VALUE AT RISK AND HEDGE FUND RETURN - DOES HIGH RISK BRING HIGH RETURN?

by

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Abstract

This paper mainly focuses on the correlation between live hedge fund return and their value at risk (VaR), and is based on the historical data from May 2000 to April 2010. The authors adopt portfolio level analyses and fund level cross-sectional regression, and find that there is significant positive correlation, both statistically and economically, between the hedge fund return and VaRs (parametric, non-parametric and GARCH). Further research is conducted by sub-dividing the overall period into pre-Financial-Crisis and Financial Crisis, and demonstrates that this correlation holds in both periods but weakens in the Financial Crisis. Besides, the authors identify the approximately negative correlation between hedge fund portfolio return and increase in VaR, and develop an effective method of selection.

Keywords: hedge funds; value at risk; VaR; return; cross-sectional regression; financial crisis; portfolios; parametric; non-parametric; GARCH

Dedication

I dedicate this paper to my beloved wife and my dearest parents. I could not have accomplished all I have in life so far without your unbounded love, endless support and encouragements.

Tao Jing

I wish to dedicate this paper to my beloved wife, dearest parents and kindest sister. I could not have completed this process without their continuous support.

Hongxiang Zhao

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1: Introduction

The hedge fund industry, first founded in 1949, has developed rapidly in the past 60 years. Especially, it has exponentially grown since 1990 both in numbers of funds and in size of underlying assets. It is estimated that the industry managed around $38 billion in 1990, $626 billion in 2002, and peaked $1.9 trillion by the end of 2007. Although the number decreased to $1.3 trillion in 2008, it is still incredible that the industry has grown from the starting $100,000.[1]

Due to the industry size, growth rate and impact on the market, there are increasing number of researchers focused on the performance measures of hedge funds. For example, Fung and Hsieh (1997), base on Sharpe (1992), extend Sharpe's framework by including hedge fund investment strategies and argue that the extended model can provide an integrated framework for style analysis. Fung et al (2009) further research US hedge funds to find out whether hedge funds deliver alpha and whether the alphas change over time. They conclude that funds with alpha were less likely to liquidate and experience greater capital inflows than beta-only funds. Brown, Goetzmann and Ibbotson (1999) examine the performance of the off-shore hedge fund industry over the period 1989 through 1995, and conclude that it is the style of strategies other than the skill of managers contribute more to the performance of the hedge fund. Ackermann, McEnally, and Ravenscraft (1999) study the hedge funds from 1988 to 1995 and find that hedge funds display several interesting characteristics that may influence performance, including: flexible investment strategies, strong managerial incentives, substantial managerial investment, sophisticated investors, and limited government oversight.

Since the debacle of the Long-Term Capital Management LP (LTCM), 1998, the risk exposure of hedge funds has increasingly become the focus of investors. Meanwhile, there are more and more academic literature on the relationship between the hedge fund

1 See "Hedge Fund Regulation on the Horizon — Don't Shoot the Messenger" by the US SEC Commissioner Luis A. Aguilar, 2009

return and risk. After Jorion (2000) introducing the VaR approach to analyze the risk level of portfolios, academics start to evaluate the risks of hedge funds using the VaR method. Gupta and Liang (2005) and Agarwal and Naik (2004) compare traditional standard deviation risk measure with VaR and conclude that VaR better measures hedge fund risk, because hedge fund returns are usually fat-tailed distribution with negative skewness and significant kurtosis, and standard deviation may not fully capture the risk characteristics, so that underestimates the tail risk of hedge funds. Bali and Gokcan (2004) use the thin-tailed normal distribution, the fat-tailed generalized error distribution, the Cornish-Fisher (CF, 1937) expansion, and the extreme value theory (EVT) to estimate VaR for hedge fund portfolios, and find that EVT and CF expansion better capture fat-tailed risk than other methods do. Bali, Gokcan and Liang (2006) calculate VaR of hedge funds that exist during period of January 1995 to December 2003, using non-parameter and CF expansion approach respectively, and argue that the VaR of hedge funds bears strong positive correlation with hedge fund return. Furthermore, they develop an investment strategy of selling low VaR portfolio and buying high VaR portfolio, and selling portfolio with high percent change of VaR (ΔVaR) and buying portfolio with low ΔVaR.

In this paper, we mainly focus on testing whether the relationship between VaR and expected return on hedge funds, which Bali, Gokcan and Liang (2006) presented, still holds during the new period of May 2005 to April 2010. We use same parametric and non-parametric techniques to calculate the VaR for the new period. Furthermore, we expand the parametric approach by estimating the VaR based on GARCH estimated volatility instead of sample historical standard deviation. Our research shows that the positive correlation between the VaRs (parametric and non-parametric VaR) and return on hedge funds still holds in our test period (May 2005 to April 2010. Furthermore, we found that this relationship is much more significant in the pre-Financial-Crisis period (May 2005 to October 2007) than in the Financial Crisis period (November 2007 to April 2010).

Besides, we review their investment strategy presented in Bali, Gokcan and Liang (2006), and find that it no longer work well in the new period. Instead, the highest return appears in the group of lowest (greatest negative value) ∆VaR and *vice versa*. Meanwhile, the group of nearly-zero ∆VaR does not bring out a high return.

This paper contributes to finding out another approach to estimate the VaR of hedge funds, that is, the VaR calculated from GARCH volatility estimation, which leads to a statistically significant result, especially in the extreme market situations, such as the 2007 Financial Crisis. Meanwhile, the paper also shows that the investment strategy established on the pre-crisis historical data might not be effective when the market become extremely volatile.

The paper proceeds as follows. Sections 2 describes the data and methodology. Section 3 presents the empirical results. Section 4 concludes the paper.

2: Data and Methodology

2.1 Data

The data involved in this paper includes original historical data of world hedges funds and the data sets adjusted by us based on the original data.

2.1.1 Original Historical Data

We obtained our original historical data of hedge funds from the HedgeFund.Net, which is owned by Channel Capital Group Inc., and provides news and historical performance data of worldwide hedge funds on the web[2]. The data set we downloaded contains factors and monthly returns of 6983 live funds[3]. Since some of those funds contain shorter periods of records, and many of them are not updated to May 2010, we use only those with more than 120 consecutive monthly returns in the 10-year-period of May 2000 to April 2010. This left us 1050 hedge funds, each with 120 months' returns[4].

2.1.2 Logarithm Return

Since the monthly returns provided by the HFN are holding period returns, whose distribution does not range from negative infinity to positive infinity, we need to convert them to log-returns, so that we can base our following computation on a normal or skewed distribution. Through this procedure, we get a new 1050 rows x 60 columns matrix and use log-return instead of the original holding period return in all our research[5]. (Hereafter, the return mentioned in this paper refers to log-return.)

2 About HedgeFund.Net, http://www.hedgefund.net/hfn_public/marketing_index.aspx?template=aboutus.html, 2010/08/03

3 Please note that our research focuses on the live funds only, and it might cause some biases if this research is extended to all the funds including live and dead.

4 We need enough number of historical data to get quality results, while, this might lead to bias by excluding hedge funds whose ages are less than 10 years

5 To make our research comparable with that of Bali, Gokcan and Liang(2006), we follow the same kind of return as they used, which is not risk-adjusted.

2.1.3 Non-normality Distribution Test

Once we have 120 monthly returns for each fund, we could compute the Skewness, Ex-Kurtosis and Jarque-Bera (JB) value to test whether the returns are normal distributed. For a normal distribution variable, the Skewness of its values is zero and Kurtosis is three (Ex-Kurtosis = Kurtosis - 3 = 0). At each month, we calculate Skewness and Kurtosis for the returns of each hedge fund from its past 60 months' return[6] in a rolling-time basis, and count the number of cases that their Skewness and Kurtosis exceeds the critical value, which are calculated as follows:

$$Critical\ Value_{Skew} = z(\alpha) * \sqrt{6/n} \tag{1}$$

$$Critical\ Value_{Kurt} = z(\alpha) * \sqrt{24/n} \tag{2}$$

where $z(\alpha) = 2.57$ is obtained at 1% significance level, and n is the number of observations. We get the percentage of exceeding numbers to the total number, which is the probability of rejecting the normality. Besides, we also used JB test to examine normality:

$$JB = n[\left(\frac{S^2}{6}\right) + \frac{(K-3)^2}{24}] \tag{3}$$

Table-1 clearly shows that zero-skewness hypothesis is rejected at 85.24% cases, zero-excess-kurtosis hypothesis 90.38% and the JB test rejects at 95.71% cases the normal distribution hypothesis of hedge fund return at a significance level of 1%.

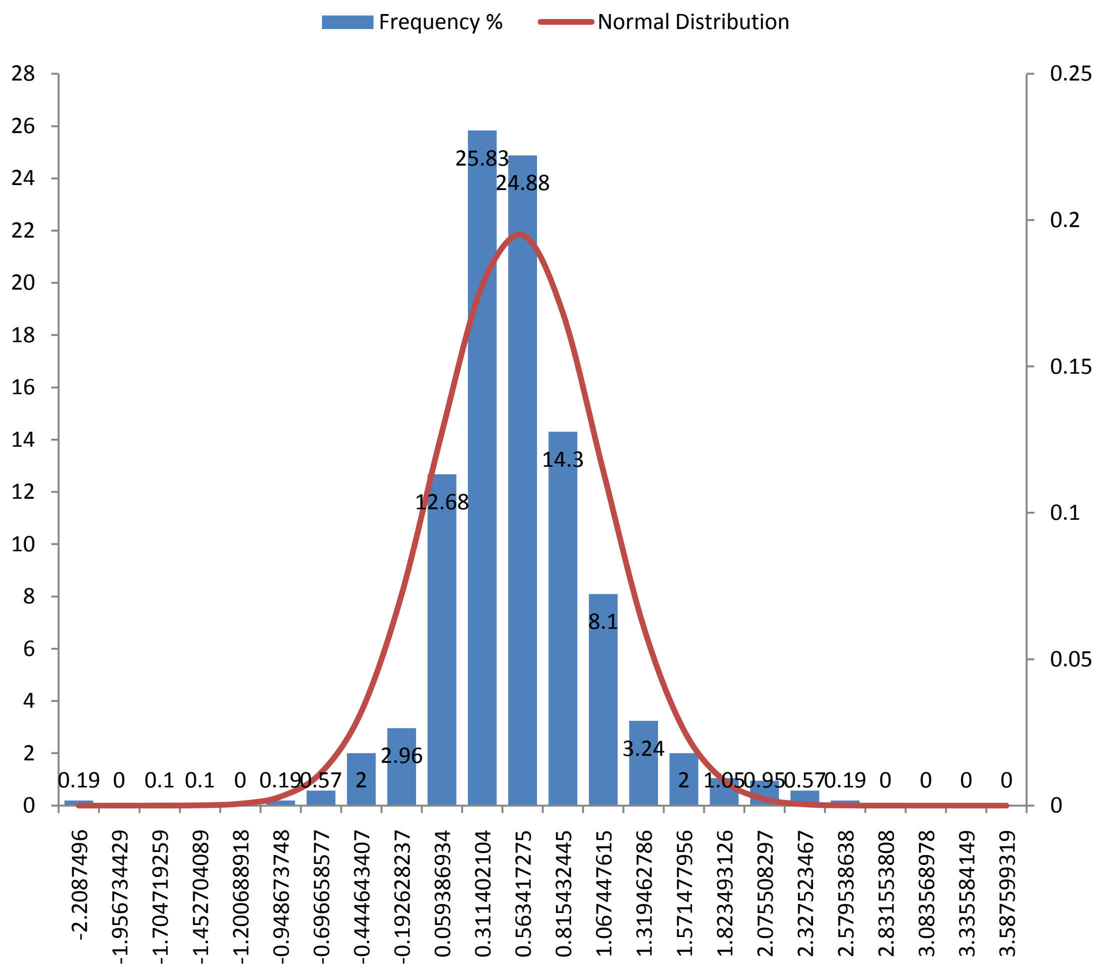
6 The Skewness and Kurtosis are calculated using Excel functions Skew() and Kurt().

Table-1 Testing non-normality of hedge funds returns

Indicators	Total number	Average	Critical value[7]	Number of Exceeds	Rejection Percentage
	1050				
Skewness		-0.8621	0.1943	895	85.24%
Kurtosis		5.7315	0.3885	949	90.38%
JB		6011.98	5.99	1005	95.71%

This table shows the result of testing the non-normality of hedge funds returns. The Total number is the number of hedge funds; the Average is the average of each of Skewness, Kurtosis and JB; The Critical value is the critic value of each indicators at 1% significance; the Exceeds is the number of hedge funds whose indicators values exceeds the critic values, and the Percentage is the exceeds to the total number.

Figure-2 Histogram of Hedge Fund Return



In this figure, the histogram is obtained from the average historical monthly return of each hedge fund over the period of May 2000 to April 2010. The red curve is the normal distribution curve. The figure shows that the hedge fund return is a non-normal distribution with negative skewness, excess kurtosis and fat-tail.

7 The critical value is calculated at 1% significance

2.1.4 GARCH Estimation of Volatility and VaR

In the paper of Bali, Gokcan and Liang (2006), they estimate Parametric VaR based on the unconditional standard deviation of the hedge funds return over the past 60 months in a rolling-time basis. In our research we introduce the GARCH estimation of volatility, which believes that the present volatility is mainly decided by the present variable value (return) and the most recent volatility, that is, the volatilities varies along the time. The 60 months' Fat-tailed GARCH(1, 1) volatilities are calculated and a new matrix of GARCH Parametric VaRs is obtained by us.

2.2 Methodology

In this section, we elucidate how to estimate the three types of VaRs, how to form and compare portfolios according to the VaRs, and how to perform the cross-sectional regression.

2.2.1 Non-parametric VaR

To estimate the non-parametric VaR, we do not need any assumption about the shape of the returns. The variables involved are the confidence level and the target horizon. In this paper, we set 95% confidence level and one-month time horizon. Based on the empirical distribution of the monthly return of each hedge fund in the past 60 months, we use the Microsoft Excel percentile function to calculate the non-parametric VaR for each month, and then roll over one month ahead until the latest month. For example, from the 60 monthly returns (May 2000 to April 2005), we can get the non-parametric VaR corresponding to May 2005. For the next month, we compute the VaR for June 2005 using the historical data from June 2000 to May 2005. Repeating this procedure until exhausting all the available data, we receive 60 non-parametric VaRs.

2.2.2 Parametric VaR

As aforementioned, the hedge fund returns are not normal distributed due to the significant skewness and kurtosis, and we need to find an appropriate model that takes into account these higher-order moments. Bali, Gokcan and Liang (2006) adopt the Cornish and Fisher (1937) expansion to adjust the skewed and fat-tailed distribution, and testify its validity. In this paper, we follow the same formula to estimate the parametric VaR:

$$VaR_{CF} = \mu + \Omega(\alpha) \times \sigma, \tag{4}$$

$$\Omega(\alpha) = z(\alpha) + \frac{1}{6}(z(\alpha)^2 - 1)S + \frac{1}{24}(z(\alpha)^3 - 3z(\alpha))K - \frac{1}{36}(2z(\alpha)^3 - 5z(\alpha))S^2 \tag{5}$$

Where μ is the mean, σ is the standard deviation of the past 60 months returns, and $\Omega(\alpha)$ is the critical value corresponding to a certain confidence level and the specific shape of the distribution of the past returns. Here, $\Omega(\alpha)$ is determined by the critical value from the normal distribution of probability ($z(\alpha)$), skewness (S) and kurtosis (K).

From the processed data including return, volatility, skewness, kurtosis, as well as the critical value at 95% confidence level (-1.645), we can figure out 60 parametric VaRs. Furthermore, replacing the unconditional standard deviation with the GARCH standard deviation, we get another group of 60 parametric VaRs.

2.2.3 Portfolios Formation Based on VaR Sorting

Similar to Fama and French (1992), we pick all the hedge funds monthly VaRs and their corresponding returns, sort the VaRs, rank them from low to high, and then form 10 equally weighted portfolios. For instance, in May 2005, we select the 1050 monthly VaRs and one-month ahead actual return, rank the VaRs, form portfolio 1 that composes of the lowest 105 VaRs, then portfolio 2 that includes the lowest 106-210 VaRs, and so on, until we group all the 1050 hedge funds into 10 equally weighted portfolios. In June 2005, we form 10 new portfolios according to the updated VaRs. By repeating the above procedure, we obtained ranked portfolios of 60 months. Finally, we average these 60 VaRs and corresponding returns of each portfolio across time series, and generate 10 portfolios and their average returns and VaRs for comparison.

We also use the same way to construct the portfolios based on the changes of VaR (ΔVaR). For example, in May 2005, we calculate the monthly changes of VaRs from May 2005 to April 2005 and the monthly return. Moving one-month ahead, in June 2006, we calculate another pair of return and ΔVaR over June 2005 to May 2005. Thus, we get altogether 59 pairs of data. Using the same portfolios formation method, we generate 10 portfolios with average monthly ΔVaRs and the corresponding returns.

2.2.4 Cross-sectional Regressions

Referring to Fama and French (1992), we run the cross-sectional regressions to compare the predictive power of VaR with other factors, i.e., asset size and age of hedge funds, at the fund level. Our selection of these two control variables is founded on the precedent research results, such as Bali, Gokcan and Liang (2006), that these two variables are significantly related with hedge funds return. Based on the 60 months' data of these variables of 1050 hedge funds and their actual one-month ahead returns, we run 60 times cross-sectional regressions. Once we obtain the 60 cross-sectional slope coefficients of each variable, we average them and compare their statistical significance by the t-statistics.

2.2.5 Lag Phase Determination

Considering the VaR might influence the hedge funds return for several months, we need to determine N, which is the number of months influenced. We hereby used the Kyock Distributed Lag Model[8] :

$$Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_k X_{t-k} + \varepsilon_t \tag{6}$$

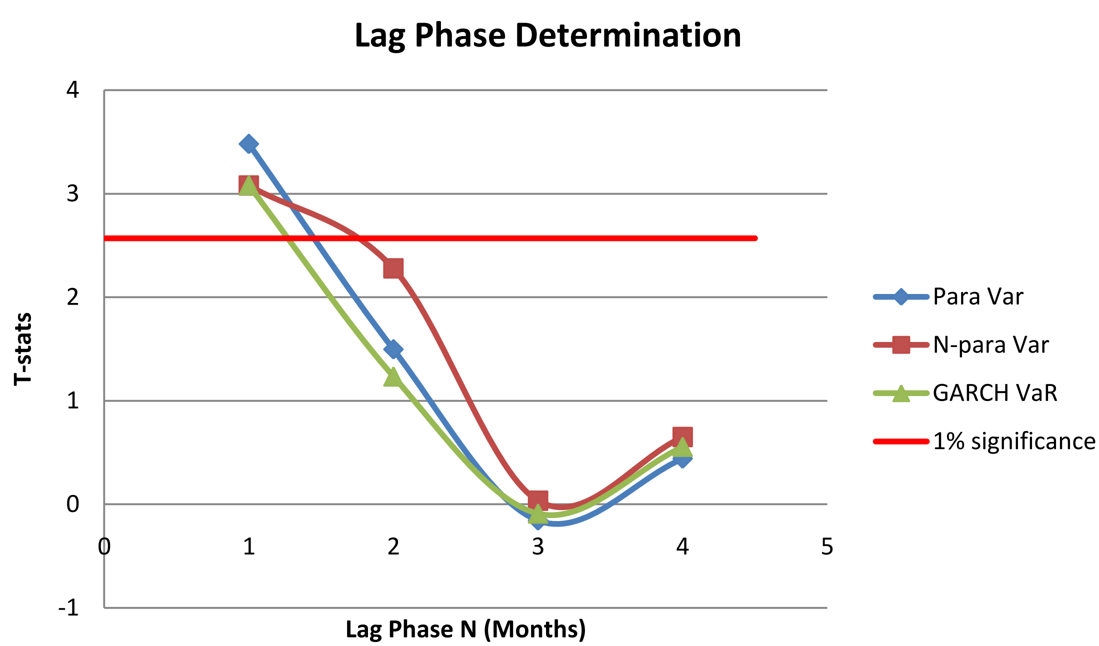
8 KOYCK, L.: Distributed Lags and Investment Analysis. Amsterdam: North-Holland Publishing Co., 1954.

Table-2 and Figure-2 show the results that only the next-month return (N=1) is statistically significantly influenced by VaR at 1% level. Hence, we use VaR and its one-month-lag return in our research.

Table-2 Lag Phase Determination (2005.05 to 2010.04)

	Beta			T-stats			R^2		
N	**Para Var**	**N-para Var**	**GARCH VaR**	**Para Var**	**N-para Var**	**GARCH VaR**	**Para Var**	**N-para Var**	**GARCH VaR**
1	0.0544	0.057	0.0502	3.481	3.0792	3.0815	0.0945	0.091	0.1056
2	0.6442	0.1915	0.0828	1.4964	2.2786	1.2355	0.112	0.1008	0.1358
3	0.2015	0.3169	0.1678	-0.1573	0.0356	-0.0885	0.1265	0.1184	0.1507
4	0.0674	0.1622	0.1643	0.4408	0.6502	0.5563	0.1443	0.1373	0.1663

Figure-2 Lag Phase Determination



2.2.6 Overall and Sub-period Analysis

Since the Financial Crisis broke out in 2007, hedge funds have suffered huge loss. Whether the model established on the pre-crisis data still validates under this extreme market change, and what kind of impact on the proven relationship between hedge fund return and VaRs the crisis results in, are the focus of this paper. Therefore, we roughly separate our data into two parts: May 2005 to October 2007 and November 2007 to April 2010, and then we perform analysis in the whole time and sub-periods respectively to see whether the results vary.

3: Empirical Results

3.1 Hedge Fund Portfolios formed by Sorted VaR

At each month, as described in 2.2.3, we sort individual hedge funds by their VaR and subdivide them into 10 equally weighted groups. In each group, we calculate their mean return and VaR at each month, and average over 60 months, to see if there is a correlation. This procedure is repeated in three time windows: (1) overall period of 60 months; (2) pre-financial crisis period of May 2005 to October 2007; (3) financial crisis period of November 2007 to April 2010, to find out whether the correlation varies in market situations of different volatility level. Please note that here the VaR is obtained from the(-1) x (the maximum likely loss), that is, the higher value of VaR, the higher expected loss there will be.

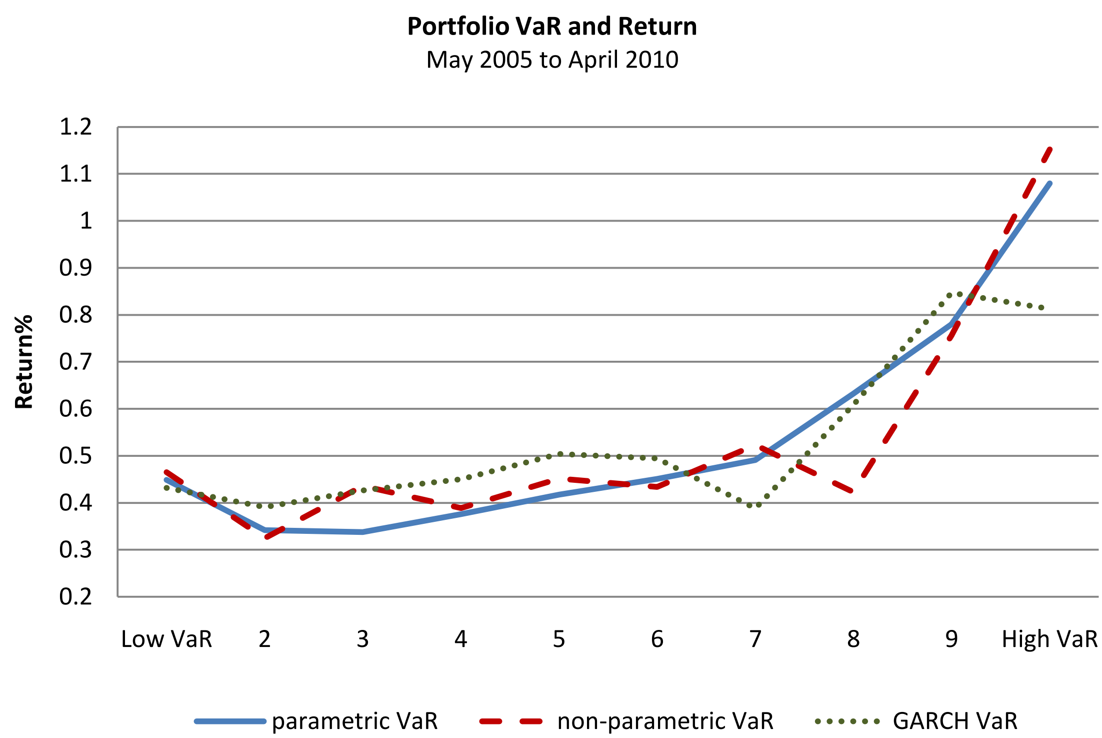
3.1.1 Overall Period

The overall period is from May 2000 to April 2010, including the period before 2007 Financial Crisis and months from the starting of Financial Crisis to present. The sorted and grouped results in Table-3 show certain positive correlation between return and VaRs (parametric, non-parametric and GARCH VaR), while there are some cases that the relation is not monotonic: decile 2 and 3 in parametric VaR, etc. From Figure-3, we could see a general trend of the positive relation between return and VaR, although it is occasionally not monotonic.

Table-3 Grouped VaR and Return (May 2005 – April 2010)

	Parametric VaR		Non-parametric VaR		GARCH VaR	
Deciles	**Return (%)**	**VaR (%)**	**Return (%)**	**VaR (%)**	**Return (%)**	**VaR (%)**
Low VaR	0.4487	0.5632	0.4653	0.6675	0.432	1.0188
2	0.3416	1.5735	0.3245	1.3911	0.3911	2.1502
3	0.3377	2.0704	0.4357	1.8481	0.4265	2.7152
4	0.3758	2.5186	0.3891	2.3026	0.4503	3.2629
5	0.4174	3.1451	0.4518	2.8232	0.5038	3.8691
6	0.4506	3.9814	0.434	3.5198	0.4947	4.6059
7	0.4912	4.9173	0.5233	4.4049	0.3882	5.6702
8	0.6322	6.1932	0.4231	5.6686	0.6085	7.2031
9	0.78	8.0559	0.756	7.518	0.847	9.6081
High VaR	1.0796	13.6534	1.152	12.4981	0.8127	17.5106

Figur-3 Grouped VaR and Return Curve (May 2005 – April 2010)



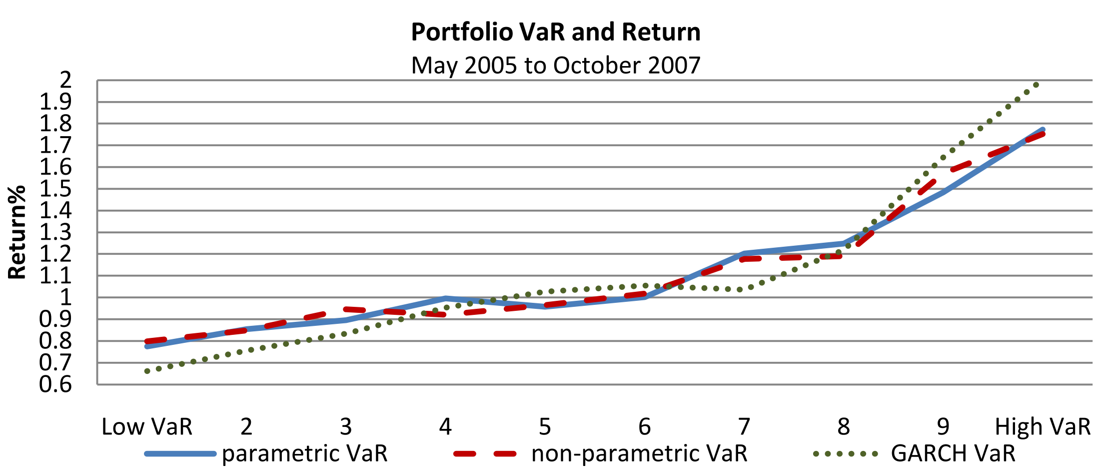
3.1.2 Pre-Financial-Crisis Period

The pre-Financial-Crisis period is from May 2000 to October 2007. The sorted and grouped results in Table-4 show strong positive correlation between return and VaRs (parametric, non-parametric and GARCH VaR), while there are a few cases that the relation is not monotonic: decile 5 in parametric VaR return, decile 4 in non-parametric VaR return, and decile 7 in GARCH VaR return. From Figure-4, we could see a strong positive relation between return and VaR, and there is only one exception in each type of VaR.

Table-4 Grouped VaR and Return (May 2005 – October 2007)

	Parametric VaR		Non-parametric VaR		GARCH VaR	
Deciles	**Return (%)**	**VaR (%)**	**Return (%)**	**VaR (%)**	**Return (%)**	**VaR (%)**
Low VaR	0.7751	0.2568	0.7983	0.371	0.6611	0.9404
2	0.8536	1.0231	0.8485	0.9601	0.7549	1.974
3	0.896	1.475	0.9462	1.3707	0.8341	2.473
4	0.9961	1.9221	0.9213	1.8405	0.9533	2.9703
5	0.9578	2.5743	0.9647	2.4149	1.027	3.5331
6	1.0019	3.5112	1.0174	3.2026	1.0544	4.2263
7	1.2022	4.4852	1.177	4.1132	1.0358	5.197
8	1.2484	5.7857	1.191	5.4211	1.2191	6.4827
9	1.483	7.6033	1.5707	7.2661	1.6448	8.4994
High VaR	1.7731	12.8076	1.7521	12.2621	2.0027	15.2513

Figure-4 Grouped VaR and Return Curve (May 2005 – October 2007)



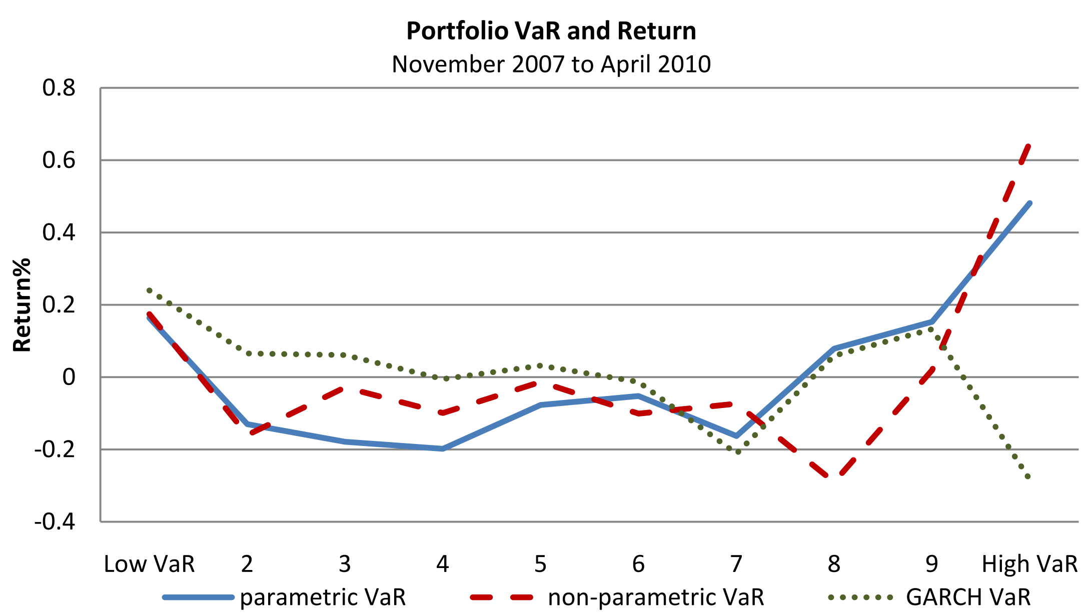
3.1.3 Financial Crisis Period

The Financial Crisis period is from November 2007 to April 2010. The sorted and grouped results in Table-5 show no obvious correlation between return and VaRs (parametric, non-parametric and GARCH VaR) and there are many cases that the relation is not monotonic. Figure-5 displays the non-monotonicity explicitly.

Table-5 Grouped VaR and Return (November 2007 to April 2010)

	Parametric VaR		Non-parametric VaR		GARCH VaR	
Deciles	**Return (%)**	**VaR (%)**	**Return (%)**	**VaR (%)**	**Return (%)**	**VaR (%)**
Low VaR	0.1631	0.8969	0.1744	0.9986	0.2393	1.1624
2	-0.1306	2.2105	-0.1605	1.9005	0.0655	2.4639
3	-0.1795	2.7841	-0.0288	2.4328	0.0608	3.1304
4	-0.1988	3.2632	-0.0995	2.9027	-0.0059	3.7633
5	-0.0771	3.9065	-0.0139	3.4062	0.0317	4.4519
6	-0.0523	4.7013	-0.101	4.061	-0.0132	5.2798
7	-0.1633	5.6628	-0.0736	4.9806	-0.2118	6.5057
8	0.0787	6.9999	-0.2909	6.2858	0.0588	8.3797
9	0.1524	9.0306	0.0189	8.2627	0.1322	11.3203
High VaR	0.4812	15.3812	0.6486	13.5593	-0.2834	20.8619

Figure-5 Grouped VaR and Return Curve (November 2007 to April 2010)



The aforementioned group research show that the results based on the pre-crisis data are very similar with that presented in Bali, Gokcan and Liang (2006) - the hedge fund return is strongly positive-correlated with VaR. However, the correlation has become less significant since the Financial Crisis. An intuitive explanation of this phenomenon is that some funds in the high VaR portfolios may yield less than before or even negative, while the funds in low VaR are less affected by the deteriorated market. The numbers in Table-3 and Table-4 support this explanation: as to the parametric VaR, for example, the decile 10 (high VaR) portfolio return decreased by 1.2922% from 1.7734% in pre-Fiancial-Crisis period to 0.4812% in the Financial Crisis period, while the decrease for the decile 1 is just 0.612% (from 0.7751% to 0.1631%).

In light of the stronger correlation of return and VaR in the pre-Financial-Crisis period, we further compare the return-VaR relationships based on different types of VaRs (parametric, non-parametric and GARCH) in this period. We find that the differences between high-VaR and low-VaR portfolio returns for the three types of VaRs are 0.998%, 0.9538% and 1.3416% respectively. This means that high-return hedge funds concentrates more in the high-VaR portfolios based on GARCH VaRs than other types of VaRs, and on the other hand, the low VaR portfolio based on the GARCH VaR absorbs more low-return hedge funds.

3.2 Cross-sectional Regression

3.2.1 Regression by VaR, Size and Age

We perform above analyses based on the portfolio level, which could lead to significant statistics results. However, by averaging among groups, this approach ignores specific factors' potential influence to individual hedge fund. Therefore, we run cross-sectional regressions of the one-month-ahead returns on selected factors: parametric VaR, non-parametric VaR, GARCH VaR, asset size and hedge fund age[9]:

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} CFVaR_{i,t} + \varepsilon_{i,t+1} \tag{7}$$

9 The regression formulas refer to Fama MacBeth(1973)

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} VaR_{i,t} + \varepsilon_{i,t+1} \tag{8}$$

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} GARCHVaR_{i,t} + \varepsilon_{i,t+1} \tag{9}$$

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} \log\left(Asset_{i,t}\right) + \varepsilon_{i,t+1} \tag{10}$$

$$R_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} Age_{i,t} + \varepsilon_{i,t+1} \tag{11}$$

We first regress across 1050 hedge funds to obtain their statistic values, such as β, t-stat and R^2, and then repeat this regression on time series to get 60 groups of results. We average these results to find out which factor has more explanatory power to the hedge fund return.

Table-6 reports that there is a significant positive relation between the hedge fund return and all of the three types of VaRs. Nevertheless, the other two factors: the asset size and age are negatively correlated with return, and neither of the relations is statistically significant. Moreover, the average R^2 values for VaR regressions are much higher than that for size and age regressions. The above results indicate that VaR is more important than other factor to forecast the hedge fund return.

Table-6 Regression of Five Factors (May 2005 to April 2010)

	Parameter VaR	Non-P VaR	GARCH VaR	Size	Age
Beta	0.0544	0.0570	0.0502	-0.0415	0.0003
Tstat	3.4810	3.0792	3.0815	-0.8830	-0.0190
R square	0.0945	0.0910	0.1056	0.0040	0.0037

3.2.2 Regression by Three Types of VaRs in Three Periods

In 3.2.1, we have already found out that VaR is significantly related to the hedge funds return. In this section, we are going to test whether the correlation varies in different periods with changed market situations.

We sub-divide the overall period into pre-Financial-Crisis (May 2005 to October 2007) and Financial Crisis (November 2007 to April 2010) periods. As shown in Table-7, the correlation holds in each of the three periods, while under the extreme volatile market situation, such as the Financial Crisis, the correlation observably weakened.

Table-7 Regression of Return on Three Types of VaRs

	Beta			t-stat			R^2		
	P	NP	GARCH	P	NP	GARCH	P	NP	GARCH
Overall period	0.0544	0.057	0.0502	3.481	3.0792	3.0815	0.0945	0.091	0.1056
Financial Crisis	0.029	0.0322	0.0051	3.2616	2.695	1.6503	0.1036	0.0956	0.1211
Pre-Financial-Crisis	0.0798	0.0817	0.0953	3.7004	3.4634	4.5126	0.0854	0.0865	0.0902

3.3 Return and Changes of VaR

Bali, Gokcan and Liang (2006) discuss the relationship between hedge fund return and changes of VaR at the portfolio level. They divide all the sample hedge funds, including live and defunct, into 10 portfolios by the above-mentioned measure, and they find that the expected to defunct funds often possess the largest increase in VaR. Meanwhile, those funds with almost no changes of VaR produce the highest return. In this paper, we try to adopt a similar method to find out whether there is a significant connection between the dynamic VaR process and the return of the live funds.

3.3.1 Delta VaR Portfolio Formation and Analysis

We first calculate the monthly change of VaR (ΔVaR)[10], rank them from low to high, and then group them into 10 portfolios with their related one-month-ahead returns. Next, we compute the average ΔVaRs and returns of the 10 portfolios respectively. Moving the time windows to the next month and repeat the above procedure until we exhaust our available data from May 2005 to April 2010, we obtain 60 pairs of average ΔVaR and returns. Averaging these results on time series, we obtain returns for each of the 10 portfolios ranked according to ΔVaRs.

Table-8 shows that over the past five years, the highest average return always occurs in the portfolios with the largest or second largest decline of VaR, while the lowest return

10 To calculate ΔVaR, we use the formula :($VaR_{i,t+1}$- $VaR_{i,t}$)/ $VaR_{i,t}$

comes with the greatest increase of VaR. Figure-6 also demonstrates this negative correlation between ∆VaRs and returns. We believe this does not conflict with our aforementioned conclusion that high VaR brings high return. We conjecture that the VaR is a relatively static parameter, which might be influenced by the hedge fund's intrinsic characteristics, such as strategy, size and age. In other words, the hedge funds that take high risk strategically would usually produce high earnings[11]. The ∆VaR, however, is affected more by the market fluctuation and fund management skills. Therefore, the increase of VaR usually reflects the risk taken passively rather than proactively.

Table-8 Average Portfolio Return Based on the Change of CF Parametric VaR

2005.5-2010.4			2005.5-2007.10			2007.11-2010.4		
Deciles	ΔVaR (%)	Return (%)	Deciles	ΔVaR (%)	Return (%)	Deciles	ΔVaR (%)	Return (%)
Low ΔVaR	-34.25	0.94	Low ΔVaR	-49.03	1.27	Low ΔVaR	-22.74	0.69
2	-7.18	1.00	2	-11.42	1.30	2	-3.71	0.78
3	-2.84	0.83	3	-5.02	1.19	3	-0.99	0.54
4	-0.54	0.64	4	-2.31	1.11	4	1.07	0.24
5	1.30	0.47	5	-0.76	0.97	5	3.31	0.04
6	3.09	0.40	6	0.37	0.96	6	5.84	-0.09
7	5.08	0.36	7	1.33	0.99	7	8.93	-0.21
8	8.22	0.36	8	2.57	1.06	8	14.03	-0.26
9	14.31	0.42	9	4.91	1.15	9	24.04	-0.24
High ΔVaR	45.44	-0.19	High ΔVaR	22.53	1.12	High ΔVaR	69.85	-1.43

The table presents the average monthly percentage changes in VaR and the one-month-ahead returns for the Parametric VaR (CF VaR) portfolios for Deciles 1-10 for live hedge funds. We find there is a significant negative correlation between the return and VaR change. The VaRs are estimated based on the past 60-month's returns from May 2000 to April 2010. The test period is from May 2005 to April 2010, which shows in the first part of the table. The other two parts exhibit the empirical results by analysis on the sub-periods.

11 This argument is based on the sample limited to live hedge funds.

Figure-6 Parametric Delta VaR & Return (2005.05 - 2010.04)

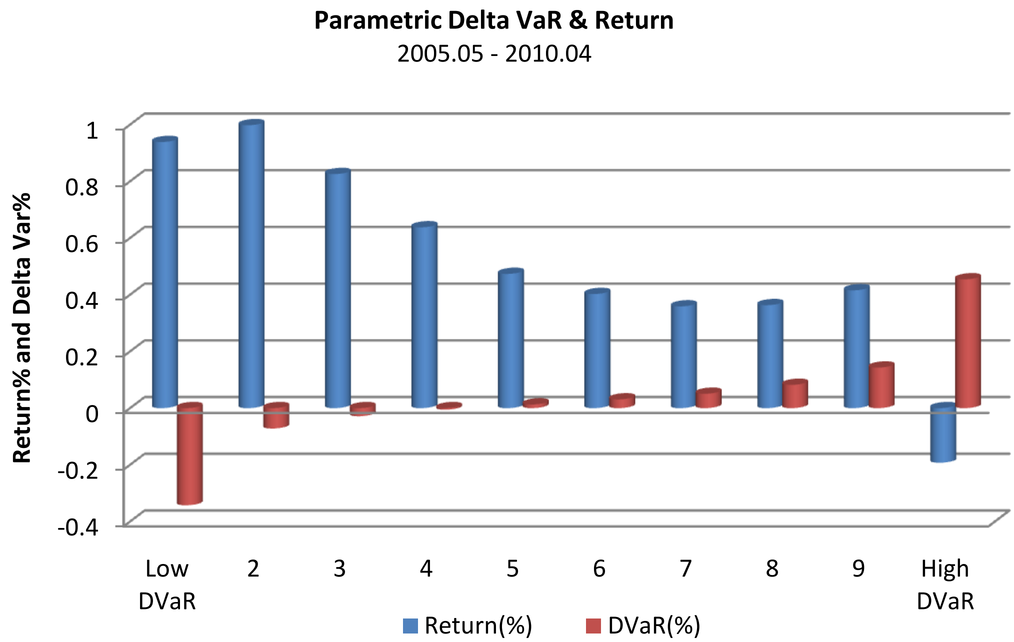


Figure-7 Parametric Delta VaR & Return (2005.05 - 2007.10)

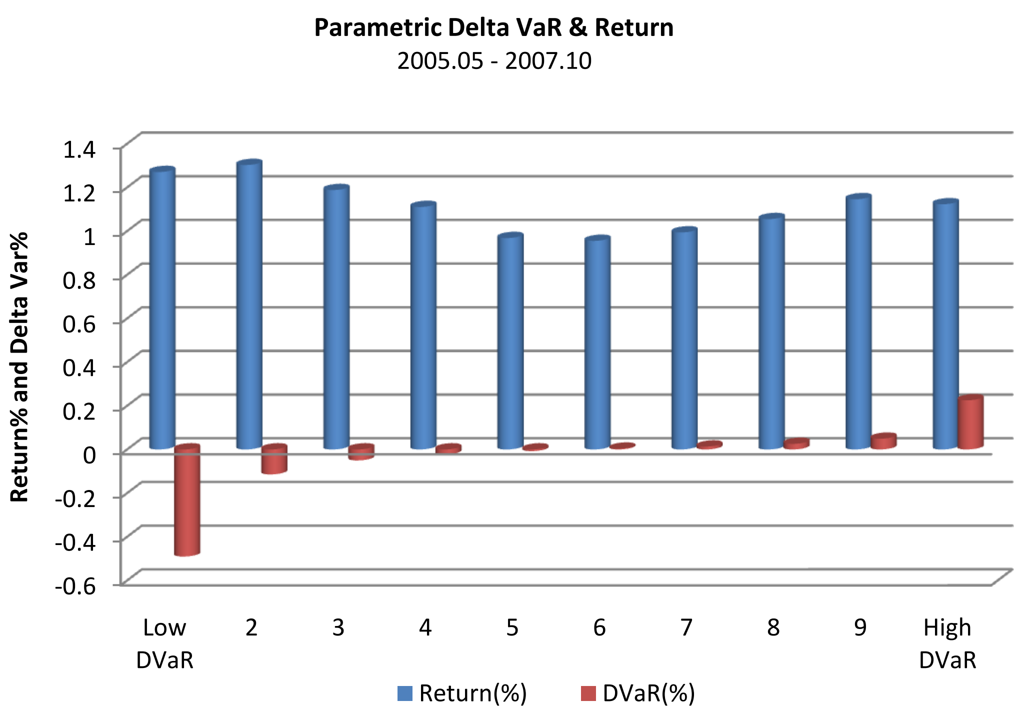
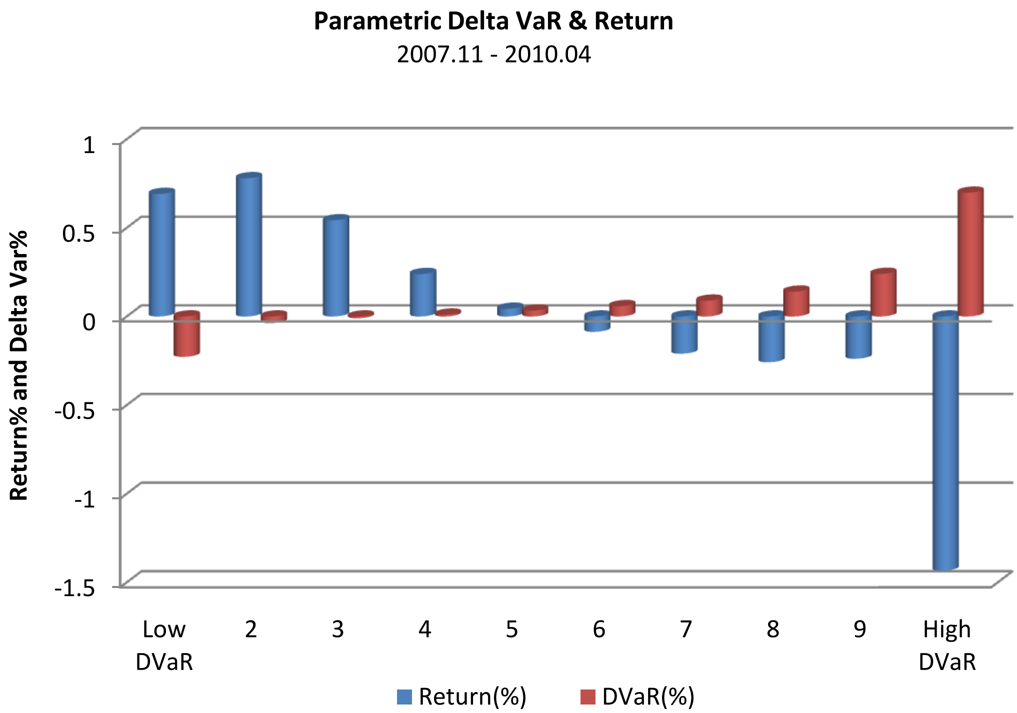


Figure-8 Parametric Delta VaR & Return (2007.11 - 2010.04)



3.3.2 Sub-period Analysis

Our conjecture mentioned in 3.3.1 is supported by the sub-period analysis. We roughly split the overall period into two sub-periods: pre-Financial-Crisis and Financial Crisis. The second part of table-8 indicates that although the highest return still occurs in the lowest ΔVaR portfolios, the portfolios with high ΔVaRs also bear relatively high return. Figure-7 shows that the average portfolio returns present an approximately "U" shape along with the increasing ΔVaRs. Nevertheless, the Financial Crisis period data shows that the negative correlation between ΔVaR and return become stronger than before. Figure-8 clearly shows the monotonic decreasing trend of the return along with the ΔVaR. This is because that when the market is prosperous, undertaking more risk would probably bring more profit; while when the market falls, the increase of VaR often means huge loss.

3.3.3 Test on Different Delta VaRs

To ensure our results are not affected by the method that we estimate VaRs, we use both non-parametric and GARCH CF VaRs to repeat the above procedure and get very similar result. (See Appendix 1 Table-9 and Table-10, Appendix 2 Figure-9 to 14)

4: Conclusion

In this paper, based on the data obtained from HFN, we discuss the relationship between live hedge fund return and its VaR, and examine the change of this relationship under different market situations, that is, pre-Financial-Crisis and Financial Crisis. We summarize the empirical results as follows:

First, we rank individual hedge funds by their parametric, non-parametric and GARCH VaR respectively, construct 10 portfolios, and find that there is a positive correlation between VaR and return, i.e., high VaR portfolio out-performs low VaR portfolio. Furthermore, breaking down the overall period into pre-Financial-Crisis and Financial Crisis periods, we observe that a deteriorated market weakens this correlation.

Second, we perform cross-sectional regression of hedge funds return on parametric VaR, non-parametric VaR, GARCH VaR, asset size and hedge fund age at individual funds level, and the results demonstrate that the VaRs are more correlated than other factors to the hedge fund return. Comparative research on the same sub-periods comes up with similar conclusion that the correlation becomes weaker in the Financial Crisis.

Above research on VaR and return shows that they are positively correlated, which basically consists with traditional risk-return theory. Although in the period of Financial Crisis, higher VaR does not always bring higher return, this is not necessarily a conflict with traditional theory, because we need to consider the risk-return relationship in a long rather than a short period.

Finally, we also analyze the relationship between the changes of VaR and the live hedge fund returns using the same grouping method as in section 3.1. The result shows that the portfolio with the greatest decrease in VaR always brings highest return, while situation of the portfolio with the greatest increase in VaR is much more complicated. Under the relative stable market situation, increasing VaR could result in higher return; in the deteriorated market, however, the rise in VaR often means greater loss.

Besides, this paper introduces GARCH model to estimate volatility and used VaRs based on it in above-mentioned procedures. Comparing with other two types of VaRs, GARCH VaRs have much different power of forecasting return in different market situations.

In the sorted VaR analysis, the correlation of portfolio return to grouped GARCH VaR is the most significant in the pre-Financial-Crisis period, while it became the least significant in the Financial Crisis period. Similar results come out from the cross-sectional regression. In the pre-Financial-Crisis period, the regression of returns on the GARCH VaRs gives highest β and t-stats values relative to other VaR regressions, which means the correlations of return to the GARCH VaR is the most sensitive and significant. In contrast, this correlation became the least sensitive and significant in the Financial Crisis period.

Appendices

Appendix 1

Table-9 Average Portfolio Return Based on the Change of Non-Parametric VaR

2005.5-2010.4			2005.5-2007.10			2007.11-2010.4		
Deciles	ΔVaR (%)	Return (%)	Deciles	ΔVaR (%)	Return (%)	Deciles	ΔVaR (%)	Return (%)
Low ΔVaR	-32.83	0.72	Low ΔVaR	-49.90	1.10	Low ΔVaR	-19.08	0.40
2	-2.74	0.74	2	-5.61	1.09	2	-0.25	0.46
3	-0.71	0.83	3	-1.48	1.26	3	-0.05	0.49
4	-0.01	0.67	4	-0.25	1.16	4	0.22	0.27
5	0.43	0.62	5	0.01	1.22	5	0.85	0.11
6	0.88	0.53	6	0.03	1.06	6	1.73	0.07
7	1.96	0.45	7	0.29	1.10	7	3.65	-0.12
8	4.41	0.31	8	1.16	1.07	8	7.74	-0.38
9	8.99	0.45	9	3.01	1.10	9	15.17	-0.12
High ΔVaR	41.25	-0.11	High ΔVaR	17.97	0.97	High ΔVaR	65.73	-1.12

Table-10 Average Portfolio Return Based on the Change of CF Parametric GARCH VaR

2005.5-2010.4			2005.5-2007.10			2007.11-2010.4		
Deciles	ΔVaR (%)	Return (%)	Deciles	ΔVaR (%)	Return (%)	Deciles	ΔVaR (%)	Return (%)
Low ΔVaR	-435.58	0.97	Low ΔVaR	-303.65	1.51	Low ΔVaR	-587.75	0.52
2	-114.71	0.72	2	-83.48	1.07	2	-151.50	0.44
3	-54.81	0.51	3	-41.02	1.02	3	-71.34	0.07
4	-26.06	0.41	4	-21.40	0.99	4	-32.14	-0.10
5	-9.43	0.38	5	-10.14	0.99	5	-9.40	-0.17
6	5.09	0.43	6	-1.62	0.92	6	11.68	-0.01
7	21.39	0.48	7	8.38	1.04	7	34.96	-0.01
8	47.78	0.40	8	23.79	0.98	8	73.35	-0.12
9	105.57	0.49	9	55.42	1.08	9	159.42	-0.02
High ΔVaR	406.15	0.43	High ΔVaR	226.23	1.51	High ΔVaR	601.15	-0.54

Appendix 2

Figure-9 Non-Parametric Delta VaR & Return (2005.05 - 2010.04)

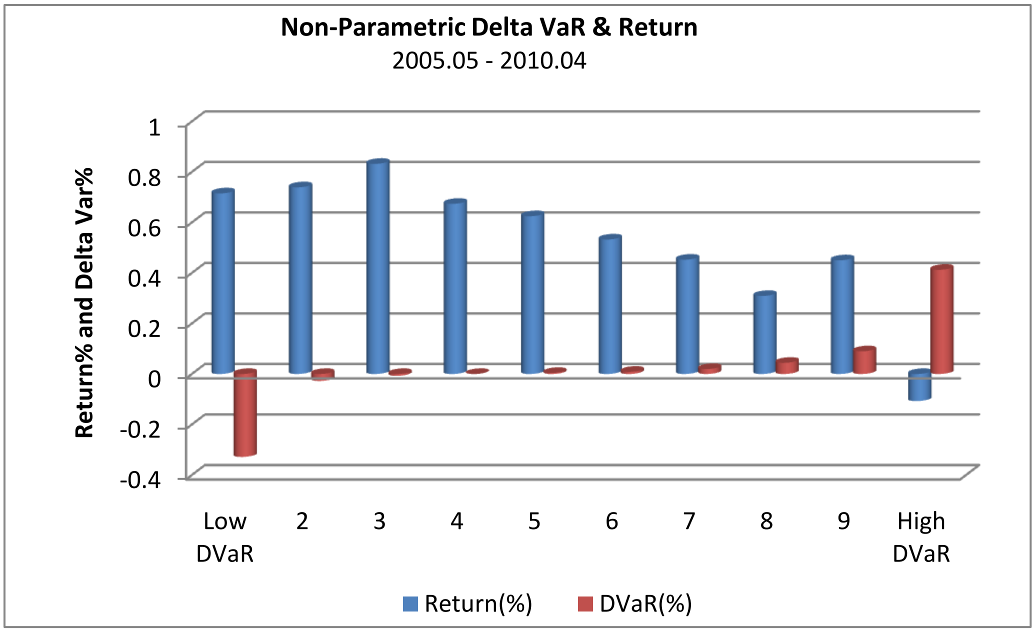


Figure-10 Non-Parametric Delta VaR & Return (2005.05 - 2007.10)

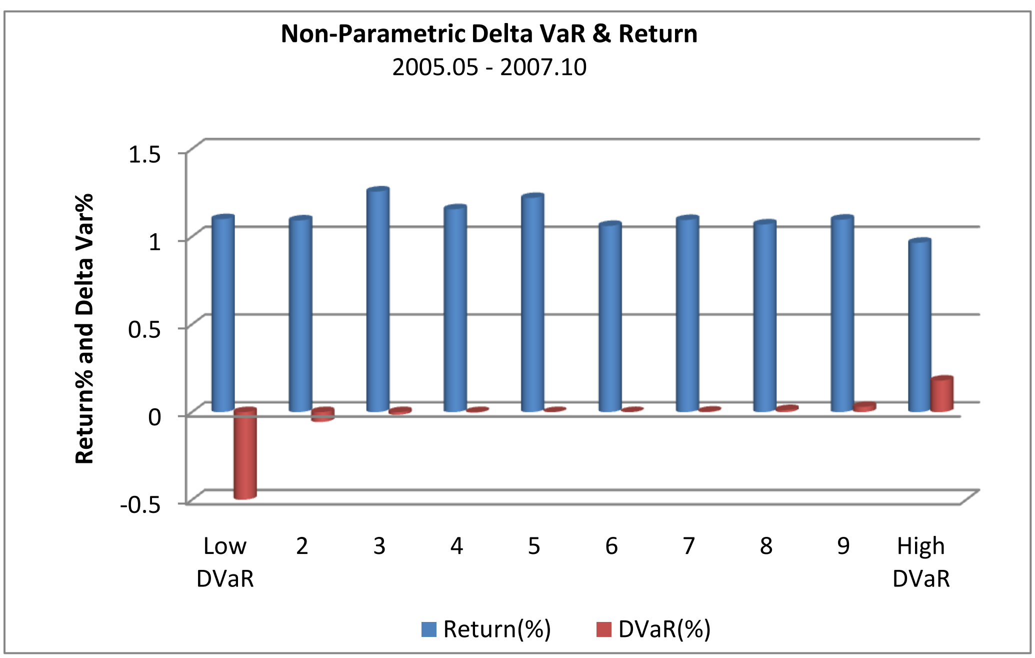


Figure-11 Non-Parametric Delta VaR & Return (2007.11 - 2010.04)

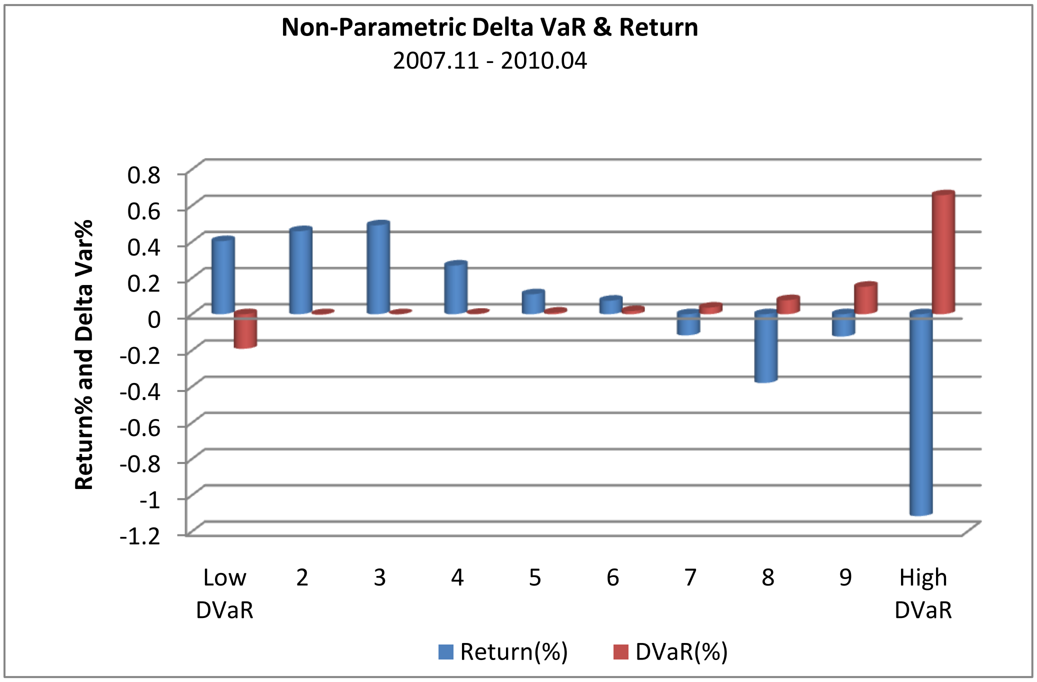


Figure-12 GARCH Delta VaR & Return (2005.05 - 2010.04)

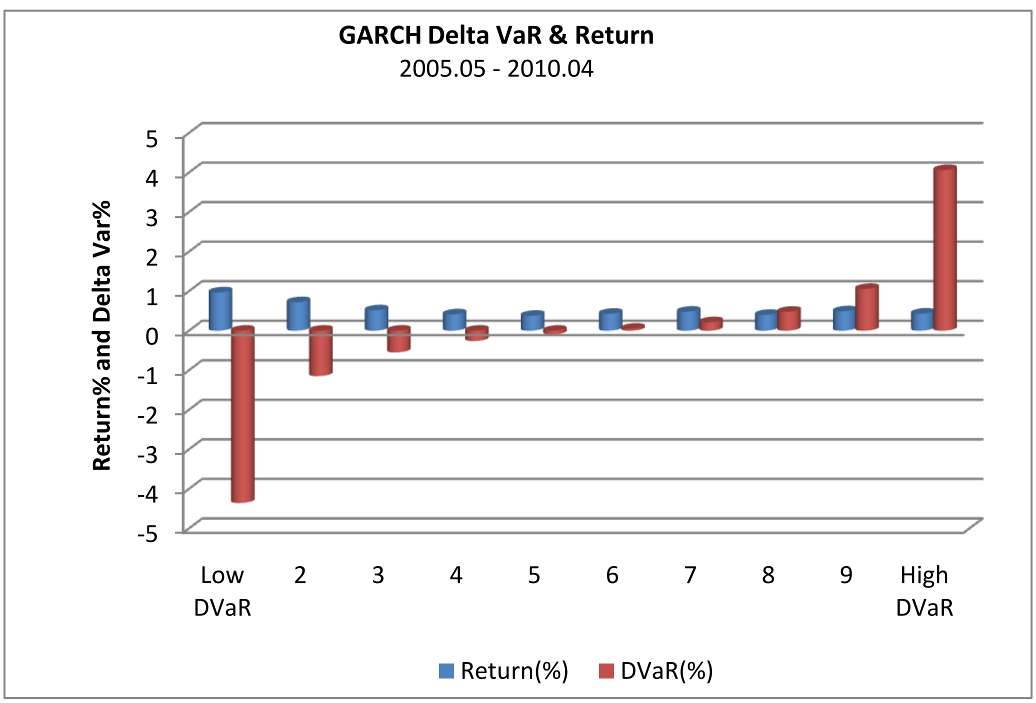


Figure-13 GARCH Delta VaR & Return (2005.05 - 2007.10)

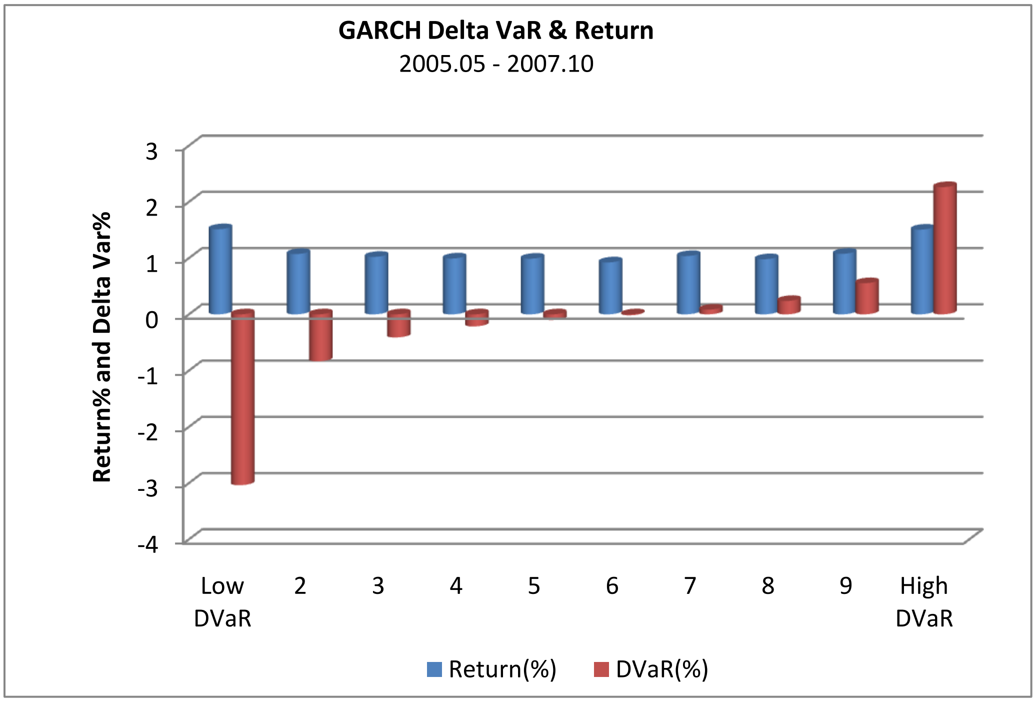
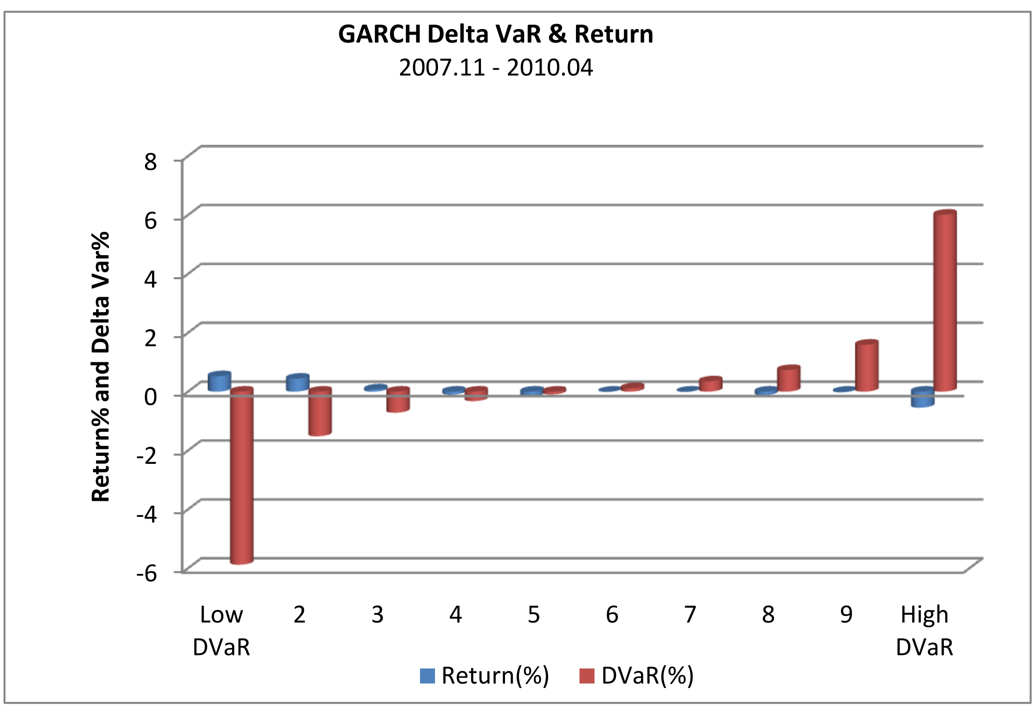


Figure-14 GARCH Delta VaR & Return (2007.11 - 2010.04)



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