CAPITAL ADEQUACY OF HEDGE FUNDS: A VALUE-AT-RISK APPROACH

by

Qiaochu Wang
Bachelor of Business Administration, Hohai University, 2013

and

Yihui Wang
Bachelor of Arts, Simon Fraser University, 2012

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Name:	**Qiaochu Wang and Yihui Wang**
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Supervisory Committee:

Dr. Peter Klein
Senior Supervisor
Professor of Finance

Dr. Jijun Niu
Second Reader
Associate Professor of Finance

Date Approved:

Abstract

This paper studies the risk profile and capital adequacy of hedge funds by extending the sample period used in the research of Gupta and Liang (2005). We apply a VaR-based approach to evaluate over 6,000 hedge funds from the Lipper Tass Academic Hedge Fund Database, including live funds and graveyard funds, and find that only a small percentage of them are undercapitalized as of September 2014. By conducting a cross-sectional regression of fund capitalization on various characteristics of hedge funds, we reach a conclusion that whether a hedge fund is adequately capitalized is related to its age and investment style. Standard deviation and leverage ratio often underestimate the market risk hedge funds face, whereas VaR-based measures successfully capture both static and dynamic risk profile of hedge funds.

Keywords: Hedge funds; Risk profile; Capital adequacy; Value-at-Risk

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Table of Contents

List of Tables

List of Figures

1: Introduction

Hedge fund industry, one of the fastest growing sectors in the financial service industry, has been attracting high net-worth and major institutional investors such as large pension funds and university endowments due to its distinctive characteristics. With a rapid rate of growth, the hedge fund industry also attracts attention of academics. They have analysed the performance of hedge funds from different perspectives and implied the necessity of further researches on hedge funds' capital adequacy.

In 2000, Fung and Hsieh used a mean-variance approach to study hedge fund exposures in some major market events. They analysed hedge fund performance during turbulent market times. But due to limitations of their research methodology, they found no obvious evidence that hedge funds would cause market prices to deviate from economic fundamentals.

Jorion (2000) is the first one to extend the analysis on hedge fund performance from a mean-variance approach to the VaR approach. He analysed the failure of Long-term Capital Management (LTCM) in 1998 and discovered that LTCM's failure is due to its strategy of maximizing expected returns conditional on a constraint of VaR, which causes a substantial amount of leverage and high sensitivity to uncertainty in asset correlations. This research also demonstrated the fact that VaR is an applicable method to illustrate the risk characteristics of investment vehicles.

Alexander and Baptisata (2003) further developed a VaR-based measure of portfolio performance called the reward-to-VaR ratio, which is closely related to Sharpe ratio. They showed that under the assumption of normal portfolio returns, reward-to-VaR ratio and Sharpe ratio give the same ranking of portfolio performance. While under non-normality, the rankings are different. Agarwal (2004) reached important conclusions that some hedge fund strategies have payoffs similar to "a short position in a put option on the market index", and a traditional mean-variance framework tends to ignore this risk. Using mean-conditional VaR framework, Agarwal examined the extent to which the mean-variance approach underestimates the left tail risk.

Though the analysis on risk characteristics of hedge funds has a huge impact on hedge fund managers and market participants, very few studies related to capital adequacy of hedge funds have been done. Gupta and Liang's (2005) paper is "the first one to address capital adequacy and risk estimation issues in the entire hedge fund industry". They used the VaR approach to study capital requirements for almost 1500 hedge funds and found that only a small amount of funds are undercapitalized as of March 2003. Del Brio, Monra-Valencia and Perote (2014) further compared the performance of risk measures using three approaches: parametric distributions, semi-nonparametric methodologies and the extreme value theory approach. They showed that the extreme value theory approach accurately forecast hedge fund VaR.

From the implication of the papers discussed above, we use a VaR-based extreme value theory approach to analyze the non-normal distribution of hedge fund returns and focus on the associated left tail risk. We base our research on Gupta and Liang's paper (2005) and extend the sample period to September 2014. Our aim here is to provide an update on hedge fund capital adequacy and examine whether the recent financial crisis has made a significant impact on it. Since hedge funds managers adjust their portfolios quite frequently and market conditions are dynamic, we also look at time variation of hedge fund capital adequacy using rolling windows.

The remainder of the paper is organized as follows: The next section is literature review, Section 3 gives an overview of VaR. Section 4 introduces the data, followed by our research methodology in Section 5. Section 6 describes the results, and Section 7 tests the robustness of our approach. We conclude in Section 6.

2: Literature Review

In this section, we will review some preceding literatures that have contributed to the development of hedge fund. These literatures analyze the characteristics of hedge fund industry and provide comprehensive evaluation from different perspectives.

Fung and Hsieh (1997) first found that hedge funds follow dynamic trading strategies that are totally different from mutual funds, and they clarified five main investment styles used in hedge funds. This clarification provided a basic framework for any further analysis on hedge fund investment styles. For example, Fung, Hsieh, Naik and Ramadorai (2008) performed an investigation on the risk characteristics and capital formation of hedge fund industry with a special focus on the investment style of funds-of-funds.

Ackermann et al. (1999) conducted a comparison between hedge funds and other traditional investment vehicles, such as mutual funds. He discovered that although hedge funds are more volatile than both mutual funds and standard market indices, they usually perform better than mutual funds. Liang (1999) found similar results that hedge funds could adapt to more complex trading strategies and possess lower systematic risk than mutual funds. Hedge funds usually provide higher Sharpe ratios than mutual funds although their returns tend to have higher volatility. Ang, Gorovyy and Inwegen (2011) discovered that hedge fund leverage is mostly influenced by economy-wide factors, and there is an obvious relationship between the volatility of hedge fund returns and leverage ratios. They found that a decrease in the volatility of hedge fund returns would predict a future increase in fund leverage.

Agarwal and Naik (2004) used mean-variance value-at-risk method to illustrate that previous mean-variance analysis on hedge funds had underestimated the tail risk of hedge funds. Hedge funds present significant left-tail risk. Buraschi, Kosowski and Trojani (2013) contributed to the risk-return profile of hedge funds by exploring a nonlinear relation between correlation risk exposure and the tail risk of hedge fund returns. Lhabitant (2001) developed a model of VaR to measure the risk figures of hedge funds, but he did not take all the risk components of hedge funds into consideration, such as credit risks and liquidity risks. George O. Aragon (2007) found that hedge funds with lockup restrictions have higher excess returns than those without them. These restrictions allow hedge funds to manage illiquid assets more efficiently. Sadka (2010) discovered that liquidity risk is an important determinant in the cross-sectional hedge-fund returns, and systematic liquidity risk should be analysed properly among all hedge fund risks.

Bali, Brown and Caglayan (2012) analysed different risk factors, such as market risk, tail risk and systematic risk, and found that systematic risk is the key determinant for cross-sectional differences in hedge fund returns. They conducted further estimations in 2014 on macroeconomic risk of hedge funds and concluded macroeconomic risk also plays an important role in explaining the cross-sectional difference in hedge fund returns. The macroeconomic risk is interpreted as a measure of economic uncertainty.

Liu and Mello (2011) investigated the fragile nature and limited arbitrage capabilities of hedge fund capital structure in time of financial crisis and found correlations between hedge fund performance and financial market fluctuations. Bali, Brown and Caglayan (2011) conducted forecasts and found a significant link between hedge fund default premium and future returns by studying on hedge fund exposures to various financial and macroeconomic risk factors.

The papers discussed above inspire us to employ a value-at-risk method on the risk profile, especially tail risk of hedge funds across investment styles. We also conduct further investigation on the relationship between hedge fund risk, capital adequacy and proceeding influential factors such as fund size, age, and leverage ratios.

3: Defining Value-at-Risk

VaR estimates the worst loss in value terms that can occur over defined period of time for a given confidence interval. For example, 10-day VaR of $1 million on an asset with a confidence interval of 95% indicates that the probability of the value of the asset dropping $1 million within any given ten days is 5%. VaR is widely used by financial institutions to measure the potential loss of their portfolios over a target horizon. Banks are required to hold reserves so that they are able to fulfil unexpected withdrawals. Similarly, it is important for hedge funds to hold enough capital in case of unexpected market movements. Consequently, we could evaluate whether a hedge fund is appropriately capitalized by comparing its assets to required capital (which is a multiple of VaR).

VaR is widely used in many financial areas as a method to quantify risk and set regulatory capital requirements. Back in 1980, Securities and Exchange Committee started to require financial institutions and firms to hold capital equal to a potential loss over one-month interval with 95% confidence (Lovelady, 2013). The potential losses were usually computed using historical returns. The Basel Committee on Banking Supervision (BCBS) stimulated the use of VaR in financial industry by recommending banks to use VaR to measure market risk. Later in Basel III, BCBS also allowed banks to use their internal VaR models to calculate their own capital requirement for market risk provided that the model is approved by the bank's supervisor (BIS, 2011). Therefore, it is reasonable to examine capital adequacy of hedge funds using the VaR measure.

There are two main components in VaR – a time period and a confidence level. The choices of these two variables are arbitrary. As the length of time period increases, VaR becomes larger. The confidence level is usually quite high so that the capital requirement is high enough to cover investment loss. Generally, the capital requirement for commercial banks is three (a supervisory multiplier) times the market risk VaR, which is calculated using 10-day period with a 99% confidence level. However, supervisor of the bank is entitled to increase the multiplier if there is poor backtesing performance. In this paper, we compute the required capital for hedge funds as three times the 99% one-month VaR. Compared to banks, hedge funds are less regulated and they are not capable of using public funding. Therefore, hedge funds are not able to react to unexpected market movements as quickly as banks. This fact is reflected with the choice of one-month horizon.

4: Data

Hedge funds consist of portfolios, and the portfolios are usually comprised with non-linear assets such as options and derivatives. Thus the returns of hedge funds should automatically reflect some features of the returns on non-linear assets. They should have option-like features that are non-Gaussian. Previous researches imply that VaR are traditionally used in situations where there is a linear relationship between portfolio returns and their corresponding underlying risk factors. When we employ the VaR approach here, it becomes a more complex task due to the hedge funds' non-linear features.

The dataset we use in our analysis is from the Lipper Tass Academic Hedge Fund Database. It is one of the oldest hedge fund available, which provides detailed performance information about live funds and graveyard funds including monthly returns from their start date to now. The performance record's start dates for some of the early live funds can go back to as far as February 1977 and the performance record's start dates for some of the early dead funds are in July 1978. As of September 2014, the dataset includes monthly returns for 5894 live funds and 13793 graveyard funds.

We employ a minimum performance record period of seven years in the return history of each hedge fund for calculations of VaR. Those funds with a performance record period less than seven years are not taken into consideration. The reason for doing this is to make sure that the hedge fund we are going to analyze experiences at least one economic downturn in its life span. By selecting the hedge funds whose return periods have covered the most turbulent times in the financial history in our dataset, we can reach a more realistic conclusion compared to using the dataset directly without any manipulation. For example, the most recent financial collapse is the Financial Crisis of 2007-2008, and our most updated hedge fund performance information covers the returns of hedge funds till September 2014. This selection process in the live funds' dataset may introduce survivorship bias by eliminating younger funds and underestimating the extent to which the funds are undercapitalized. However, our consideration of graveyard funds helps fix this problem because those funds have not survived. By studying both live hedge funds and graveyard hedge funds, we can understand the difference in the worst loss between these two groups. This comparison will also help us improve our evaluation results. Under the condition of a minimum of seven-years return history, eligible number of live funds and graveyard funds is 2747 and 3394 respectively. Our further analysis is based on the performance information of these 2747 live hedge funds and 3394 graveyard hedge funds.

When we analyze the capital adequacy of hedge funds, we classify them in accordance with their investment styles defined by the Lipper Database. There are thirteen investment styles in total. To be specific, there are 27 live and 81 dead convertible arbitrage funds, 138 live and 165 dead emerging markets funds. Fund of funds style is adopted the most by both live funds (1122) and dead funds (1277) among thirteen styles, while option-strategy style has the least amount of funds in both live fund category (1) and dead fund category (13) among all styles.

We also obtain detailed data on fund characteristics from the database, such as leverage ratio, management fee, and lockup periods. These data are used later in the paper when we look into the determinants of capital adequacy.

5: Research Methodology

As we have mentioned that we use VaR to measure a threshold for losses on hedge funds over a given time horizon. This threshold value illustrates the amount of capital that a hedge fund manager should reserve in case of fund performance failure during the targeted period of time. We focus on the 99-percentile return in the left tail of the hedge funds' return distributions when estimating VaR. Extreme Value Theory (EVT) is used to deal with the extreme deviations in hedge funds return distribution. By emphasizing on the potential effect of extreme events in the financial markets, we can control the loss in a more efficient way. There are two approaches to implement the EVT models, "fitting one of the three standard extreme value distributions to block maxima values in a time series", Frechet, Weibull or Gumbel (Gupta & Liang, 2005), and a generalized Pareto distribution (GPD) that models the distribution of data exceeding a certain threshold. We use the GPD approach since it is more appropriate to use when there is not a large amount of data (Pickands, 1975). We estimate the parameters, tail index ξ and scale parameter σ, which we need for the calculations of the 99-percentile return in the left tail by using maximum likelihood methods. After that, we substitute the tail the tail index and scale parameter into the following formula from Gupata and Liang's (2005):

$$R_{99\%} = \mu + \frac{\sigma}{\xi}\left[\left(\frac{N}{n}p\right)^{-\xi} - 1\right], \text{ for } \xi \neq 0, \quad (1)$$

$$R_{99\%} = \mu + \sigma \log\left(\frac{n}{N}p\right), \text{ for } \xi = 0. \quad (2)$$

VaR is then estimated as follows:

$$VaR = (0 - R_{99\%}) \times TA, \quad (3)$$

where VaR is value-at-risk over a month at 99% confidence interval, $R_{99\%}$ is the 99-percentile return calculated using EVT, and TA is the total asset of each fund.

The VaR we achieve from the estimation process is related to a zero return. As it is shown in formula (3), we use the difference between 0 and $R_{99\%}$ instead of the difference between the mean return and $R_{99\%}$. The reason we use a zero return instead of a mean return is that there would be biases and errors when we calculate the mean return as a standard rate of return for a hedge fund. For a fund manager, the mean of the fund's serial of returns may not be his expectation for the fund. Another reason is that we need to pay attention to the absolute dollar loss that an extreme event can cause rather than the relative dollar loss that is usually compared to an expected rate of return. By using the zero return as a benchmark, we can introduce the value of equity capital that stands for the capital reserve we need to keep in case of unexpected financial risks.

To evaluate the capital adequacy of hedge funds, we introduce the capitalization ratio, which is used to measure whether a hedge fund is undercapitalized. It is also for future efficiency to analyze the hedge funds by the classification of whether they are undercapitalized or not. The formula for capitalization ratio is as follows:

$$Cap = \frac{E_{\text{actual}} - E_{\text{required}}}{E_{\text{required}}}, \tag{4}$$

where E_{actual} is the actual assets that a hedge fund possesses, and $E_{required}$ is the required capital that a hedge fund should keep to avoid an absolute loss over the corresponding given period of time. $E_{required}$ is calculated as three times VaR, as suggested by the Basel Committee.

A negative Cap ratio indicates the undercapitalization of a hedge fund. If the Cap ratio is negative, it means the actual assets that a hedge fund possesses are smaller than the amounts that the hedge fund manager should keep. Thus we can tell whether a hedge fund has enough capital by referring directly to its Cap ratio. By increasing the amount of capital reserve according to the value of its Cap ratio, a hedge fund may reduce chances of failure in the long run.

We also estimate tail conditional loss (TCL), which can be used to assess the capital adequacy of a hedge fund from other perspectives. TCL is a useful risk measure tool in financial risk assessment. It measures the average expected amount of loss that would happen to a hedge fund during a given period of time if the loss exceeds a specific quantile, which is VaR in our context (Necir, Rassoul & Zitikis, 2010). The good thing about introducing TCL is that it could make up the shortfall of VaR. Although VaR could only imply the minimum loss that could happen to the hedge fund during 1% of the given period of time, the estimation of TCL could show us the average amount of loss that would probably happen. The formula for TCL is as follows (Gupta & Liang, 2005):

$$TCL = (0 - E[R|R < R_{99\%}]) \times TNA, \tag{5}$$

where is $E[R|R < R_{99\%}]$ is the expected loss in the tail of a hedge fund return distribution. It is calculated as follows (Kellezi & Gilli, 2000):

$$E[R|R < R99\%] = \frac{R99\%}{1-\xi} + \frac{\sigma - \xi\mu}{1-\xi}. \tag{6}$$

Besides the average amount of loss that could probably happen to the hedge funds, TCL could also be combined with the 99% VaR to give further insights on the capital adequacy of hedge funds. For example, the ratio between the value of TCL and the corresponding VaR of a hedge fund helps identify whether the multiplier three we used in the calculation of the required capital is appropriate. If none of the ratio of TCL/VaR for the hedge funds is larger than three, then three is an appropriate multiplier to use. If not, then we will have to adjust the multiplier for more adequate values. We will give further explanation on the multiplier in Table 7.

Most of the risk related researches on hedge funds tend to assume their return distributions as normal distributions, while in reality the return distributions of hedge funds are not normal. This difference in measure premises leads to an error between the VaR evaluated from the EVT approach and that estimated under the assumption of normal distribution. To see the difference between these two methods, we re-calculate the 99% VaR of the hedge fund returns following the assumption of normal distribution. The formula for the 99% VaR under normal distribution is as follows:

$$VaR = [(-2.58 \times \sigma_R) \times TA], \tag{7}$$

where σ_R is the standard deviation of the returns of a hedge fund and TA is the total asset of each fund.

We re-compute Cap ratio using the same formula (4) with the new VaR and use it to determine whether the hedge funds have enough capital. The Cap ratios calculated under the assumption of normality are quite different from those calculated using ECT. This difference reflects an error that lies in the assumption of normal distribution of hedge fund returns. We will talk about this in details in the following section.

6: Results

6.1 The capital adequacy of hedge funds

Tables 1 demonstrates the characteristics of hedge funds grouped in style. All of the reported data are medians of funds adopting the same style. We can see that both live and dead funds exhibit different distributions in terms of mean, standard deviation, median, skewness and kurtosis across styles, therefore it is more intuitive to study these funds by style rather than looking at them as a whole. Live funds have a slight higher average monthly median return (0.60%) than dead funds (0.57%). In addition, a median live fund is less volatile with a standard deviation of 2.36, smaller than a median dead fund with a standard deviation of 2.64. These results support Liang's (2000) finding that poor performance is the major contributor to a fund's death. Almost all the funds are slightly negatively skewed, except both live and dead global macro and managed funds style, as well as dead dedicated short bias funds. The negative skewness implies that investors have a greater possibility of making extreme losses in general. Moreover, all funds exhibit kurtosis higher than three. In particular, live convertible arbitrage and other style funds have high median kurtosis of 12.14 and 10.38. Option-strategy and other style dead funds have median kurtosis of 13.00 and 12.76. These results are consistent with Gupta and Liang (2005) and they indicate that the distribution of hedge funds has fatter tails and more extreme outcomes compared to normal distribution. Therefore, instead of assuming normal distribution for calculating VaR, we estimate VaR using an extreme value theory approach.

Table 2 presents fund assets and values of VaR calculated using the EVT approach as we mentioned in the previous section. The mean and median values for both variables are classified into fund investment styles. Fund assets indicate the size of a hedge fund. As of September 2014, for live funds, global macro funds have the largest amount of assets ($1265.7 million), while dedicated short bias funds have the smallest amount of asset ($16.8 million). There is also a huge discrepancy between live global

Table 1: Descriptive statistics for hedge fund returns

Style	Live funds						Dead funds					
	No.	Mean	Std.dev.	Median	Skew	Kurt	No.	Mean	Std.dev.	Median	Skew	Kurt
Convertible arbitrage	27	0.67	2.82	0.67	-1.08	12.14	81	0.62	2.04	0.78	-0.60	7.13
Dedicated short bias	3	0.27	4.22	0.71	-1.25	6.34	23	0.28	6.30	0.00	0.37	5.25
Emerging markets	138	0.95	5.68	0.91	-0.22	6.87	165	0.86	5.40	0.88	-0.17	7.08
Market neutral	62	0.57	2.51	0.56	-0.53	6.28	116	0.49	2.32	0.54	-0.03	5.83
Event driven	106	0.76	2.63	0.80	-0.66	8.02	220	0.75	2.06	0.84	-0.59	7.06
Fixed income arbitrage	54	0.82	0.99	0.83	-0.28	8.44	106	0.65	1.97	0.73	-0.62	7.15
Fund of funds	1122	0.36	1.81	0.54	-0.82	6.33	1277	0.33	1.86	0.49	-0.84	6.74
Global macro	81	0.82	3.47	0.59	0.45	5.10	110	0.74	4.06	0.59	0.32	4.70
Long/short equity hedge	574	0.74	3.63	0.77	-0.12	5.40	785	0.86	4.03	0.80	0.00	5.49
Managed futures	174	0.72	4.31	0.47	0.29	3.96	242	0.67	5.21	0.43	0.28	4.52
Multi-strategy	340	0.85	1.48	0.86	-0.42	6.42	220	0.69	2.15	0.72	-0.44	6.31
Option-strategy	1	0.83	3.94	1.11	-0.68	8.07	13	0.49	2.47	0.52	-0.66	13.00
Other	65	0.69	2.47	0.79	-0.54	10.38	36	0.49	2.20	0.63	-1.03	12.76
Total	2747	0.60	2.36	0.68	-0.43	6.11	3394	0.57	2.64	0.61	-0.30	6.09

Table 2: Hedge fund VaR based on Extreme Value Theory

Fund assets and EVT VaR are in millions of dollars.

Style	Live funds					Dead funds				
	No.	Fund assets		EVT VAR		No.	Fund assets		EVT VAR	
		Mean	Median	Mean	Median		Mean	Median	Mean	Median
Convertible arbitrage	27	265.7	149.1	41.4	27.7	81	258.1	31.1	29.9	3.8
Dedicated short bias	3	16.8	16.8	3.6	3.6	23	112.9	24.8	33.5	7.1
Emerging markets	138	228.5	33.0	63.9	15.6	165	96.6	18.5	11.8	2.5
Market neutral	62	83.9	23.3	8.4	4.0	116	485.5	41.2	65.9	6.5
Event driven	106	311.5	100.9	76.8	15.3	220	64.0	18.0	5.9	2.0
Fixed income arbitrage	54	348.7	46.6	40.7	1.6	106	185.7	23.4	63.4	8.1
Fund of funds	1122	118.5	19.7	13.1	1.9	1277	171.7	12.3	53.5	3.6
Global macro	81	1265.7	58.4	307.6	13.0	110	174.7	32.9	19.5	3.9
Long/short equity hedge	574	127.1	43.3	28.8	9.8	785	154.7	13.7	27.9	2.5
Managed futures	174	169.2	37.2	40.2	7.4	242	128.1	4.6	39.3	1.4
Multi-strategy	340	180.1	13.6	25.9	0.6	220	40.3	13.7	20.2	4.5
Option-strategy	1	170.0	170.0	52.5	52.5	13	305.7	42.4	37.6	7.2
Other	65	378.6	73.8	44.6	13.1	36	43.9	11.0	7.9	1.9
Total	2747	190.4	26.4	33.8	3.4	3394	146.9	21.0	29.5	3.7

macro funds and live dedicated short bias funds in terms of absolute VaR, which ranges from \$3.6 million dollars to \$307.6 million. In the dead funds group, a similar conclusion can be drawn. While market neutral funds have the highest asset value of \$485.5 million, the multi-strategy funds have the smallest asset of \$40.3 million. The corresponding absolute VaR ranges from \$65.9 million to \$5.9 million. In contrast with Gupta and Liang (2005), the number of dead funds exceeds the number of live funds as of September 2014. A substantial amount of funds entered the graveyard database since they did not survive the 2007-2008 financial crisis. Furthermore, since March 2003, the average fund assets of live funds decreased slightly from \$198.9 million to \$190.4 million; however, an average dead fund asset increased from \$48.1 million to \$146.9 million. The huge increase in dead fund assets can be explained by the fact that some funds that recently enter the graveyard have large assets. We then do a comparison between live and dead funds as of September 2014 from two aspects. Firstly, live funds are larger than dead funds. This result is consistent with Gupta and Liang (2005), and it is also consistent with Liang's finding in 2000 that poor performance is a main contributor to fund death. Since dead funds tend to perform worse than live funds, dead funds lose more capital than live funds. Secondly, funds with certain styles, including dedicated short biases, emerging markets, market neutral and event drive, tend to have a great difference in absolute VaR between live funds and dead funds. For example, the mean (median) of live EVT VaR for dedicated short bias is \$3.6 million (\$3.6 million) and the corresponding value in the dead funds part is \$33.5 million (\$7.1 million). The reason for this phenomenon is that funds adopting a certain style with high EVT VaR values are more likely die. Those with lower absolute VaR have higher probability of survival.

We then examine whether hedge funds have enough equity to cover the risk of their portfolio and organize the results by investment styles in Table 3. As mentioned in Section 4, a negative Cap ratio indicates fund undercapitalization. Similar to Gupta and Liang (2005), only a small percentage of the funds are undercapitalized, 8.1% for live funds and 12.3% for dead funds. For live funds, the emerging markets funds and managed futures funds are particularly undercapitalized with 30.4% and 19.0% undercapitalized funds, respectively. For dead funds, dedicated short bias funds (39.1%),

Table 3: Undercapitalization based on VaR from EVT

Style	Live funds					Dead funds				
	Total funds	No. U-cap	% U-cap	Cap ratio		Total funds	No. U-cap	% U cap	Cap ratio	
				Mean	Median				Mean	Median
Convertible arbitrage	27	2	7.4	0.8	0.8	81	4	4.9	10.5	9.5
Dedicated short bias	3	0	0.0	0.5	0.5	23	9	39.1	3.1	2.4
Emerging markets	138	42	30.4	0.6	0.0	165	54	32.7	9.9	9.3
Market neutral	62	1	1.6	2.4	1.8	116	2	1.7	8.5	6.2
Event driven	106	12	11.3	1.3	1.0	220	7	3.2	8.1	6.9
Fixed income arbitrage	54	1	1.9	8.3	5.9	106	2	1.9	3.2	1.9
Fund of funds	1122	27	2.4	3.5	2.4	1277	33	2.6	3.8	2.7
Global macro	81	12	14.8	2.4	0.6	110	18	16.4	13.0	11.7
Long/short equity	574	82	14.3	0.7	0.3	785	196	25.0	10.2	8.0
Managed futures	174	33	19.0	1.8	0.3	242	80	33.1	3.0	2.1
Multi-strategy	340	5	1.5	7.9	6.4	220	9	4.1	1.8	1.4
Option-strategy	1	0	0.0	0.1	0.1	13	1	7.7	11.2	7.4
Other	65	5	7.7	3.0	1.8	36	1	2.8	6.2	5.1
Total	2747	222	8.1	3.5	1.8	3394	416	12.3	1.6	0.9

emerging markets funds (32.7%), long/short equity hedge funds (25.0%) and managed futures funds (33.1%) all exhibit high levels of undercapitalization. The median and mean Cap ratio of live funds (3.5, 1.8) are both higher than those of dead funds (1.6, 0.9), implying that live funds are better capitalized than dead funds. These results are consistent with Gupta and Liang (2005), and support the proposition that hedge funds fail due to undercapitalization. However, since 87.7% of the dead funds are properly capitalized before the end of their performance date, undercapitalization is not necessarily the main reason for fund disappearance. Other factors, such as poor performance, needs to be considered when studying the death of hedge funds.

6.2 Determinants of the Cap ratio and importance of EVT approach

Since whether a fund is undercapitalized plays an important role in determining its performance, we take a further look into some characteristics that potentially have an impact on capital of hedge funds. A comparison of these characteristics between adequately capitalized funds and undercapitalized funds is listed in Table 4. By doing this comparison, we can determine the key factors that would usually influence capitalization of a hedge fund. Table 4 also illustrates the comparative characteristics between live and dead hedge funds. Some interesting points are as follows. First, the average asset of the undercapitalized live funds is $88.4 million and the corresponding value for the capitalized funds is $206.1 million. This difference is statistically significant at the 1% level. Gupta and Liang (2005) do not find a significant difference between the capitalized and undercapitalized funds for the dead fund group. In contrast, we find a statistically significant difference at the 5% level with average asset of $103.5 million for the undercapitalized dead funds and $200.8 million for the capitalized funds. These results indicate that fund size does have an impact on hedge fund capitalization. Secondly, similar to Gupta and Liang, while the Cap ratios of adequately capitalized hedge funds are positive for both live and dead funds, the average Cap ratio of both live and dead undercapitalized funds category is -0.3%, implying on average only 70% of the

Table 4: Comparative characteristics of undercapitalized funds

Variable	Live funds					Dead funds				
	Adequate-cap		Under-cap		t-Stat	Adequate-cap		Under-cap		t-Stat
	Mean	Std.dev.	Mean	Std.dev.		Mean	Std.dev.	Mean	Std.dev.	
Asset ($m)	206.1	987.6	88.4	179.2	-9.9***	200.8	805.4	103.5	320.6	2.4**
Cap ratio	4.0	4.9	-0.3	0.2	-8.9***	2.2	3.2	-0.3	0.2	15.7***
Mean return	0.6	0.6	1.1	0.7	-15.5***	0.6	1.5	1.2	1.1	-7.2***
Median return	0.7	0.4	1.0	0.8	-6.6***	0.6	0.5	1.0	0.9	-12.3***
Std.dev	2.9	4.8	8.1	4.4	1.6	3.2	13.3	8.0	3.4	-7.3***
Skewness	-0.6	1.8	0.2	1.4	-7.0***	-0.6	2.0	0.3	1.2	-9.1***
Kurtosis	10.1	15.7	8.4	9.4	13.1***	10.9	14.5	7.9	7.8	4.2***
Age(months)	137.1	48.2	161.7	68.5	-3***	126.3	40.1	147.3	51.4	-9.6***
Leverage ratio	36.3	125.8	23.4	58.7	1.8*	47.6	198.4	35.9	87.9	1.1
Max leverage raio	83.6	194.5	64.6	120.1	1.3	91.8	295.0	68.2	145.9	1.53
Management fee	1.4	0.7	1.5	0.7	1.3	1.4	0.7	1.6	1.1	-5.2***
Incentive fee	12.4	8.8	17.4	6.6	-2.7***	13.2	8.4	17.5	6.9	-9.8***
Leverage dummy	0.5	0.5	0.7	0.5	-2.6***	0.5	0.5	0.7	0.5	-6.0***
Watermark dummy	0.5	0.5	0.7	0.4	-0.1	0.5	0.5	0.5	0.5	2.0**
Lockup period(months)	2.0	5.9	3.1	6.0	-8.2***	2.1	5.7	3.5	6.6	-4.6***
Minimum investment($m)	1.1	6.5	1.1	6.9	-5.6***	9.6	205.5	3.0	49.6	0.6
Open-end fund dummy	0.4	0.5	0.6	0.5	-3.6***	0.6	0.5	0.6	0.5	-2.1**
Open-to-public dummy	0.1	0.3	0.2	0.4	0.4	0.2	0.4	0.2	0.4	-1
Derivatives trading dummy	0.2	0.4	0.2	0.4	-5.3***	0.2	0.4	0.2	0.4	-0.9

***Significant at the 1% level.

**Significant at the 5% level.

*Significant at the 10% level.

required capital is satisfied. Thirdly, although Gupta and Liang (2005) does not find a significant difference in age between the adequately capitalized and undercapitalized funds, we find that age of adequately capitalized funds is statistically smaller than age of undercapitalized funds at the 1% level for both live and dead funds. Lastly, we could not tell a significant difference between adequately capitalized and undercapitalized funds in terms of maximum leverage ratio and open-to-public dummy. Based on these results, our next step in the analysis is to further examine the quantitative effect of these characteristics on fund capitalization.

Table 5 demonstrates the cross-sectional regression results of fund capitalization on various characteristics as of September 2014. We also include the investment style of each fund as an independent variable to test if there is any relationship between fund capitalization and investment styles. Specifically, the regression equation is (Gupta and Liang, 2005):

$$Log(Cap_i) = \alpha_0 + \alpha_1 log(size_i) + \alpha_2 log(age_i) + \alpha_3(mgmtfee_i) + \alpha_4(incfee_i) + \alpha_5(leverage_i) + \alpha_6(watermark_i) + \alpha_7(lockup_i) + \sum_{j=1}^{11} \beta_j(dummy_{ij}),$$

where $log(Cap)$ is used as a proxy for fund capitalization, and $dummy_j$ represents 11 style dummy variables.

To minimize the potential evaluation error, we construct five models consisting of five different sets of variables, which are the same models used by Gupta and Liang (2005). P-values are shown in the parentheses below each parameter. We have several interesting findings from this table. First, fund size is not significantly correlated with Cap ratio in any of the five models. This is surprising to us given the significant difference in fund size between adequately capitalized and undercapitalized funds as we find in Table 4, and funds with greater capitals, in reality, are considered to be more stable since they usually have higher probabilities of meeting their capital requirement in economic downturns. Another finding consistent with Gupta and Liang (2005) is that age has a statistically significant negative correlation with its Cap ratio in Model 2. The negative correlation may be explained by the fact that it is difficult for new funds to

Table 5: Cross-sectional regression of Cap ratios on fund characteristics

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	1.470***	0.313	1.576**	1.975***	1.871***
	(0.007)	(0.665)	(0.021)	(0.004)	(0.007)
Log(size)	0.013	0.018	0.010	0.016	0.015
	(0.464)	(0.433)	(0.621)	(0.443)	(0.452)
Log(age)	-0.040	-0.141*	-0.027	-0.071	-0.083
	(0.710)	(0.302)	(0.819)	(0.554)	(0.489)
Management fee	0.0670	0.151***	-0.064		-0.049
	(0.128)	(0.058)	(0.371)		(0.494)
Incentive fee		0.017	0.011		0.017***
		(0.009)	(0.095)		(0.020)
Leverage ratio		0.102***	-0.068	-0.057	-0.061
		(0.139)	(0.294)	(0.378)	(0.348)
Watermark dummy		-0.247**		-0.163*	-0.236
		(0.039)		(0.089)	(0.021)
Lock up (months)		-0.013**		-0.004	-0.003
		(0.040)		(0.511)	(0.553)
Convertible arb			-0.645*	-0.681*	-0.655*
			(0.076)	(0.061)	(0.071)
Emerging markets			-0.848*	-0.890***	-0.894***
			(0.003)	(0.002)	(0.002)
Market neutral			-0.426***	-0.417	-0.442**
			(0.228)	(0.240)	(0.212)
Event driven			-0.619	-0.588**	-0.625**
			(0.027)	(0.036)	(0.025)
Fixed income arb			-0.696**	-0.676*	-0.713**
			(0.044)	(0.051)	(0.040)
Fund of funds			-0.199**	-0.394	-0.238
			(0.432)	(0.112)	(0.353)
Global macro			-0.623	-0.680*	-0.649***
			(0.088)	(0.066)	(0.076)
Long/short			-0.372*	-0.365	-0.386
			(0.134)	(0.142)	(0.119)
Managed futures			1.114	1.066**	1.072**
			(0.013)	(0.034)	(0.033)
Multi-strategy			0.628**	0.573*	0.594**
			(0.032)	(0.051)	(0.042)
Option-strategy			-1.342**	-1.283	-1.32
			(0.144)	(0.164)	(0.150)
Adj R-square (%)	0.29	4.48	30.96	31.05	31.83

Table 6: Undercapitalization based on VaR assuming normal distributions

Style	Live funds					Dead funds				
	Total funds	No. U-cap	% U cap	Cap ratio		Total funds	No. U-cap	% U cap	Cap ratio	
				Mean	Median				Mean	Median
Convertible arbitrage	27	1	3.7	3.1	3.0	81	0	0.0	8.8	6.5
Dedicated short bias	3	0	0.0	2.8	2.8	23	1	4.3	2.2	1.7
Emerging markets	138	4	2.9	2.2	1.1	165	3	1.8	6.1	5.5
Market neutral	62	0	0.0	6.4	6.1	116	0	0.0	5.8	5.1
Event driven	106	0	0.0	4.7	4.0	220	0	0.0	6.2	4.6
Fixed income arbitrage	54	0	0.0	19.4	16.0	106	0	0.0	2.0	1.2
Fund of funds	1122	2	0.2	8.5	6.5	1277	1	0.1	2.9	2.1
Global macro	81	2	2.5	6.0	2.7	110	0	0.0	9.4	5.8
Long/short equity hedge	574	2	0.3	2.9	2.3	785	17	2.2	7.6	5.2
Managed futures	174	1	0.6	5.0	2.1	242	5	2.1	2.3	1.4
Multi-strategy	340	0	0.0	16.1	12.0	220	0	0.0	1.2	0.8
Option-strategy	1	0	0.0	2.3	2.3	13	1	7.7	6.5	4.1
Other	65	1	1.5	7.7	4.6	36	0	0.0	4.5	5.6
Total	2747	13	0.5	8.3	5.4	3394	28	0.8	4.7	3.4

survive when they first come into market, so fund managers of younger funds tend to be more cautious than those dealing with older funds. This conservative attitude of investing would usually lead to a high level of Cap ratio during younger stage of a fund's life. The last three models capture the relationship between the Cap ratio and investment styles. As we can see from Table 5, among all the styles, only managed futures and multi-strategy funds have positive relationships with Cap ratios, and other styles tend to be negatively correlated with Cap ratios. The insight is that hedge funds adopting these two styles seem to be better capitalized than others.

We then calculate the values of Cap ratios calculated assuming the returns of hedge funds follow normal distributions. Table 6 demonstrates the results. The reason for constructing this table is to determine whether it is necessary to use the EVT approach as a base for our VaR calculation. The EVT approach is much more complicated than the normal distribution method; if we could confirm the assumption of normal distribution is reasonable with our data, we would use the normal distribution approach instead. Under the assumption of normal distribution, VaR is simply calculated as -2.58 multiplied by the standard deviation of the fund. We compare the results from Table 3 with those in Table 6, and check whether the assumption makes a difference in our assessment. The number (percentage) of undercapitalized funds measured with the method of EVT is 222 (8.1%) for live funds, while the number (percentage) of undercapitalized live funds assuming normality is only 13 (0.5%). We can get a similar result for the dead funds. These results are consistent with Gupta and Liang (2005); the normality assumption dramatically underestimates the level of undercapitalization for both live and dead funds. The reason behind the underestimation is that we ignore the fat tails that actually exist by assuming normality in the return of the hedge funds. However, lower returns are located in the left tails. Therefore we actually ignore some of the lower returns if we calculate the Cap ratio by assuming normality. At the same time the competitive feature of EVT method is that it covers all the extreme situations. In conclusion, if we evaluate whether a hedge fund is capitalized by assuming the historical returns exhibit a normal distribution, we would underestimate the amount of capital cushions required for extreme events and face financial risk in the long run. Another widely used parameter for risk analysis is leverage ratio. However, based on the results in Table 4, there is no significant difference in leverage ratios between capitalized and undercapitalized funds for dead funds, indicating that leverage ratio is neither a better measurement of hedge funds' risk than VaR.

7: Robustness test

7.1 Tail conditional loss and 99.94% VaR

As mentioned above, the required capital is calculated as three times the one-month 99% VaR. Now we examine whether it is safe to use three as a multiplier. Firstly, we calculate the value of TCL using formula (5), and then calculate the ratio of TCL to the corresponding 99% VaR. Results organized by fund investment style are shown in Table 7. The ratios for live funds are around one for all styles, and slightly greater than one for dead funds. None of the style has a TCL/VaR ratio over three. We also report the ratio of 99.94% VaR to 99% VaR to support our conclusion. The mean and median ratios are 2.24 and 1.19 for live funds, and 1.25 and 1.16 for dead funds. Again, similar to Gupta and Liang (2005), none of the mean or median ratio is over three among all the thirteen investment styles. We conclude that the expected losses are very unlikely to exceed three times the VaR even under extreme circumstances. Therefore we think that three is a safe multiplier and it is logical to follow the recommendation of the Basel committee with a multiplier of three for calculating VaR.

7.2 The effectiveness of using VaR to measure risks

Though we have employed VaR as a method to measure the risk profiles of all the live and dead hedge funds and have reached some conclusions from the analysis, we also need to check whether VaR provides an effective measure of risk and capital adequacy for the hedge funds. As we mentioned already, a commonly used financial parameter to detect risk is standard deviation. Since the returns of hedge funds also have option-like non-Gaussian features and it is only valid under the assumption of normality, using standard deviation as a measure of risk in this case would significantly underestimate the risks hedge fund actually take. Leverage ratio does not convey any valuable information is this case either since there is no significant relationship between the adequately capitalized and undercapitalized funds.

Table 7: Tail conditional loss and 99.94% VaR ratio

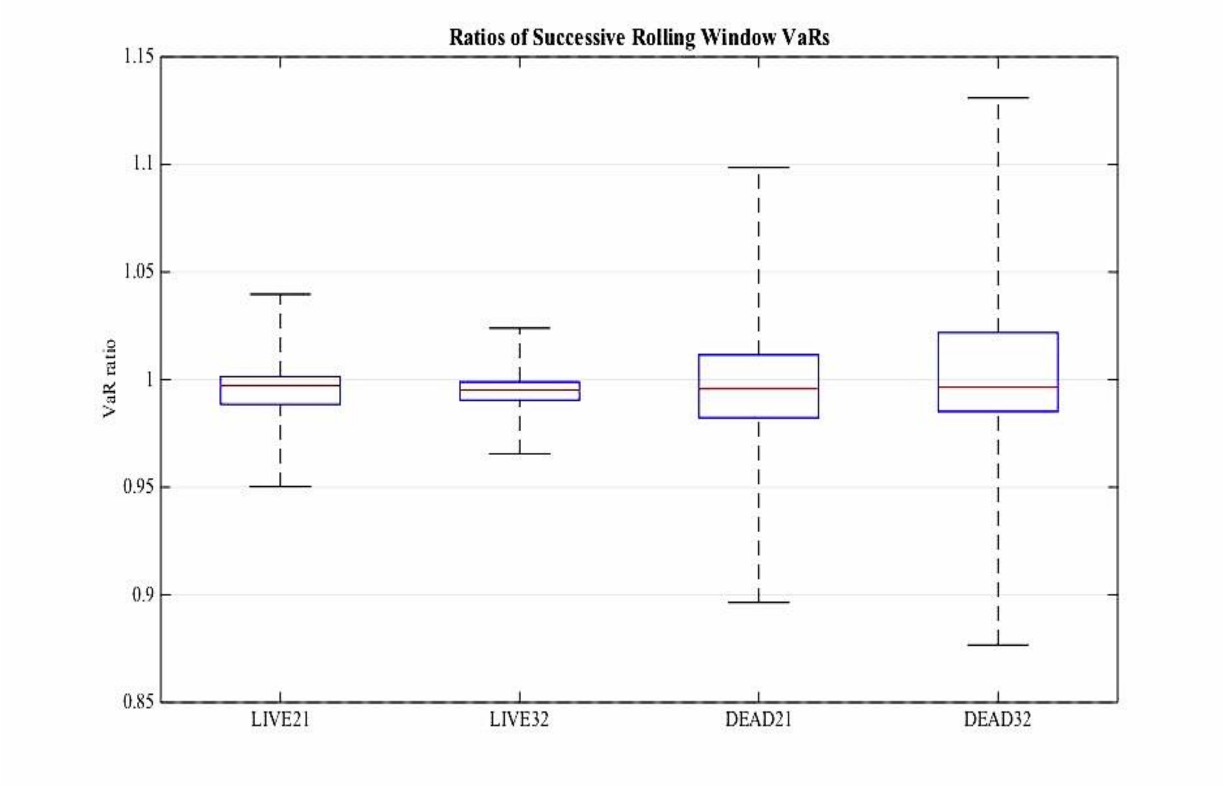
Style	Live funds					Dead funds				
	No.	TCL/VaR		99.4%/99% VaR		No.	TCL/VaR		99.4%/99% VaR	
		Mean	Median	Mean	Median		Mean	Median	Mean	Median
Convertible arbitrage	27	1.040	1.035	2.090	1.147	81	1.054	1.035	1.264	1.190
Dedicated short bias	3	1.040	1.037	2.360	1.211	23	1.046	1.036	1.182	1.148
Emerging markets	138	1.031	1.024	2.183	1.162	165	1.034	1.023	1.227	1.174
Market neutral	62	0.170	1.062	2.830	2.866	116	1.049	1.033	1.384	1.186
Event driven	106	0.964	1.042	1.540	1.126	220	1.073	1.045	1.292	1.143
Fixed income arbitrage	54	1.052	1.034	1.560	2.599	106	1.039	1.032	1.205	1.173
Fund of funds	1122	1.051	1.049	1.264	1.205	1277	1.044	1.036	1.151	1.131
Global macro	81	1.049	1.036	1.180	1.145	110	1.036	1.022	1.435	1.179
Long/short equity hedge	574	1.042	1.031	2.610	1.207	785	1.045	1.037	1.496	1.195
Managed futures	174	1.065	1.049	1.471	1.159	242	1.041	1.034	1.251	1.126
Multi-strategy	340	1.053	1.042	1.671	1.195	220	1.037	1.034	1.164	1.084
Option-strategy	1	1.027	1.027	1.101	1.101	13	1.044	1.043	1.312	1.319
Other	65	1.014	1.014	1.282	1.282	36	1.042	1.041	1.195	1.154
Total	2747	0.842	1.033	2.240	1.192	3394	1.042	1.032	1.250	1.163

In order to prove that VaR is an effective measure of hedge funds' risk, we check if it is able to capture the changes of risk in the hedge funds' recorded performance history. Hedge funds should present higher risk when it gets close to the end of its live span, therefore we predict that dead hedge funds should exhibit higher VaRs as they approach dead dates and such pattern should not occur with live funds.

Data we use here are funds with a return history of more than nine years. Instead of using a rolling window of five year as Gupta and Liang (2005) did, we assign each window a length of seven years to make sure our data covers recent economic downturns of the 2007-2008 financial crisis. For live funds, the last window, which is also the most recent one, includes fund returns from September 2007 to September 2014. Since we set a one-year interval between consecutive windows, the second window covers the period from September 2006 to September 2013, and the first window starts from September 2005 and ends in September 2012. For dead funds, the end date of the last window is the death date, the end date of the second window is one year before the death date, and the end date of the first window is two years before the death date. In order to detect the changes in VaR for each fund during these three windows, only funds with at least nine years of historical returns are selected. This step will also help eliminate estimation errors by making sure each fund that we compare in the sample dataset exists in all three windows.

As we know from formula (3), VaR is a multiplication of negative R99% and total assets. For the three consecutive rolling windows we employ here, there are not any significant changes in assets between any two consecutive windows. Therefore we compare $R_{99\%}$ calculated for each window for simplicity. We denote the value of $R_{99\%}$ from the third window over $R_{99\%}$ from the second window for a dead fund as DEAD32. DEAD21, LIVE32, and LIVE21 are defined in a similar manner. We present these ratios accordingly with boxplots in Figure 1. 1848 live funds and 1962 dead funds with at least a nine-year return history are used. Each boxplot in Figure 1 demonstrates the 25th, 50th and 75th quantile of the estimated ratio distribution, as well as upper and lower extreme values.

Figure 1: Ratios of Successive Rolling Window VaRs



As we can see from the graph, the medians of the VaR ratios are 0.9979, 0.9954, 0.9956 and 0.9963 from left to the right. Dead funds have a larger variation in VaR ratios than live funds. To reach further conclusions, we will first focus on the difference between DEAD21 and DEAD32. DEAD 32 has a higher median than DEAD21 and it also has a wider range of quantile values. DEAD32 seems like an integral stretching of DEAD21. It is reasonable to see it in this way because the VaR ratios for DEAD32 are calculated by comparing the VaR values of the third window to those of the second window. Since the third rolling window is closer to the death date of a dead fund, it is reasonable to find the third rolling window with a higher VaR value. Therefore, DEAD32 is greater the DEAD21. Although the median values of these two graphs are both close to one, VaR value can still capture the risk of hedge funds effectively by presenting a higher consecutive VaR ratio and a wider range of ratio volatility. A risk boost that presents in the dead funds is not seen in the live funds because there should not be any huge increases in their VaR values if the funds stay alive. Therefore we can conclude that VaR is an effective measure that reflects and captures the risk profiles of hedge funds, and it is reasonable to use it for determining the capital adequacy of hedge funds.

8: Time-series variation in capital adequacy

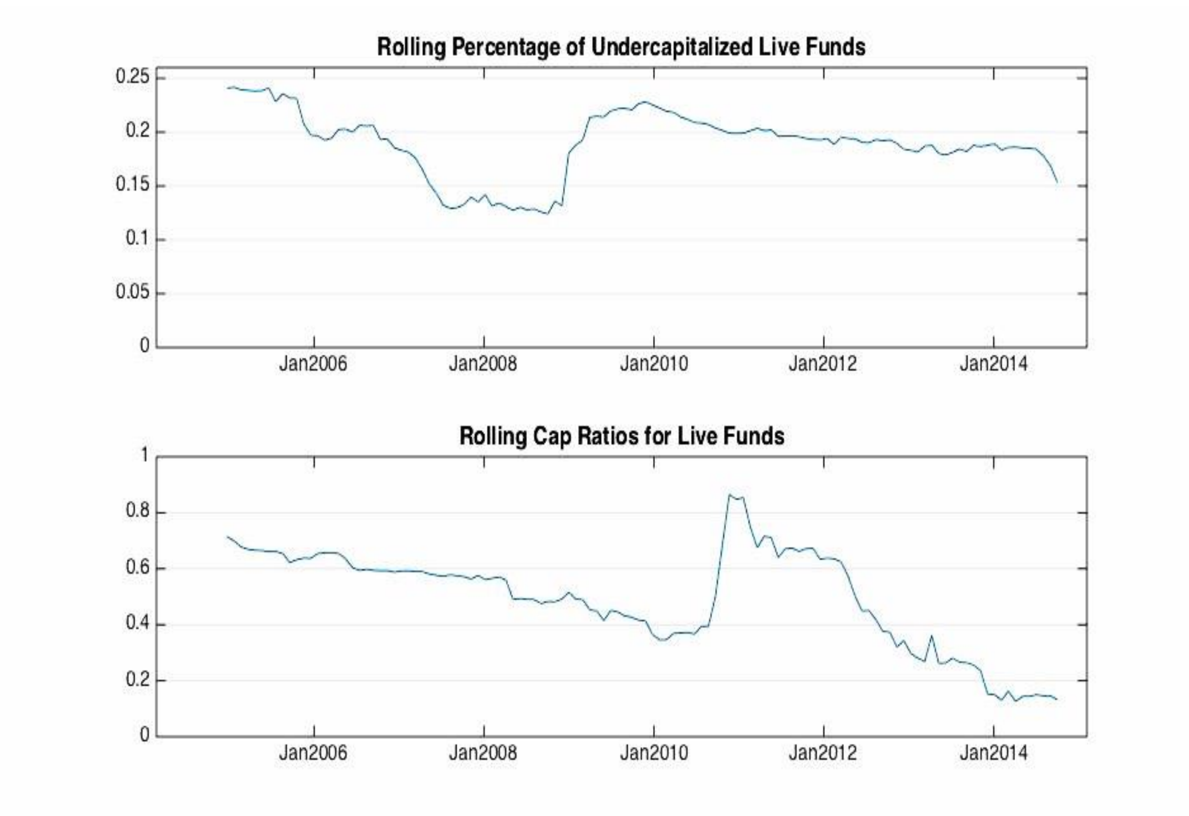
The results in Table 2, Table 3 and corresponding analysis can only explain the static features about the capital adequacy of hedge funds as of September 2014. Due to constant portfolio changes in hedge funds and frequent fluctuations in financial market, it is intuitive to extend our research to dynamic risk profile of hedge funds.

To obtain a visualized impression on whether the hedge funds have enough capital throughout recent financial history, we compute Cap ratios using hedge fund returns over a rolling window of 84 months (a seven-year period) for 120 times. By doing this, we hope to capture the capital adequacy of hedge funds from a dynamic perspective. We already know how to calculate the Cap ratio for any hedge fund with a complete return history as of September 2014, and now we apply the same method to 120 datasets. We define each sub-dataset to be 84 months and set an interval of one month between any two consecutive sub-datasets. To be specific, the last window in our analysis is from September 2007 to September 2014. By moving back one month at a time for 120 times, we obtain 120 rolling windows with the first window starting in September 2004.

The first graph in Figure 2 shows changes in the degree of undercapitalization for live funds monthly from September 2004 to September 2014. As we can see from the graph, the percentage of undercapitalized decreases from 24.08% in September 2004 to a minimum of 12.39% in November 2008, and then it increases to 22.82% in December 2009 and decreases smoothly to 15.32% in September 2014. In particular, the fraction of undercapitalization declines quite quickly during the financial crisis of 2007 to 2008. This happens since those funds that did not survive the crisis were removed from live fund database and funds that survived tend to be better capitalized. In other words, this relatively low fraction of undercapitalization is because it only takes the hedge funds that survived the crisis into consideration. Although the percentage of undercapitalized live funds fluctuates a lot over the past ten years, there is not a monotonic trend that Gupta and Liang (2005) find in their paper.

The historical fluctuation pictures a trend in the capital adequacy of the live hedge funds and also reflects the reaction of hedge funds' capital reserve to the constant changes in the financial market. A relative high ratio of undercapitalization may illustrate an unstable financial market situation since most of the live hedge funds stay deficient in capital during the corresponding period of time; however, a low undercapitalization percentage does not necessarily reflect stable market situations. For example, the undercapitalization rate of live hedge funds reaches its minimum of 12.39% in November 2008 as a result of the crisis as we mentioned before.

Figure 2: Historical rolling window capitalization



The second graph in Figure 2 demonstrates the trend of the median Cap ratio for live funds from September 2004 to September 2014. We can get a coincidental conclusion from graph 2 as we get from the first graph of Fig. 1. The median Cap ratio decreases gradually from 0.71 in September 2004 to 0.35 in February 2010, followed by a sharp increase to 0.88 in November 2010 and a consecutive decreasing till September

2014. Gupata and Liang (2005) find that the median Cap ratio from January 1995 to January 2003 fluctuates around 2.5, whereas the median Cap ratio in the past ten years has been around 0.5. Therefore the extent of adequately capitalization for live funds has reduced over the years. Overall, we get a basic understanding of the dynamic variation in capital adequacy of live hedge funds from Figure 2.

9: Conclusion

In this paper, we conduct researches on evaluating the risk profiles and capital adequacy of hedge funds. 2747 live funds and 3394 dead funds from Lipper Tass Academic Hedge Fund Data are used during our analysis.

We use Cap ratios to determine whether hedge funds are adequately capitalized. As of September 2014, 8.1% of live funds and 12.3% of dead funds are undercapitalized. Although live funds are better capitalized than dead funds in general, capital deficiency is not necessarily the most important reason for hedge fund death since over 85% of dead funds are adequately capitalized right before their death date. That being said, holding enough capital is essential for hedge funds to survive in the long run.

We conduct further analysis on differences in fund characteristics between capitalized and under capitalized hedge funds and examine how Cap ratios vary according to these characteristics by conducting cross-sectional regression. The result implies that younger hedge funds tend to be more capitalized since they are managed more carefully; however, fund size is not statistically correlated with Cap ratios. We also find a relationship between investment styles and Cap ratios. Till our assessment time, managed futures and multi-strategy are better capitalized and consequently have lower probabilities of default than other styles.

We evaluate whether VaR-based measures are appropriate for assessing hedge fund risk and prove that traditional measures, such as standard deviation and leverage ratio, tend to introduce errors in the process and underestimate the risks that hedge funds take. To analyze the effectiveness of VaR method, we draw boxplots of ratios for successive rolling window VaRs and reach the conclusion that VaR can reflect the risk changes of hedge funds efficaciously. VaR-based measures also capture risks of hedge funds dynamically.

In this paper, we grasp an understanding of the risk characteristics and capital adequacy of hedge funds. It is meaningful for the hedge fund managers and researchers to conduct further evaluation on hedge fund risk profile and its relationship with various factors. An accurate generalization and forecasts will contribute to the operational efficiency of the hedge funds industry.

Appendices

Appendix A

Figure 2: Rolling percentage of undercapitalized live funds

This code is used to organize assets of each fund that are used in Figure 2. The first row represents fund number, followed by historical asset of each fund along the column. Returns of each fund are also organized in a similar way.

```
clc
clear all
close all
format compact
warning off all

% Load raw data
[num,~,~] = xlsread('ProductPerformance');
prodRef = num(:,1);
assets = num(:,5);
[grps] = grpstats(assets,prodRef,{'gname'});

grps = str2double(grps);
A = table(prodRef,assets,'VariableNames',{'ProductReference' 'Assets'});

[num2,txt2,raw2] = xlsread('ProductDetails');
B = table(num2(:,1),num2(:,51),'VariableNames',{'ProductReference' 'Length'});

C = join(A,B);  % Ref Assets Length

D = C(C.Length>2555,:);   % Delete funds less than 7 years

% Organize assets based on Reference
[num1,~,~] = xlsread('table2part1');
data(1,:) = (num1(:,1)).';
Fundref = data(1,:);
Fundassets = table2array(D(:,2));
Find = table2array(D(:,1));

for i = Fundref
   [row,col] = find(Find == i);
      j = find(Fundref == i);
      data(2:numel(row)+1,j) = Fundassets(row,1);
      % Data save as Table2b2(vertical)(1)
end
```

Appendix B

Figure 2: Rolling percentage of undercapitalized live funds

```
clc
clear all
close all
format compact
warning off all

% Load raw data
data = xlsread('Table2b2(vertical)');         % Returns(>7yrs)
assets = xlsread('Table2b2(vertical)(1)');  % Assets(>7yrs)

% Pre-allocate space
time = nan(1,120);
R = nan(size(data,2),120);
required = nan(size(data,2),120);
cap = nan(size(data,2),120);
underornot = nan(size(data,2),120);
under = nan(1,120);
notunder = nan(1,120);
total = nan(1,120);
percent = nan(1,120);

% Loop to calculate the percentage of undercapitalized live funds in each window
tailProb = 0.01;
p = 0.01;
for x = 1:size(data,2)
   flipped = flip(data(2:end,x));
   [r,c] = find(flipped~=0);
   flipped2 = flipped(r(1):end);
   data2 = flip(flipped2);

   for y = 1:120
      try
         % Find asset of each fund at the end of each rolling window
         window = data2((end-83-(y-1)):(end-(y-1)));
         endposition = length(data2)-(y-1);
         endasset = assets(endposition+1,x);

         mret = mean(window);
         adjustret = -1*(window-mret);
         u = quantile(adjustret,1-tailProb);
         tailRet = u-adjustret(adjustret<u);
```

```
            % Estimate parameters – tail index and sigma
            pparams = gpfit(tailRet);
            tailIndex = pparams(1,1);
            sigma = pparams(1,2);

            % Calculate R & var
            N = numel(window);
            n = numel(tailRet);
            if tailIndex == 0
               R(x,y) = u + sigma*log(n/N*p);
            else
               R(x,y) = u + sigma/tailIndex*((N/n*p)^(-tailIndex)-1);
            end

            time(1,y) = 735873 - 30*(y-1);

            required(x,y) = R(x,y)*endasset/100*3;
            cap(x,y) = (endasset-required(x,y))./required(x,y);

            if cap(x,y) < 0
               underornot(x,y) = 1;
            else
               underornot(x,y) = 0;
            end

            under(1,y) = numel(find(underornot(:,y)==1));
            notunder(1,y) = numel(find(underornot(:,y)==0));
            total(1,y) = under(1,y) + notunder(1,y);
            percent(1,y) = under(1,y)./total(1,y);

         catch exception
            warning('Not enough returns.');
            continue
         end
      end
   end

   % Organize results
   result = [time;percent];
   for i = 1:120
      if result(2,i)==0
         result(:,i) = [];
      end
   end
```

```
% Plot Figure 2
plot(time,percent);
datetick('x',28)
title('Rolling Percentage of Undercapitalized Live Funds');
```

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