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Research Article

A Practical Risk Analysis of The Brent Oil Prices

Brent Petrol Fiyatları Üzerine Pratik Bir Risk Analizi

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Abstract

This research investigates three approaches to determine the best model for identifying risk in Brent oil prices: Value at Risk, Monte Carlo Simulations, and Conditional Value At Risk (CVaR).

The study also aims to contribute to the literature by examining whether it is possible to measure risk in advance for Brent oil prices and compares the performance of various risk measurement models to determine the best-performing method in measuring risk.

Our findings show that the VaR model underestimated risk at the 95% confidence level. This may be due to the non-normal distribution of returns. Our results on conditional value at risk (CVaR) indicate that CVaR produced superior results compared to VaR in cases where the distribution of returns was highly skewed or had fat tails. This is because the expected shortfall measure takes into account expected loss beyond the VaR threshold.

Keywords*: VaR, Monte Carlo Simulation, CVAR, Expected Shortfall, Risk Management, Asset Management.*

Jel Codes*: G11, G17, G24, G41*

Öz

Bu çalışma, Brent petrol fiyatlarındaki riski ölçmek için en iyi modeli belirlemek amacı ile üç yaklaşımı incelemektedir: Riske Maruz Değer, Monte Carlo Simülasyonları ve Koşullu Riske Maruz Değer (CVaR).

Çalışma ayrıca Brent petrol fiyatları için riskin önceden ölçülmesinin mümkün olup olmadığını inceleyerek literatüre katkıda bulunmayı amaçlamakta ve risk ölçümünde en iyi performans gösteren yöntemi belirlemek için çeşitli risk ölçüm modellerinin performansını karşılaştırmaktadır.

Bulgularımız VaR modelinin %95 güven düzeyinde riski olduğundan daha düşük tahmin ettiğini göstermektedir. Bu durum, getirilerin normal olmayan dağılımından kaynaklanıyor olabilir. Koşullu riske maruz değer (CVaR) ile ilgili elde ettiğimiz sonuçlar, getiri dağılımının yüksek oranda çarpık olduğu veya kalın kuyruklu (fat tailed) olduğu durumlarda CVaR'ın VaR'a kıyasla daha üstün sonuçlar ürettiğini göstermektedir. Bunun nedeni, Koşullu Riske Maruz Değer (CVAR) ölçütünün VaR eşiğinin ötesinde, beklenen kaybı da dikkate almasından kaynaklanmaktadır.

Anahtar Kelimeler*: Riske Maruz Değer, Monte Carlo Simülasyonları, Koşullu Riske Maruz Değer, Varlık Yönetimi*

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Introduction

The issue of ''risk'' has been a popular subject of study in financial markets over the last decade, due mainly to increased financial volatility from a global perspective. Liquidations of many financial and nonfinancial institutions resulted from the lack of proper risk management tools. Financial intermediaries developed simple and useful tools to measure and control market risks. They were not much of a help as observed in the 2008 subprime mortgage crisis, despite the improvement in methodologies in measuring risk.

Risk management is critical for financial institutions. Analyzing trends in asset prices is critical for portfolio managers, traders, investors, and other market participants. Predicting trend reversals, due to downside risks, is highly critical in managing financial losses.

The Value-at-risk (VaR) and Expected Shortfall are the main models used in finance to measure risk and quantify the potential loss of an asset over a given time frame. VaR is a measure of the maximum loss for an asset or portfolio in a given time with a confidence level, while the CVaR measures the loss in excess of VaR in a period with a given confidence level.

Value at Risk (VaR) is a risk management technique measuring the maximum loss of an asset/portfolio expected over a time period and at a given confidence level. It is commonly used by financial institutions to assess the level of risk in their assets/portfolios. For example, a portfolio may have a one-day VaR amounting to $1 million with a 99% confidence level. That indicates that there is a 1% probability that the portfolio may lose more than $1 million over one day.

Conditional Value at Risk (CVaR) is also a risk measure that represents the expected loss of an asset/portfolio in the worst-case scenario (when the loss is greater than the VaR threshold). Unlike VaR, which only considers the most extreme losses, CVaR takes into account the entire distribution of possible losses. CVAR is also known as the expected shortfall.

Monte Carlo Simulation is a method that is used to estimate VaR/CVAR by generating random samples of possible outcomes for an asset. This method involves running a large number of simulations using different assumption sets about the distribution of returns and other factors that may affect the asset's value. The results of these simulations can then be used to estimate the probability of different levels of loss for the asset.

This paper is structured in three stages;

In the first stage, literature is reviewed and Value at Risk (VaR), Monte Carlo Simulation, and CVaR (Expected Shortfall) methods are reviewed.

In the second stage, we analyze the models and results to detect the applicability of each method, through the analysis of each method.

In the last stage, results of models and backtests are provided, and results are compared to the literature.

1. Literature Review

There has been a significant amount of academic research on these risk measures. Some studies have compared the performance of VaR, CVaR, and Expected Shortfall in various contexts and have found that they can yield different results. Other research has focused on the properties and limitations of these measures, as well as how they can be used and interpreted.

This literature review outlines the main methods for estimating Value at Risk (VaR), Expected Shortfall, and Monte Carlo simulation, and their respective strengths and limitations. The Linear VaR, Historical VaR, and Monte Carlo methods are all approaches to estimating VaR, while the Expected Shortfall method is a specific measure of risk that takes into account losses beyond the VaR threshold.

The VaR may be less effective in cases where the distribution of returns is skewed or has a high probability of extreme events, in which case Expected Shortfall may be a more appropriate measure. Monte Carlo simulation is noted as a popular method for estimating both VaR and Expected Shortfall, but it is important to carefully consider the assumptions used in the simulation as they can affect the results.

There is a wide range of empirical research on the accuracy and effectiveness of different methods for estimating VaR and Expected Shortfall, including Monte Carlo simulation. While these studies have generally found that Monte Carlo simulation can be a useful tool, there is an ongoing debate among researchers about the best approach to take in different circumstances.

As per (Jorion, 2000), Value At Risk estimates the maximum loss that occurred in a specified time horizon and level of confidence. In contrast, Expected Shortfall, Conditional Value-at-Risk (CVaR), also known as the Expected Tail Loss, or tail VaR, measures the probability of a loss exceeding VaR at a given confidence level.

Study	**Methodology**	**Findings**
Jorion (2000)	Monte Carlo simulation	The historical simulation approach provides an accurate estimate of Value-at-Risk.
Acerbi et al. (2001)	Historical and Monte Carlo simulation	The expected shortfall approach provides a more accurate risk measure for high losses.
Altay and Kucukozmen (2006)	ANN and backpropagation algorithm	ANN approach shows better performance in credit risk prediction than traditional methods.
Nieppola,F. (2009)	VaR, CVaR, MCS	The MCS was found to be the most accurate VaR model. The mean-CVaR optimization method was found to be superior to the mean-variance method in terms of risk-return tradeoff.
White et al (2015)	VAR, quantile regression	The proposed method was more robust and provided more accurate tail dependence estimates than existing methods.
Nguyen et al. (2019)	VaR, CVaR, MCS	The use of VaR and CVaR in combination with MCS improves risk management for renewable energy investments.
Chen et al. (2020)	VaR, CVaR, Particle Swarm Optimization	The proposed hybrid algorithm outperforms traditional methods in portfolio optimization with VaR and CVaR constraints.
Bai et al. (2020)	VaR, CVaR, Grey Wolf Optimizer	The proposed approach achieves superior performance in portfolio optimization compared to traditional methods.
Ou et al. (2020)	VaR, CVaR, Multi-period optimization	The proposed model effectively manages risk and transaction costs in multiperiod portfolio optimization with VaR and CVaR constraints.
Wang et al. (2020)	VaR, ARIMA, GARCH model	The proposed model achieves superior performance in forecasting stock market volatility using VaR with a hybrid ARIMA-GARCH model.

Study	Methodology	Findings
Zhang et al. (2020)	VaR, GARCH model, Dynamic Copula Models	The proposed approach effectively estimates VaR for a non-stationary wind farm with high penetration level using GARCH and dynamic copula models.
Bouri et al. (2021)	VaR, CVaR, Extreme Value Theory, Copulas	Copulas combined with VaR and CVaR outperform Extreme Value Theory in estimating risk for emerging market portfolios.
Kuchuk-Iatsenko et al. (2021)	VaR, MCS, Generalized Pareto Distribution	The proposed approach outperforms traditional methods in predicting electricity spot prices using VaR and MCS with a Generalized Pareto Distribution.
Abbas et al. (2021)	VaR, CVaR, GARCH model	The proposed approach effectively manages risk for crude oil using VaR and CVaR measures with a GARCH model.

The studies mentioned providing various findings related to the use of VaR and CVaR in combination with different methods for managing risk in different investment scenarios:

Some studies (Acerbi et al., 2001 and Altay and Kucukozmen, 2006) have suggested that CVaR provides a more accurate assessment of risk compared to VaR due mainly to its coherency as a risk measure. However, the use of different models for estimating VaR and CVaR can affect the results, leading to the ongoing debate on the topic.

Nguyen et al. (2019) found that using VaR and CVaR in combination with Monte Carlo simulation improves risk management for renewable energy investments.

Chen et al. (2020) proposed a hybrid algorithm that outperforms traditional methods in portfolio optimization with VaR and CVaR constraints. Bai et al. (2020) proposed an approach that achieves superior performance in portfolio optimization compared to traditional methods using VaR and CVaR in combination with the Grey Wolf Optimizer.

Ou et al. (2020) proposed a model that effectively manages risk and transaction costs in multiperiod portfolio optimization with VaR and CVaR constraints. Wang et al. (2020) found that a proposed model achieves superior performance in forecasting stock market volatility using VaR with a hybrid ARIMA-GARCH model.

Zhang et al. (2020) proposed an approach that effectively estimates VaR for a non-stationary wind farm with high penetration level using GARCH and dynamic copula models. Bouri et al. (2021) found that copulas combined with VaR and CVaR outperform Extreme Value Theory in estimating risk for emerging market portfolios.

Kuchuk-Iatsenko et al. (2021) proposed an approach that outperforms traditional methods in predicting electricity spot prices using VaR and Monte Carlo simulation with a Generalized Pareto Distribution.

Abbas et al. (2021) found that using VaR and CVaR measures with a GARCH model effectively manages risk for crude oil.

Overall, the studies suggest that VaR and CVaR, when combined with appropriate methods, can effectively manage risk and transaction costs in various investment scenarios.

In this context, this paper compares VaR and CVaR measurements of brent oil prices using Monte Carlo Simulation. This study also aims to evaluate the characteristics of brent oil prices to determine the accuracy of these measures.

The Conditional Value-at-Risk was introduced as a way to address the limitations of the VaR model. While VaR estimates the maximum potential loss, it does not provide information about the magnitude of loss that may occur beyond that threshold. CVaR, also known as Expected Shortfall or Expected Tail Loss, aims to quantify the risk of losses exceeding the level of VaR. It has been suggested that CVaR is a more coherent risk measure compared to VaR (Acerbi et al., 2001 Altay and Kucukozmen, 2006).

2. The Models

2.1. The Value at Risk (VaR) Model

The VaR model was developed by J.P. Morgan in the 90s and it has been used as a benchmark since then. Developed by Jorion (1997), VaR measures the maximum loss of an investment at a certain level of confidence. In other words, VaR measures the worst-case scenario for a given probability, at a certain level of confidence under normal market conditions. VaR also measures the minimum expected loss with a given probability, at a certain confidence level, under an unusual market environment (Longin 2001). The first perspective focuses on the center of the distribution, while the latter focuses on the distribution of the tail.

One limitation of the VaR model is that it assumes a normal distribution, which ignores the fat tails. Subsequently, the risk of the high quantiles is underestimated (see Jorion 1996). In such a case, the VaR measure may not accurately reflect the distribution of actual losses. That can result in an underestimation of the risk of extreme events, such as the 2008 subprime mortgage crisis. In contrast, CVaR focuses on tail distribution and can provide a more comprehensive assessment of the potential impact of extreme events.

2.2. The Conditional Value at Risk (CVaR) Model

It should be noted that the use of different parametric and nonparametric models for estimating VaR and CVaR can affect the results and this remains an open debate. However, in cases where VaR is inadequate for quantifying risk, the use of CVaR may be beneficial. CVaR is often used as a complementary measure to VaR and can provide additional insights into the potential losses of a financial asset.

Initially, Rockafellar and Uryasev (2000) introduced the term CVaR to measure the quantity of loss in tail events, while VaR does not provide information regarding the magnitude of loss above the threshold. Hence, CVaR of a certain financial asset is equal to or greater than VaR of the same asset. When the VaR fails to quantify the degree of loss than, CVaR is used. Pflug (2000) suggested that CVaR is a cohesive risk meter. According to Alexander (2004), CVaR is the value of losses, in excess of VaR.

There have been several studies that have evaluated the accuracy of the VaR model to measure risk. According to Nieppola (2009), VaR models tend to underestimate risk. White (2015) similarly found that VaR models may not be reliable due to the non-normal distribution of assets in the banking sector. Yoon and Kang (2007) also found that VaR underestimates risk, even when the assumption of a normal distribution was made. However, they found that VaR performed better at a 95% confidence level. Samanta and Nard (2003) similarly found that conventional VaR methods tend to underestimate risk, but they found that the Historical Simulation method of VaR was a reliable model.

3. Computation of The Models

The return on a financial asset is computed as the difference between the logarithm of the financial asset's price on a day and the logarithm of the asset price on the previous day. This can be expressed mathematically as follows:

$$R_t = \ln(\frac{P_t}{P_{t-1}}) \quad (1)$$

R_t refers to the return on day t, P_t refers to the closing price on day t and P_{t-1} represents previous day's closing price.

There are several methods for calculating the VaR, including Monte Carlo simulation model, the historical simulation approach, and the variance-covariance model. Among these;

The Normal Linear VaR is the simplest and most widely used method. It only requires the moments; namely, mean and standard deviation as input parameters. The simple VaR model;

$$VaR(\alpha) = \mu + Z(\alpha)\sigma \quad (2)$$

where μ is mean of returns; Z is the standard normal distribution function; σ is the standard deviation of returns.

The Historical Simulation approach: As per Van den G and Vlaar (1999), the Historical Simulation approach is based on the assumption that the future risk will be repeated as in the past events. This method involves selecting a sample size of t and calculating the VaR as the pth percentile of the chosen sample. Following Van den Goorbergh and Vlaar (1999), the formula is given as follows:

$$VaR_t = -R_t^P \quad (3)$$

$\boldsymbol{R_t^P}$ is the pth percentile of the sample t.

The Monte Carlo simulation This simulation method has the assumption that returns will be distributed normally. However, this is a more flexible model, compared to the Normal Linear VaR method. One can simulate a lot of independent standard normal variables to calculate VaR. The Monte Carlo simulation VaR is based on generating random numbers from a normal distribution function $\boldsymbol{z_t}$ with a standard deviation of σ. The returns are equal to:

$$\mathbf{ln}\left(\frac{\boldsymbol{R_t}}{\boldsymbol{R_{t-1}}}\right) = \boldsymbol{z_t \sigma} \quad (4)$$

Pseudo Random Number Generator (PRNG) is used to generate these random numbers. The VaR is computed as the pth percentile of a set of simulated returns, where the number of simulations is equal to 10,000 multiplied by the standard deviation.

The Conditional VaR (Expected Shortfall) Expected Shortfall (ES) is a measure of risk that was proposed as an improvement upon VaR. While VaR is a useful risk measure, it does not capture all aspects of market risk. As per Artzner et al. (1997, 1999), ES is a superior measure of risk compared to VaR because it provides information about the expected size of returns exceeding the VaR threshold, and thus describes the potential size of large losses. ES is defined as the expected size of returns that exceed the VaR at a given probability level p, for a given risk X.

$$\mathbf{ES_p} = \mathbf{E(X|X)} > \mathbf{VaR_P}) \quad (5a)$$

The Basel III framework is a set of international banking regulations that were developed to improve the regulation and supervision of the banking sector. One of the components of the Basel III framework is the use of ES as a risk measure. ES is defined as the average of potential losses that exceed the VaR at a given level of confidence. Other risk measures that capture similar concepts include CVaR and Expected Tail Loss (ETL). These measures are used to quantify the risk of loss in a given time period. VaR is a quantitative risk measure that represents the maximum loss that is expected to occur with a given level of confidence. ES, CVaR, and ETL are all related to VaR, but they provide additional information about the potential size and likelihood of large losses.

$$CVaR(\alpha) = \frac{1}{\alpha}\int_0^{\alpha} VaR(x)dx \quad (5b)$$

4. Data and Methodology

This section of research aims to study the volatility of daily Brent oil prices and to use this information to model the distribution of tails of the daily returns. To do this, we will use historical daily closing prices of Brent oil in US dollars, covering the period from July 18, 2018 to May 27, 2022. The period is chosen to end on May 27 to capture the impact of the Ukraine-Russian war (started on February 24, 2022) on oil prices. Before analyzing the data, we will conduct preliminary tests and exploratory analyses to understand the characteristics of the data. The empirical analysis will involve modeling the distribution of tails of the daily returns. The ultimate goal of this research is to gain a better understanding of the risk associated with Brent oil prices and to develop more accurate models for predicting future price movements.

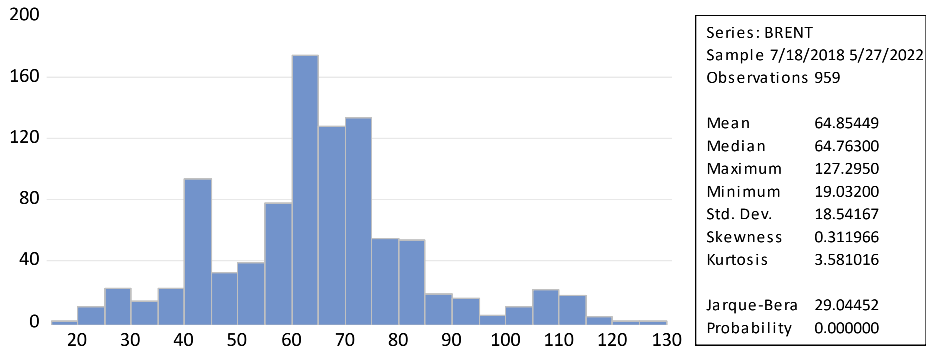
4.1 Preliminary testing and exploratory analysis.

Figure-1: Brent Oil Prices Per Cubic Meter

The daily Brent oil price plot (Figure 1) indicates a significant rise in oil prices since Q1 2020, with several variations.

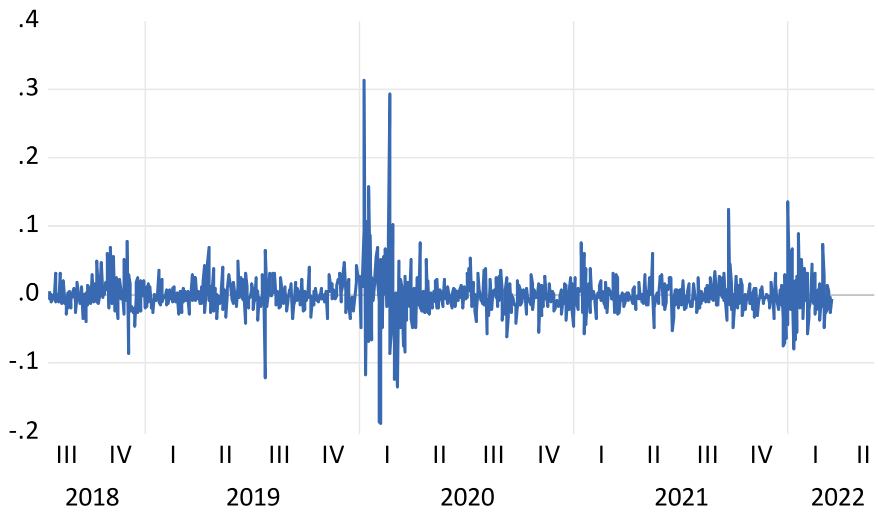
Figure 2 is a histogram of daily closing prices of Brent oil, along with the outcome of a Jarque-Bera test. This is a statistical test that assesses whether a data sample follows a normal distribution. It measures the departure from normality using the skewness and kurtosis of the data. Under the null hypothesis, the skewness and excess kurtosis are both zero. In this case, the Jarque-Bera statistic is large, and the p-value is zero, indicating that the distribution of Brent oil prices is not normal. In our case, a kurtosis value of 3.58 suggests the presence of fat tails, or extreme values, in the data. Additionally, the skewness value indicates that the distribution of prices skews to the right. This suggests that there are more high price observations than expected under a normal distribution.

Figure 2 Histogram of Daily Brent Oil Prices



Based on the Jarque-Bera test results, it can be concluded that Brent oil prices are not normally distributed, and instead have positive skewness and large tails. Asymmetric distributions like this are characterized by having different properties in the left and right tails. To accurately model the Brent oil price distribution, it is necessary to separately model the left and right tails to capture their unique characteristics. For positively skewed distributions, it is common to examine the absolute values of gains, while for negatively skewed distributions, the absolute values of losses are often analyzed. This is because the distribution of returns is often skewed in one direction or the other, and examining the absolute values can help to better understand the distribution of the data.

Figure 3 Daily Brent Oil Price Returns



The Brent oil daily price returns given in Figure 3 are computed as the differences in the natural logarithms of the Brent prices. The daily return graph (Fig. 3) demonstrates the volatile nature of the Brent oil market.

4.2 Exploratory Data Analysis

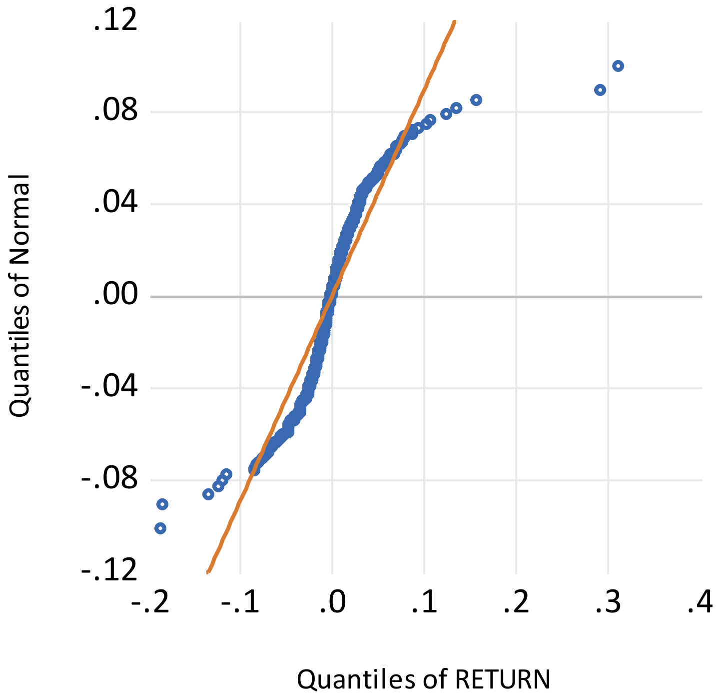
Exploratory Data Analysis (EDA) can be used to determine the presence of fat tails in a distribution. Given the normal distribution, the mean and standard deviation are used to characterize the distribution. However, to identify fat tails, the third and fourth moments, known as skewness and kurtosis, are often used. Skewness measures the symmetry and lopsidedness of a distribution. Distribution is symmetric If the skewness is 0. The distribution is skewed to the left, when the skewness has a negative value, with a long tail on the left side. Finally, the distribution is skewed to the right, with a long tail on the right side, If skewness has a positive value. (Kemp, 2011).

Kurtosis measures the heaviness of the tails. If the kurtosis has a value of 3, the distribution has a normal tail and is called mesokurtic. If the kurtosis has a higher value, the distribution has a heavy tail, called leptokurtic. The lower the value of the kurtosis, the lighter the tail of the distribution, referred to as platykurtic (Reiss and Thomas, 2007).

A quantile-quantile plot is a graphical tool used to assess whether a distribution fits a reference distribution. It does this by comparing the quantiles of the data's distribution to the quantiles of the reference distribution. If the two distributions are similar, the qq-plot will be linear. However, if the plotted values deviate significantly from a straight line, it is likely that the data comes from a different distribution, possibly one with "fat tails," or outliers that occur more frequently than expected.

Normally, if a qq-plot is used to compare data with fat tails to a normal distribution, it should have an S-shape. This is because the normal distribution does not have fat tails, so any deviation from a straight line in the qq-plot indicates the presence of fat tails in the data (Gnanadesikan, 1972). The qq-plot is a useful tool for visualizing the deviation of a distribution from normality and identifying the presence of fat tails.

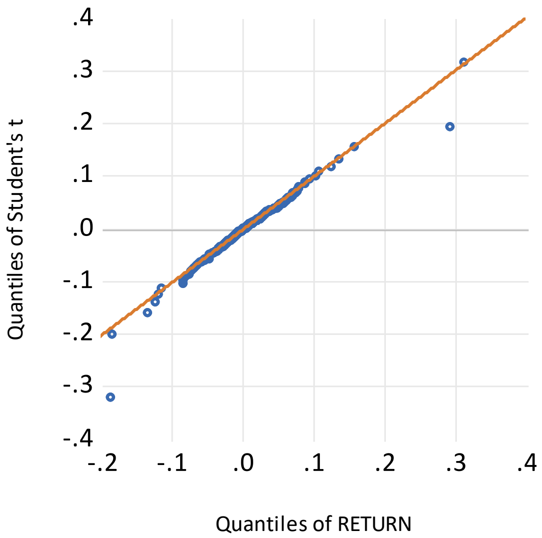
Figure 4a Normal Qq Plot of Brent Oil Price Returns



In this context, "Figures 4a and 4b" are referring to two graphs that show the results of using a qq-plot to compare the distribution of the data to two different reference distributions: the normal distribution and the Student's t-distribution. According to the descriptions provided, the qq-plot for the normal distribution (Figure 4a) shows that the data has a "fatter left tail" compared to the normal distribution, while the qq-plot for the Student's t-distribution (Figure 4b) shows that the data has a "fatter right tail" compared to the Student's t-distribution. This means that the data has more extreme values in the left tail compared to the normal distribution, while the more extreme values in the right tail are compared to the Student's t-distribution.

The qq-plots, in this case, show that the distribution of the change in daily Brent oil prices deviates significantly from both the Student's t distributions and the normal distribution, which suggests that there are "fat tails" present in the data. In other words, the data has more extreme values (outliers) than would be expected based on these reference distributions. The qq-plot is a tool for visualizing the deviation of a distribution from a reference distribution and identifying the presence of fat tails. These results confirm that fat tails are present in the distribution of the change in daily Brent oil prices.

Figure 4b Student's t distribution QQ plot of Brent Oil Price Returns



The qq-plot in Figure 4b, which compares the returns data to the Student's t distribution, indicates that data has fat tails compared to the Student's t distribution. The Student's t distribution is a distribution that is commonly used to model data with heavy tails because it is more flexible and able to accommodate a greater range of data than the normal distribution. However, the deviation of the qq-plot from the reference distribution suggests that the data has even fatter tails than the Student's t distribution can accommodate. This supports the conclusion that the data has fat tails.

4.3 Assessment of Linear Normal VaR, Monte Carlo Simulation and CVaR:

To assess VaR and CVaR, the stationarity of the daily brent oil returns data was examined using the Augmented Dickey-Fuller (ADF) test. The ADF test determines whether a time series data has a unit root, which would indicate non-stationarity. The results of the ADF test showed that the data is stationary, meaning that it does not have a unit root. Three different models were used to calculate VaR and CVaR for the data: Linear Normal VaR, Monte Carlo Simulation VaR, and CVaR. These models were calculated using daily returns of Brent oil prices, and the confidence level was set at 95%. The results of these tests are given in Table 1.

Table 1 Linear Normal VaR Estimation

Confidence Level	**VaR (1 Day)**
0.99	-6.91
0.95	-4.86

The VaR reflects the worst-case scenario for the market price of Brent oil over a single trading day, given a certain level of confidence. The VaR is calculated as the loss that is expected to occur given a certain probability, such as 1% or 5%.

The table shows the VaR estimates for a 1 day holding period at 99% and 95% confidence levels. At 99% confidence level, the VaR estimate is -6.91, which means that under normal conditions, we can be 99% confident that our daily loss will not exceed 6.91% in a single trading day. If we have an investment of $1 million, this would translate to a loss of $69,100 with a probability of 1%.

Similarly, at 95% confidence level, it is -4.86. Similarly, the VaR at a lower quantile, at the 95th percentile, is -4.86. This indicates that the market value of Brent oil could be expected to lose 4.86% within a single trading day with 95% confidence. The Normal Linear VaR estimate for different confidence levels may differ by a few percentage points, as shown in this example. VaR allows investors to quantify the potential size of their losses under different scenarios.

Table 2 CVaR (Expected Shortfall) Estimation

Confidence Level	VaR (1 Day)
0.99	-7.74
0.95	-6.06

Table 2 presents the estimates and confidence intervals of ES for two different confidence levels (99% and 95%). The estimates show that the expected size of losses that exceed the VaR is relatively small, but it may vary slightly depending on the level of confidence. In this study, the ES estimates exceeded the VaR by 0.83-1.2% with 99% and 95% confidence levels, respectively. Overall, the results in Table 2 provide insight into the potential losses that could be expected in the market for Brent oil, given different levels of confidence.

Table 3 Monte Carlo Simulation VaR Estimation

Confidence Level	M.C VaR (1 Day)
0.99	-9.98
0.95	-8.04

Table 3 presents the outcome of a Monte Carlo simulation for estimating VaR. A Monte Carlo simulation is a method that involves generating many possible outcomes for a given model and using these outcomes to estimate the probability of different outcomes occurring. In this case, the Monte Carlo simulation is being used to estimate the VaR for the market for Brent oil.

The results in Table 3 show that the Monte Carlo Simulation VaR estimates exceed both the VaR and ES results by 3.07% and 2.24% at the 99% confidence level, and by 3.18% and 1.98% at the 95% confidence level, respectively. These results suggest that the Monte Carlo Simulation VaR method is more conservative than the other methods, and it generates higher estimates of VaR. This may be because the Monte Carlo Simulation VaR takes into account a wider range of possible scenarios, which may lead to more conservative estimates of risk.

5. Backtesting Results

Backtesting is a process used to determine the accuracy of a model's estimates, such as the estimates of Value at Risk. It involves comparing the model's estimates to actual outcomes that have occurred in the market, to determine whether the model is producing accurate results. This is important because an inaccurate model may not effectively capture the risk of an investment portfolio, which could lead to incorrect decisions being made based on the model's estimates.

Various methods can be used for backtesting, and it is important to ensure that the observations exceeding the VaR are independent, meaning that they are equally spaced in time. This is because the VaR takes into account the expected losses under normal market conditions, and an accurate VaR should provide a reliable number of deviations that are independent of each other. If the observations are not independent, it may indicate that the method is not capturing the risk of the portfolio accurately.

5.1 Backtesting VaR

The Kupiec POF (proportion of failure) test is a commonly used method for backtesting Value at Risk (VaR) estimates. It was introduced by Kupiec (1995) and is used to investigate whether the number of exceptions to the VaR estimates is in line with the level of confidence.

The test works by comparing the actual losses to the VaR estimates. If the actual losses exceed the VaR estimates more or less frequently than expected, it may indicate that the VaR estimates are not accurate. For example, if a 1 - q probability level is used to calculate the VaR, the loss is expected to exceed the VaR estimate q% of the time. If the actual losses exceed the VaR estimates more frequently than q% of the time; it may indicate that the VaR estimates are underestimating the risk of the portfolio. On the other hand, if the actual losses exceed the VaR estimates less frequently than q% of the time, it may indicate that the VaR estimates are overestimating the risk of the portfolio.

The null hypothesis for the Kupiec POF test is that the proportion of times that the loss exceeds the VaR estimate is equal to q. The alternative hypothesis is that the proportion of times that loss exceeds the VaR estimate is not equal to q. If the null hypothesis is rejected, it indicates that the VaR estimates are not accurate.

The null hypothesis and the alternative hypothesis for the Kupiec POF test are as follows:

$$H_0 : q = \frac{x}{T} \quad (6)$$

$$H_1 : q \neq \frac{x}{T} \quad (7)$$

where x is the number of days the loss exceeded the estimated VaR, $\widehat{VaR}_t$ and T is the amount of days for VaR estimation.

The Kupiec POF test is often accompanied by a likelihood ratio (LR) test, which is used to assess the null hypothesis. LR test, developed by Kupiec (1995), measures the goodness of fit of the null hypothesis by comparing the null hypothesis to the alternative hypothesis. LR test determines whether the null should be rejected in favor of the alternative hypothesis.

The LR test can be used in conjunction with the Kupiec POF test to more rigorously evaluate the accuracy of the VaR estimates. If the LR test indicates that the null should be rejected, it may be evidence that the VaR estimates are not reliable and should be revised.

The likelihood ratio test, LR is given below as follows;

$$LR = -2\ln\left(\frac{(1-q)^{T-x}q^x}{(1-\left(\frac{x}{T}\right))^{T-x}\left(\frac{x}{T}\right)^x}\right) \quad (8)$$

where q, T, and x are as defined above.

The likelihood ratio is calculated by comparing the maximum probability of the result that is observed to the null; the maximum probability of the result that is observed in the alternative hypothesis. If the LR is greater than the critical value of the chi-squared distribution, then the null is rejected and the model is considered to be inaccurate.

The Kupiec test is used to determine whether the model is rejected at a particular confidence level. The critical value for the chi-squared distribution is given for the 95% and 99% confidence levels. In our case, the model is rejected at the 95% confidence level because likelihood ratio exceeds the critical value. However, it is accepted at the 99% confidence level since the likelihood ratio is below the critical value. This means that the model underestimated risk at the 95% confidence level, but it is reliable at the 99% confidence level.

The likelihood ratio test, LR is calculated by the formula (8). If the computed LR is above a critical value, the null hypothesis and model accuracy are rejected for the given confidence level.

The Brent oil prices with 33 exceptions are taken into account at the 95 % confidence level during the 959 trading/working days.

Table 4 Backtesting VaR Results

Confidence Level	Critical Value χ^2	Likelihood Ratio (LR)	Test Result	Decision
95%	1.92	5.48	Exceeds	Reject

Confidence Level	Critical Value χ²	Likelihood Ratio (LR)	Test Result	Decision
99%	10.48	2.63	Below	Accept

Based on the test results, the VaR model underestimates the risk with 95% confidence level, but the VaR estimation is reliable with 99% confidence level.

The critical value χ² for the Chi-Squared Distribution for 95 % confidence level is 1.92, while the Likelihood Ratio (LR) test result is 5.48. The LR exceeds 1.92. The Kupiec test, therefore, indicates that the model is rejected at the 95 % confidence level. That is to say, the null hypothesis is rejected with 95 % confidence. The critical value for 99 % confidence level is 10.48, while the LR result is 2.63. In this case, LR is below the critical value. As per Kupiec test, we accept that the model given by the null hypothesis is good with 99% confidence. According to the test results, we can conclude that VaR model underestimates the risk with 95% of confidence. However, that is not the case with %99 confidence level as per the VaR estimation is reliable.

5.2 Backtesting Expected shortfall

The Acerbi-Szekely test is a method that can be used to directly test the accuracy of Expected Shortfall (ES) estimates. It was introduced by Acerbi and Szekely (2014) and has the advantage of having a single, significant critical value that can be used to test the distribution of the stochastic loss variable under various assumptions. This makes it a practical and easy-to-use method for testing the accuracy of ES estimates.

Following the Acerbi-Szekely test, the null hypothesis of the ES estimates is accurate, while the alternative hypothesis is that the ES estimates are not accurate. These hypotheses are stated as follows:

Null hypothesis: The ES estimates are accurate.

Alternative hypothesis: The ES estimates are not accurate.

To test both hypotheses formulas are given below,

$$H_0: F_t^q = P_t^q \quad (9)$$

$$H_1: F_t^q \neq P_t^q \quad (10)$$

where Ft is the true distribution of the data, while Pt is the model distribution.

The Acerbi-Szekely test compares the observed number of exceptions to the expected number of exceptions based on the ES estimates to test the null hypothesis. If the observed number of exceptions is highly different from the expected number of exceptions, then it may be the case that the ES estimates are not accurate and the null hypothesis is rejected.

Overall, the Acerbi-Szekely test is a useful tool for evaluating the accuracy of ES estimates and determining whether they are reliable for risk management purposes. It can be used in conjunction with other methods, such as the Kupiec POF test, to more rigorously assess the reliability of risk measures.

To test the null hypothesis, a test statistic is calculated using the number of observations (T), and the probability level (1 - q) used in the VaRq measure. Actual loss at each time point L_t , estimated ES at each time point $\widehat{ES}_t^q$. The term J_t is defined by Equation 11, and given below. The expected value of the test statistics; Z is E(Z) = 0, which means that values close to zero show that the ES estimations are close to the actual stochastic loss variables. While large negative values of the test statistic show an underestimation of market risk, large positive values point to an overestimation. If the null is accepted, it implies that the ES belongs to the true distribution of the stochastic loss variable. However, if the null is rejected, it means that ES belongs to a distribution that systematically underestimates risk.

$$Z = -\frac{1}{T_q}\sum_{t-1}^{T}\frac{L_t J_t}{T(1-q)\widehat{ES}_t^q} + 1 \qquad (11)$$

$$J_t = \begin{cases} 1, \ if -r_t > \widehat{VaR}_t \\ 0, \ if \ -r_t \leq \widehat{VaR}_t \end{cases} \qquad (12)$$

The Z statistic test results for %99 confidence level is 1.75 for ES estimates, below the critical value of 7.91. The Z statistic value for %95 confidence level is -2.21, below the critical value of 2.68 as given below in the table.

Table 5 Backtesting Expected Shortfall Results

Confidence Level	Z Statistic	Critical Value	Test Result	Decision
99%	1.75	7.91	Below	Neither
95%	-2.21	2.68	Below	Neither

Based on the Z test results, we can conclude that the ES estimates are neither underestimated nor overestimated by the model at both 99% and 95% confidence levels. The Acerbi-Szekely test is a useful tool for evaluating the accuracy of ES estimates and determining whether they are reliable for risk management purposes and can be used in conjunction with other methods, such as the Kupiec POF test, to more rigorously assess the reliability of risk measures.

6. Conclusions

Risk management has become a critical aspect of asset management in recent years. VaR calculations, which aim to predict the potential future loss of financial assets, have played a particularly important role in informing investor decision-making. However, as there is no perfect method for accurately forecasting the future, it is necessary to conduct backtesting procedures to evaluate the validity of VaR models.

Our findings on VaR were consistent with those of Nieppola (2009), White (2015), and Yoon and Kang (2007), who also found that the VaR model underestimated risk at the 95% confidence level. This may be due to the non-normal distribution of returns. Our results on conditional value at risk (CVaR) were similar to those of Acerbi et al. (2001) and Altay and Kucukozmen (2006), who found that CVaR produced superior results compared to VaR in cases where the distribution of returns was highly skewed or had fat tails. This is because the expected shortfall measure, which is used to calculate CVaR, takes into account expected loss beyond the VaR threshold.

When comparing different calculations of VaR, we found that linear VaR produced the lowest values, while Monte Carlo simulations produced the highest values. The results of our backtesting showed that potential risks may exist in the market, and that it is important to take necessary measures to protect assets against these risks in asset management.

We used daily closing price data for Brent oil from a data provider called Matriks. Daily returns for Brent oil prices were calculated throughout July 18, 2018 - May 27, 2022 and used as the key parameters in each model. The Kupiec test, also known as the "Proportion of Failure test," was used to test the VaR results, and takes into account only the number of exceptions, not when the exceptions occur. The Kupiec test indicated that the VaR specification was rejected at the 95% confidence level due to its underestimation of risk. However, the VaR results were accepted at the 99% confidence level, indicating that the model was reliable.

Overall, it is important for asset management firms to include backtesting as a key part of their process.

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Araştırma Makalesi

Brent Petrol Fiyatları Üzerine Pratik Bir Risk Analizi

A Practical Risk Analysis of The Brent Oil Prices

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Genişletilmiş Özet

"Risk" konusu, özellikle küresel perspektifte artan finansal volatilite nedeniyle son on yılda popüler bir çalışma konusu olmuştur. Finansal kurumlar piyasa risklerini ölçmek ve kontrol etmek için basit ve kullanışlı araçlar geliştirmişlerdir. Risk ölçüm metodlarındaki gelişmelere rağmen, 2008 subprime mortgage krizinde görüldüğü üzere, bu araçların pek de yardımcı olmadığı açıktır.

Riske Maruz Değer (VaR) finansal bir varlığın potansiyel kaybını; riskini belirli bir zaman diliminde ölçmek için kullanılan ana modeldir. VaR, bir varlık için belirli bir zaman diliminde ve belirli bir güven seviyesinde maksimum kaybın ölçüsüdür; CVaR (Beklenen Kayıp (Expected Shortfall (ES)), ise belirli bir güven seviyesinde belirli bir zaman diliminde VaR'ı aşan kaybı ölçer.

Koşullu Riske Maruz Değer (CVaR) de en kötü senaryoda (kayıp VaR eşiğinden büyük olduğunda) bir varlığın/portföyün beklenen kaybını (Expected Shortfall (ES)) temsil eden bir risk ölçüsüdür. Yalnızca en uç kayıpları dikkate alan VaR'ın aksine, CVaR olası kayıpların tüm dağılımını dikkate alır. CVAR aynı zamanda beklenen kayıp (ES) olarak da bilinir.

Monte Carlo Simülasyonu (MCS), bir finansal varlık için olası sonuçların rastgele örneklerini oluşturarak VaR/CVAR'ı tahmin etmek için kullanılan bir yöntemdir. Bu yöntem, getirilerin dağılımı ve varlığın değerini etkileyebilecek diğer faktörler hakkında farklı varsayım setleri kullanılarak çok sayıda simülasyonun çalıştırılmasını içerir. Bu simülasyonların sonuçları daha sonra varlık için farklı seviyelerde kayıp olasılığını tahmin etmek için kullanılabilir.

Risk üzerine yapılmış önemli sayıda akademik çalışma bulunmaktadır. Bazı çalışmalar VaR ve CVaR ın performansını çeşitli bağlamlarda karşılaştırmış ve farklı sonuçlar verebileceklerini ortaya koymuştur. Diğer araştırmalar ise bu ölçütlerin özellikleri ve sınırlamalarının yanı sıra bunların nasıl kullanılabileceği ve yorumlanabileceği üzerine odaklanmıştır.

VaR modeli 90'lı yıllarda JP Morgan tarafından geliştirilmiştir ve o zamandan bu yana finansal riski ölçen bir ölçüt olarak kullanılmaktadır. Jorion (1997) tarafından geliştirilen VaR, belirli bir güven seviyesinde bir yatırımın maksimum kaybını ölçer. Diğer bir deyişle VaR, normal piyasa koşulları altında belirli bir güven seviyesinde en kötü senaryoyu ölçer. VaR aynı zamanda olağandışı piyasa koşullarında belirli bir olasılıkla, belirli bir güven düzeyinde beklenen minimum zararı da ölçer (Longin 2001). İlk bakış açısı dağılımın merkezine odaklanırken, ikincisi kuyruk dağılımına (tail distribution) odaklanmaktadır.

VaR'ın risk ölçümünde yetersiz kaldığı durumlarda CVaR kullanımı düşünülebilir. CVaR, genellikle VaR'ı tamamlayıcı bir ölçüt olarak bir finansal varlığın potansiyel kayıplarına ilişkin ek bilgiler sağlar.

İlk olarak, Rockafellar ve Uryasev (2000) tarafından, zaman serisinin dağılımında, kuyrukta meydana gelebilecek olan kayıp miktarını (tail loss) ölçmek için CVaR terimi ortaya atılmıştır. VaR eşiğin

üzerindeki kaybın büyüklüğü ile ilgili bilgi sağlamamaktadır. Dolayısıyla, belirli bir finansal varlığın CVaR'ı aynı varlığın VaR'ına eşit veya daha büyüktür. VaR risk derecesini ölçmede başarısız olduğunda, CVaR kullanılır. Pflug (2000) CVaR'ın uyumlu bir risk ölçer olduğunu öne sürmüştür. Alexander'a (2004) göre CVaR, VaR'ı aşan kayıpların değeridir.

Son yıllarda yapılan çalışmalar; VaR ve CVaR kısıtlamaları altında riski etkin bir şekilde yönetmek, portföy optimizasyonu ve yenilenebilir enerji, ham petrol gibi yatırım türleri açısından riski tahmin etmek için yeni modeller ve algoritmalar önermektedir. Bulgular, önerilen yöntemlerin risk yönetimi ve portföy optimizasyonunda performans açısından geleneksel yaklaşımlardan daha iyi performans gösterdiğini ortaya koymakla birlikte, bu yöntemler uygulama alanında yer bulamamamışlardır.

Doğrusal VaR, Tarihsel VaR ve Monte Carlo yöntemlerinin hepsi VaR'ı tahmin etmeye yönelik yaklaşımlardır; CVaR yöntemi ise VaR eşiğinin ötesindeki kayıpları dikkate alan özel bir risk ölçüsüdür.VaR, getiri dağılımının çarpık olduğu durumlarda daha az etkili olabilir, bu durumda CVaR daha uygun bir ölçüt olabilir. Monte Carlo simülasyonu hem VaR hem de CVaR değerini tahmin etmek için popüler bir yöntem olarak öne çıkmaktadır.

MCS da dahil olmak üzere, VaR ve CVaR'ın tahmin edilmesine yönelik farklı yöntemlerin doğruluğu ve etkinliği konusunda çok çeşitli ampirik araştırmalar bulunmaktadır. Bu çalışmalar genel olarak Monte Carlo simülasyonunun faydalı bir araç olabileceğini ortaya koymuş olsa da, araştırmacılar arasında farklı durumlarda benimsenecek en iyi yaklaşım konusunda tartışmalar devam etmektedir.

Bu bağlamda, bu makale Monte Carlo Simülasyonu, VaR ve CVaR ölçümlerini karşılaştırmaktadır. Bu çalışma aynı zamanda bu ölçümlerin Brent petrol fiyatları üzerinde etkin olup olmadığını test etmeyi amaçlamaktadır.

VaR modelinin limitlerini aşmak için kullanılan bir yöntemdir. VaR maksimum potansiyel kaybı tahmin ederken, bu eşiğin ötesinde meydana gelebilecek kaybın büyüklüğü hakkında bilgi vermez. Beklenen risk olarak da bilinen CVaR, VaR seviyesini aşan kayıp riskini ölçmeyi amaçlamaktadır. CVaR'ın VaR'a kıyasla daha tutarlı bir risk ölçüsü olduğu ileri sürülmektedir (Acerbi vd., 2001 ve Altay ve Kucukozmen, 2006).

Riski ölçmek için VaR modelinin doğruluğunu değerlendiren çeşitli çalışmalar yapılmıştır. Nieppola (2009) a göre, VaR modelleri riski olduğundan düşük gösterme eğilimindedir. White (2015) da benzer şekilde VaR modellerinin güvenilir olmayabileceğini tespit etmiştir. Yoon ve Kang (2007) da normal dağılım varsayımı yapıldığında bile VaR'ın riski olduğundan daha düşük tahmin ettiğini ifade etmiş, VaR'ın %95 güven düzeyinde iyi performans göstermediğini tesbit etmişlerdir. Samanta ve Nard (2003) benzer şekilde geleneksel VaR modellerinin riski olduğundan düşük gösterme eğiliminde olduğunu, ancak simülasyon yönteminin güvenilir bir model olduğunu ifade etmişlerdir.

Brent petrol fiyat oynaklığını incelemek için 18 Temmuz 2018'den 27 Mayıs 2022'ye kadar olan dönemi kapsayan ABD doları cinsinden brent petrolün tarihsel günlük kapanış fiyatlarını kullandık. Ukrayna-Rusya savaşının (24 Şubat 2022'de başladı) petrol fiyatları üzerindeki etkisini incelemek için zaman aralığı 27 Mayıs'ta bitecek şekilde seçildi. Bu araştırmanın nihai amacı, Brent petrol fiyatlarıyla ilişkili riski daha iyi anlamak ve gelecekte oluşacak riskleri tahmin etmek için doğru modellerin seçimidir.

Bu çalışmada, VaR tahminlerini geriye dönük test etmek için yaygın olarak kullanılan Kupiec POF (başarısızlık oranı) testi kullanılmıştır. Kupiec (1995) tarafından ortaya atılan bu test, VaR tahminlerindeki istisna sayısının güven düzeyiyle uyumlu olup olmadığını araştırmak için kullanılmıştır.

Acerbi-Szekely testi, CVaR model sonuçlarını doğrudan test etmek için kullanılabilecek bir yöntemdir. Acerbi ve Szekely (2014) tarafından ortaya atılan ve çeşitli varsayımlar altında stokastik kayıp değişkeninin dağılımını test etmek için kullanılabilecek tek ve önemli bir kritik değere sahip olma avantajına sahiptir. Bu da testi, tahminlerin doğruluğunu test etmek için pratik ve kullanımı kolay bir yöntem haline getirmektedir.

Bu çalışma, Brent petrol fiyatlarındaki riski ölçmek için en iyi modeli belirlemek amacı ile üç yaklaşımı incelemektedir: VaR, MCS ve CVaR.

Çalışma ayrıca, Brent petrol fiyatları için riskin önceden ölçülmesinin mümkün olup olmadığını inceleyerek literatüre katkıda bulunmayı amaçlamakta ve risk ölçümünde en iyi performans gösteren yöntemi belirlemek için çeşitli risk ölçüm modellerinin performansını karşılaştırmaktadır.

VaR ile ilgili bulgularımız, VaR modelinin %95 güven düzeyinde riski olduğundan düşük tahmin ettiğini tespit eden Nieppola (2009), White (2015) ve Yoon ve Kang'ın (2007) bulgularıyla benzer sonuçlar taşımaktadır. Bu durum, getirilerin normal olmayan dağılımından kaynaklanıyor olabilir. Koşullu riske maruz değer (CVaR) ile ilgili sonuçlarımız, getiri dağılımının yüksek oranda çarpık olduğu veya kalın kuyruklu olduğu durumlarda CVaR'ın VaR'a kıyasla daha iyi sonuçlar verdiğini tespit eden Acerbi ve diğerleri (2001) ile Altay ve Küçüközmen'in (2006) sonuçlarıyla benzerlik göstermektedir. Bunun nedeni, CVaR'ı hesaplamak için kullanılan ölçütünün, VaR eşiğinin ötesinde beklenen kayıpları dikkate almasıdır.

Farklı VaR hesaplamalarını karşılaştırırken, doğrusal VaR'ın en düşük değerleri ürettiğini, MCS'nın ise en yüksek değerleri ürettiğini gördük. Geriye dönük testlerimizin sonuçları, piyasada potansiyel risklerin var olabileceğini ve varlık yönetiminde bu risklere karşı varlıkları korumak için gerekli önlemlerin alınmasının önemli olduğunu göstermiştir.

Brent petrol için Matriks veri sağlayıcısından alınan günlük kapanış fiyatlarını kullandık. Brent petrol fiyatlarının günlük getirileri 18 Temmuz 2018 - 27 Mayıs 2022 dönemi için hesaplanmış ve her bir modelde temel parametreler olarak kullanılmıştır. VaR sonuçlarını test etmek için "Hata Oranı testi" olarak da bilinen Kupiec testi kullanılmış olup, istisnaların ne zaman gerçekleştiği değil, yalnızca istisna sayısı dikkate alınmıştır. Kupiec testi, VaR spesifikasyonunun riski olduğundan az göstermesi nedeniyle %95 güven düzeyinde reddedildiğini göstermiştir. Ancak, VaR sonuçları %99 güven düzeyinde kabul edilmiş ve modelin güvenilir olduğunu göstermiştir.