Optimization
Iranian Journal of Optimization
Volume 14, Issue 3, 2022, 157-171
Research Paper

Online version is available on: www.ijo.rasht.iau.ir

Islamic Azad University
Rasht Branch
ISSN: 2588-5723
E-ISSN:2008-5427

Dynamic GAS Based Modeling for Predicting and Assessing the Memory Free Value at Risk of Tehran Stock Exchange Total Index

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Revise Date 25 June 2022
Accept Date: 16 August 2022

Keywords:
Capital Market
Mathematical Modeling for Finance
GAS model
Gold
Value at Risk

Abstract

The first step in risk management in the field of investment is to calculate the variable that explains the risk accurately. One of the most widely used criteria for calculating risk is the value at risk, which has been the focus of financial researchers for the past three decades. Traditional parametric models for calculating value at risk have assumptions that do not correspond to the current complexity and reality of financial markets. The aim of the present study is dynamic modeling and variable time by applying a technique called Generalized Autoregressive Score (GAS) to estimate the value at risk in the Tehran exchange total index by using daily data from 2010 to 2020 and assuming the distribution of t-student. Its results are compared with the results of known AR and GARCH models. The results showed that for TSE, only two models, GAS and GARCH, are suitable for estimating value at risk and the GAS model is preferable. Besides that, the new model VaR based GAS technique is memory free and thus is more reliable than GARCH and AR in financial turmoils.

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INTRODUCTION

The real world of human beings is full of uncertainty, and in many cases, future events are unpredictable. Only past events can be said for sure, but the investment is only relevant to the future (Krezolek, 2021). Given the history of the financial crisis and unimaginable fluctuations in global financial markets, including the variable interest rate system of 1971, the oil price shock of 1973, and the unprecedented collapse of US capital markets on the so-called Black Monday in 1987. , 1989 Japan Capital Market Crisis, 1997 Southeast Asian Financial Crisis, September 2001 Wall Street Price Fall, 2007-2008 Catastrophic Financial Market Crisis, and Early 2020 All financial markets, including the sudden collapse of the corona, stocks, commodities, and cryptocurrencies, were evidence of the need for risk management and the attention of institutional and real investors (Nasir & Du, 2018; Ahelegbey & Giudici 2018; Sheikh et al., 2020, Tronzano, 2020 and Yoo et al., 2021). Therefore, the risk is fundamentally an essential criterion for both day traders and investors of feasible assets. Therefore, risk identification, measurement, and management are the primary concerns of financial market participants and researchers in this area worldwide, demonstrating their importance, especially over the last three decades. The complexity of financial markets, such as globalization, financial innovation, technological advances, new regulations, deregulation, and increased global penetration of financial markets due to the expansion of communication areas, is becoming a new financial model for providing more efficient solutions. Leads to risk detection, measurement, and management (Zomordian et al., 2015; Ahmadi et al., 2007). A reasonable estimate of price fluctuations in financial assets over the investment period is a starting point and an important point for risk management and management (Taeibsany and Ashtiani, 2018). Value at risk (VaR) is one of the most important criteria for measuring risk, especially in the case of price fluctuations; it only represents the maximum loss amount for a particular period and level in a single number (Krezolek, 2021). In many financial texts, how to calculate value at risk, such as a specific distribution by distribution of the probability of asset return, establishing a linear relationship between market risk factors and asset prices, or a secondary function of investor attractiveness. In the real world, the complexity of financial markets, the external environment, and economic factors violate these assumptions, and it is assumed that the models derived from them are not sufficiently efficient (Spadarofa et al., 2018). Accordingly, modeling of return on total assets forecasts to calculate new value at risk (VaR) criteria has been ignored in this area, which does not reduce its accuracy in the market turmoil event, in addition to the drawbacks of traditional models' lack. On the other hand, the development of a country's capital markets is closely linked to that country's economic growth, so that prediction is doubly important for both investors and political decision makers (Takaishi, 2018; Ardia et al., 2019; Zivkov et al., 2021; Kwon, 2021 and Qarni & Gulzar, 2021). This study dynamically models value-at-risk for Tehran exchange total index to address the challenges of measuring value-at-risk criteria and close the theoretical gap,. To do this, a time series statistical method and a method called Generalized Autoregressive Score (GAS) were also compared with the results of this new model using the traditional GARCH and AR models. In what follows, the study's theoretical basis is first expressed, and then the background of the relevant empirical study is examined. Subsequently, research hypotheses are presented, and methods, including modeling with GAS technology, are explained. The next step is to analyze the hypothesis test results and make practical research recommendations based on the summary and conclusions.

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Theoretically, financial risk is generally defined as the degree of uncertainty about the future return on assets and other financial instruments (Manganelli & Engle, 2001). Over the last 50 years, this has increased investor awareness of risk management and resulted in significant losses considered unlikely to occur. Risk is generally a qualitative variable, so risk variables need to be quantified to manage risk (Basak et al., 2019). As the knowledge of financial engineering evolved, the variance of risk measurement measurements, including the measurement of the negative risk dimension, was replaced by more complex criteria (Burdekin et al., 2021). One of the most widely used measures of unfavorable risk measurement is the value at risk standard, first proposed by Baumol in 1963 as a new standard for quantifying risk (Alexander & Baptistab, 2002). Value at risk is a measure of risk primarily due to market risk and has been regarded as an important measure of risk since it was introduced by JP Morgan in 1994. The maximum loss expected with a particular probability over a particular time period defines a value at risk indicator.

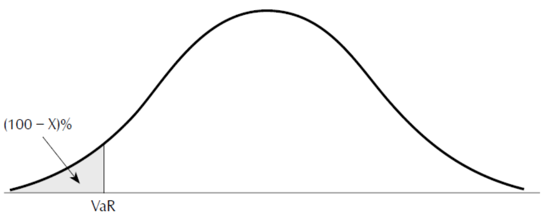

Fig.1. Showing the value at risk assuming a normal society

More than 20 years have passed since the Risk Value Scale was introduced, and it is now recognized by well-known financial institutions and organizations such as the New York Stock Exchange, the US Securities, and Exchange Commission (SEC), and the Basel Commission. Basel Committee on Banking Supervision (BCBS), Bank for International Settlements, and other central banks, central insurers, and major stock exchange regulators use the world as a standard for integrated risk management. Over the last three decades, researchers have proposed different risk modeling and measurement methods. Its application considers different assumptions, which leads to different results. (Cheung et al., 2020). The variance-covariance method is one of the first methods to calculate the value at risk index. This distribution is explained by only two parameters, and considering the central limit theorem, the distribution of financial asset returns is assumed to be normal. Therefore, assuming normal returns, the value at risk is calculated as follows:

$$VaR_t = -P_{t-1} \times (\mu_t - \sigma_t z_\alpha) \qquad (1)$$

This value base is the risk for the next period, P_{t-1} is the current stock price, $\mu_t$is the average return for the period σ_t is the standard deviation of the return for period t, and $z_\alpha$is the standard normal variable value in α Error level. (Glosten et al., 1993). One of the unique characteristics of parametric methods is the ability to estimate value at risk for a particular time period at any confidence level. For a normal distribution, the value of the parameter z_α is given as the desired confidence level and considers the holding period of the financial asset at μ_t and σ_t. If $\mu_t$and σ_t are the mean and standard deviation of the returns for a particular period, respectively, then the mean and standard deviation of the returns for the h period for that period is estimated using the following equation:

$$\mu(h) = h\mu \qquad (2)$$

$$\sigma^2(h) = h\sigma^2 \Rightarrow \sigma(h) = \sqrt{h}\sigma \qquad (3)$$

If these relationships are replaced by the value-at-risk equation, the formula VaR over h over time and at the α-error level is as follows:

$$VaR_{ht} = -P_{t-1}\left(h\mu_t - \sqrt{h}\sigma_t z_\alpha\right) \qquad (4)$$

This method is based on the assumption that the distribution of returns is normal, but in reality, the distribution of returns on financial assets is unusual and wide. Over time, a historical simulation approach was introduced to solve the problem of the variance-covariance method. This assumes that the history needs to be repeated for future estimates. This is financial data. There were defects that were not considered (Mehrani et al., 2021; Fung et al., 2021). This is not a good solution, as earnings fluctuations over time are interdependent and unconditional distributions are related to investment returns (Shahzad et al., 2018). It is needed to consider two key components, including return and volatility forecasts to provide risk modeling. Contrast these two components to complete the overall mystery of risk modeling and open up the possibility of risk quantification. This is because these two components provide a diagram of the probability distribution of asset returns.

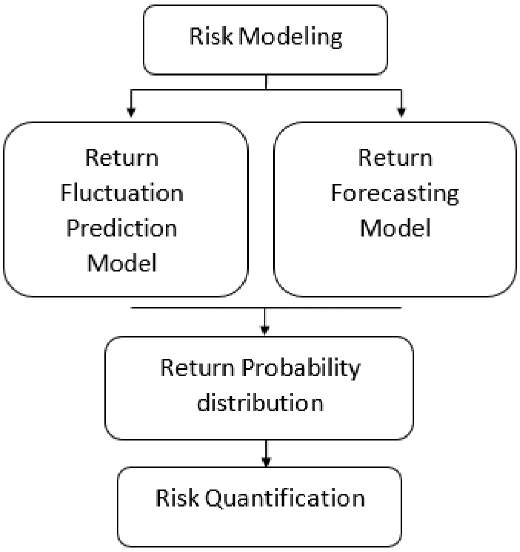

Fig. 2. Two-part flowcharting of risk modeling

The GAS method and its model family have excellent theoretical skills in predicting the conditional distribution of return on assets, making it a potential method for predicting the distribution of return on financial assets dynamically and temporally. You can use that advantage to measure, in particular, a risk index for estimating the value at risk. In addition, unlike traditional models, the GAS method can respond to economic shocks and price fluctuations has no unrealistic limitations, and has variable time characteristics that lead to a description of the model. The predictor becomes dynamic. Risk application and modeling with methods that have the above characteristics and dynamically predict the distribution of returns have been ignored. This paper introduces the GAS method used to measure value at risk to fill the theoretical gap. In the following, this method was used to predict the Tehran exchange total index value at risk and compare the results with the non-linear AR and GARCH methods.

Review of the research background

Over the last few decades, many theoretical and experimental studies have devoted themselves to formulating suitable vibration models. By Mandelbrot's famous study of cotton price fluctuations in 1963, economists now know that the standard geometric extrinsic movements proposed by Bachelier in 1900 cannot explain these empirical facts. Jorion (2000) concluded that as the number of assets in a portfolio increases, the linearly estimated value-at-risk error becomes very high, leading to many researchers estimating value-at-risk. They used a non-linear model. In 2002, Bronz used the GARCH model to estimate the value at risk of US stock market data for 70 years and concluded that the model produced better results. Then, in 2003, Engelbrecht used various methods such as the variance-covariance model, historical simulation, and Monte Carlo simulation to calculate risk values for different portfolios, and the results of this researcher turned risk. Showed that you are exposed. In 2003, Mittnik & Paolella, and 2004, Giot & Laurent concluded that the unconditional density distribution function of returns around an average financial asset is longer than the normal distribution and has a broader sequence. Therefore, researchers conclude that the GARCH family model, which uses the distribution function of the student theorem, can better assess the value at risk of financial assets. Palaro & Hotta (2006) used univariate and bivariate GARCH in EWMA and concluded that the GARCH family estimates were superior to other models in estimating risk values. In 2007, Lima & N´eri discovered that the GARCH model could better estimate the risk value of the Sao Paulo Capital Markets Index than ARCH, using the ARCH and GARCH models. It is a basket of commodities. Before 2012, much research was done on the correlation between gold and other assets and the factors influencing the gold price. Zijing & Zhang (2016) use models from the GARCH family to estimate fluctuations and global gold ounce risk values, which are better estimates than traditional models for estimating exposure values. I concluded that I have the ability. You are at risk of gold. In two studies by Chen & Qu and Wang et al. in 2019, it was concluded that a non-linear model that explains the non-uniformity of the dispersion affects the profitability of precious metals such as gold, silver, and platinum (Burdekin et al., 2021) Using the GARCH family model in a study to estimate risk levels, they found that DCCGRACH performed better. In a 2006 domestic survey, Ahmadi and Shahriyar used parametric techniques such as simple variance-covariance, autoregressive variance, and GARCH model to calculate the risk value of a portfolio of four equities and use a non-linear model when estimating the value at risk. Several studies have been conducted to estimate the value of gold exposure, which are listed below. In 2014, Fallahpour and Ahmadi combined the roles of GARCH to tackle market risk. Their results display that these models are more accurate than traditional models. In 2020, a study using the FIAPARCHUNG model, Das Fakhfekh et al. are the best models for estimating the risk value of coin futures contracts that worked well when fluctuating. The estimated student distribution of gold risk works better than the normal distribution. In addition, of the GARCH models, the PGARCH model has the highest global gold ounce risk estimates and is superior to the linear model. Also, according to the existence and investigation of crises in most countries over the last few decades, many failures in financial markets can be traced back to the same modern theories and traditional assumptions in markets and hypotheses (Samadi et al., 2016).

Therefore, the main problem is the lack of a dynamic model with acceptable accuracy. This allows you to predict the distribution of financial asset returns and more accurately model your model for estimation without compromising accuracy in turbulent market conditions. Value at risk. It has been ignored. Recently, Basak et al. (2019), in addition to the research by Creal et al. (2013) modeled the average and the conditional variance of financial asset returns. SD models are called Generalized Autoregressive Scores or Dynamic Conditional Score models. These models are a common framework for modeling the temporal variation of parametric models. The GAS method and its model family have excellent theoretical skills in predicting the conditional distribution of asset returns, making it a potential method for predicting and further estimating the distribution of financial asset returns. The value at risk of each asset is dynamic and changes over time. In this regard, in addition to assessing the GAS family's ability and modeling of model models in predicting the distribution of financial asset returns, the risk values of investments, and the Tehran exchange total index are estimated. They analyzed the experimental distribution of revenues for these assets and dynamically investigated the validity of the predicted distribution of revenues for these assets based on modeling conditional distribution forecasts for revenues for these assets.

RESEARCH HYPOTHESES

According to the characteristics and theoretical capabilities of the GAS model in the review of the research background section and in line with the direction of measuring its efficiency with traditional models, the following hypotheses are proposed:

Hypothesis 1: Generalized Autoregressive Score (GAS) model can estimate the value at risk for the Tehran exchange total index at a 95% confidence level.

Hypothesis 2: Generalized Autoregressive Score (GAS) model, in terms of estimated loss, has a better model to measure the value at risk for Tehran exchange total index than traditional AR and GARCH methods.

Hypothesis 3: The duration of time between VaR based Generalized Autoregressive Score (GAS) model violations (no-hits) are independent and not cluster.

DQ, CC and UC tests were used to answer the first hypothesis. QL ratio tests were used to answer the second hypothesis and likelihood ratio test statistic were used to answer the third hypothesis. All the mentioned tests are explained in Inferential Statistics section.

RESEARCH METHODOLOGY

This study is practical because it was created to model new risk metrics for managing investment risk. This research approach is based on the daily past returns of the Tehran exchange total index from 2010 to 2020 (10 years) and contains 2,753 price data elements. In this regard, the prices of financial assets selected from credible sources are first extracted from the price data across the Rahavardovin software version 3 Tehran exchange total index, and then these returns are obtained. Will be. Assets are extracted by $x_t = Ln\left(\frac{P_t}{P_{t-1}}\right)$. in the first step, and the time series properties of the returns of the two assets are examined and evaluated. The next research step is to conditionally return on investment in the training group by splitting the sample into two training groups and a test group using the GAS method to eliminate the weaknesses of traditional models in new modeling.

Based on Pedro et al. (2020) results based on Krill et al. (2013) study, GAS is defined by defining $Y_t \in \mathcal{R}^N$as a next random N vector at time t with the following conditional distribution:

$$\mathrm{Y_t|Y_{1;t-1} \sim p(Y_t;\theta_t)} \qquad (5)$$

Where $Y_{1;t-1} \equiv (Y'_1،\ldots،Y'_{t-1})$holds the previous values of Y_t until t-1 and $\theta_t \subseteq \mathcal{R}^J$is the vector of time-varying parameters which fully exemplifies p (.) It is conditional on $Y_{1;t-1}$. The time variable $\theta_t$vector and the main feature of the GAS model are based on the above conditional distribution score, which involves the following autoregressive component:

$$\mathrm{\theta_{t+1} \equiv \alpha + \phi \varrho_t + \varphi \theta_t} \qquad (6)$$

Where α, ϕ, and φ are matrices of coefficients which control $\theta_t$transformations and require to be estimated from the data by the maximum likelihood method. The vector which corresponds to the conditional distribution score is shown by $\varrho_t$and is as follows:

$$\varrho_t \equiv \vartheta_t(\theta_t)\nabla_t(Y_t،\theta_t) \qquad (7)$$

Where $\vartheta_t = J * J$ is a definite positive scaling matrix known at time t and $\nabla_t(Y_t،\theta_t) \equiv \frac{\partial\, ln\, p(Y_t،\theta_t)}{\partial\theta_t}$ distribution points is a condition computed in θ_t. Regarding the time-varying mechanism regarded for the distribution parameters, the conditional distribution of a GAS model can continuously change based on the dynamic model's intended data.

The vector of hyperparameters Φ with maximum likelihood is in the following format.

$$\widehat{\Phi_t} = \arg\max_{\Phi} \sum_{t=1}^{N} \ln p(Y_t،\theta_t) \qquad (8)$$

The logarithm-orthogonality function of the GAS model is easy to estimate and evaluate. Since the form model is closed, it is enough to consider $ln\, p(Y_t،\theta_t)$for each Φ value. However, evaluating an analytical solution to achieve maximum work accuracy can be difficult and sometimes impossible. Therefore, numerical solutions using comprehensive optimization techniques such as L-BFGS are often used. The details of the forecasting process and the out-of-sample confidence intervals for variable time parameters are discussed to predict and simulate future scenarios. This works as follows:

1. Concerning ($\widehat{\Phi_t}$ and the filtered state θ_{t+1}, S is the value of $Y^1_{t+1}،\ldots،Y^S_{t+1}$of the conditional density estimated at t + 1 is produced: $Y_{t+1} \sim p(Y_{t+1};\widehat{\theta_{t+1}})$for s=1،…،S

2. Using $Y^1_{t+1}،\ldots،Y^S_{t+1}$and the component $\theta_{t+1} \equiv \alpha + \phi\varrho_t + \varphi\theta_t$filtered values $\widehat{\theta^1_{t+2}}،\ldots،\widehat{\theta^S_{t+2}}$are provided.

3. By repeating steps 1 and 2 H times for H step forward, new values of Y and θ are generated for each scenario s.

When the process is complete, S scenario for observations within the forecast horizon, ،Y^S_{t+k} for k=1،…،H and s=1،…،S in R simulation software environment be. The flowchart in figure 3 shows the mathematical modeling of the return distribution forecast using the GAS method to estimate the value at risk.

In the fourth step, the distribution parameters and properties such as the probability of time variation are tested by examining the estimates. The fifth step then predicts the conditional distribution of return on investment progress based on an estimation model and evaluates the forecast's accuracy using appropriate statistical tests and training group data. Also, in the fifth stage, the results of the proposed method are compared with conventional methods such as GARCH and AR models, and finally, as much as possible to estimate the risk value of the Tehran exchange total index.

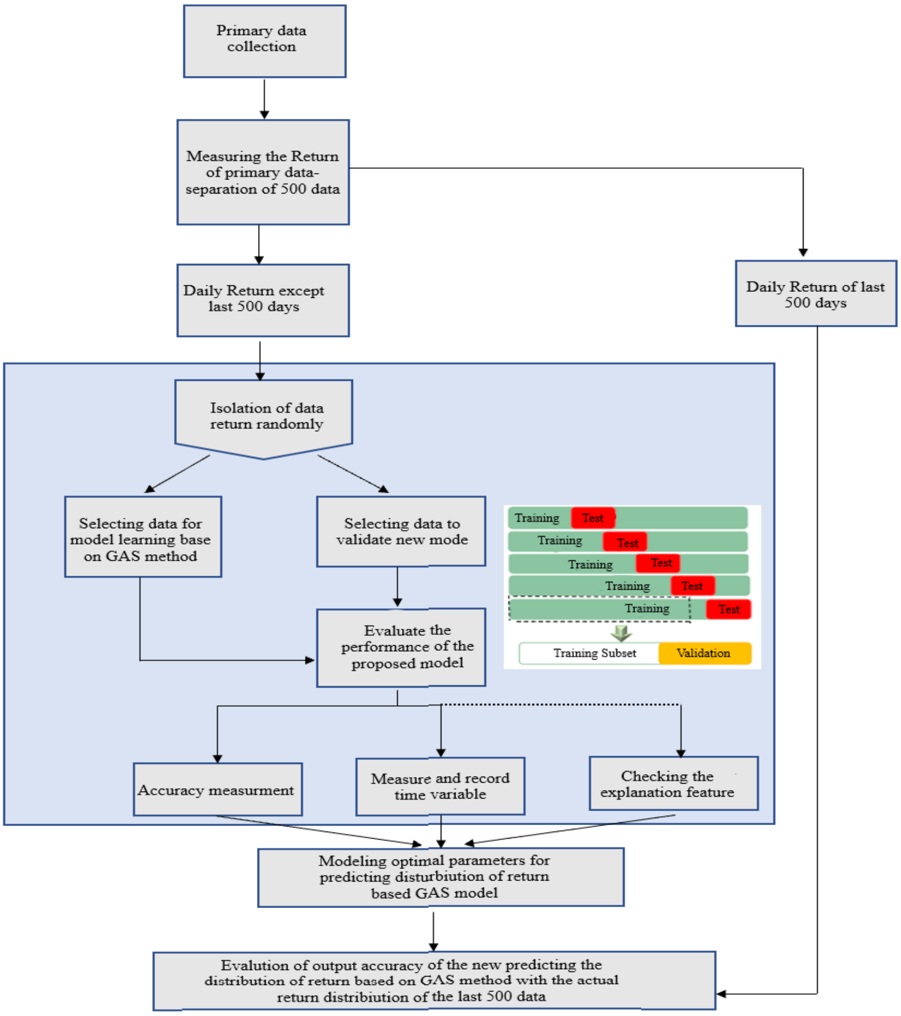

Fig. 3. Flowchart of modeling the forecast distribution of VaR estimation efficiency by the GAS method

RESEARCH FINDINGS

Findings of the research are presented in two sections: 1-Descriptive statistics and 2- Inferential statistics:

Descriptive statistics

Figure number 4 shows the development of the logarithm of the Tehran exchange total index and their logarithmic returns over the sample period. To better understand the time series of asset returns investigated, descriptive statistics are shown in Table 1.

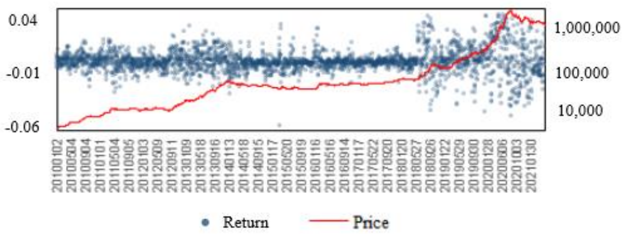

Fig. 4. The Logarithm of the total stock price index and its return

It also provides descriptive statistics in Table number 1 for the Tehran exchange total index and its daily returns, including mean, mean, maximum, minimum, standard deviation, skewness, elongation, observations, and Jark-Bra test results. The description of the normal distribution table of investment return is as follows.

Table 1: Descriptive statistics of data

Total stock index returns	Statistics
0.0017	Mean
0.0006	Median
0.0438	Maximum
-0.0567	Minimum
0.0106	Standard of deviation
0.1899	Skewness
3.3218	Kurtosis
1282 (0.000)	Jark-Bra test
	Test) probability (value
2753	Total observations

References: Study Findings

The main central indicator is the mean, a good indicator of the distribution's center of gravity and the data's centrality. The average return of the Tehran exchange total index is 0.17%. On the other hand, the standard deviation as the main variance index in the descriptive statistics of the entire stock index is 1.06%. Considering that the significance level of the Jark-Bra test variable for the Tehran exchange total index is less than 5%, it indicates that the returns of these assets are abnormal. Therefore, the density distribution maps in Figs 5 and 6 and the returns on the two assets are plotted for the ease of investigation.

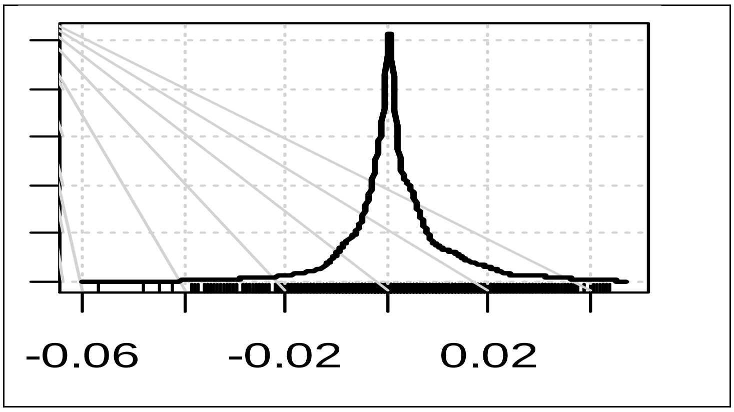

Fig.5. Density distribution of Tehran exchange total index

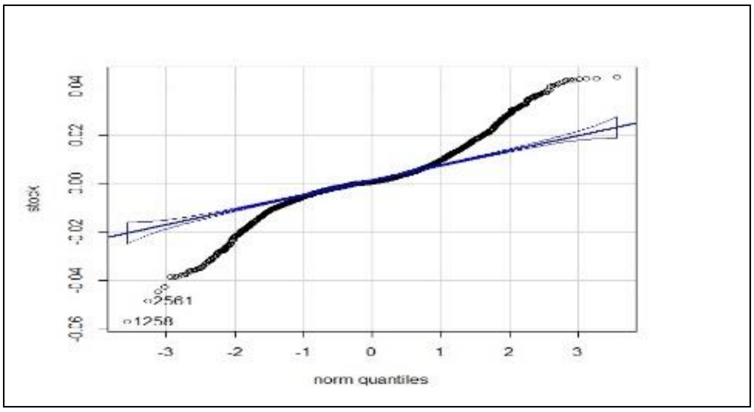

Fig. 6. Chart of multiple returns of Tehran exchange total index

Reference: Study Findings

As you can see from the graph above contain figs 5 and 6, there is no normal return distribution. Therefore, the conditional student model is a better option for modeling the return on the index to estimate the value at risk.

Inferential Statistics

Since the anonymity of time series data invalidates statistical conclusions based on standard asymptotic theory, it is necessary to first examine the significance level of the variable using the unit root test before analyzing the data for modeling. Table 2 shows the results of the ADF unit root test for the two return variables.

Table 2: Generalized Dickey Fuller unit root test

Total stock index returns	Single root test
14	Optimal interrupt (Akaike criterion)
-10.0	Test statistics
0.000	Probability value

Reference: Study Findings

Given that the ADF test in Table 2 has a single route in the test's zero assumption, efficiency variables at the 95% confidence level do not have a single route, so a continuous process and modeling steps can be performed. A procedure called Back-Test is used to evaluate the reliability of VaR predictions and the suitability of statistical models and compare their performance. The test aims to confirm the prediction's accuracy by separating the evaluation window from the evaluation period. After the VaR time series has been calculated from the forecast of the conditional distribution of return on investment, you can retest. This process usually begins by checking correct coverage at the Left–tail of the conditional and unconditional distribution of returns. To this end, an unconditional Correct Coverage (UC) test was first proposed by Kupiec (1995), and a Conditional Correct Coverage (CC) was proposed by Christoffersen (1998). The main difference between the two methods lies in the distribution they take into account. The correct left UC covers the efficiency margin distribution and the CC operates with conditional density. In other words, UC was achieved by multiplying 0.05 by 500, with the percentage of expected violations at the confidence level (5%) selected during the forecast period (500 periods) being 25 times higher in this study. Detected the number of violations. With data. Will be taken into account. One of the most recently introduced tests, especially for dynamic models, is Engle and Manganelli Test (2001), known as the Dynamic quantile test (DQ), which tests UC and CC together. Gradually, table 3 shows the results of the UC, CC, and DQ tests on the accuracy of estimating the value at risk for the total stock index.

Therefore, DQ, CC and UC tests have been used to answer the first hypothesis.

Table 3: Post-test tests of VaR forecast of Tehran exchange total index

Number of violation	DQ Test	CC Test	UC Test	Model
24	10.07	0.61	0.04	GAS
	0.18	0.73	0.83	Probability value
29	10.21	3.53	0.64	GARCH
	0.17	0.17	0.42	Probability value
87	218.3	116	101.5	AR
	0.00	0.00	0.00	Probability value

Reference: Study Findings

As seen across the Tehran exchange total index, the GAS and GARCH models work well with a confidence level of 95, as tested. Figs 7-6 show the predicted risk value for the step forward (black curve) and the realized return for each period (circles). The corresponding observation circle is red if the realized return is lower than the predicted VaR.

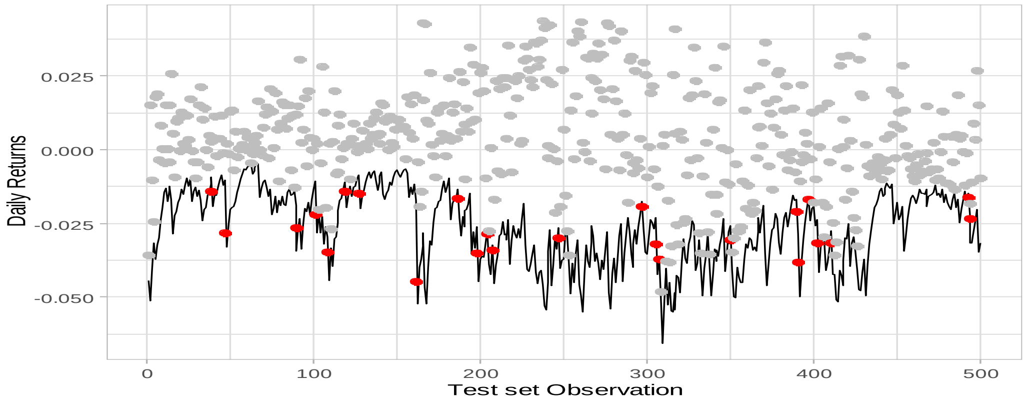

Fig. 7. Value at Risk Prediction GAS Model Return on Tehran exchange total index

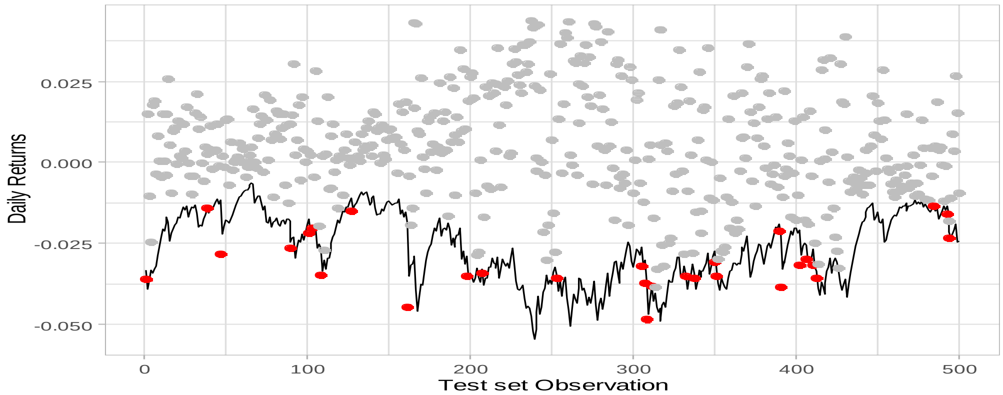

Fig. 8. Value at risk GARCH model predicts the return of Tehran exchange total index

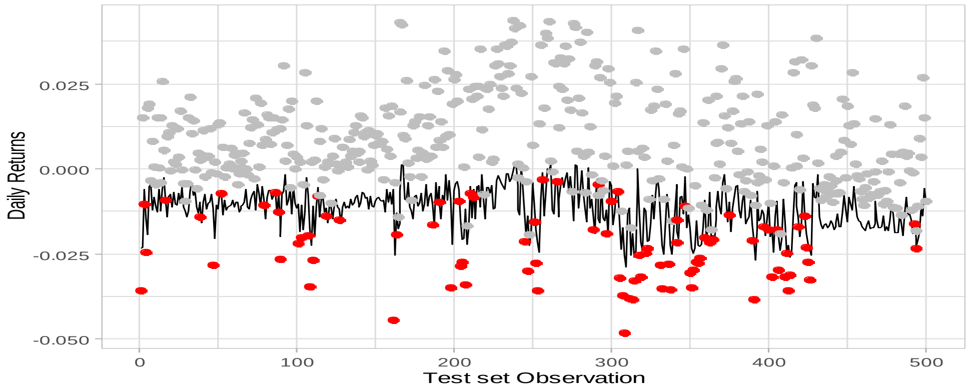

Fig. 9. Value at risk of predicting AR model Return on Tehran exchange total index
Reference: Study Findings

As you can see from the graph above, the GAS model has fewer errors in the total stock index than the two models, AR and GARCH, and you can see the results in Table 3. Both the GAS and GARCH models have successfully tested the index back test. The duration of time between VaR violations (no-hits) should ideally be independent and not cluster and should have no memory. Following Christoffersen and Pelletier's (2004) study, since the only continuous distribution which is memory free is exponential, the test can be conducted on any distribution which embeds the exponential as a restricted case, and a likelihood ratio test is then conducted to see whether the restriction holds. Therefore, likelihood ratio test statistic were used to answer the third hypothesis.

Table 4: Var duration test for Tehran exchange total index

Model	Test statistics	Unrestricted Log-Likelihood value	Restricted Log-Likelihood value	Likelihood Ratio Test Statistic	Result
GAS	0.95	-93.7	-93.8	0.78	Memory free duration
GARCH	0.95	-108.1	-108.7	0.29	Memory free duration
ARIMA	0.95	-234.8	-234.8	0.02	memory duration

As shown in Table 4, GAS and GARCH model memory free duration; thus they are reliable Var model. According to the table above, the likelihood Ratio Test Statistic of GAS mode is bigger than the GARCH model, so in more reliable in conditions of capital market turmoil. In cases where two models are reliable, researchers face the problem of choosing a more favorable model. We have to use the comparison method to choose a better model. This is done by defining a loss function in this situation. The most common is the Quantile Loss Rate (QL) (Koenker and Bassett, 1978; Beik khormizi et al., 2020). You can identify preferred models by comparing the average loss rates of different models by calculating the loss rate for each forecast period and then calculating the average for the entire forecast period for each model. To this end, the percentile loss rate is defined as the result of dividing the average percentile loss of the first model by the second model. If this ratio is less than 1, the first model takes precedence over the second model (Gonzalez Rivera, 2004). Therefore, Table 4 shows the QL ratios to compare the model's performance in predicting the VaR of the Tehran exchange total index. Therefore, QL ratio tests were used to answer the second hypothesis.

Table 5: QL Ratio Comparison of VaR Predictive Performance of Models

Result Model with) (better performance	QL ratio	Null hypothesis	Asset
GAS	0.989	Same performance of GAS and GARCH models	Total stock index
GAS	0.771	Same performance of GAS and AR models	
GARCH	0.779	Same performance of GARCH and AR models	

As you can see, the GAS model is the most preferred model for predicting the VaR Tehran exchange total index. Therefore, the tests generally show that the GAS model performs better predicting the Tehran exchange total index VaR than the two models, AR and GARCH.

CONCLUSION AND DISCUSION

In this study, using generalized modeling, dynamic and time-varying ones, the Tehran exchange total index from early 2010 to 2020. Estimated the value at risk of daily data. A comparison of a method called Self-Scoring Score (GAS) with known GAS and AR methods. Preliminary results of the data show that there is an anomaly and a broad sequence in the lognormal distribution of the Tehran exchange total index of daily returns, so the Student's distribution test was used. The modeling procedure was performed because there is no single route for the logarithmic return of Tehran exchange total index to test the first hypotheses using the UC, CC, and DQ tests according to Tables 3 the new GAS model estimates risk values for Tehran exchange total index. For predicting Tehran exchange total VaR it was used non-linear AR and GARCH models compatible with Anatolyev and Gospodinov (2010), Beauvoir and Rafk (2016), Chu et al. (2017), Fong et al. (2021), Big Khormizi and Rafie (2020), and Keshavarz Haddad and Zabol (2020) Studies. Percentile loss tests are used to determine the model's priority in estimating risk values according to the second hypothesis and the results for the best risk value of Tehran exchange total index of the GAS model. Finally, considering the estimated number of risky low-value violations, the Generalized Autoregressive Score (GAS) model has been approved as the most appropriate and efficient for risk-averse investors in the capital market. As a result, GAS models have a stronger stochastic structure that is more efficient in calculating turbulence and risk than traditional linear models and GARCH modeling classes. Besides that, according to the third hypothesis, the new model VaR based GAS technique is memory free and thus is more reliable than GARCH and AR in financial turmoil. Therefore, real investors and financial institutions in Iran are suggested to use the GAS model to estimate VaR for risk management. It is suggested that by using the new method of measuring value at risk, policy makers can predict the maximum expected fall during the growth of the market and take the necessary measures before it occurs. In the field of research, it is proposed to use the methods presented in this study to determine the value at risk of other assets such as industries indexes, derivatives such as silver and saffron futures contracts, and investment portfolios, and you need to measure its accuracy.

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