a systemic event. Adrian and Brunnermeier (2009) propose that financial institutions systemic risk can be measured using the *CoVaR*, which is defined as the Value-at-Risk (*VaR*) of the financial system conditional on an individual financial institution being in distress. The first systemic risk measure of the paper is Co-Expected Shortfall (*CoES*), which extends the *CoVaR* by capturing the whole conditional loss distribution. Acharya, Pedersen, Philippon, and Richardson (2010) propose that financial institution systemic risk can be measured using Systemic Expected Shortfall (*SES*). The *SES* depends on financial institution's leverage and its Marginal Expected Shortfall (*MES*). The paper uses the *MES*, which predicts financial institutions' equity loss during a systemic crisis, as a second systemic risk measure. Throughout the paper, Expected Shortfall (*ES*) is used as a traditional risk measure. The role of market beta is also addressed as an additional robustness test.

2.1 Expected Shortfall

Two traditional measures for riskiness of financial institution are Value-at-Risk (*VaR*) and Expected Shortfall (*ES*). These risk measures aim to measure the potential total loss incurred by financial institution i in an extreme event. Both measures are easy to estimate, since they are not dependent on any conditional return distribution, as systemic risk measures are depending.

The *VaR* is defined as the q quantile of the unconditional probability distribution.

$$\Pr\left(R^i \leq VaR_q^i\right) = q, \tag{1}$$

where R^i is return of financial institution i for which the VaR_q^i is defined. According to

Artzner, Delbaen, Eber, and Heath (1999), *VaR* is not a coherent risk measure.[3] Therefore, I measure fund-specific risk using *ES*, which fulfills the properties of a coherent risk measure. The ES_q^i is defined as the q quantile

$$\mathrm{E}\left[R^i | R^i \leq \mathrm{VaR}_q^i\right]. \tag{2}$$

Hence, ES_q^i is implicitly defined by the expectation over q-tail of the unconditional probability distribution. In other words, the expected shortfall is the average of returns when the loss exceeds its *VaR* limit.

2.2 Co-Expected Shortfall

Adrian and Brunnermeier (2009) propose *CoVaR* approach for measuring systemic risk. The objective of the *CoVaR* approach is to measure which institutions are likely to be in financial difficulties when a systemic risk event occurs, and how financial difficulties of one institution spill over to others. The *CoVaR* approach does not distinguish whether the fund's systemic contribution is causal or simply driven by a common factor. This property is not a shortcoming, since it allows one to measure systemic risk driven by common risk factors even though there is no direct causal link. Therefore, Adrian and Brunnermeier (2009) argue that it is particularly well-suited for measuring hedge fund systemic risk even in case that hedge funds do not cause any systemic crises.

Adrian and Brunnermeier (2009) define *CoVaR* as the *VaR* of financial system, conditional on an individual financial institution being in distress. Formally, the *CoVaR* is defined as the q quantile of the conditional probability distribution

$$\Pr\left(R^{system} \leq CoVaR_q^{system|i} | R^i \leq VaR_q^i\right) = q, \tag{3}$$

where R^{system} is return of the portfolio of all financial institutions. Said differently, $CoVaR_q^{system|i}$

[3] The *VaR* is not a coherent risk measure, since the *VaR* of the sum of two portfolios can be higher than the sum of their individual VaRs.

is the VaR of the portfolio of financial system conditional on institution i being at its VaR level.

Following Adrian and Brunnermeier (2009) financial institution i's contribution to systemic risk can be defined as the difference between the financial system's VaR conditional on financial institution i in distress, and the financial system's VaR conditional on financial institution i functioning in its median state

$$\Delta CoVaR_q^i = CoVaR_q^{system|i} - CoVaR_{median}^{system|i}$$

Hence, $\Delta CoVaR_q^i$ measures how much a particular hedge fund "adds" to an overall systemic risk in the financial system.

In this paper, hedge funds' systemic risk is measured using a Co-Expected Shortfall ($CoES$), which is defined as a fund's expected shortfall conditional on the whole financial system being in distress. The $CoES_q^i$ is defined in the context of hedge funds as the ES_q^{system} of financial system conditional on the (unconditional) ES of an individual hedge fund i. This indicates that $CoES_q^i$ is implicitly defined by the expectation over q-tail of the conditional probability distribution:

$$\mathrm{E}\left[R^{system}|R^{system} \leq \mathrm{CoVaR}_q^i\right]. \tag{4}$$

Individual hedge fund i's marginal contribution to systemic risk in the financial system can be obtained as a difference of the financial system's ES conditional on financial institution functioning in its median state:

$$\Delta CoES_q^i = \mathrm{E}\left[R^{system}|R^{system} \leq \mathrm{CoVaR}_q^i\right] - \mathrm{E}\left[R^{system}|R^{system} \leq \mathrm{CoVaR}_{median}^i\right]. \tag{5}$$

I rely on the Adrian and Brunnermeier's quantile regression approach in estimating hedge funds' $CoES$ ratios. The estimation procedure is presented in Appendix.

2.3 Marginal Expected Shortfall

Acharya, Pedersen, Philippon, and Richardson (2010) propose a novel theoretical model of systemic risk regulation suggesting that financial institution systemic risk can be measured using Systemic Expected Shortfall (*SES*). Their simplified model is based on the assumption that the externality depends on the aggregate capital shortfall in the financial industry. The advantage of the model is that it captures two generally well accepted aspects of financial regulation. The main reason for the regulation of financial institutions is that there are externalities from their failures and even undercapitalization that spill over to others in the economy. In addition, these externalities may not be internalized by financial institutions, thus excess risk-taking may take place.

Based on the Acharya, Pedersen, Philippon, and Richardson (2010) model's predictions, the financial institutions' systemic risk should vary cross-sectionally on the firm's expected equity return conditional on the systemic event, and on the firm's leverage. Hence, financial institutions' contribution to systemic risk depends on their losses in the tail of the aggregate shortfall of financial institutions and on their leverage. The model's cross-sectional prediction about leverage is difficult to test in the context of hedge funds. The capital structure of hedge funds differs significantly from other financial institutions like banks. In addition, it is extremely difficult to measure hedge funds' leverage due to limited data. Therefore, in the empirical analysis, I measure hedge fund systemic risk using *MES* that is defined as a fund's loss during a systemic event.

In the context of hedge funds, the MES_q^i is defined as the q quantile

$$\mathrm{E}\left[R^i | R^{system} \leq \mathrm{VaR}_q^{system}\right]. \tag{6}$$

Hence, the *MES* measures hedge fund i's losses when financial system as whole doing poorly.

Throughout the paper, I estimate *MES* using a historical estimator based on past returns on each individual hedge fund and financial system. Of course, the *MES* could be estimated using sophisticated econometric methodologies, fox example, following the Brownless and

Engle (2011) approach. In that sense, the results of the paper are conservative, since Brownless and Engle (2011) show that their sophisticated *MES* forecasts are more accurate than can be obtained using only a historical *MES* estimator.

Finally, it is important to note that *MES* is defined conditional on *the financial system* doing poorly, while *CoVaR* (*CoES*) is conditional on *an individual financial institution* being in distress. Indeed, Adrian and Brunnermeier (2009) argue that by reversing the conditioning of *CoVaR*, one can obtain the "exposure *CoVaR*" sharing properties similar to *MES*.

3 Data

3.1 Aggregate hedge fund database

I estimate hedge fund risk measures using a comprehensive hedge fund database. The aggregate data set contains hedge funds provided by BarcleyHedge, TASS and HFR.[4] The sample period is from January 1994 to December 2009 containing 16,449 individual hedge funds. To obtain reliable risk measure estimates for individual hedge funds, I require that the fund has at least 36 return observations. This filter leaves me 10,026 hedge funds containing 3,955 alive and 6,071 defunct funds. The appendix provides futher details about the data.

Hedge funds' reporting to the databases is voluntary. Hence, the risk measures can potentially suffer from several biases. I minimize the survivorship bias using the post-1994 data, since it consists of both alive and defunct funds. Fung and Hsieh (2006) report that hedge fund data suffer from a liquidation bias that refers to the fact that hedge fund managers stop reporting returns to a database prior to the possible final liquidation value of a fund. In addition, risk measures may also suffer from the backfilling bias and the self-selection bias. When new funds enter the database, its prior track record is "backfilled" to the database, while the self-selection bias may arise, when only funds with good performance choose to market their performance via data vendors. The nature of liquidation, backfilling

[4] The appendix provides the details of the merging process.

and self-selection suggests that *CoES*s and *MES*s may underestimate the level of systemic risk.

3.2 Descriptive statistics for risk measure estimates

I estimate Δ*CoES, MES* and *ES* estimates at 10 % level for hedge funds which have at least 36 monthly return observations. The sample contains 10,026 hedge funds over the time period from January 1994 to December 2009. Table 1 presents the descriptive statistics of ratios in percentile terms without a sign conversation. The descriptive statistic includes the mean and standard deviation of risk measures within a specific category.

[Insert Table 1]

Table 1 also reports the Spearson rank correlation between Δ*CoES, MES* and *ES* ratios across investment strategies. The results suggest that when the risk is measured using the *CoES* and *MES* approaches, it leads to different rankings between funds compared to a case when the risk is measured using the conventional *ES* approach. In particular, the overall rank correlation between Δ*CoES (MES)* and *ES* is only 0.31 (0.29). Hence, the funds that are risky in isolation may not be associated with a higher systemic risk. In addition, the rank correlation between systemic risk measures *CoES* and *MES* is 0.41. This suggest that the systemic risk measures also differ from each other. Based on these preliminary findings about the properties of risk measures, it is interesting to examine further the determinants of the systemic and fund-specific risks as well as their ability to capture cross-sectional differences in hedge fund performance and failures.

4 Determinants of systemic risk measures

To understand how hedge fund systemic risk differ from the fund-specific risk, I conduct a multivariate analysis in which different risk measures are explained by fund-specific characteristics and investment strategies. To examine the determinants of systemic and fund-specific risk measures, I estimate the following pooled regression:

$$\begin{aligned} Risk_{i,t} &= \gamma_0 + \gamma_1 CompensationStructure_{i,t-1} + \gamma_2 Liquidity_{i,t-1} \\ &\quad + \gamma_3 AvgLeverage_i + \gamma_4 ControlVariables_{i,t-1} \\ &\quad + \sum_{s=1}^{11} \gamma_{5+s} I\left(Strategy_{i,s}\right) + \sum_{s=1}^{14} \gamma_{16+s} I\left(Year_{i,s}\right) + \varepsilon_i, \end{aligned}$$

where $Risk_{i,t}$ is the fund's Co-Expected Shortfall (*CoES*), Marginal Expected Shortfall (*MES*), or Expected Shortfall (*ES*).[5] $CompensationStructure_i$ is a vector including the fund's *management* and *incentive fees* as well as the indicator variable whether the fund has imposed a *high-water mark* provision as well as lagged *manager's option delta*. $Liquidity_i$ vector contains the lagged *level of asset liquidity* based on Getmansky, Lo, and Makarov (2004) measure and the vector of share restrictions including the length of the *lockup*, *redemption* and *notice periods* as well as the lagged fund's capital *flow*. *Avr.Leverage* denotes the fund's average level of leverage.[6] $ControlVariables_i$ is a vector including the lagged fund's *size*, and *age*. Following Petersen (2009), I control for effects related to strategies and calender time, and adjust standard errors for within-cluster correlation, heteroskedasticity, and autocorrelation. Finally, based on the practise in the literature, I do not apply sign convention for the risk measures.

Table 2 presents the results of three model specifications for each of the risk measures. The overall findings show that the determinants of systemic and fund-specific risks do not share

[5] All the risk measured are estimated using 36 months' rolling window at 10% level.

[6] Hedge fund databases do not provide time-varying leverage. Using the TASS database, I confirm the issue by collecting five snapshots from different years. Almost each of the hedge funds, the average leverage remains unchanged through these snapshots.

similar properties suggesting that systemic and fund-specific risks differ fundamentally from each other. Hence, hedge funds that are highly exposed to systemic risk do not necessarily exhibit risk in isolation, as assessed by fund-specific risk.

[Insert Table 2]

The results show systemic risk decrease with variables related to hedge fund compensation structure. The coefficients for management and incentive fees, manager's option delta and high-water mark turned out to be positive when these variables explain systemic risk. Specifically, the coefficient for option delta (incentive fee) is positive and significant when systemic risk is measured using *CoES* (*MES*). Hence, there is a negative relation between systemic risk and managerial incentives. These findings are consistent with Titman and Tiu (2008) and Sun, Wang, and Zheng (2009). According to Titman and Tiu (2008) skilled managers choose to hedge away systemic risks, and, therefore have lower R-squares with respect to systematic risk factors. Sun, Wang, and Zheng (2009) argue that skilled managers are more likely to pursue unique investment strategies that deliver superior risk-adjusted performance. Finally, the relation is not similar for the fund-specific risk, since the respective coefficients are either negative or indistinguishable from zero.

The results suggest that there is a negative relation between hedge fund systemic risk and liquidity. The positive coefficients across model specifications for the Getmansky, Lo, and Makarov (2004) asset liquidity measure suggest that funds investing in illiquid assets have a higher systemic risk. In addition, the coefficients for investor's capital flows are significantly positive suggesting that hedge funds' systemic risk increases with low funding liquidity measured using investors' redemptions.

Hedge funds which invest in illiquid assets tend to impose high share restrictions in the form of lockup, notice and redemption periods in order to manage illiquid assets more efficiently. These variables are expected to be greater for funds with illiquid assets. Thus, these variables have negative coefficients if they are related to a higher systemic risk. The results show that coefficients for redemption and lockup periods are negative, but only the coefficients for redemption period are significantly negative in both model specification. However, the coefficients for a notice period are positive, but they do not differ statistically from zero. For the expected shortfall, the coefficient for a lockup period is negative, while the coefficient for a notice period is significantly positive. This suggests that funds with longer notice periods, perhaps, allow hedge funds to manage illiquid asset efficiently.

The findings show that there is no significant relation between the hedge fund's systemic risk and the level of average leverage. At first glance, the result seems not to be expected. However, Liu and Mello (2009) argue that hedge funds' capital structure is fragile, since equity can be redeemed at investors' discretion and prime brokers may impose strict limits on leverage and reduce the availability of credit. Their structural model predicts that a hedge fund's optimal cash holdings are high compared to banks, since hedge funds' equity is more fragile than banks' equity. Therefore, hedge funds may not opt to use as high leverage as banks do to magnify returns especially when there is a high probability of a systemic event. To support this view, Ang, Gorovyy, and van Inwegen (2011) document that hedge fund leverage was relatively low during the recent financial crises compared to listed financial intermediaries. These results are also consistent with Brunnermeier, Dong, and Palia (2011), who examine the contribution of a bank's non-interest income to systemic bank risk without finding a significant relation between the bank's $CoVaR$ and the level of leverage.

Next, I turn on the relationship between the hedge fund's systemic risk and investment strategy. The results show that the hedge funds' systemic (fund-specific) risk increases (decreases) with the convertible arbitrage, the event driven and the fixed income arbitrage strategies. Thus, these strategies relying on relative bets are not risky in isolation, while during the times of financial distress, they tend to perform poorly. The result is consistent with Xiong's (2001) model proposing that convergence traders reduce asset price volatility and provide liquidity by taking risky positions against noise traders. However, when an unfavorable shock occurs, such strategies may suffer capital losses due to forced fire-sales.

The findings show that the hedge fund's systemic risk decreases (increases) with the managed futures (global macro) strategy. The low systemic risk of managed futures strategy during the systemic events is in the line with Asness, Moskowitz, and Pedersen (2009). According to Fung and Hsieh (2001), the managed futures strategy is based on trend-following. Hence, they tend to play short-term reversal or momentum strategies. Asness, Moskowitz, and Pedersen (2009) show using a large set of asset classes that momentum strategy outperforms during the times of distress.

The dedicated short bias strategy shows an interesting behavior, since the systemic (fund-specific) risk decrease (increase) with the dedicated short bias strategy. The results is expected, since the strategy relies on short-selling, which is often profitable when financial sector or overall markets does poorly. On the other hand, the dedicated short bias strategy can be also associated with high systemic risk, since their short positions may push security prices further away from their fundamental values. However, Brown, Green, and Hand (2010) find no such evidence that the short bias funds are associated with opportunistic wide-spread bear raids. In addition, Baber and Pagano (2010) provide comprehensive cross-country evidence suggesting that short-selling may not increase equity price drawdowns.

Finally, the overall results suggest that the determinants of the hedge fund's systemic risk and fund-level risk exposure differ significantly from each other. Therefore, these funds with high systemic risk are not necessarily the same that have a high financial risk exposure. It is interesting to note that using the value-at-risk approach that when hedge funds' risk is measured in isolation, Gupta and Liang (2005) find that the majority of hedge funds fulfill the proposed capital requirements. These findings suggest that a particular hedge fund's capital adequacy based on the traditional risk measure may be very different compared to a case when it is determined by taking systemic risk into account, for example, following *CoVaR* or *MES* approaches proposed by Acharya, Pedersen, Philippon, and Richardson (2010) and Adrian and Brunnermeier (2009). In addition, since the properties of the risks differ significantly from each other, it is interesting to study whether systemic or fund-specific risks able to capture the cross-sectional performance differences across hedge funds especially during the times of financial stress.

5 Systemic risk and Hedge fund performance

I conduct univariate and multivariate analyses based on portfolio sorts and Fama-MacBeth regressions to examine whether hedge fund systemic risk is related to fund performance. One advantage of the portfolio sorts is that they allow one to gauge the economic significance of investment strategies that are based on the level of fund systemic risk. Using the multivariate analysis, I am able to control for the role of other risk measures and fund characteristics that might have an impact on fund performance.

5.1 Multivariate evidence based regressions

To investigate whether hedge fund systemic risk is related to the cross-section of hedge fund returns, I estimate the following Fama-MacBeth (1973) regression:

$$Return_{i,t} = \gamma_0 + \gamma_1 \Delta CoES_{i,t-1} + \gamma_2 MES_{i,t-1} + \gamma_3 ES + \gamma_4 Controls + \varepsilon_i, \tag{7}$$

where $Return_{i,t}$ is the fund's monthly return, $\Delta CoES_{i,t-1}$ is the fund's *lagged* co-expected shortfall, $MES_{i,t-1}$ is the fund's *lagged* marginal expected shortfall, and $ES_{i,t-1}$, is the fund's *lagged* expected shortfall.[7] As control variables, based on Asness, Krail, and Liew (2001) and Getmansky, Lo, and Makarov (2004), I include the fund's lagged returns, $Return_{i,t-1}$ and $Return_{i,t-2}$, to control for autocorrelation or return smoothing in fund returns. The lagged returns also control that there is no mechanical relation between hedge fund returns and lagged risk measures.[8] Finally, I control for fixed effects related to strategies and adjust standard errors for heteroskedasticity, and autocorrelation following Newey and West (1987).

To examine time-varying cross-sectional relation between systemic risk and hedge fund returns, I divide the sample into three subperiods including: (i) the whole period 1997-2010, (ii) only the financial crisis 2007Q3-2009Q1, and (iii) the "normal" period, which excludes

[7] All the risk measured is estimated using 36 months' rolling window at 10% level.

[8] Additional robustness tests also show that the main results remain unchanged even after inclusion of market beta and other fund characteristics related to share restrictions, managerial incentives as well as fund's age, flows and size. The results of the test are available upon a request.

the recent financial crisis. The working hypothesis is that hedge funds with a high systemic risk should generate excess returns most of the time, but they should face significant losses when a systemic event occurs. It is important to note that this can be seen as a test of how well the proposed systemic risk measures can capture hedge fund performance differences when a systemic event occurs.

The results in Table 3 show that there is a time-varying cross-sectional relation between the hedge fund's systemic risk and fund returns. Indeed, I find that there is an insignificant average relation between hedge fund systemic and fund-specific risk, since in all model specifications the coefficients for them are negative but insignificant.[9] During the financial crisis 2007-2009, the coefficients for both systemic risk measures are positive and significant suggesting that hedge funds having high systemic risk exposure deliver poor performance during the crisis. On the other hand, the coefficient for expected shortfall is not significant implying that fund-specific risk does not explain poor performance during the financial crisis. In contrast, I find that during "normal" times, the coefficients for systemic risk measures are negative and highly significant suggesting that hedge funds taking exposure to systemic risk outperform. Taking together, the *MES* ratio seems to capture time-varying cross-sectional relation better compared to other systemic risk and fund-specific risk measures.

[Insert Table 3]

To control that the results are not driven by common risk factors in hedge fund returns, I re-run Fama-MacBeth regression using Fung-Hsieh (2004) alphas as a dependent variable.[10] The alpha is estimated using the Fung-Hsieh (2004) model with the Pastor and Stambaugh (2003) liquidity factor. Specifically, following Carhart (1997), I first calculate monthly fund alpha as fund excess returns minus the factor realizations times loadings estimated over the entire sample period. Then, I estimate the Fama-MacBeth regression in which these alphas are used dependent variable instead of returns.

[9] Brown, Hwang, In, and Kim (2011) document a significant relation between systemic risk measured using MES and hedge fund returns. I also find such a relation when I am not controlling for the role of autocorrelation using lagged returns properly.

[10] The Fama-MacBeth regression methodology follows Carhart (1997) in which mutual fund alphas are explained using fund characteristics.

The main result is clearly not driven by common factors in hedge fund returns, since I again find that the coefficients for systemic risk are positive during the financial crisis. The coefficient for *MES* is statistically significant and larger than the coefficient for *CoES*. However, the coefficients for systemic and fund-specific risk measures are insignificant during the "normal" times. This implies that common risk factors explain largely the excess return that hedge funds with high systemic risk generate most of the time. Importantly, during the financial crisis hedge funds returns are lower than their exposure to common risk factors would suggest. I interpret this as evidence that hedge funds with high systemic risk are exposed to tail risk that cannot explained by common risk factors. For hedge funds having high systemic risk, it seems that hidden tail risk is realized when a systemic event occurs.

5.2 Univariate evidence based on portfolio sorts

To gauge the economic significance of the performance of systemically important hedge funds, I form decile portfolios based on a lagged hedge fund systemic and fund-specific risk measures. The overall results are almost similar as in multivariate analysis.

Figure 1 shows the cumulative returns for the high and low systemic risk portfolios formed using *MES* ratio. According to Figure, the high systemic risk portfolio outperforms most of the times. However, during the recent financial crises, the high systemic risk portfolio faces higher drawdown then the low systemic risk portfolio. Indeed, at end of the period, the cumulative returns of high and low systemic risk portfolios almost coincide.

Table 9 presents the returns and the alphas of portfolio sorts. Again, the analysis is based on three periods: (i) whole sample, (i) recent financial crisis, and (iii) "normal" period. Portfolio sorts based on systemic risk measured using *MES* show the highest mean spreads between the highest and the lowest systemic risk portfolios. The spreads are the next wider to another systemic risk measure namely to *CoES*. They are always insignificant for *ES* that measures the fund-specific risk. This suggests that systemic risk is more important in explaining cross-sectional performance difference among hedge funds.

[Insert Table 4]

Specifically, during the recent financial crisis the highest systemic risk decile portfolio underperformed the lowest by -3.33 (-1.93) percent per month when systemic risk is measured using *MES* (*CoES*). The mean return for the lowest systemic risk decile is also positive in absolute terms being 0.61 (0.11) for respective measure, while the lowest expected shortfall decile has a negative mean return of -0.21.

In contrast, during the "normal" times the mean spreads are significantly positive implying that hedge funds generate excess return by taking on exposure to systemic risk. However, as in case of Fama-MacBeth regressions the spread between top and bottom systemic risk hedge funds can be explained using common risk factors. Indeed, the mean spread between the highest and the lowest systemic risk hedge funds is not anymore significant for risk-adjusted terms with respect to liquidity factor augmented Fung-Hsieh (2004) model.

Importantly, the common risk factors can not explain performance difference hedge funds sorted based on their systemic risk exposure. During the recent financial crisis the highest systemic risk decile portfolio underperformed the lowest by -0.89 per month in risk-adjusted terms when systemic risk is measured using *MES* ratio. There is also a negative mean spread of -0.33 when systemic risk is measured using *CoES*, but it is insignificant. Hence, it seems that the tail risk of hedge funds exposed to systemic risk was realized during the financial crisis.

5.3 Additional evidence from LTCM failure and 2001 recession

The classification of "good" and "bad" times is always ad-hoc. Therefore, I perform an additional test in which instead of the recent financial crisis 2007-2009, I use the LTCM episode and the burst of technology stocks in 2001 as test periods. The working hypothesis is that the LTCM case and the recent financial crisis have been associated with systemic risk, whereas the turndown related to technology stocks was not systemic. Hence, I expect that hedge funds with high systemic risk should experience poor performance during the LTCM, but not during the 2001 recession.

To test this idea, I re-run Fama-MacBeth regressions using the alternative period specification. The results in Table 5 show that during the LTCM episode the coefficients for both systemic risk measures are positive and highly significant suggesting that hedge funds with high systemic risk deliver low returns. The results also show that hedge funds with high systemic risk do not underperform during the recession from March 2001 to November 2001. Specifically, the coefficients for both systemic risk measures are negative, but insignificant suggesting that during this time hedge funds with high systemic risk do not underperform.

[Insert Table 5]

These results shed additional light about the role of systemic risk in explaining hedge fund performance. During the periods that are likely systemic, hedge funds that have a high systemic risk tend to deliver poor returns. However, during the "bad" times that are not likely systemic, there seem not to exist such a relation between systemic risk and hedge fund performance.

6 Hedge fund failures and systemic risk

To test whether hedge funds with a high systemic risk are associated with higher failures rates, I perform survival analysis using the Cox semiparametric hazards model. Following Liang and Park (2010), I use the counting process style input (CPSI) of Andersen and Gil (1982) to incorporate time-varying covariants. One advantage of the approach is that I can incorporate calender time effects without assuming the time homogeneity.

In the Cox regression model the fund hazard rate i is

$$h\left(t|z_i\right) = h_0(t)\exp\left(z_{i,t},\beta\right),$$

where $h_0(t)$ is the hazard rate for fund i at time t, $z_{i,t}$ is the vector of explanatory variables, and β is the maximum likelihood estimates of coefficients. The vector of explanatory variables contains systemic risk and fund-specific risk measures and a set of variables that controls for the role of other fund characteristics that are found to be related to fund failures. Systemic risk is measured using *CoES* and *MES* ratios, while fund-specific risk is measured using *ES*.[11] Based on Brown, Goetzmann, and Park (2001), I include in the survival models several control variables related to the fund use of leverage, share restrictions, manager's compensation structure, the fund's size and age. Finally, all model specifications include strategy fixed effects, and the standard errors are adjusted for autocorrelation and heteroskedasticity.

[Insert Table 6]

Table 6 presents the results of the survival analysis. The results show that the fund's systemic risk measured using *CoES* is not associated with the fund's future failures. However, systemic risk measured using *MES* is a significant determinant of fund failures. The coefficient for the *ES* is also significant suggesting that high fund-specific risk is associated with high failure probability. Liang and Park (2010) document that it is the most important risk measure related to fund failures. Hence, it is interesting to test whether systemic risk has explanatory power in predicting fund failures when the role of fund-specific risk is controlled for. In the last model specification, all the risk measures are included into analysis simultaneously. The results show that systemic risk measured using *MES* and financial risk are significant suggesting that the probability of fund failure increases with both systemic risk and fund-specific risk.

Taken together, I find evidence that hedge fund systemic risk measured using *MES* and firm-specific risk measured by *ES* are important determinants in explaining fund failures along with other variables documented in prior literature. Finally, it is interesting to note that Acharya, Pedersen, Philippon, and Richardson (2010) show that optimal macroprudential regulation should be based on the two components. The first one is based on an institution-risk component and the second on is based on a systemic-risk component. Hence, these results are consistent with their theoretical model and the recent proposals that finan-

[11] Liang and Park (2010) document that it is the most important risk measure related to fund failures.

cial institutions' capital requirements should be based on macro-prudential measures that take systemic risk into account.

7 Conclusion

This paper investigates the relation between systemic risk and hedge fund performance. Using Co-Expected Shortfall and Marginal Expected Shortfall systemic risk measures, I document a significant time-varying cross-sectional relation between hedge fund performance and systemic risk. Specifically, hedge funds that are exposed to systemic risk tend to generate steady positive return most of the time, whereas they severely underperform during the times of financial distress. Finally, hedge funds having large systemic risk exposure are associated with higher failure probability even after controlling for the role of financial risk and fund-specific characteristics that are documented to explain fund failures.

Given that the fund's systemic risk is related to the fund characteristics and it is highly persistent, the paper also provides new insights to investors and regulators. Specifically, investors may find that an individual fund's systemic risk is useful for risk management purposes, and when making their style allocation and fund selection decisions, whereas regulators would be able to identify hedge funds for further investigation using the information contained on the estimates of fund systemic risk.

The findings suggest that systemic risk measures explain performance differences better compared to traditional risk measures such as expected shortfall or market beta. Overall, the results of the paper provides evidence that systemic risk measures proposed by Acharya, Pedersen, Philippon, and Richardson (2010) and Adrian and Brunnermeier (2009) can be successfully applied in explain cross-sectional variation in hedge fund returns and failures. As a future extension, it would be interesting test how well econometrically sophisticated systemic risk measures are capable to explain performance differences across hedge funds.

Appendix

Hedge fund data

Merging Process

To be added.

Variables related to leverage

Leverage has many different definitions, but all of them attempt to measure the amount of assets being funded by each investment dollar. The most traditional definition is made in balance-sheet terms by defining the leverage as the ratio of assets to net worth, *i.e.*, equity capital. Traditionally, hedge funds get access to leverage through margin borrowing, which is accounted for on the fund's balance sheet. There is also off-balance sheet leverage assessed through exposure to derivatives such as futures, forwards, swaps, and other derivative contracts, where all or part of the notional value of the contract is off-balance sheet.

The databases provide information on variables related to hedge funds' use of leverage. BarcleyHedge and TASS provide a single updated snapshot about hedge funds' use of leverage and average leverage, but HFR provides only a leverage dymmy. Since, I have several snapshots for TASS and BarcleyHedge, I obtain time-series for the average leverage. However, the avarage leverage is almost unchanged suggesting that hedge funds report their average leverage only once for the data vendors.

Variables related to liquidity and compensation structure

To control for the role of other fund characteristics to systemic risk, I construct several variables based on the fund's asset and funding liquidity as well as compensation structure.

To measure the level of asset liquidity, I use the return-based Getmansky, Lo, and Makarov (2004) approach. They assume that hedge funds' true economic return is not observed. This is based on the fact that hedge fund returns are often serially correlated, mainly because of the illiquidity of hedge fund assets and return smoothing. Prior literature suggests that hedge funds' return smoothing can be either deliberate or unintentional.[12] Thus, I only observe the hedge funds' reported returns. Specifically, $R^o_{i,t}$, the observed return for hedge fund i at time t, is a weighted average of the fund's true return over the most recent $s+1$ periods, which can be expressed as follows:

$$\begin{aligned} R^o_{i,t} &= \theta_0 R_{it} + \theta_1 R_{i,t-1} + \ldots + \theta_s R_{i,t-s}, \\ 1 &= \theta_0 + \theta_1 + \ldots + \theta_s, \\ \theta_j &\in [0,1], j = 0, 1, \ldots, s. \end{aligned}$$

I impose a 3-year filter to obtain estimates for θ_0, θ_1, and θ_2.[13] When the value of θ_0 is close to one, the hedge fund is interpreted to invest in liquid assets. The databases provide information on hedge funds' share restrictions. Hedge funds tend to impose share restrictions in the form of lockup, notice and redemption periods on investors' redemptions. I find that 28% of funds have imposed a lockup period, while a typical hedge fund imposes a one-year lockup period, a 30-day notice period and allows monthly redemptions. In addition, the level of investors' redemptions is measured using the fund's money flow that is defined as previous year's net inflows and outflows.

The hedge funds' compensation structure includes management and incentive fees. The incentive fee is typically subject to hurdle rate and high-water mark provisions. A typical manager has a 1.5 % management fee and a 20% incentive fee, while 64% of managers tend to impose a high-water mark provision. In addition, I measure managerial incentives using a manager's option delta proposed by Agarwal, Daniel, and Naik (2009). Finally, the fund's size is defined as a logarithm of the fund's asset under management, and the fund's age is measured using the fund's inception date.

[12]Getmansky, Lo, and Makarov (2004) provide a comprehensive discussion about the sources of serial correlation in hedge fund returns. Agarwal, Daniel, and Naik (2007) and Bollen and Pool (2008) provide empirical evidence about the hedge funds' performance smoothing.

[13]Following, Getmansky, Lo, and Makarov (2004), Aragon (2007), and Ding, Getmansky, Liang, and Wermers (2008), I estimate a model using two lags.

Investment strategy

The hedge fund investment strategies follow closely TASS definitions:

Convertible arbitrage: The strategy seeks to exploit the pricing anomalies of convertible securities and their underlying stock. A typical strategy is to buy a convertible bond and then hedge part of or all of the associated risk by shorting the corresponding stock. These positions are designed to generate profits from the fixed income security as well as from the short sale of stock, while protecting the principal from market moves.

Emerging markets: Equity or fixed income investing in emerging markets around the world. Often emerging markets do not allow short selling, or provide liquid futures or other derivative products with which to hedge. As a consequence emerging market investing employs a long-only strategy. The strategy is characterized to have a low correlation with the developed countries.

Equity market neutral: The strategy exploits equity market inefficiencies by being simultaneously long and short matched equity portfolios of the same size within a country. The aim of the market neutral portfolios is designed to be either beta or/and currency neutral. A well-constructed portfolio typically concentrates on industry, sector, market capitalization and other types of exposures. Leverage is frequently applied to enhance returns.

Event-driven: Equity-oriented market investing designed to capture extra ordinary situations or significant corporate restructuring events. Trades are based on a heavy fundamental analysis, which exploits events like spin-offs, mergers, bankruptcy reorganization and share buybacks.

Fixed-income arbitrage: The aim of the strategy is to profit from price anomalies within and across global fixed income markets. Futures are used to hedge interest rate risk. Profits are customarily generated from interest swap rates arbitrages, forward yield curve arbitrages, and US and non-US government bond arbitrage.

Global macro: A top-down global approach based on an overall market direction influenced by major economic trends and/or events. Managers speculate on the direction of the market prices of securities. The portfolios are constructed from stocks, bonds, currencies and commodities in the form of cash or derivatives instruments. The strategies typically concentrate on market timing and the derivatives are implemented to accentuate the impact of market moves. The strategy can be seen as a developed form of tactical asset allocation.

Long only: The strategy contains equity and fixed income funds that take only long positions.

Long/short equity: The strategy attempts to take advantage of both the long and short sides of the market, shifting among value to growth, small, medium and large capitalization stocks, and net long and short positions. Derivatives are used to hedge exposure. The focus can be regional or the investors may concentrate on a specific sector. Typically long/short equity holds portfolios that are substantially more concentrated than traditional stock funds.

Managed futures: The strategy exploits systematic or discretionary trading in listed financial and commodity futures markets and currency around the world. Systemic trading enhances price trends through the use of technical trading methods that are based on quantitative models. A discretionary trader bases on trading decisions on fundamental and technical analysis.

Multi-strategy: The style takes advantages from all of these strategies to gain profit for investors.

Risk-adjusted hedge fund returns

Throughout the paper, hedge fund risk-adjusted performance is measured using the augmented Fung and Hsieh (2004) model. The model contains eight factors, which are excess return on S&P 500 index, spread between the Wilshire small cap and large cap returns, the Pastor and Stambaugh (2003) liquidity factor, the duration adjusted change in the 10-year Treasury yield, the credit spread between the 10-year Treasure bonds and Moody's Baa bonds as well as the excess return on portfolios of lookback straddles on the bonds, currencies, and commodities. I obtain the data for two stock factors from the Data Stream and for the two bond factors from the Federal Reserve Board's H.15 reports. The three primitive trend following factors are downloaded from David Hsieh's webpage.

Estimation of Co-Expected Shortfall

I rely on the Adrian and Brunnermeier's quantile regression approach in estimating hedge funds' *CoES* ratios. For a given probability q, the qth quantile of $\{R_t\}$ is obtained by quantile regression regressing the return on the financial system $\hat{R}_q^{system,i}$ on a particular hedge fund i:

$$\hat{R}_q^{system,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i R^i, \tag{8}$$

where $\hat{R}_q^{system,i}$ is the predicted value for the quantile q conditional on hedge fund i. I measure the return on financial system using the value weighted portfolio of the banking sector obtained from the Kenneth French website. Using the definition of Value-at-Risk, it follows directly that:

$$\text{VaR}_q^{system}|R^i = \hat{R}_q^i, \tag{9}$$

which indicates that using the predicted value from quantile regression of the system on return i, one can obtain the Value at Risk of the financial system on hedge fund i, because R^i is the conditional quantile. Hence, using a realization $R^i = VaR^i$ one can obtain the $CoVaR_q^i$. This can be summarized within the quantile regression framework as follows

$$CoVaR_q^i := VaR_q^{system}|VaR_q^i = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i. \tag{10}$$

Then, $\Delta CoVaR_q^i$ is given by

$$\Delta CoVaR_q^i = \hat{\beta}_q^i \left(VaR_q^i - VaR_{median}^i\right) \tag{11}$$

To calculate *CoES* ratios, I estimate $CoVaRs$ for quantiles ranging from 1% to 10%. I then take the average from these $CoVaRs$ in order to obtain *CoES* ratios.

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Figure 1: Systemic Risk and Hedge Fund Performance 1997−2010

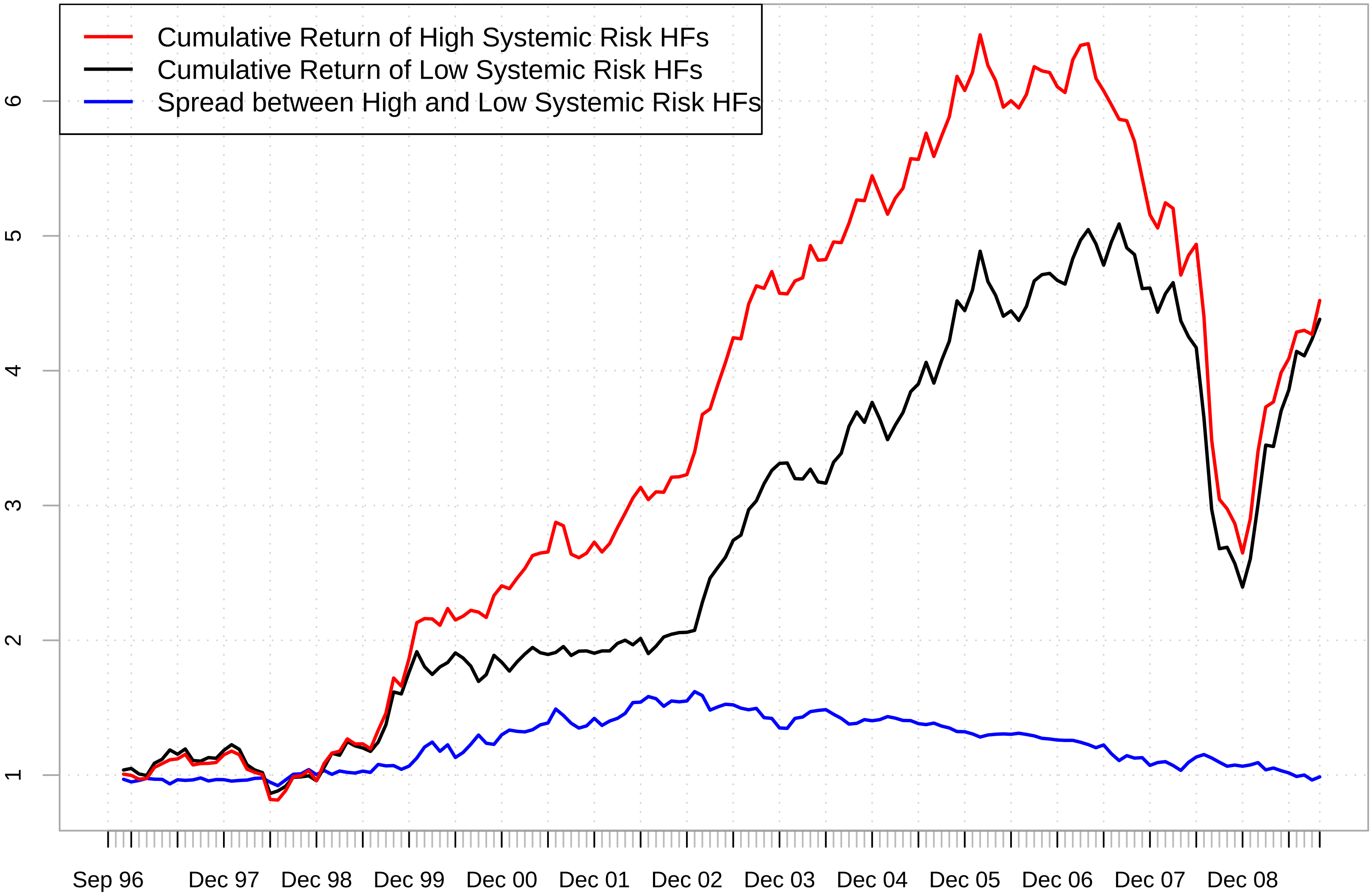

Table 1

Descriptive statistics of *CoES*, *MES* and *ES* estimates

Table 1 presents co-expected shortfall (*CoES*), marginal expected shortfall (*ES*) and expected shortfall (*ES*) estimates at 10% level for hedge funds across investment strategies estimated using quantile regressions for funds which have at least 36 monthly return observations. The total sample contains 10,026 hedge funds over the time period from January 1994 to December 2009. Ratios are expressed in percentile terms without a sign conversation. *Mean* denotes the mean of risk measures within a specific category. *Std* denotes the standard deviation of risk measures within a specific category. *Rank correlation* is a Spearson rank correlation between risk measures.

		CoES		Mes		ES		Rank Correlations		
Sample	N	Mean (%)	Std (%)	Mean (%)	Std (%)	Mean (%)	Std (%)	CoES vs MES	Mes vs ES	CoES vs ES
All funds:	10026	-0.126	0.071	-0.009	0.034	-0.073	0.055	0.413	0.299	0.313
Strategies:										
CONVERTIBLE ARBITRAGE	305	-0.108	0.057	-0.006	0.016	-0.044	0.049	0.354	0.554	0.502
DEDICATED SHORT BIAS	59	-0.054	0.054	0.031	0.043	-0.091	0.055	0.565	-0.155	0.100
EMERGING MARKETS	894	-0.168	0.087	-0.025	0.039	-0.104	0.071	0.471	0.633	0.462
EQUITY MARKET NEUTRAL	591	-0.102	0.061	0.000	0.017	-0.045	0.027	0.377	0.180	0.302
EVENT DRIVEN	767	-0.129	0.059	-0.009	0.023	-0.049	0.043	0.342	0.488	0.321
FIXED INCOME ARBITRAGE	571	-0.118	0.068	-0.009	0.031	-0.049	0.051	0.307	0.711	0.349
GLOBAL MACRO	572	-0.116	0.072	-0.005	0.033	-0.076	0.058	0.347	0.162	0.160
LONG ONLY	130	-0.157	0.085	-0.036	0.033	-0.101	0.046	0.456	0.441	0.586
LONG/SHORT EQUITY	3634	-0.131	0.068	-0.013	0.036	-0.077	0.051	0.392	0.291	0.337
MANAGED FUTURES	950	-0.109	0.063	0.003	0.040	-0.080	0.063	0.260	-0.054	0.093
MULTI-STRATEGY	1580	-0.117	0.069	-0.001	0.029	-0.072	0.050	0.415	0.082	0.130

Table 2

Determinants of risk measures

Table 2 presents the estimates of the panel regressions, in which Co-Expected Shortfall (*CoES*), (ii) Marginal Expected Shortfall (*MES*), and (iii) Expected Shortfall (*ES*) are explained using fund characteristics. As fund characteristics are used: *Avg. Leverage* denoting the average level of the fund's leverage, variables related to the fund's portfolio's asset liquidity and share restrictions including the *lockup*, *redemption* and *notice periods* as well as *the fund's flow*, variables related to the fund's *Compensation Structure* including the *management* and *incentive fees*, and the dummy variable indicating whether the fund has imposed a *high-water mark provision* as well as *the manager's option delta*, control variables including the fund's *size* and *age*. All specifications include time dummies to control for calendar fixed effects. The standard errors are adjusted for autocorrelation, contemporaneous correlation across panels, and heteroskedasticity. The *t*-statistics are reported in the parentheses.

Variable	$\Delta CoES_t$	MES_t	ES_t
ManagementFee	0.312	0.187	-0.533
	(2.77)	(1.58)	(-2.63)
IncentiveFee	0.023	0.041	0.004
	(1.67)	(3.84)	(0.23)
$Delta_{t-1}$	0.006	0.002	-0.005
	(2.93)	(1.33)	(-1.94)
HighWaterMark	0.001	0.001	0.000
	(0.45)	(0.41)	(0.17)
$\theta_{0,t-1}$	0.011	0.001	-0.005
	(8.42)	(0.47)	(-2.64)
Lockup	-0.001	-0.003	-0.003
	(-1.25)	(-3.03)	(-2.01)
Redemption	-0.005	-0.007	-0.011
	(-2.07)	(-2.60)	(-2.20)
Notice	0.014	0.008	0.034
	(1.80)	(1.25)	(2.94)
$FLOW_{t-1}$	0.003	0.003	-0.001
	(4.62)	(2.28)	(-0.78)
AvgLeverage	0.000	0.000	0.000
	(-0.08)	(0.94)	(1.71)
$SIZE_{t-1}$	0.000	0.002	0.008
	(-0.98)	(3.07)	(10.06)
AGE_{t-1}	-0.002	-0.004	-0.004
	(-1.48)	(-3.61)	(-2.77)

Table 2 Continues

Determinants of risk measures

	$\Delta CoES_t$	MES_t	ES_t
Convertible Arbitrage	-0.009	-0.007	0.010
	(-2.44)	(-2.75)	(1.80)
Dedicated Short Bias	0.048	0.024	-0.029
	(4.29)	(2.14)	(-1.65)
Emerging Markets	-0.028	-0.025	-0.038
	(-9.70)	(-9.55)	(-7.79)
Equity Market Neural	0.004	-0.000	0.016
	(1.05)	(-0.08)	(4.16)
Event Driven	-0.021	-0.009	0.011
	(-7.53)	(-4.14)	(2.67)
Fixed Income Arb	-0.009	-0.007	0.004
	(-2.22)	(-3.15)	(0.82)
Global Macro	-0.007	-0.008	-0.005
	(-1.81)	(-2.95)	(-1.16)
Long only	-0.036	-0.031	-0.037
	(-9.49)	(-10.15)	(-6.19)
Long/Short Equity	-0.016	-0.010	-0.017
	(-6.33)	(-4.99)	(-4.50)
Managed Futures	0.011	0.005	-0.015
	(3.24)	(1.64)	(-2.66)
Multi-Strategy	-	-	-
Time Fixed Effects?	Yes	Yes	Yes
Clustered Standard Errors?	Yes	Yes	Yes

Table 3

Multivariate evidence on systemic risk relation to hedge fund returns

Panel A in Table 3 presents the estimates of the Fama-MacBeth (1973) regressions, in which where hedge fund excess returns are explained using the fund's lagged (i) Co-Expected Shortfall (CoES), (ii) Marginal Expected Shortfall (MES), and (iii) expected shortfall (ES). As a control variables are included lagged returns to control for autocorrelation or return smoothing in fund returns.

All denotes the whole analysis period from January 1994 to December 2009. *Financial Crisis* is from June 2007 to March in 2009. *Normal* excludes the observation during the financial crisis.

Panel B in Table shows the estimates of the Fama-MacBeth (1973) regressions, in which alpha is used instead of returns. Alphas are estimated using an intercept and residual obtained from regressions with eight factors, which are excess return on S&P 500 index, spread between the Wilshire small cap and large cap returns, liquidity factor, the change in the 10-year Treasury yield, the credit spread between the 10-year Treasury bonds and Moody's Baa bonds as well as the excess return on portfolios of lookback straddles on the bonds, currencies, and commodities.

All specifications include strategy to control for strategy fixed effects. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1997). The t-statistics are reported in the parentheses.

	Panel A. Excess Returns											
	A1. All				A2. Financial crisis				A3. Normal			
$\Delta CoES_{t-1}$	-0.011			-0.005	0.078			0.027	-0.025			-0.010
	(-0.955)			(-0.564)	(3.381)			(1.208)	(-2.067)			(-1.016)
MES_{t-1}		-0.021		-0.011		0.195		0.197		-0.056		-0.045
		(-0.961)		(-0.557)		(3.493)		(4.295)		(-3.049)		(-2.764)
ES_{t-1}			-0.017	-0.013			0.045	0.022			-0.027	-0.018
			(-1.025)	(-0.811)			(0.850)	(0.437)			(-1.642)	(-1.150)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Panel B. Alphas											
	B1. All				B2. Financial crisis				B3. Normal			
$\Delta CoES_{t-1}$	0.003			-0.003	0.028			-0.002	-0.006			-0.003
	(0.451)			(-0.415)	(1.510)			(-0.176)	(-0.720)			(-0.439)
MES_{t-1}		0.024		0.029		0.089		0.103		-0.006		-0.003
		(1.593)		(1.854)		(2.144)		(2.565)		(-0.404)		(-0.242)
ES_{t-1}			-0.006	-0.013			0.012	-0.005			-0.007	-0.009
			(-0.547)	(-1.062)			(0.281)	(-0.098)			(-0.605)	(-0.727)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4

Univariate evidence on systemic risk relation to hedge fund returns

Panel A in Table 4 presents the mean returns for portfolio sorts based on the fund's lagged (i) Co-Expected Shortfall (CoES), (ii) Marginal Expected Shortfall (MES), and (iii) expected shortfall (ES) for different periods. Panel B presents the mean alphas for portfolio sorts based on the fund's lagged (i) Co-Expected Shortfall (CoES), (ii) Marginal Expected Shortfall (MES), and (iii) expected shortfall (ES) for different periods. Alphas are computed using the intercept and residual obtained from the Fung and Hsieh (2004) seven factor model with a Pastor and Stambaugh (2003) liquidity factor. *All* denotes the whole analysis period from January 1994 to December 2009. *Financial Crisis* is from June 2007 to March in 2009. *Normal* excludes the observation during the financial crisis. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1997).

Panel A. Mean Returns									
	A1. All			A2. Financial crisis			A3. Normal		
Portfolio	$\Delta CoES_{t-1}$	MES_{t-1}	ES_{t-1}	$\Delta CoES_{t-1}$	MES_{t-1}	ES_{t-1}	$\Delta CoES_{t-1}$	MES_{t-1}	ES_{t-1}
1	0.480	1.083	0.638	-1.815	-2.713	-2.458	0.857	1.706	1.147
2	0.766	0.792	0.655	-1.595	-2.019	-1.622	1.154	1.254	1.029
3	0.562	0.670	0.580	-1.564	-1.479	-1.178	0.911	1.023	0.869
4	0.608	0.521	0.505	-1.402	-1.141	-0.984	0.938	0.793	0.750
5	0.464	0.435	0.466	-1.129	-1.011	-0.785	0.725	0.673	0.672
6	0.473	0.390	0.446	-1.181	-0.605	-0.630	0.745	0.554	0.623
7	0.479	0.298	0.348	-0.567	-0.548	-0.689	0.651	0.437	0.518
8	0.378	0.268	0.343	-0.470	-0.599	-0.592	0.517	0.411	0.496
9	0.314	0.208	0.280	-0.101	-0.217	-0.567	0.383	0.278	0.420
10	0.112	-0.029	0.375	0.111	0.619	-0.209	0.112	-0.135	0.471
1 - 10	**0.369**	**1.111**	**0.264**	**-1.926**	**-3.332**	**-2.249**	**0.746**	**1.841**	**0.676**
t-Value	**(1.17)**	**(1.98)**	**(0.50)**	**(-2.41)**	**(-2.28)**	**(-1.13)**	**(2.61)**	**(3.86)**	**(1.45)**

Panel B. Mean Alphas									
	B1. All			B2. Financial crisis			B3 .Normal		
Portfolio	$\Delta CoES_{t-1}$	MES_{t-1}	ES_{t-1}	$\Delta CoES_{t-1}$	MES_{t-1}	ES_{t-1}	$\Delta CoES_{t-1}$	MES_{t-1}	ES_{t-1}
1	0.262	0.484	0.409	-0.001	-0.084	0.139	0.305	0.577	0.453
2	0.519	0.373	0.417	0.186	-0.131	0.149	0.573	0.456	0.461
3	0.404	0.400	0.433	0.193	0.116	0.347	0.439	0.447	0.447
4	0.465	0.342	0.395	0.285	0.164	0.317	0.494	0.372	0.408
5	0.374	0.355	0.377	0.226	0.129	0.333	0.399	0.392	0.384
6	0.372	0.363	0.400	-0.025	0.258	0.322	0.437	0.381	0.412
7	0.388	0.331	0.319	0.309	0.255	0.168	0.401	0.343	0.344
8	0.328	0.367	0.324	0.240	0.231	0.085	0.343	0.390	0.363
9	0.316	0.363	0.295	0.378	0.376	0.075	0.306	0.361	0.332
10	0.321	0.369	0.382	0.326	0.805	0.184	0.320	0.297	0.414
1 - 10	**-0.059**	**0.115**	**0.027**	**-0.327**	**-0.889**	**-0.044**	**-0.015**	**0.280**	**0.039**
t-Value	**(-0.48)**	**(0.42)**	**(0.12)**	**(-1.30)**	**(-1.99)**	**(-0.05)**	**(-0.11)**	**(0.92)**	**(0.17)**

Table 5

Robustness using Additional periods

Table 5 presents the estimates of the Fama-MacBeth (1973) regressions, in which where hedge fund excess returns are explained using the fund's lagged (i) Co-Expected Shortfall (*CoES*), (ii) Marginal Expected Shortfall (*MES*), and (iii) expected shortfall (*ES*). As a control variables are included lagged returns to control for autocorrelation or return smoothing in fund returns.

LTCM includes the observation during LTCM episode in Spetember 1998. *Recession 2001* includes the observations during the recession from March 2001 to November 2001.

All specifications include strategy to control for strategy fixed effects. Standard errors are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987). The t-statistics are reported in the parentheses.

	LTCM period				**2001 Recession**			
$\Delta CoES_{t-1}$	0.581			0,018	0.005			0.012
	(4.74)			(0,14)	(-0.155)			(0.403)
MES_{t-1}		1.358		1,445		-0.039		-0.04
		(13.83)		(13,76)		(-0.919)		(-0.987)
ES_{t-1}			-0.1811	-0.347			0.007	0.014
			(-2.62)	(-5.30)			(0.256)	(0.542)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6

Hedge fund failures and systemic risk

Table 6 presents the results from survival analyses of hedge funds in which Cox semiparametric hazards rate model using the counting process style input (CPSI) of Andersson and Gill (1982) is applied to predict fund failures. Fund failures are explained using the fund's lagged (i) Co-Expected Shortfall (*CoES*), (ii) Marginal Expected Shortfall (*MES*), and (iii) expected shortfall (*ES*). The control variables includes: Leveraged dummy indicates whether the hedge fund uses leverage or not, the lockup, redemption and notice periods, management and incentive fees as well as the indicator variable that indicates whether the fund has imposed a high-water mark provision as well as manager's option delta, the fund's size and age. For them associated parameter estimates, hazard rates and associated p-values are reported in table. The sample period is from January 1994 to December 2009. All specifications include strategy fixed effects. Standard errors are adjusted for heteroskedasticity and autocorrelation.

	(1)		(2)		(3)		(4)	
	Parameter Estimate	**Hazard Rate**	**Parameter Estimate**	**Hazard Rate**	**Parameter Estimate**	**Hazard Rate**	**Parameter Estimate**	**Hazard Rate**
$\Delta CoES_{t-1}$	-0.048	0.95					0.510**	1.67
MES_{t-1}			-1.800***	0.17			-1.265***	0.28
ES_{t-1}					-1.811***	0.16	-1.502***	0.22
Lockup	0.030	1.03	0.020	1.02	0.015	1.02	0.011	1.01
$FLOW_{t-1}$	-0.530***	0.59	-0.523***	0.59	-0.532***	0.59	-0.528***	0.59
IncentiveFee	1.858***	6.41	1.924***	6.84	1.770***	5.87	1.811***	6.11
$Delta_{t-1}$	-0.409***	0.66	-0.389***	0.68	-0.369***	0.69	-0.366***	0.69
HighWaterMark	-0.198***	0.82	-0.198***	0.82	-0.192***	0.83	-0.194***	0.82
$SIZE_{t-1}$	-0.182***	0.83	-0.181***	0.83	-0.178***	0.84	-0.178***	0.84
Leveraged	0.164***	1.18	0.164***	1.18	0.160***	1.17	0.159***	1.17
AGE_{t-1}	-0.098***	0.91	-0.099***	0.91	-0.101***	0.90	-0.101***	0.90
Strategy Fixed Effects?	Yes		Yes		Yes		Yes	