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ESTIMATION OF VALUE AT RISK FOR GOLD FUTURES CONTRACTS

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ABSTRACT

Value at risk (VAR) is an important measure to assess the level of risk in financial markets which expresses the market risk in the form of a number. This paper addresses the risk assessment of futures contracts using the value-at-risk approach. Risk matrix, historical simulation, bootstrap historical simulation and Monte Carlo simulation have been used to assess the VAR. Kupiec test has also been used to examine the effectiveness of VAR assessment methods. The results of estimating the value at risk at 95% confidence level show that the Monte Carlo simulation method has the lowest value at risk estimation compared to other methods, and the historical simulation method has the lowest value at risk estimation at 99% confidence level compared to other methods. Furthermore, the results of Kupiec test show that all the VAR estimation methods are reliable, and the failure rate of the VAR estimations show that the Monte Carlo simulation model is more effective for estimating VAR at 95% confidence level than other methods. Moreover, historical simulation, bootstrap simulation and Monte Carlo simulation models are more effective for estimating VAR at 99% confidence level.

Keywords: *value at risk, futures contracts, historical simulation, Monte Carlo simulation, Kupiec test.*

INTRODUCTION

One of the most important goals of financial institutions is to increase returns. But it may cost them higher risks, namely an uncertainty to achieve the desired returns. Therefore, risk managers in these institutions seek to create a balance between risk and returns which will ultimately result in maximizing the wealth of investors. Risk management aims at providing protection against the undesirable consequences of risk tolerance and also giving assurance that the benefits of risk acceptance are met. Risk management is a process in which managers attempt to identify, measure, decide, and monitor all kinds of risk to the firm. The importance of risk has led to an increase in the importance of risk management for financial institutions. In addition, the bitter experience of some countries, such as Southeast Asian countries or even Western countries, have led to greater attention from administrators and legislators to this issue. The political and economic instability in the world followed by rapid changes in the corporate environments has doubled the risk of financial institutions. These factors have increased the importance of risk management and also resulted in researchers paying more attention to the issue.

One of the most important components of risk management is risk measurement. Risk measurement and risk quantification are very old challenges that have occupied the minds of mathematicians, managers and policymakers. A policymaker in order to be able to pursue a

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fair and transparent policy on risk and also to supervise its implementation needs to have a basic knowledge about risk. A manager seeks to create a balance between the investment return and risk. Mathematicians are also seeking to develop powerful, yet simple mathematical tools to meet these needs.

Various methods have been developed to measure risk in the fields of mathematics and financial engineering in recent years. One of the methods of risk measurement is VAR method. VAR expresses the maximum loss which the portfolio value decrease in a set time period with a given coefficient of confidence will not exceed it.

People who participate in futures markets also face uncertainty regarding the price of underlying asset. This creates uncertainty and risk in the future price of the underlying assets. The price of futures contracts as the most important factor in concluding contracts is influenced by factors such as political and economic conditions, behavioral reactions of market participants, and so on. Designating all these factors is somewhat difficult; but the price of futures contracts can be used as a substitute for all of these factors; so the price of futures contracts can be used to calculate the VAR for these types of contracts. Therefore, we are seeking to estimate the VAR for gold coin futures contracts in the present paper.

It should be noted that futures contracts are one of the derivative contracts in which the buyer and seller agree to trade the underlying asset with a specified quality at a predetermined price and at a specified place and time. Underlying assets may include financial assets (such as stocks, stock index) and physical assets (such as gold coins, copper, iron, agricultural products, etc.). At present, futures contracts in Iran Mercantile Exchange include physical assets only. The futures contracts for gold coins have been made in Iran Mercantile Exchange since 2008.

THEORETICAL FOUNDATIONS

One of the most important goals of financial institutions is to increase returns. But it may cost them higher risks, namely an uncertainty to achieve the desired returns. Therefore, risk managers in these institutions seek to create a balance between risk and returns which will ultimately result in maximizing the wealth of investors. This goal is not achievable without knowing the types of risks that are present in the activities of financial institutions.

Types of financial institutions risks

Credit risk: the risk from a failure to repay loans or fulfilling contracts of the institution

Liquidity risk: the risk of liquidating claims by customers instantaneously and the need for a bank to convert assets immediately to cash

Interest rate risk: risk of depreciation of assets due to interest rate fluctuations

Market risk: risk of depreciation of assets and payments due to some changes, such as changes of exchange rates

Off-balance sheet risk: the institution's risk arising from the results of activities related to contingent payments or assets (payments that must be made because of a specific period of time and changes of time condition).

Exchange rate risk: the risk of a change in the value of institution's assets or debts overseas due to some changes, such as exchange rate changes

Risk of capital inadequacy: the risk of lack of sufficient capital to offset asset depreciation

Risk measurement

Webster's Dictionary defines risk as “to expose to hazard or danger”. Investment dictionary defines risk as “the potential risk of capital which can be calculated”. Risk is a qualitative concept, indicating uncertainty about future expectations. As long as this uncertainty is not quantified, pricing of risk-taking assets remains a mystery, as the risk present in financial assets is one of the determinant factors of the rate of return expected by investors. So far, various risk measures have been introduced by the experts, each of which refers to an aspect of uncertainty and sometimes they complement each other. Risk measurement indices were first calculated through studies on the measures of dispersion, and since then, newer methods such as duration, undesirable risk, and ultimately VAR were proposed. Markovitz (1952) presented a quantitative model for risk measurement. By introducing a model based on risk and return and proposing the efficient frontier line, he put risk and return together. He regarded the standard deviation as a risk measure. William Sharpe introduced the beta index for relative changes in the value of a share in relation to exchange market value by introducing a profile line. By introducing a model for pricing capital assets he founded portfolio scientific management. McCullough introduced the duration measure as a criterion for measuring the risk of fixed-income securities, based on which assets and debts management and the design of risk management strategies, including duration compliance and immunity were presented. The continuation of McCullough’s work led to a nonlinear relationship between the value of fixed income securities and the market interest rate, and the convexity criterion was introduced as a more precise indicator for calculating the risk of these securities. In 1996, the JP Morgan introduced the value at risk model. This measure summed up all types of risk in a single number and determined the portion of the capital of an institution that was exposed to loss (Radupour et al., 2009).

The concept of VAR was first proposed by Bamwell (1963) in 1963 when reviewing a model entitled "confidence level criterion of expected return" almost four decades ago, but more generally, "safety-first models" were first introduced by Ray in 1952 and Teulsar in 1955 among financial professors. Eventually, Till Goldman can be considered the inventor of the term "value at risk" (Radpour et al., 2009).

VAR expresses the maximum loss which the portfolio value decrease in a set time period with a given coefficient of confidence will not exceed it. In other words, VAR measures the worst expected losses under normal market conditions over a specified period of time and at a certain level of confidence. VAR responds to the question of how much of the value of assets or portfolio of assets is at risk maximally with a x% probability and over a given time horizon. For example, the value at risk at a 99% confidence level for a ten-day period suggests that the maximum imposed loss over the next ten days exceeds the value at risk only once per 100 samples.

In other words, we can say that VAR is a decrease in the market value of an asset or a portfolio that can be expected not to go beyond a certain number over a given time interval and with a certain probability.

Mathematically, the value at risk can be represented as follows.

$$Pr\{p_0 - P_1 \geq VaR\} \leq \alpha \ , \qquad Pr\{P_1 - p_0 \leq -VaR\} \leq \alpha \qquad (1)$$

In the equation (1), P_0 is the value of the portfolio at time zero, and P_1 is the value of the portfolio at time 1, and α is the error level. The above equation suggests that the probability that portfolio depreciation will exceed the value at risk in the future period is at most equal to α. If the cumulative distribution function of the portfolio value in the upcoming period be shown in the form of $F(P)$, its inverse, $F_P^{-1}(\alpha)$ represents the percentiles of the portfolio's value in the second …. In this manner, the value at risk of a portfolio is obtained from the following (Alexander, 2008).

$$VaR = p_0 - F_P^{-1}(\alpha) \qquad (2)$$

Value at risk is applicable to all liabilities reflected in the balance sheet or off-balance sheet, such as futures contracts, forward contracts, swap contracts and option contracts (Taleb Nia, Fathi, 2010).

METHODOLOGY

Generally, the following three methods can be used to calculate value at risk.

Parametric Method:

This method consists of two basic assumptions, which of course result in limitations for this method. These two assumptions are: asset return has normal distribution. There is a linear relationship between market risk factors and asset value. In the parametric method, historical data is used to calculate the required parameters for the covariance matrix, including the mean and standard deviation. This information is usually available. Moreover, for calculating VAR in this method, it is not necessary to know the value of the individual assets in the portfolio, the required parameters are standard deviation and the correlation coefficient of assets only. The calculation of VAR by the parametric method is relatively easy and does not need considerable computing power. These characteristics have made the parametric method as the most common method for calculating VAR.

Risk metrics model is a parametric method for calculating value at risk to measure the market risk. Currently, risk metrics is considered as the most commonly used method for calculating value at risk. The hypothesis of the risk metrics model regarding the distribution of return-related data is that the returns have been distributed in a conditional normal form which shows the data distribution better than normal distribution. In order to avoid issues related to moving average with equal weights, this model uses the "exponentially weighted moving average" method to measure the fluctuation index. The following equation is used in this model to predict fluctuations (Morgan, 1996).

$$\sigma^2_{(t+1|t)} = (1-\lambda)\sum_{t=0}^{\tau} \lambda^t (r_t - \bar{r})^2 \qquad (3)$$

In this equation, λ is the parameter of the model located between 0.9 <λ <1. The expression $\sigma^2_{(t+1|t)}$ does not give, prediction of the fluctuations of time is used as predictor for the fluctuations of the next day. In this method value at risk is calculated using the following equation.

$$VaR = \sigma^2_{(t+1|t)} \times Z_\alpha \times V \qquad (4)$$

In this equation Z_α is the critical value of the normal distribution at the α error level and V is the value of the assets. This method can be used to calculate the risk of individual assets or to calculate the risk of a portfolio of assets. In a risk metrics based on a diverse global portfolio, the value is set at 0.94 for the daily period and 0.97 for the monthly period (Radpoor et al., 2009).

Historical simulation method:

The historical simulation method is the simplest nonparametric method, and there is no need for assumption regarding the distribution of probability of return on assets or financial assets. Therefore, this method does not have a model. In this method, it is assumed that the behavior of the return on financial assets is the same as its past behavior, and the distribution of the probability of return in the past is also the distribution of the future probability of financial assets, and the trend of price changes in the past will continue in the future. The foundation of this method is that that the near future is to some extent like the near past. Therefore, the information related to the past can be used to predict future risks. In other words, changes of the parameters of the market in the past is evaluated, and according to that, the existing portfolio is evaluated similar to the changes of the past and its risk is calculated. In this method the historical simulation data is used directly to estimate the risk, and no modifications are made to this data.

In this model, firstly the components of the financial institution portfolio are determined, then the value of the portfolio is calculated based on market prices in the past days. The calculations are repeated for each N day before. To estimate the value at risk, it is sufficient to extract the alpha percentile of the distribution of returns. For this purpose, the historical calculated values are arranged ascending (from lowest to highest), then the position of the desired percentile is designated. Then, based on the error level the VAR is calculated based on historical data. This method is applicable for evaluating the price of option contracts and various combinations of risk factors. It is not surprising that many institutions use this method.

Historical simulation through bootstrap:

Bootstrap is a simple but useful way which helps to improve the historical simulation method. The Bootstrap method has a high perceptual capability and is easy to use. The basic Bootstrap method is very simple. We begin with an original sample in the size of n. Then, we extract a random sample of the same size from this original sample, and repeat this to a very large number, for example, 1000 times. Extracting these samples requires having a random number generator for choosing a random number from one to n. For a better understanding, imagine that we have written each of the numbers 1 to n on small and similar balls, and we have put them in a wheel. Each time we turn the wheel, we remove a ball. Each ball has a number that represents a number of the original sample. Each time a particular number is selected. Just keep in mind that this sampling is done by placement. When we randomly select numbers n times, we will have a sample that is as large as the original sample. In this way, we continue the sampling process so that a large number of these equivalent samples are created. We use the new samples to estimate the intended parameter. Each of these samples provides a new estimate of the desired parameter. Since in calculating VAR we seek out percentiles of return distribution, each new sample presents a new VAR estimate. We can consider the average of the estimates of new samples as the best estimate of VAR (Radpour et al., 2009).

Monte Carlo simulation method:

The Monte Carlo simulation has been used for the first time in the field of financial science since 1970 for pricing derivatives and estimating Greek immunity ratios (Radpoor et al., 2009).

Currently, the use of these methods to estimate VAR and other financial risk measurements has increased. These methods are very flexible and powerful, and are very effective in solving complex problems.

In this method, it is not necessary for the returns to have normal distribution. However, the Monte Carlo simulation method, unlike the historical simulation method, does not use historical information; instead, using random processes and a large number of simulated samples generated by the computer, the prediction of future changes is done.

The idea of Monte Carlo simulation is the frequent simulation of the random process governing the price or return of the intended financial instrument. In the VAR estimation of each simulation, the probable value of the portfolio is presented at the end of the maintenance period. If there are enough of these simulations, the simulated distribution of the portfolio's value will be close to the distribution of the correct but unknown portfolio, and we can use this distribution to deduce VAR.

Monte Carlo simulation steps to compute VAR are:

1. Selecting a model for the intended variable or random variables and determining the possible processes and estimating the process parameters for the financial variables based on our judgments or historical or current market data.
2. The hypothetical price simulation for all the used variables using the random number process, in which each set of random numbers generates a set of hypothetical final price for the financial instrument existing in the portfolio.
3. Calculation and determination of the price of assets or financial assets at time T and return according to the simulated prices and calculation of the investment portfolio value
4. Repetition of the steps many times in order to create a distribution of portfolio value probability to ensure that the simulated distribution is close to the correct and unknown distribution of the portfolio's value.

Extraction of VAR from this representative distribution.

Post-test of Value at Risk

After creating the model and before it is used in practice, its validity should be carefully examined. Moreover, while using the model, its performance should be evaluated regularly. One of the key attributes of validating a model is a post test that involves the use of quantitative methods to determine the degree of correspondence between the predictions of the model and the assumptions that the model is based on. Incorrect distribution assumptions in statistical models, large changes in the oscillation of market risk factors, challenges associated with modeling time dependencies in portfolio fluctuations and lack of coherence are among the

factors that lead to erroneous estimates of risk. In fact, these factors are major factors that may lead to the rejection of a risk model in post-tests (Radpour et al., 2009).
The first logical way to assess the prediction of VAR models is to count the number of times that actual loss has been greater than the expected loss by VAR models. If the actual loss is more than the amount estimated by the model, then this event is considered as a failure. If the actual loss is less than the estimated loss, it is deemed a success. If the VARs of each course be assumed as independent, then the comparison of the realized earnings and losses with the calculated VAR will result in a binomial distribution. The above statement indicates that the total number of failures from VaR has binomial distribution with T and α parameters. An important criterion for this hypothesis is to consider the ratio of failure, which is obtained by the number of failures on the total number of predictions. In order to test the above hypothesis, the hypothesis of failure ratio and coverage level can be tested by the Kupiec Contract, 1995.
The test of the probability of Kupiec failure is as follows.

$$LR_{\mathrm{PF}} = 2\ln\left[\frac{\hat{\alpha}^{T_1}(1-\hat{\alpha})^{T-T_1}}{\alpha^{T_1}(1-\alpha)^{T-T_1}}\right] \quad (5)$$

In Equation (5), LR_{PF} is the ratio of the probability of failure, T_1 is the number of failures, T is the number of predictions, α is coverage level. This equation has a chi-square distribution with a degree of freedom. If the probability of failure is greater than the chi-square distribution with a degree of freedom and an error level α , the hypothesis will be null and it cannot be accepted that the value at risk model is correctly estimated.

RESEARCH BACKGROUND

Several studies have been carried out on estimating the risk of assets using the value-at-risk value in the outside and inside, some of which are referred in below.
Cera and Gerdy (2013) have estimated the value at stake for Albany's exchange rate. They used GARCH models to evaluate the value at risk. The results of the research confirm the model's stability and that this model is a suitable model for estimating the value at risk of exchange rate. Iorgulescua (2012) has investigated the pretest of value at risk for the Romanian capital market. In this paper, four types of GARCH model are used to calculate the value at risk. Also, for non-conditional convergence tests and independence tests are used for evaluating the pretest of value-at-risk. The results of the research show that the performance of risk models is mainly influenced by the characteristics of the estimated data from them. Independence test also shows that volatility is a real threat for simple and combined value at risk approaches. Sun & et al. (2011) in an article have examined the value at risk of portfolios of oil exporting countries in the FSU regions. In this research, the BEKK model is used to estimate the value of risk. The results of this study show that the risk of portfolios of oil exporting countries and risk of volatility of those countries have a greater impact on the risk of the Chinese oil importer than the EU. Chen and Rongda (2013) have reviewed the value at stake in the Shanghai stock market. In this paper, three methods of variance-covariance, historical simulation and Monte Carlo simulation are used to estimate VaR. The results indicate that a higher level of certainty results in greater value risk, and the lower the confidence level, the value at risk is the same for

the different approaches, although the value at risk is different for different approaches at higher confidence levels.

Several studies have also been carried out on the value at risk in the domestic context, which is referred in below.

Sajjad and Gorgji (2012) in a paper have estimated the value at risk using the Bootstrap open sampling method in Tehran Stock Exchange. In this paper, a bias correction process based on the Bootstrap resampling method was performed to eliminate the defects of the normal fungal model in relation with the proper VaR estimation. The results show that the bias correction process has improved the ability to estimate the VaR of a normal fungal model in the VaR estimation for Tehran Stock Exchange Index, at least at the final probability levels. The historical simulation model and the filtered historical simulation have also been reviewed to compare the results of applying the correction process. Sajjad and Hedayati (2014) in another paper have estimated the value at risk using extreme value theory in Tehran Stock Exchange. In this paper, the value at risk is calculated using seven different methods, such as extreme value theory and for three levels of confidence, for the logarithmic yield of the Tehran Stock Exchange index, the daily dollar and euro equivalence rate. Also, the fungal model has been used to predict the yield volatility. In order to examine the accuracy of the applied models, the tests of Kupiec failures, Christopherson and the Lopez loss function are used. The results show that computing the value at risk using traditional methods does not necessarily lead to appropriate results and in some cases, the use of the extreme value theory and considering conditional volatility for the data causes better results. These results are more evident at higher levels of confidence.

Mirghaffari (2012) has reviewed R-Sharp test based on value at risk for evaluating performance in Tehran Stock Exchange companies. In this research, the performance evaluation of investment companies and major metals companies in Tehran Stock Exchange has been compared and tested with two methods of calculating Sharp index and R-Sharp index from 2006 to 2010. The results of this research show that the use of R-Sharp index in companies with diverse portfolios (investment companies) does not make a significant difference in the ranking of companies. In the case of companies that do not have portfolios (companies producing basic metals) or don't have a variety of portfolios, despite the apparent difference in ranking, this difference is not statistically significant. Khalili Araqi and Zare (2010) in an article have estimated the risk of the Tehran Stock Exchange (TSE) market based on the value-at-risk model. In this research, value at risk method has been used to evaluate the risk of the Tehran Stock Exchange market using the Monte Carlo simulation method. For this purpose, a one-day time period and a confidence level of 99% are considered and to predict the volatility in return, the method of Exponentially Weighted Moving Average is used and to test the model pre-test, Kupiec test is used. The results of computing value at risk indicate that the industry of "other transportation equipment" and the industry of "rubber and plastic" have the lowest value at risk and the industry of "industrial contract" and the industry of "manufacturing devices and communication devices" have the highest value at risk. The results of computing value at risk indicate that the industry of "other transportation equipment" and the industry of "rubber and plastic" have the lowest value at risk and the industry of "industrial contract" and the industry of "manufacturing devices and communication devices" have the highest value at risk. Peykarjou and Hosseinpour (2010) in an article have measured the value at risk in insurance companies. In this paper, firstly, the value at risk was calculated using ARMA and GARCH models, and then with prediction of the model for the future years with the condition of the company's decision-making process in the selection of insurance risks, it was found that the company was in a good condition and an unconventional risk will not threaten it.

Mahdavi and Samadi (2012) have investigated the value-at-risk comparison using the non-modified and modified Monte Carlo simulation model for car insurance claims of an insurance company, Rahnamay Roodposhti and Mirghffari (2011) have estimated the value at risk of Tehran Stock Exchange using risk assessment techniques and GARCH, Mohammadi et al. (2008) have examined the value at risk of Tehran Stock Exchange by using heterogeneity models of conditional variance and Nikumaram and Zomorodian (2014) using econometric methods estimated the value at risk of Iran's Bourse Investment Companies.

No study has been conducted in estimating value at risk for future gold contracts so far, and only two studies have examined the risk coverage of future gold coin contracts which are referred to below.

Bahrami et al. (2012) have reviewed risk coverage using future gold coin contracts. In this research, the method of minimizing variance and expanded Gini coefficient to the mean for investigating risk coverage have been used. The results indicate that the optimal risk coverage ratio of the minimum variance is greater than the optimal ratio of the average risk coverage of the Gini coefficient expanded to the mean and average of Gini coefficient expanded to the mean. The average risk coverage ratio of the extended Gini coefficient to the mean for lower degrees of risk aversion is smaller than the optimal risk coverage ratio of Gini coefficient expanded to the mean.

Also, Bahrami and Mirzapour Babajan (2012) re-evaluated the risk coverage ratio in future gold coin contracts. In this paper, the optimal coverage ratio of variance minimization risk for future gold coin contracts traded in Iranian stock exchange has been estimated and compared using various econometric approaches. The results indicate that considering different due dates as future prices changes the value of optimal risk coverage ratio generally; so that if the first due date is considered as the price of the future contract, the optimal risk coverage ratio is greater than a state that the second due date to be considered as the future price. Also, the results indicate that the optimal risk coverage ratios of different methods are superior to the simple risk coverage strategy (risk coverage ratio equal to 1). Finally, the optimal ratios of variable risk coverage over time that are estimated using different states of the GARCH method, do not necessarily have more ability to reduce risk in comparison with the optimal ratios of fixed risk coverage.

RESEARCH FINDINGS

In this research, risk assessment, historical simulation, historical simulation of Bootstrap and Monte Carlo simulation have been used to estimate the future gold coin value at risk. Then, using Kupiec test, the efficiency of each model is compared with each other, and the most efficient method for estimating the value at risk is specified for the future gold coin contract. The price agreed by the parties in future transaction is called the price of the future contract. The prices that are considered as future prices in this research are settlement price. The settlement price is not the last transaction price per day, but usually the average price is the price at which are traded at the end of the working day. The prices of future gold coin contracts are extracted from the Website of Iran Stock Exchange Company. The research population in this article is the future gold coin contracts. These contracts have been traded on the Stock Exchange since 2008. For the selection of the research period, the sample of the last completed contract and the nearest contract to 2015 is selected that the future gold coin contract delivered in January 2014 is selected as the sample of the research. In this research, logarithmic return is extracted using the following method.

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (6)$$

In Equation (6), P_t is equal to the price of the future contract per year. Table 1 shows the results of estimating the value at risk using the matrix risk method at a confidence level of 95% and 5%.

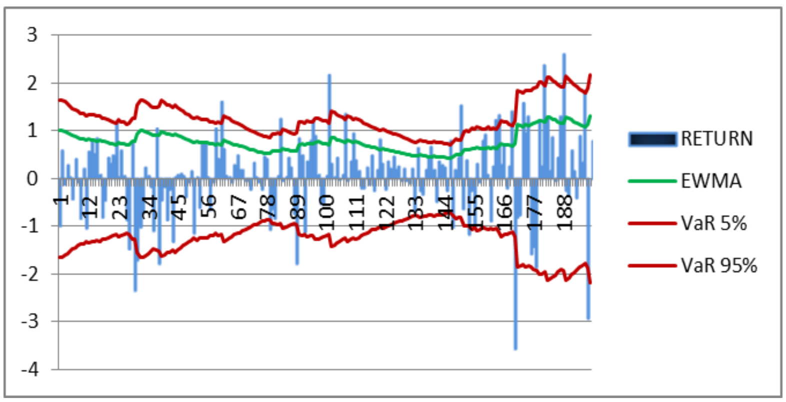

Diagram 1: Value at risk at 95% confidence level and 5% using matrix risk method

In this diagram, volatility of return of future contract are shown linearly in the form of a column diagram and a risk value of 95%. Also, diagram (2) shows the value at risk using the matrix risk approach at a 99% confidence level.

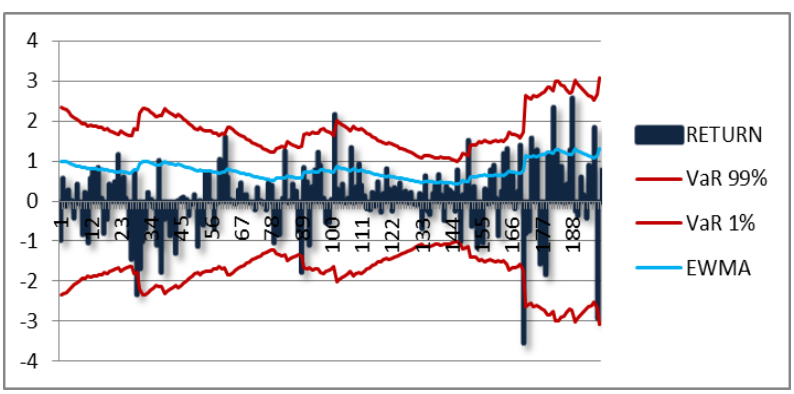

Diagram 2: Value at risk at a 1% confidence level using matrix risk method

Estimate of value at risk with historical simulation method:

by having data related to historical simulation of return, it can estimate the value at risk by plotting the yield diagram on a simple histogram. The histogram of these observations is presented in the following diagram.

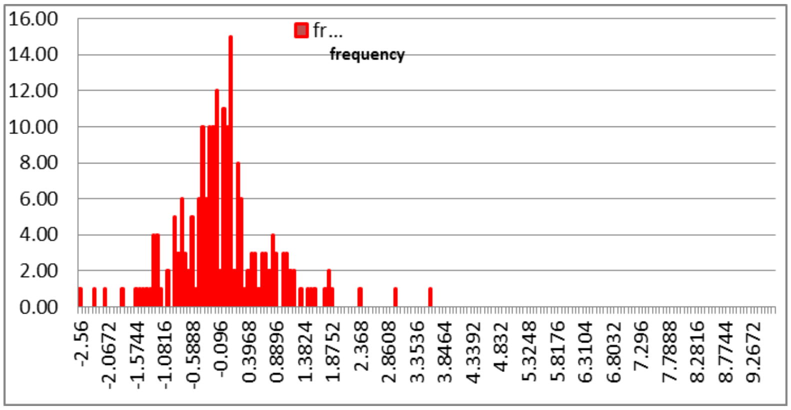

Diagram 3. Histogram diagram of return of future gold coin prices

In this diagram, we first determine the position of the alpha percentile and then determine the value at risk at the alpha confidence level. Estimates of the value of risk at the 95% and 99% confidence levels using the histogram diagram are as follows.

Table 1: Estimating value at risk using historical simulation method

%95 VaR	%99 VaR
-1,31	-2,31

Estimating value at risk with the Bootstrap historical simulation method: In bootstrap simulation, we start with a basic sample in amount of n. Then we extract a random sample with the same size from this original sample and repeat this to a very large number, for example, 1000 times. Each new sample presents a new VaR estimate, and we can consider the average estimates of new samples as the best estimate of VaR. In this research, bootstrap simulation is repeated 1000 times, and each 1000 times sampling for a thousand samples is computed a value at risk, and then we consider the average of all value at risk using the Bootstrap simulation method. Diagram (4) shows the value at risk at a 95% confidence interval in number of 1 to 1,000 times simulations. This diagram shows that the simulated value at risk is initially unstable, but it converges with increasing number of simulations to its correct value, ie, -1.318.

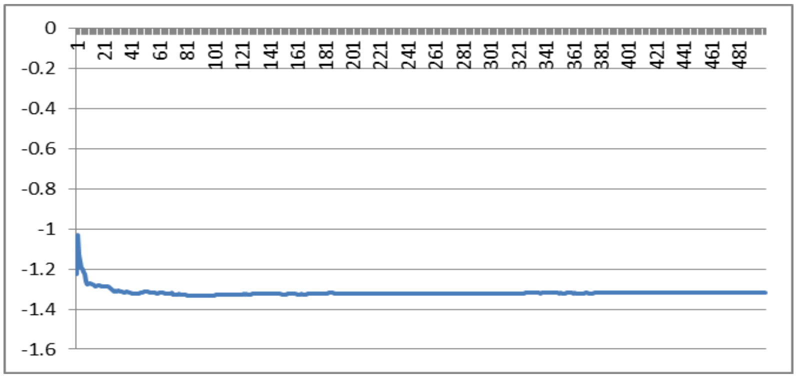

Diagram 4: Estimating value at risk at 95% confidence level with Bootstrap historical simulation method

Also, diagram (5) shows the value at risk at a confidence level of 99% with a simulation of 1 to 1,000 times. This diagram shows that the simulated value at risk is initially unstable, but it converges by increasing number of simulations to its correct value, ie, -2.3.

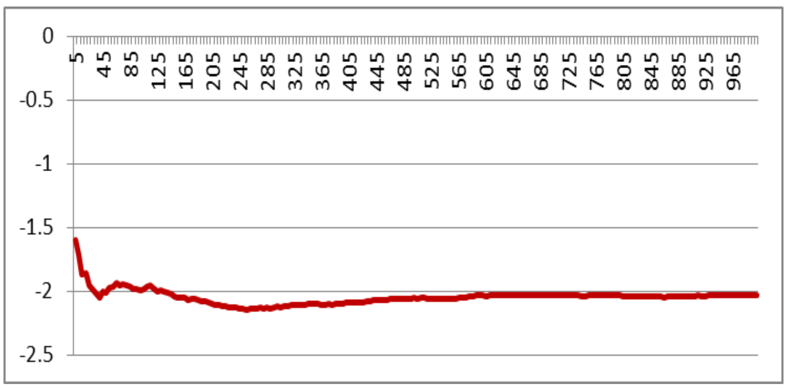

Diagram 5: Estimating value at risk at 99% confidence level with Bootstrap historical simulation method

Estimate of value at risk with Monte Carlo simulation:

Diagram 6 shows the simulation results of the estimated value at risk at 95% confidence level using the Monte Carlo simulation method with an increase in the number of repetition of simulations in amount of 5000 times. This diagram shows that the simulated value at risk is initially unstable, but it converges by increasing the number of simulation to its correct value i.e -1.44.

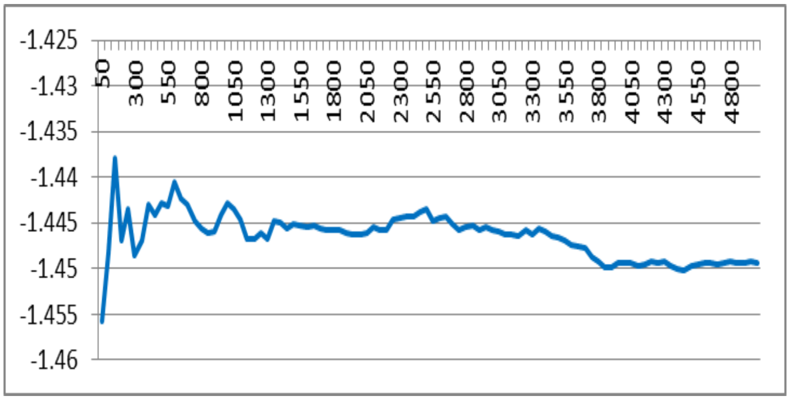

Diagram 6: Estimating value at risk by Monte Carlo simulation method at 95% confidence level

Also, the diagram (7) shows the simulation results of the estimating value at risk at a 99% confidence level using the Monte Carlo simulation method with an increase in the number of replication of simulation in amount of 5000 times. This diagram shows that the simulated value at risk is initially unstable, but it converges with increasing number of replication of simulations to its correct value, ie, -2.1.

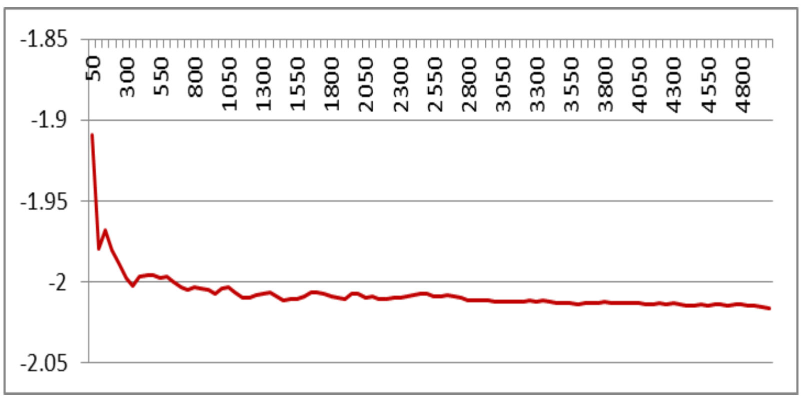

Diagram 7: Estimation of value at risk at a 99% confidence level by Monte Carlo simulation method

Kupiec test results

Using the Kupiec test, the efficiency of each of the models estimating value at risk is compared with each other and the most efficient method for estimating the value at risk is specified for the future gold coin contracts. In this test, if the probability ratio of the Kupiec is larger than the chi-square distribution with a degree of freedom and an error level α , then the null hypothesis is rejected and it cannot be accepted that the value at risk model is correctly estimated. If the null hypothesis is rejected $\widehat{\alpha} > \alpha$, then the value-at-risk model is estimated upstream and, if $\widehat{\alpha} < \alpha$, the value at risk model is estimated downstream. Table 2 shows the degree of Kupiec statistics on the risk models of simulation, historical simulation, historical simulation of Bootstrap and Monte Carlo simulation at 95% and 99% confidence levels.

Table 2. Results of investigating Kupiec test

Model Estimation VaR	statistics for Kupiec test %95 VaR	statistics for Kupiec test %99 VaR	Critical value of the Kupiec test on the %95 level	Critical value of the Kupiec test on the %99 level	Rusilt the Kupiec test
matrix risk	0/1243	1/6064	3/8414	6/6349	Not rejecting the zero hypothesis
historical simulation method	0/00106	0/4584	3/8414	6/6349	Not rejecting the zero hypothesis
historical simulation method **bootstrap**	0/00106	0/4584	3/8414	6/6349	Not rejecting the zero hypothesis
Monte Carlo simulation	0/08871	0/4584	3/8414	6/6349	Not rejecting the zero hypothesis

The Kupiec test results show that the null hypothesis cannot be rejected for all estimated models at 95% and 99% confidence levels, and all estimate methods of value at risk are reliable. The table also shows the failure ratio for each of the VaR estimates at 95% and 99% confidence levels. The less the failure rate, the more efficient the model will be.

Table 3. Results of failure ratio to investigate the efficiency of VaR estimation methods

Model Estimation VaR	Estimated failure ratio VaR 95%	Estimated failure ratio VaR 99%
matrix risk	0.055555556	0.02020202
historical simulation method	0.050505051	0.015151515
historical simulation method **bootstrap**	0.050505051	0.015151515
Monte Carlo simulation	0.045454545	0.015151515

In this table, the failure ratio in the VaR estimation at 95% confidence level for the Monte Carlo simulation model is lower than that other models; therefore, the Monte Carlo simulation model for VaR estimation at 95% is more efficient than other methods. For VaR estimate, at 99% confidence level, historical simulation models, bootstrap simulation, and Monte Carlo simulation are more efficient.

CONCLUSION

The purpose of this study is to estimate the value at risk of the future gold coin contract. For this purpose, the estimation of the value at risk was investigated using risk assessment, historical simulation, historical simulation of Bootstrap and Monte Carlo simulation. Then, using the Kupiec test, the efficiency of each model is compared with each other and the most efficient method for estimating the value at risk is specified for the future gold coin contract. The results are as follows:

- The results of VaR estimate at 95% confidence level show that Monte Carlo simulation method has the lowest VaR estimate compared to other methods.

- The results of VaR estimate at a 99% confidence level show that the historical simulation method has the lowest VaR estimate compared to other methods.
- Kupiec test results show that all methods for estimating value at risk are reliable.
- Regarding the failure ratio for VaR estimates, the Monte Carlo simulation model for VaR estimation ate 95% confidance level is more efficient than other methods. For VaR estimate, at 99% confidence level, historical simulation models, bootstrap simulation, and Monte Carlo simulation are more efficient.

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