Comparison of Performance of Traditional Value at Risk Models with Switching Model in Tehran Stock Exchange

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ABSTRACT

The problem of portfolio optimization has made many advances since Markowitz proposed an average-variance-based optimization. It can be said that the most important achievement of the Markowitz model was the introduction of variance as a risk indicator and indeed, the introduction of a quantitative benchmark into it. This research is a model for predicting value at risk. This model extends the previous methods to provide a prediction model for switching to increase the effectiveness of predictions. The switching model is explicitly designed to solve the problem with risk managers who do not trust a particular Value-At-Risk model and allows the model to calculate the value at risk in different times and conditions. In this study, predictive methods such as EWMA, historical simulation, Monte Carlo and constant variance model will be discussed. This approach is explicitly designed to predict the predictive problems of managers who do not estimate their estimates for a specific VaR model, and allows the estimated model to change over time. This approach assumes that investors at any point of time use only the historical information available to select a model, and that the choice of model is based on a pre-determined selection criterion, and then the choice of model used to predict value at a later date. The results of the research indicate that the switching model is highly desirable compared to other models over time.

Keywords:

Value at Risk, Switching Model, Historical Simulation, Monte Carlo, Fixed Variance.

1. Introduction

Modeling of variance as one of the methods for calculating and predicting risk is applied in various financial areas and the incremental use of these models in the research indicates their positive results. On the other hand, studies on financial markets have introduced more precise concepts of risk, one of the most important concepts of value at risk and conditional risk value. Bamwell (1963) first presented the concept of value at risk, which represents the maximum loss at a specified level of certainty at a given time.

The most striking feature of value at risk is that it provides an intuitive measure of the potential risks of financial assets, and several methodologies and processes have been proposed and evaluated to estimate the value at stake. (Jorion, 2006; Kuester et al., 2006; Lee and Su, 2011). The choice of the value criterion at the appropriate risk, which in practice is also a good answer, is an important but difficult task. Hendrix (1996) employed risk-sharing methods in exchange rate portfolios, and found that none of them was better than all. Quest et al. (2006) found that most approaches are not appropriate, although some models are accepted under the existing rules regarding the adequacy of the model. Hendricks (1996) also suggested that more research into combining the good features of the tested approaches could be valuable.

However, there are many approaches to the value at stake in financial literature (Kuester et al., 2006; Drakos et al., 2010; Fuertes and Olmo, 2013), where the estimation of the asset distribution function is the common goal of all of them. The most commonly used approach is a fully parametric state of an econometric model for oscillatory dynamics with the assumption of conditional normality. For example, the GIS RiskMetrics model Morgan (1996) is a particular type of parameterization of the volatility of returns using the EWMA, which assumes that the conditional variance of the totalized yield of the previous error squared error with exponential decreasing weights. Another line of research is the parametric models that characterize the distribution of returns. Khinardova et al. (2011), for example, support a stable density that makes it possible to work on obesity sequences, and may be less impartial, with better empirical results.

The main issue in this study is the more accurate calculation of the value at risk. When value-at-risk values are always updated with different models, we can improve the predictive value of the risk based on the "predictive switching strategy". This approach is explicitly designed to predict the predictive problems of managers who do not estimate their estimates for a specific VaR model, and allows the estimated model to change over time. This approach assumes that investors at any point of time use only the historical information available to select a model, and the choice of model is based on a pre-determined selection criterion, and then the selection model used to predict value at a later date. For example, the loss function can be the criterion for choosing a particular model in the prediction strategy of switching, this criterion reflects the potential risk problem. That is, the value-at-risk model has the lowest loss at any given time.

2. Literature Review

When risk managers switch from model to model using new empirical evidence, they are moderating the model dynamically to reflect the latest market effects, in the hope that value-at-risk estimates also in the same way, it will improve. Compared to the Bioliou and Polzon regime switching approach (2000), which switches between different distributions / different regimes, our switching prediction model is switched between alternative value-driven value models. Our approach is simply implemented, and in value literature, there is a new danger.

Peter Volar, in 1999, to assess the value of exposures to loan portfolios to examine the dynamics of interest rate structure in order to accurately estimate the value at risk. He used historical simulation approaches, Monte Carlo simulations, and variance-covariance methods to estimate ten-day value. His research results suggest that the combined method of variance-covariance and Monte Carlo simulation results in better results by using normal distribution. In this method, the combination of variance is obtained through the Monte Carlo simulation approach and with the distribution of t-student and the seismic of the variance-covariance method to estimate the value at risk. The method of time structure of the interest rate with the distribution of t-student gives the worse results. (Vlaar, 2000)

In 2001, Pahaqua and Fender, in their study, argued that although the existence of widespread sequences in financial data is an essential feature, and the use of metric risk method with the assumption of normal distribution does not take into account this feature, the cause Extensive and frequent reviews of this model. They argue that one reason for this is due to a very short time horizon for predictions. Another reason is that selecting a significant level at the time of calculating VaR has mainly led to the use of these models easily and only with the coefficient of oscillation in a fixed coefficient for this purpose. (Feizabad, 2008)

In 2002, using three types of one-to-three-year securities, one to eight years, and eight more years in Indian securities, it came to the conclusion that, in a situation where the distribution of securities returns is widespread, The VaR parametric method, based on the assumption of the normal distribution of returns, provides an estimation of the risk of risk false. Using the GARCH model (1.1), which is the same as the general metric risk spreading model, does not provide efficient results in the securities market. However, the use of Garch rank models yields more efficient results after eliminating serial correlations in the data. (Feizabad, 2008)

In his dissertation, Ansari examines the impact of using different time scales in calculating risk-weighted value by using wavelet theory. In this research, the value of portfolio risk is composed of twenty companies from 50 more active Tehran Stock Exchange companies that have been traded over 75% of the trading day between 2001 and 2006, calculated on eight time scales. . His research results show that risk is reduced by increasing the time scale. In other words, the risk is higher at higher frequencies. (Ansari, 2007)

Research hypothesis

As stated above, the main goal of this study is to evaluate the efficiency of the switching model compared to the fixed-value calculation models of the risk. Therefore, the main hypotheses of the research will be:

- The prediction model for switching to calculate value at risk is more accurate than the EWMA's value model.
- The prediction model for calculating value at risk is more accurate than the value model at historical risk.
- The prediction model for calculating value at risk is more accurate than the Monte Carlo value model.
- The prediction model for switching to calculate value at risk is more accurate than the value model at constant risk of variance.

Also, as sub-hypotheses, the performance of each model (except for the switching model) will be examined in relation to each other.

3. Methodology

After extracting the daily index data, for the period 2012 to 2016, it calculates daily returns for data. Daily returns were calculated logarithmically. According to the formula:

$$R_t = Ln(\frac{S_t}{S_t - 1})$$

The reason for using this method is that the yield in the logarithmic method is calculated continuously. After calculating daily returns, we calculated the value at risk for each of the indicators based on the research models. It should be noted that the 100-day initial period is used to estimate the value at risk of the first prediction period. Then, using the Rolling Window method for the total time period studied, the risk value was calculated on a daily basis. The process of estimating each of the models is as follows:

Historical simulation

As previously explained, this model uses past-time data to estimate the value of a future exposure risk. The method of computing value at risk in this model is that in a given time period, which is 100 days in this research, sort sorting is sorted by using the sort of data. Given the desired error level (in this study at two levels of error α = 1% and α = 5%), the lower percentage of the arranged intervals of the preceding (historical) interval is VaR% α.

We move one day forward according to Rolling Window function. That is, the n-day interval is composed of n-1 data replicated in VaR, t day t, and the historical date of t. We now calculate VaR_{t+1} in the same way. This process continues until the end of the day.

This process is performed for all indicators throughout the study period.

Monte Carlo method

In this method, calculating the value at risk, the first 100-day interval is selected. In this interval, the mean and variance (μ and s) are calculated. In order to produce a scenario in which 10,000 scenarios are considered in this research, it is necessary to convert the mean and variance numbers into matrices. Therefore, the numbers μ and s are calculated in matrices of dimensions (1 × 10 000) with a value of one multiplicity. Now, by putting the matrices obtained in the following formula, the yield is produced by the standard normal distribution.

$$R+= \mu + dz.\sigma$$

Now it is necessary to calculate the normal random number (dz). A normal random number is generated by the following statement.

$$dz = \text{norminv}\ (\text{rand}\ (10.000))$$

This means that at first, 10,000 rand are generated between the 1-0 range, then standard norminv () random numbers are standardized, and a Z number is generated for each one. Now that dz is a dimensional matrix (10,000 * 1), we put it in the above formula, and 10,000 returns with a standard normal distribution are generated randomly.

Now, according to the above-mentioned method for the error level α% (in this research, α = 1% and α = 5%), the value is computed.

We proceed one day forward according to the Rolling Window method, and the value is exposed at the risk of a new day (t + 1) with n-1 returns and returns on the t-day.

We will continue to do so until the end of the day, and for each day, an estimated value is estimated. This operation is repeated for all indicators.

EWMA method

As we know, parametric methods, such as different types of estimation of conditional fluctuations, differ in their calculation of the s method. Since the purpose of this study is not to compare the types of parametric methods, only the EWMA model has been chosen to represent these different models.

As we know, in a normal distribution of number z, the formula:

$$Z = \frac{R_i - \mu}{\sigma}$$

is obtained. In estimating the value at risk, the goal is to estimate Ri at% α, which is, with other variables of the equation, Ri is estimated. Therefore, the formula VaR is calculated as follows:

$$VaR=\mu+z\sigma$$

As it is stated, the difference in parametric methods of estimating the value at risk is due to the difference in the calculation of their variance. In EWMA, the variance is calculated as follows:

$$\sigma_{t=1} = R_{t=1}^2$$

$$\sigma_t = (1-\lambda) r_{t-1}^2 \times \sigma_{t-1}$$

According to the risk metric, the adjustment number is λ equal to 94%. For each day, the variance is calculated by the above method. Thus, for the 100-day interval, the gain of μ is obtained, and s obtains the 100th day with the formula (28-3), and we put it in formula (27-3) and the value is computed in the risk. According to the Rolling Window rule, we move one day ahead, and thus, for all days of the study period, value is computed. We repeat this for all indices.

Fixed variance method

This model is a basic model for calculating value at risk. The average and variance (μ and σ) for the first 100 days period are calculated. Then these variables are computed in the formula for calculating the value at risk and the value is computed in the risk.

$$VaR=\mu+z\sigma$$

The variance is calculated by the formula:

$$\sigma^2 = {}^1\!/_{n-1} \sum (R_i - \mu)^2$$

Each of the models presented so far has its own advantages and disadvantages. Each model of computation of the value at risk that the researchers have achieved is, in certain circumstances, the best model. Our goal in this research is to provide a model that has the flexibility and general application in different market conditions. For example, some models are well responsive in terms of stress and crisis and have high accuracy. Others are better at normal market conditions and ... The purpose of the proposed switching model is to provide a model for organizational decision makers who do not have to use only one method to calculate VaR, but it can be created that managers can Use each model's potential at any moment. This ability to replace the model in different conditions is provided by the switching model.

Switching model

In this model, for each indicator, all VaR calculation methods, which are historical method, Monte Carlo, EWMA, and constant variance, are valued at the risk based on the 4-week initial interval. Then we evaluate the accuracy of each model using the following function:

$$Loss = \begin{cases} 1 + (VaR_i - R_i)^2 & VaR > R_i \\ 0 & otherwise \end{cases}$$

Then we define the sum of errors as a function of cumloss.

$$Cumloss = \sum_{i=1}^{\tau} Loss_i$$

On day t, when the switching model is to decide which initial model to use, the cumloss function of all the initial models is computed. That model, which has the lowest total error for the last 4 weeks, is selected as the superior function, and the VaR value estimated by that model for the next day is the same value at the risk of the switching model.

Then moving forward one day using Rolling Window. In the new range, the same operation will be repeated, and this will continue until the end of the studied period in the research. Then, through the steps outlined above, there will be five risk-worthy time series with a series of real-time returns.

Now, to test the research hypotheses and find the best model, we test the output of each of the models. In the first step, it is necessary that the test model is efficient and appropriate. In this step, the Kupeic test is used.

$$I_t(\alpha) = \begin{cases} 1 & if\ r_t < -\%VaR_{t|t-1}(\alpha) \\ 0 & otherwise \end{cases}$$

In the next step, if the model during the study period had the optimal performance to estimate the value at risk, then the Lopez rating criterion is used to identify the best model.

$$C_{t+1} = \begin{cases} 1 + \left(R_{t+1} - VaR_{\alpha,t}\right)^2 & if\ R_{t+1} < VaR_{\alpha,t} \\ 0 & if\ R_{t+1} \geq VaR_{\alpha,t} \end{cases}$$

After the output of each model, they will be tested. First, using the Kupeic test, the overall performance of the models will be evaluated. Then models that have acceptable performance will be compared to the Lopez benchmark. Finally, using the Diabold Mariano Test, the statistical accuracy of the results will be verified.

4. Results

To conduct this research, 30 companies were selected from Tehran Stock Exchange (TSE), which estimated the research requirements. The following table shows the symbols of these companies:

Table 1-Companies' symbol included in portfolio

No.	Company name	No.	Company name	No.	Company name
1	Walber	11	Khshargh	21	Velsapa
2	Fbahner	12	Dkimi	22	Vsakht
3	Vbuali	13	Vkar	23	Vsandogh
4	Kechad	14	Ghasemin	24	Sefares
5	Shekarbon	15	Vmaaden	25	Vsanat
6	Dejaber	16	Bmoto	26	Sorud
7	Dkowsar	17	Shabharn	27	Sepaha
8	Derazak	18	Vniki	28	Setran
9	Desobha	19	Vnovin	29	Vetusa
10	Khatufa	20	Koravi	30	Webshahr

In the next step, the portfolios comprised of these stocks were compiled and portfolio efficiency was calculated. The chart below shows the trend of portfolio depreciation changes over the ten years of 2007-2017. The descriptive statistics of the portfolio's returns are as follows.

Table 2- Descriptive statistic

Mean	0.000554
Median	0.000227
Mode	0
SD	0.007845
Sample variance	6.15E-05
Kurtosis	4.089091
Skewness	0.505597
Range	0.10039
Min	-0.03388
Max	0.066508
Total	1.306651
Size	2360

In the historical simulation model, at first a part of the data (in this 100-day interval) is selected and the data are sorted by sort order in MATLAB software and the value at risk for that period was calculated. Then, with the sill window method, it moved on the returns and the value at risk was calculated for subsequent periods. Finally, the value of exposed exposures was compared with that day's returns. If that day's efficiency is lower than the value at stake, it mean that the model failed to adequately cover the risk on that day. In the following, the results of the simulation model are schematically represented.

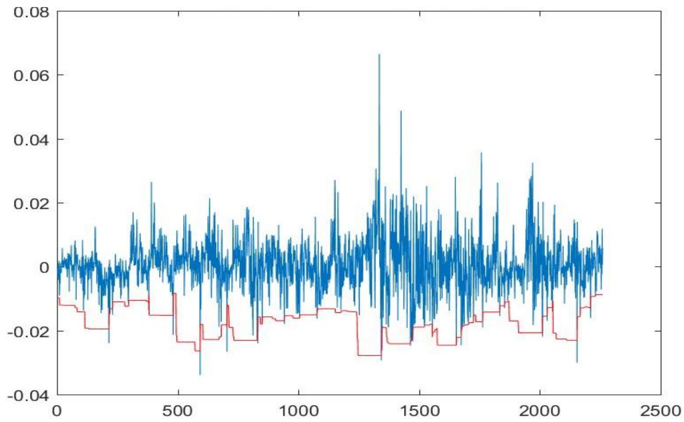

Figure 1. Historical VaR for portfolio Ret at 1%

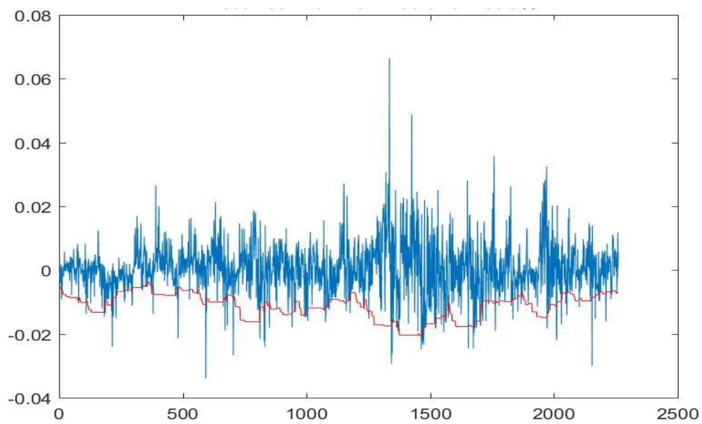

Figure 2. Historical VaR for portfolio Ret at 5%

The above graphs show the value of computed risk at two levels of confidence of 1% and 5%. The blue lines represent the return of the portfolio every day. And red lines show the value at computed risk. The number of times a blue line hits a red line is actually the number of times a model has failed to correctly predict. Given the assumed levels of confidence, the number of collisions between the two blue and red lines is expected to be at a confidence level of 5%, which is clearly indicated in the two abovementioned cases.

For the Monte Carlo simulation method, first select 100 primary yields, and the mean and its variance are calculated to produce random numbers with the historical data specification using the Monte Carlo method. For this purpose, 10,000 random numbers are generated that have a mean and variance similar to that of historical data. With these generated numbers, value is expected to be at risk for the next period. The same is repeated for all studied courses, as shown below, shows the value of computed risk for different periods.

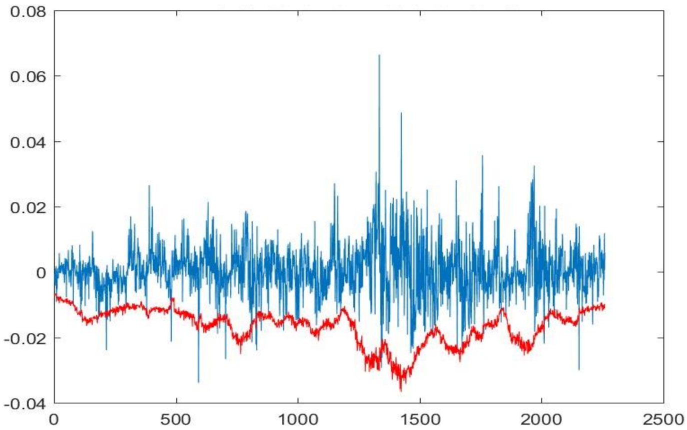

Figure3. Monte Carlo VaR for portfolio Ret at 1%

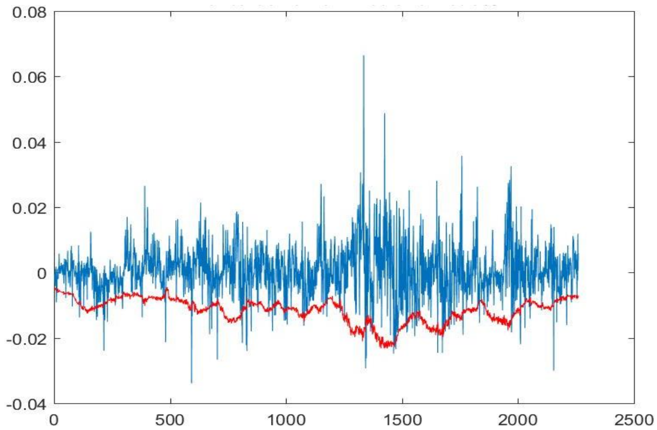

Figure4. Monte Carlo VaR for portfolio Ret at 5%

In the above figure, the blue line shows the historical returns and the red line in the computed value.

In the EWMA model, the value at risk for the first 100 days is calculated using the method described in the previous chapter. The figure below shows the output of the VaR calculated in this model.

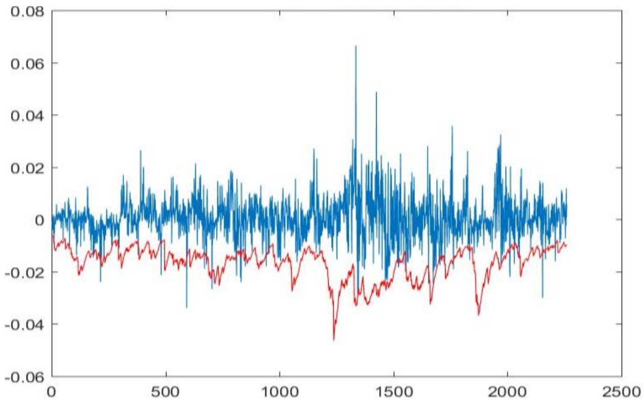

Figure 5. EWMA VaR for Portfolio Ret at 1%

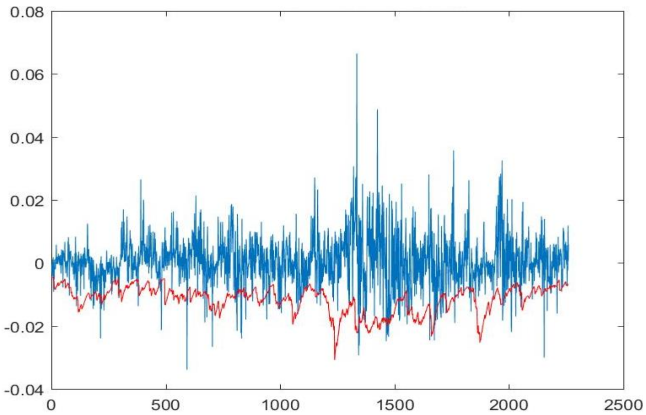

Figure 6. EWMA VaR for Portfolio Ret at 5%

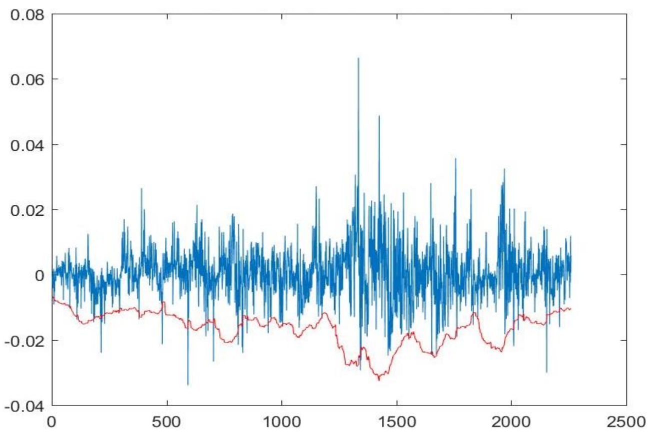

Figure 1. Constant Variance VaR for Portfolio Ret at 1%

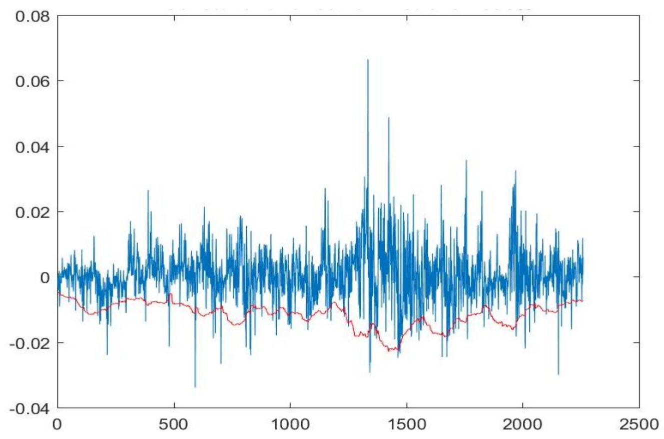

Figure 8. Constant Variance VaR for Portfolio Ret at 5%

For a constant variance model, the mean and returns are calculated for the first 100 first data and calculated by putting it in the formula mentioned in the previous sections, the risk value is calculated for each day. The following diagram shows the outputs related to the constant variance model.

Finally, for the switch model, we compute the value at risk by defining an initial filter to identify the models that had a better performance in the previous periods. In fact, this method does not introduce a specific model for calculating value at risk, but by identifying the best performance of different models, the VaR number introduces the estimated value of that model as being at risk.

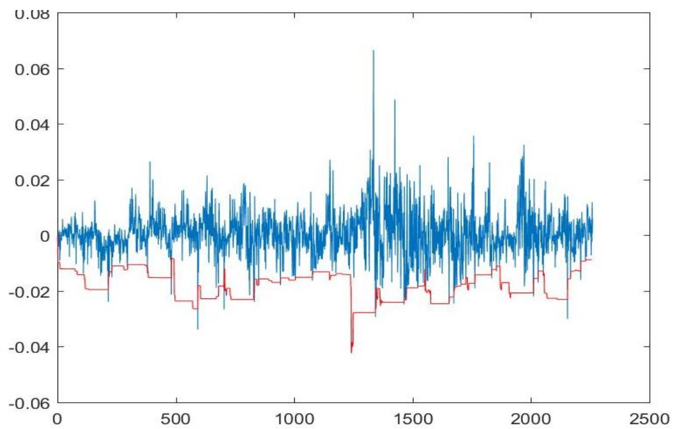

Figure 9. Switching VaR for Portfolio Ret at 1%

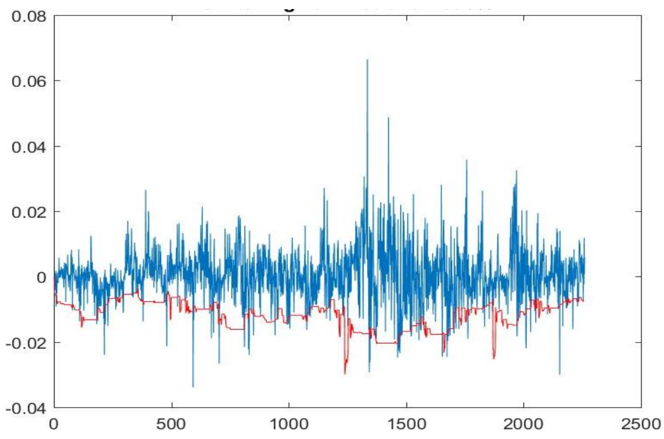

Figure 2- Switching VaR for Portfolio Ret at 5%

The output of the Kupeic cover test for the top 30 companies at the 1% level is as follows. Chi square distribution statistics shall be equal to 9.935 in error level with freedom degree one. As we know, if output value is greater than unconditional average (chi distribution statistics shall be equal to one with freedom degree one in error level 1% it results to lacking acceptance of H0.

Ho: sum of number of times in which loss is greater than value of endanger it closes to number of times.

H1: number of timers in which loss is greater than value of endanger is more than numbers anticipated.

Table 3. Unconditional Coverage Test- 1%

Row	Kupeic	Kupeic _result
Historical Simulation	6.780388	OK
Constant Variance	4.342516	Failed
EWMA	1.341516	OK
Monte Carlo Simulation	1.219275	OK
Switching Model	1.004347	OK

The test output shows that all models except the fixed variance model are approved to estimate the value at risk for this index and at this level of error. Therefore, the constant variance model does not have the required 1% error level and thus the results obtained from the Lopez test cannot be reliable.

The Kupeic cover test for the top 30 companies at the 5% level is as follows:

The Chi-square distribution will be at an error level of 5% with a degree of freedom equal to 3.8415. Therefore, if the output number obtained from the unconditional cover test is larger than this, then the H0 assumption will be rejected.

The output of the Kupeic cover test for the top 30 companies at the 5% level is as follows.

Table 4. Unconditional Coverage test- 5%

Row	Kupeic	Kupeic _result
Historical Simulation	1.298675	OK
Constant Variance	0.937055	OK
EWMA	0.341129	OK
Monte Carlo Simulation	0.083144	OK
Switching Model	0.702994	OK

The test output shows that all models are approved for estimating the risk value for this indicator and at this level of error.

5. Discussion and Conclusions

The purpose of this study is to estimate the value of risk in a switching model, which means that different tools and methods of VaR estimation can be used in different situations and situations. For this reason, in Chapter II, the basics for understanding the concept of value at risk are stated. In the third chapter, the research methodology used in this study was explained. The predictive model of switching at any point of time faces the problem of choosing an estimate from alternative estimates. When the value-at-risk estimates are constantly updated with different models, we can improve the predictive value of the risk based on the "predictive switching strategy". This approach is explicitly designed to estimate the predictive problems of managers who do not qualify their estimates for a specific VaR model, and allows the estimated model to change over time. This approach assumes that investors at any point in time use only the historical information available to select a model, and choosing a model based on a pre-determined selection criterion, and then selecting the model used to predict value at a later date. For example, the loss function can be the criterion for choosing a specific model in the prediction strategy of switching, this criterion reflects the potential risk problem. That is, the value-at-risk model has the lowest loss at any given time. When risk managers switch from model to model using new empirical evidence, they are modulating the model in a dynamic way to reflect the latest market effects, in the hope that the estimation of the value at risk is also in the same way, it will improve. Compared to the Bioliou and Polzon regime switching approach (2000), which switches between different distributions / different regimes, our switching prediction model is switched between alternative value-driven value models. Our approach is simply implemented, and in value literature, there is a new danger.

As explained in the preceding chapters, after extracting the daily prices of the 30-share portfolio, for the 10-year return period, the logarithmic returns of each single share and, finally, the total return on the portfolio were calculated. Then the value at risk was estimated using 5 models (historical simulation, Monte Carlo, EWMA, fixed variance, and switching).

In this research, the effectiveness of the proposed models for calculating the value at risk was investigated by a coup test. The validity of the hypotheses discussed at the beginning of the research was evaluated through the Lopez ranking test, which shows that at the level of error of 5% and 1%, H0 is not confirmed in all hypotheses. In fact, 95% and 99% probability, the prediction of risk value in all indicators by switching method has a significant difference with prediction with other methods (Monte Carlo, fixed variance, historical, and EWMA).

In the end, to compare the prediction validity, we used the Diabold Mariano Test. The results showed that for all indicators of research, at 99% and 95% confidence level, there is a significant difference between the prediction of switching and the other model.

Therefore, all tests used in the research confirm the efficiency of the switching model in computing the value at risk. The following tables show the results of the model test:

Table 5. Lopez Criteria

Row	Var1	Rank	Var1	Rank
Switching Model	18.02468	1	82.06672	1
EWMA Model	18.02708	2	92.07652	2
Historical Model	21.03577	3	103.0768	5
Constant Variance Model	-	-	111.0826	4
Monte Carlo Model	39.04431	4	112.0782	3

Kupeic test considers number of violations merely and doesn't consider size of error. For this reason, in order to compare models perfectly, we use Lopez ranking criteria. Lopez ranks models in terms of scale of their error to calculate values endangered. Since fixed variance model did not have necessary conditions in error level 1% in terms of Kupeic test, above table shows results of Lopez ranking for other cases. As indicated, in two errors levels 1% and 5%, switching model has better ranks compared with other models.

But in order to test significant model, we use Daibold Mariano model which its results are on below table.

Table 6. Diabold Mariano Test

Row	1%	5%
Switching Model-Historical Simulation	-11.9467	-7.92157
Switching Model-Constant Variance	-3.38742	-5.02391
Switching Model-EWMA	-0.31412	-1.98782
Switching Model-Monte Carlo Simulation	-3.4461	-2.52498

But according to hypothesis of Daibold Mariano, if absolute value of test is greater than 2.57 in error level 1% (s>2.58) and test value is greater than 10.96 in error value 5% (s>1.96), Ho hypothesis is not confirmed. Thus, predication oft wo models and negatively sign shows better performance (switching). according to above table, switching model has negative sign which shows better performance for model and there is significant difference between switching in error level 1% instead model EWMA.

The results of this research, that is, the higher efficiency in the operation of the switching model compared to all models individually, confirmed the results obtained in the research of Yen-Chen Chu and Yuan Chuang. In their paper, for the first time, the presentation of the switching method showed that the definition of the loss function in choosing the model used to calculate VaR could be better than a single model.

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