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Original Article

Value-at-Risk and Extreme Returns Stock Market of Iran

Ayrin Parvin[1]*, Gholamreza KeshavarzHaddad[2], Tayebeh Abbasnejad[3]

[1] *Department of Executive Management, Science and Research Branch, Islamic Azad University, Hormozgan, Iran*
[2] *Sharif University of Technology, Tehran, Iran*
[3] *Hormozgan University, Bandar Abbas, Iran*

*Corresponding author's e-mail: agrin.parvin@gmail.com

ABSTRACT

Risk measurement is a problem occupies the mind of researchers for many years. Various approaches have been developed in this area. These approaches can be divided in three categories, parametric, semi parametric and nonparametric based on statistical techniques used in. Risk measures quantify risk in the frame of these approaches. Among the risk measures, value-at-risk is a new one. In this study, we examine the performance of parametric value-at-risk in forecasting Tehran price and dividend index risk. The result of value at-risk models back testing indicated that the models in which the return and volatility dynamics are considered, have better performance than others. In this study these models respectively include arma and garch. The other result shows that the models which are flexible in attribution of distribution to data such pot have much better performance in forecasting index risk. On the other hand, the average waiting time for an index to present a daily return below the 0.01 threshold is 3 days and also, in a fixed period of time, the probability of observing during a minimum daily return above the 0.01 threshold, during the next day, is 27 present.
Keywords: Value-at-Risk, Extreme Returns, Stock Market

INTRODUCTION

When making investment decisions, investors simultaneously consider the risk and return of investment choices. These two investment dimensions (i.e. risk and return) are undoubtedly the most important dimensions on investment decisions, if not the only influencing factors. Following the studies, various tools have been introduced for measuring risk. Each of these tools often has been developed to measure a certain type of risk. In recent years, a general measure for measuring risk has entered into the finance literature. It has become the standard measure to measure different types of risk due to its features. A case in point is the Convention Committee on Banking Supervision, i.e. Basel for quantifying the risk of financial institutions, especially banks. This convention recommends banks to use the models of this measure to measure the market, credit, and operational risk.

The extreme value theory (EVT) has attracted special attention of researchers in recent years [1, 2] and has had many applications in the field of finance [3, 4, 5]. The unconditional extreme value theory is applicable for forecasting value-at-risk or expected loss over a long period. But sometimes we want to apply conditional EVT on some dynamic structures. This requires distinguishing between and random factors stimulating it. The use of conditional or dynamic EVT is useful when we are dealing with short periods and when a dynamic structure that can be modeled has. For example, if one can model the random variable by the GARCH process, a good opportunity will be provided to use the conditional EVT. In this case, we seek to use the GARCH process to explain the random variable variations and then to use the extreme value theory to model the errors caused by the GARCH process. McNeil and Frey [6] proposed the following two-step process for this:

We use a GARCH model for forecasting return volatility, and after estimating the model parameters, we extract errors. Obviously, such errors are derived from subtracting the expected return from the actual return, and the expected return is obtained through the formation of price return. It is expected that these errors have independent and identical distributions. At the end of this stage, the expected volatility and future return are estimated. We used the extreme value theory for standardized errors. Thus, we gain estimates of VAR, taking into account a dynamic structure (i.e. GARCH) and using the EVT for residuals.

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One of the most referred articles on this subject is the paper by Fama et al. [7]. The article claims that the beta index (systematic risk) cannot explain the return differences in growth and value stocks. In this study, the B/M and E/P ratios were the basis for determining growth and value stocks. The used data included stocks in the New York, NASDAQ and OMX stock exchanges from 1963 to 1990. They classified companies into ten groups: the first group included growth stocks and the tenth group included value stocks. The results showed that the return of value stocks is higher than growth stocks, while beta is not statistically significant in different groups.

In another article, Fama et al. [7] claimed that on most of the world markets, value stocks have a greater return than growth stocks. The used ratio to determine growth and value stocks in that study was P/B and the used data were for the period 1975-1995. Groot and Gasper [8] examined the relationship between the expected return, firm size and the M/B ratio. For that research, they used data from India, South Korea, Malaysia, Taiwan and Thailand. They showed that in small firms, average stock return is higher than large ones, but value stocks have higher average return than growth stocks. Fama et al. [7] conducted another research in relation to growth and value stocks. In this paper, they examined the constituent elements of stock return in both portfolios of growth and value stocks. Using data from 1926 to 2006, they concluded that value stocks are better able to explain the market risk compared to growth stocks.

Using the extreme value theory to analyze the Iranian stock market and estimate value-at-risk using the extreme value theory and comparing the results with estimation of normal and experimental value-at-risk. And the results show that extreme value method in estimating the variance has a very cautious approach than traditional methods for determining investment requirements/needs. We calculate the using segment lengths from each month both for minimum return (long positions) and maximum return (short positions) and then estimate the extreme value theory VAR according to the extreme index. Therefore, we aim to use the extreme value hypothesis to analyze the Iranian stock market and recognize what type of asymptotic distribution of extreme value has the greatest suitability with extreme historical events.

MATERIALS AND METHODS

Analyses are in the form of parametric value-at-risk, that finally reported the performance of this measure in predicting the volatility of the Tehran Stock Exchange index and if possible, generalize this performance to all stocks traded on this exchange. Next, the methods of calculating value-at-risk for the logarithmic return of the Tehran Stock Exchange price index are presented and compared. Moreover, for a fixed period of time, the probability of observing the minimum daily return above the threshold -0.01 is about 10% for the next day. This study was carried out in four parts including:

- Selecting models
- Estimating parameters and calculating value-at-risk
- Post-trial of value-at-risk models
- How to calculate the average waiting time and the minimum return below a certain threshold
- Other characteristics of the study

Selecting models

This study includes selecting two model classes. These selections are:

- Selecting value-at-risk methods
- Selecting post-trial methods

In this study, two applications were used. Excel was used for data classification and MATLAB was used for quantifying things and drawing diagrams. MATLAB was selected because it contains the econometric models and statistical distributions used in the study. Models we wanted to discuss in this article are presented in the following table.

Table 1. Models used in this study

Model Name	Return Model	Fluctuation Model	Distribution
Normal SMA	Random Walk	SMA	N
Normal EWMA	Random Walk	EWMA	N
Normal GARCH	Random Walk	GARCH (1,1)	N
t-student SMA	Random Walk	SMA	t
t-student EWMA	Random Walk	EWMA	t
t-student GARCH	Random Walk	GARCH (1,1)	t
Normal ARMA (p,q) ARCH (q)	ARMA (p,q)	ARCH (q)	N
Normal ARMA (p,q) GARCH (p,q)	ARMA (p,q)	GARCH (p,q)	N
Normal ARMA (p,q) TGARCH (p,q)	ARMA (p,q)	TGARCH (p,q)	N
Normal ARMA (p,q) EGARCH (p,q)	ARMA (p,q)	EGARCH (p,q)	N
t-student ARMA (p,q) ARCH (q)	ARMA (q)	ARCH (q)	t
t-student ARMA (p,q) GARCH (p,q)	ARMA (p,q)	GARCH (p,q)	t
CPOT Normal AR (p,q) GARCH (p,q)	AR (p,q)	GARCH (p,q)	GP
CPOT Normal AR (p) GARCH (p,q)	AR (p)	GARCH (p,q)	GP

Of course, with any combination of the return prediction models and fluctuation prediction and also by taking into account the distributional assumptions, many models can be achieved. Permutations of these models reach to (4 × 4 × 2 =) 32 models. However, this permutation does not consider the rank of the ARMA and GARCH models. The models in the above table were selected in this study because of the frequency of their use in previous research. However, there are logical reasons for these choices. For example, when using simple volatility models such as SMA and EWMA, we noticeably ignore volatility dynamics, it does not seem logical to use the ARMA model to forecast the return because based on the evidence, time volatility autocorrelations have been proven while such correlations are less observed in financial series. This is why in the above models, the ARMA models are not side by side the SMA and EWMA models. Finally, to avoid increasing the number of models and thus increasing the research size, we avoided studying all the models and we sufficed to the models in the above table.

RESULTS

To understand the correlation in the index return series more clearly, we examine the autocorrelation and partial autocorrelation graphs. Figures 1 and 2 show autocorrelation values for different lags up to the 20-period lag. The upper and lower straight lines show 2 SD for the standard estimation error which represent roughly 95% of the confidence level. Both graphs indicate the existence of autocorrelation in the return raw series. We plotted autocorrelation and partial autocorrelation charts for squared returns to visually examine the structure of their correlations. As shown in Figures 3 and 4, there is temporal autocorrelations in the squared returns of the index. This confirms empirical studies that there is temporal volatility autocorrelations in financial return series.

Table 2 shows the number of expected violations and the number of violations resulted from the SMA and EWMA models. In Table 2, k is sample size, CR is coverage rate, T is the number of observations, EV is the number of expected violations and OV is the number of observed violations. Table 3 shows the results of the number of violations for the VaR models containing GARCH.

After comparing the value-at-risk with associated actual returns and extracting the sequence of violations, we attempt to test the hypotheses. Table 5 shows the results of testing the post-trial hypotheses for the SMA and EWMA.

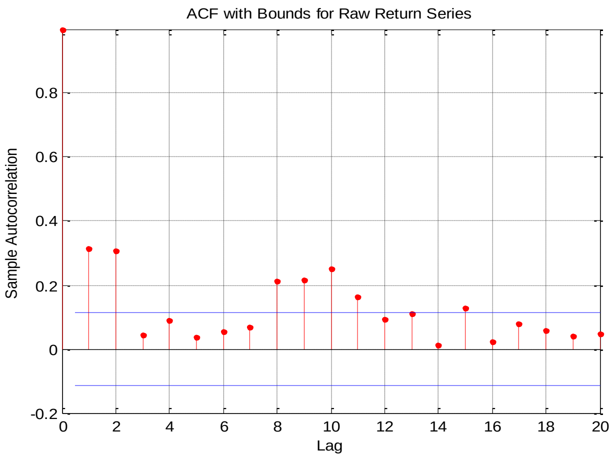

Figure 1. Autocorrelation of dividend and price index return

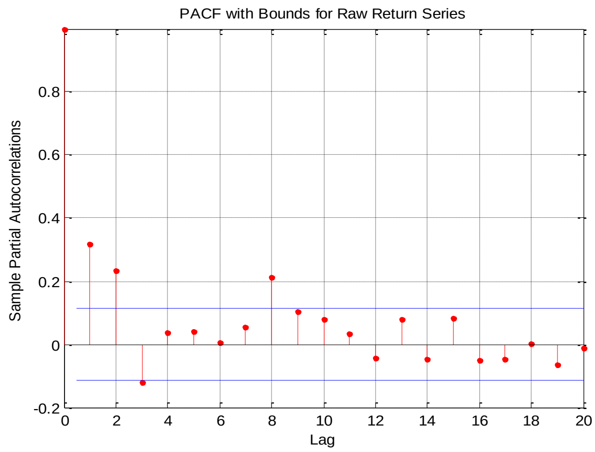

Figure 2. Partial autocorrelation of dividend and price index return

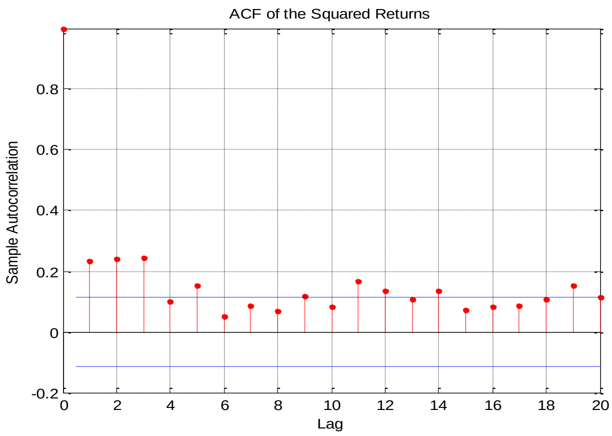

Figure 3. Autocorrelation of the squared returns of the dividend and price index

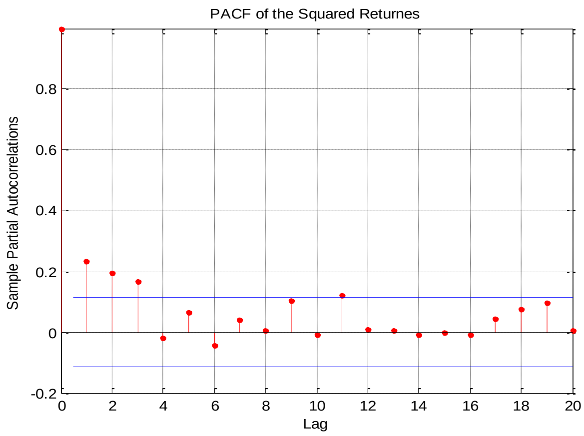

Figure 4. Partial autocorrelation of the squared return of the dividend and price index

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Table 2. Number of expected and observed violations for the SMA and EWMA models

Model	k	CR	T	EV	OV
Normal SMA	300	5%	360	18	11
		1%	360	4	5
t-student SMA	300	5%	360	18	8
		1%	360	4	2
Normal EWMA	50	5%	610	31	50
		1%	610	6	34
t-student EWMA	50	5%	610	31	43
		1%	610	6	17

Table 3. Number of expected and observed violations for models containing GARCH

Model	k	CR	T	EV	OV
Normal GARCH	300	5%	360	18	4
		1%	360	4	3
Normal ARMA (1,1) ARCH (1)	300	5%	360	18	6
		1%	360	4	2
t-student GARCH	300	5%	360	18	4
		1%	360	4	2
t-student ARMA (1,1) GARCH (1,1)	300	5%	360	18	7
		1%	360	4	4
Normal ARMA (1,1) TGARCH (1,1)	300	5%	360	18	7
		1%	360	4	4
Normal ARMA (1,1) EGARCH (1,1)	300	5%	360	18	10
		1%	360	4	5

Table 4. Number of expected and observed violations for models containing CPOT

Model	k	CR	T	EV	OV
CPOT Normal GARCH (1,1)	300	5%	360	18	8
		1%	360	4	4
Conditional POT GARCH (1,1) ARMA (1,1)	300	5%	360	18	13
		1%	360	4	5
CPOT Normal GARCH (1,1) AR (1)	300	5%	360	18	13
		1%	360	4	5

Table 5. Post-trial results for the SMA and EWMA models

Model	k	CR	UC	Ind	CC	MD	DQ	BT	L
Normal SMA	300	5%	A	R	R	...	...	...	...
		1%	A	R	A	R	R		...
t-student SMA	300	5%	R	A	R			...	...
		1%	A	A	A	R	R		0.0109
Normal EWMA	50	5%	R	R	R	...	...	...	...
		1%	R	R	R	...	...		...
t-student EWMA	50	5%	R	R	R	...	...	...	...
		1%	R	R	R	...	...		...

Table 6. Post-trial results for the GARCH and CPOT models

Model	CR	UC	Ind	CC	MD	DQ	BT	L
Normal GARCH (1,1)	5%	R	A	R	...	...	...	...
	1%	A	A	A	A	A		0.0054
Normal ARMA (1,1) ARCH (1)	5%	R	A	R	...	...	...	...
	1%	A	A	A	A	A		0.0109
t-student GARCH (1,1)	5%	R	A	R	...	...	...	...
	1%	A	A	A	A	A		0
Normal TGARCH (1,1)	5%	R	A	R	...	...	...	...
	1%	A	A	A	A	A		0
Normal EGARCH (1,1)	5%	R	A	R	...	...	...	...
	1%	A	A	A	A	A		0.0054
CPOT Normal GARCH (1,1)	5%	R	A	R	...	...	...	...
	1%	A	A	A	A	A		0
CPOT NormalGARCH (1,1) ARMA (1,1)	5%	A	A	A	A	A	A	0.025
	1%	A	A	A	A	A		0.0054
CPOT Normal GARCH (1,1) AR (1)	5%	A	A	A	A	A	A	0.025
	1%	A	A	A	A	A		0.0054

In Table 6, UC is unconditional coverage test, Ind is independence test, CC is conditional coverage test, MD is bet difference test, DQ is dynamic percentile test, BT is a Berkowitz Transformation-based test and L is the Lopez's first post-trial. The value of the Lopez's first post-trial is equal to the absolute value of the subtraction of the expected model of the Lopez's first post-trial from the desired model of this post-trial. The lower the value, the higher the model rank will be.

Note that the first three post-trials (UU, Ind, and CC) were calculated in any conditions for the model. The fourth and fifth tests are performed if the null hypothesis (A) of the third post-trial (CC) is accepted (failed to reject). The reason is that the fourth and fifth tests are the generalized state of the third test. If the null hypothesis is rejected with a simple test like CC, there is no need to use complicated tests. We perform the sixth post-trial (BT) when the third post-trial is accepted for both coverage rates of 5% and 1%. This is because the BT post-trial examines the model's conditional efficiency for all coverage rates. When the model's conditional efficiency is rejected based on the CC post-trial either one or both coverage levels, then we do not need a complex post-trial such as BT. Finally, we must say that we do Lopez's first post-trial when the null hypotheses of the first three post-trials are accepted because we consider the acceptance of the first three post-trials as the minimum requirements for an efficient model and only in this way the model can be ranked.

DISCUSSION

This study aimed to assess the value-at-risk and extreme returns in the stock market and the Bahar-Azadi coin market in Iran using the extreme value theory. The results indicate that generally in the Normal SMA model, the number of observed violations for both coverage rates of 5% and 1% does not differ statistically from the number of expected violations. That is, this model passed the unconditional coverage test. But these violations are not independent and did not pass the independence test. This model also did not pass the conditional coverage test. Note that in the 1% coverage rate, the number of violation (numerically, not statistically) is more than the expected number. This refers to denser tails of index return distribution than the normal distribution. This result is consistent with the results of Shahbndy [9], Ghalibafasl [10], Raee and Shavkhizavareh [11] and Kazemi [12].

The t-student SMA model in the 5% coverage rate has violations less than the expected number. This means that, the model overestimated risk in this coverage rate. At the 5% coverage rate, this model did not pass the independence and conditional coverage tests. It can be said that it presented very little estimates of the value-at-risk .

The Normal EWMA and t-student EWMA models presented very low estimates of the value-at-risk in both coverage rates. Comparison of observed and expected violations indicates that these two models underestimated the risk. The models containing GARCH, including ARCH, TGARCH and EGARCH submitted acceptable forecasts of the value-at-risk at the 1% coverage rate. At this coverage rate, they passed all the tests except Berkowitz Transformation. However, at the 5% coverage rate, the number of their violation was less than the number of expected violations. Moreover, the sequences of violations caused by all these models are independent of each other .

All the CPOT models provided reasonable predictions of the value-at-risk at both coverage rates. These models all passed the post-trials. In this study, they are the only models that passed the Berkowitz Transformation test. This is due to the flexibility of the generalized distribution of radiation in the fit with the data related to the index return. The average waiting time for an index - indicating the daily return below the threshold of 0.01 - is 3 days. In other words, during 3 days, the probability that our loss exceeds 0.01 will occur at least once. For a fixed period, the probability of observing at least one daily return over the 1% threshold for the next day is 27%. In other words, for a fixed period (one day later), the probability that a loss over 1 percent will occur is 0.27. Moreover, the probability of observing the maximum return below the -0.01 threshold for the next day is 72%. In other words, for a fixed period (one day later), the probability that a loss below 1% will occur is 0.72.

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