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Market Risk Analysis with Value at Risk Models using Machine Learning in BIST-30 Banking Index

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Abstract

Market risk is one of the most crucial risks that portfolio managers need to calculate. According to Basel criteria, banks are required to conduct Value at Risk (VaR) analysis at regular intervals. Developments in artificial intelligence offer many methods and alternatives for VaR calculation. This allows for the construction of more precise and sophisticated models.

In this study, portfolio diversification was constructed by using Monte Carlo simulation from the shares of the four major banks dominating the Banking Index (AKBNK, GARAN, ISCTR, YKBNK), and they were analyzed with three different Value at Risk (VaR) methods (historical, Monte Carlo simulation, and parametric). Daily stock market data for 5 years was used to calculate 10-day VaR results. Out of the obtained results, 122 were used for training the models, and 4 were used for comparing predictions. The Random Forest algorithm was employed for portfolio construction and prediction. Additionally, to increase the algorithm's accuracy, variables such as VIX (fear index), USD/TRY, Gold/TRY, and Brent/TRY were added. Machine learning regularization methods, including Ridge, Lasso, and Elastic Net regression models, were used to test the effect of variables. These models help to measure the impact of each variable on the portfolio more accurately. For each VaR model, the stock distribution was redefined in the last 4 periods, and VaR values were recalculated and compared with the actual VaR values. The findings indicate that parametric VaR provides the best results in the first period, while historical VaR yields values closest to actual results in the other three periods. There was no significant difference observed among the effects of variables according to Ridge, Lasso, and Elastic Net regression models.

A significant difference is observed between the calculated VaR values, which are the main aim of the article, and the actual VaR values. The findings indicate that the results are more optimistic than the actual data and do not closely approximate by more than 30%. The reason for the larger-than-expected difference could be attributed to the underpricing of bank stocks in the last two years and the rapid movements in the stock market during the last 4 periods, independent of the stock.

Keywords

Market Risk, Value at Risk, Machine Learning, BIST-30, Banking Index

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BIST-30 Bankacılık Endeksi'nde Makine Öğrenmesi Kullanılarak Riske Maruz Değer Modelleri ile Piyasa Riski Analizi

Öz

Piyasa riski portföy yöneticilerinin hesap etmeleri gereken en önemli risklerden biridir. Basel kriterleri gereği bankalar sık aralıklarla Riske Maruz Değer (RMD) analizi yapmalıdır. Yapay zekadaki gelişmeler RMD hesaplaması için birçok yöntem ve alternatif sunmaktadır. Bu sayede daha hassas ve karmaşık modeller kurgulanabilmektedir.

Bu çalışmada Bankacılık Endeksinde baskın olan 4 büyük bankanın (AKBNK, GARAN, ISCTR, YKBNK) hisselerinden Monte Carlo simülasyonuyla oluşturulan portföyler 3 farklı RMD yöntemiyle (tarihsel, Monte Carlo simülasyonu ve parametrik) analiz edilmiştir. Hisselerin 5 yıllık, günlük borsa verileriyle 10-ar günlük RMD sonuçları hesaplanmıştır. Elde edilen sonuçların 122 tanesi modelleri eğitmek için, 4 tanesi ise tahminleri kıyaslamak için kullanılmıştır. Portföylerin oluşturulması ve tahminleme amacıyla Random Forest algoritması çalıştırılmıştır. Ayrıca algoritmanın hassaslığını artırmak için VIX (korku endeksi), Dolar/TL, Altın/TL ve brent/TL değişkenleri de eklenmiştir. Değişkenlerin etkisini test etmek için makine öğrenmesi düzenlileştirme metotları olan Ridge, Lasso ve Elastic Net regresyon modelleri kullanılmıştır. Bu modeller her bir değişkenin portföye etkisini daha hassas ölçmeyi sağlamaktadır. Her bir RMD modeli için son 4 periyotta hisse dağılımı tekrar yapılarak RMD değerleri hesaplanmış ve bunlar gerçek RMD değerleriyle karşılaştırılmıştır. Bulgular sonucunda ilk periyotta parametrik RMD en iyi sonucu verirken diğer üç periyotta tarihsel RMD reel sonuçlara en yakın değerleri vermiştir. Ridge, Lasso ve Elastic Net regresyon modellerinin ortaya koyduğu etki sonuçları arasında belirgin bir farklılık gözlemlenmemiştir.

Makalenin ana amacı olan RMD hesaplamalarıyla gerçek RMD değerleri arasında belirgin bir fark görülmektedir. Bulguların, gerçek verilerden daha iyimser olduğu ve %30'dan daha az oranda yaklaşamadığı gözlemlenmiştir. Farkın beklenenden fazla olmasının sebebi olarak banka hisselerinin son iki yılda değerinin altında fiyatlanması, seçilen zaman aralığının son 4 periyodunda borsa hareketlerinin – hisse senedinden bağımsız olarak – hızlı olması gösterilebilir.

Anahtar Kelimeler

Piyasa Riski, Riske Maruz Değer, Makine Öğrenmesi, BIST-30, Bankacılık Endeksi

Introduction

Understanding and evaluating market risk is an important task for portfolio managers. Analysis of market risk is conducted in various forms, and with the advancements in the field of software, Value at Risk (VaR) has evolved over time in accordance with Basel criteria. Three different methods are employed for VaR and Conditional Value at Risk (cVaR) estimation: the Linear VaR approach, historical simulation approach, and Monte Carlo simulation technique. The primary concern in VaR analysis is the measurement of tail risk. In this phase, estimation techniques for VaR diversify into parametric, semi-parametric, and non-parametric approaches. In VaR and cVaR models, fundamental variables in the risk factor category can include indices, interest rates, commodities, and foreign exchange. Additionally, variables such as volatility indices, global risk appetite indices, investor sentiment indices, global financial stress indices, and so forth can be utilized (İskenderoğlu & Akdağ, 2020;105). The selection of variables varies depending on the analyzed portfolio structure.

The data generation process has seen the emergence of numerous new and hybrid models and approaches over time. Some of these models are derivatives of each other, such as EWMA, MA, ARMA, ARIMA, GARCH, EGARCH, FI-APARCH, and more. Machine learning models have also contributed to the enrichment of these methods. In addition to traditional statistical approaches, machine learning methods like Decision Tree, Random Forest, Support Vector Machine, k-Nearest Neighbors (kNN), Recurrent Neural Networks (RNN), XGBoost, Light GBM, Long Short-Term Memory (LSTM), bi-variate LSTM, and many other deep learning methodologies are utilized in practice. Furthermore, there are various methods based on different approaches such as parametric, semi-parametric, and non-parametric, including Extreme Value Theory (EVT), generalized extreme value distributions, logistic distribution, Student t-distribution, Cornish-Fisher expansion, Fourier Transform, and more.

When looking at the methods mentioned above, it's evident that there are numerous alternatives available. Indeed, the literature is replete with articles covering each of these methods. The extensive diversity makes it virtually impossible to achieve a "correct result," "best prediction," or the "optimal solution." Therefore, the quest for "improvement" continues in this regard. For every portfolio that can be constructed, and every method applied, both positive and negative critiques can be made.

The banking sector index consists of shares that are included in the portfolios of almost all portfolio managers. Most investors initially enter BIST-30 shares and bank shares. Therefore, in this study, a portfolio was created from bank shares and those included in BIST-30. The selected shares represent approximately 72% of the index. Therefore, the RF method served as the foundation for this study. The time frame for data used in various studies can differ, ranging from one year to 45 years. To train the ML and DL algorithms and to ensure sufficient depth in general usage, 5 years of data have been utilized.

While setting up and optimizing algorithms, using a dataset of more than 5 years can lead to increased data fluctuation and breakpoints, making the algorithms prone to overfitting. Multiple factors can be used as variables. However, the absence of other macro variables - especially daily data - can lead to data incompatibility, resulting in the inability to establish the algorithm. Therefore, it is necessary for the variables used to have the same sample level. At this point variable limitation was used, among the synthetic data generation and variable limitation options. Variable limitation was chosen because synthetic data cannot be generated without knowing the sub-elements that make up these variables, and if the sub-elements that make up the variables are processed in the algorithms, the study would focus on macroeconomic variables rather than market risk.

As a limitation of the study, one dominant and fundamental risk variable has been selected from each different variable groups. At this stage, one might question why certain variables were included or excluded. However, the same question could be asked for every included or excluded variable. Furthermore, the selected variables were chosen to ensure compatibility among data cross-sections. There are several potential drawbacks to using a large number of variables in these algorithms. Some of the problems that may arise include overfitting, training difficulty, interpretability issues, and data requirements dependent on the variable.

Hence, VIX, gold, Brent oil, and USD/TRY were selected. Depending on the chosen VaR approach, the impact of variables and the distribution of weights among the shares vary. In these stages, optimization was performed using RF. VaR was calculated for each method over four periods and compared with real data. Out of the 10-day VaR data, 122 were used as training and testing data.

In the literature, analyses are generally conducted by applying ML/DL methods to a single VaR calculation method. Some studies, however, perform VaR calculations using a single ML/DL method (see theoretical background section). In this study, unlike general VaR analyses, multiple VaR methods have been analyzed. Additionally, the results have been compared with real data to assess their consistency. The accuracy of the findings has been verified using error metrics. Another difference is the relatively new measurement of the impact of variables on regression models using Ridge, Lasso, and Elastic Net. Thus, it was calculated how effective the selected variables were in each period. It is possible to reach different results with different variables. However, to ensure effective diversity and avoid data incompatibility, one variable from each market variable group has been selected. Increasing variables, selecting different variables, and/or using another ML/DL model can be done in further studies. Here, what is tested is not the variables but the results of VaR methods. The banking sector was chosen while constructing the portfolio. The results will vary for portfolios constructed in different ways. While diversifying the stocks, over 10,000 iterations were performed using Monte Carlo simulation, and various "best" portfolio diversifies were created for each period and each VaR method. This distribution is provided in Table 4.

The article consists of four sections following the introduction. In the literature review section, market risk, fundamental risk factors, and VaR models were examined. The methodology section explains the data, variables, and the RF method. In the findings section, the robustness of the variables was tested by providing Ridge, Lasso, and Elastic Net regression methods used to explain the data. The results of VaR models were compared with actual data. The last section is dedicated to conclusions and discussions.

Theoretical Background

VaR calculations can be broadly classified into three main categories: parametric, semi-parametric, and non-parametric. On the other hand, there are three fundamental approaches: historical simulation, Monte Carlo simulation, and Linear VaR approach. By incorporating ML and DL methods into the analyses, a wide range of analytical possibilities emerges (See Figure 2). There are studies in the literature related to all these branches. For example, Ciu et al. (2021:381) worked on European options and path-dependent exotic contracts using the historical VaR method. Kakade et al. (2022:1) used GARCH and LSTM models for historical VaR forecasting. Omaniec et al. (2022:1) compared GARCH and LSTM methods for historical VaR estimation, while Gurrola-Perez and Murphy (2015:ii) simulated multiple historical VaR models for the same purpose.

Pokou et al. (2024:1) utilized directional double deep Q-Network to develop a semi-parametric VaR-GARCH model, pushing the boundaries by applying Deep Q-Learning and Reinforcement Learning methods, pioneering future researches. Jiang et al. (2017:5642) applied GARCH and RF models for semi-parametric multi-period VaR prediction in a conference presentation. Behera et al. (2023:1) selected stocks for mean-VaR calculation using portfolio optimization with various ML algorithms. Chen et al. (2021:1) utilized an ML method named Improved Firefly Algorithm XGBoost (IFAXGBoost) for mean-variance portfolio optimization. Arian et al. (2022:500) compared 12 different VaR algorithms for portfolio matching. Al Jabani (2022:864) worked on parametric VaR for market risk modeling and optimal portfolio selection, conducting portfolio analysis using ML techniques. Kaushik and Giri (2020:1) focused on F/X rate forecasting using historical data, studying SVM, RNN, LSTM, and VAR models. Zhang et al. (2018) applied non-parametric GARCH and online sequential extreme learning machine (OS-ELM) for real-time VaR calculation. As observed, with the advancement of AI and models, the number of alternatives is increasing. Due to the wide range of options available, it is deemed more appropriate to provide theoretical background with literature from this point forward.

Market Risk Analysis

Market risk analysis is a critical aspect of financial risk management. It involves the assessment and measurement of potential losses in financial markets due to various factors such as interest rate changes, commodity price fluctuations, foreign exchange rate volatility (Carmo et al., 2023:339). To effectively analyze market risk, it is important to utilize sophisticated tools and techniques that provide accurate and reliable predictions. Risks can have various sources. They can arise from economic and social reasons, as well as political and conventional conditions. Types of risks can also affect not only the prices of securities but also the investment amounts (Usta ve Demireli, 2010:27). Market risk is a type of risk that arises from uncontrollable factors. It can be seen as the impact of changes and fluctuations in the markets on investment returns. This widespread effect on the overall market more profoundly and directly affects stocks on the stock exchange (Dağlı, 2004: 325).

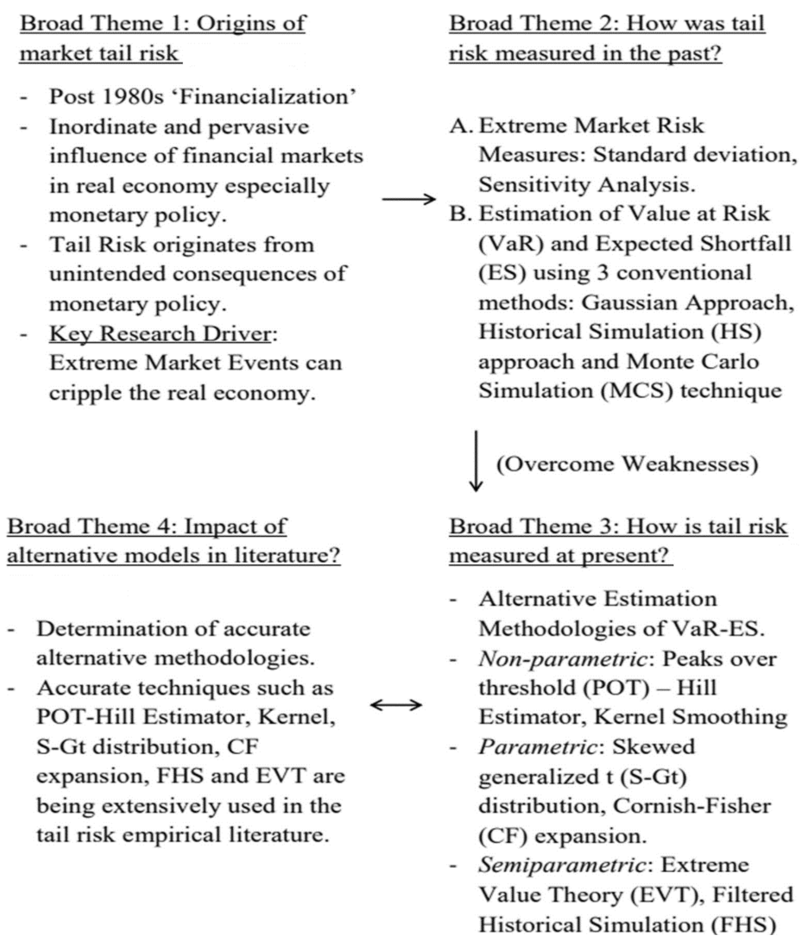
Initially, in 1988, the term "risk-weighted assets" used in the Basel regulations was further elaborated upon in subsequent Basel criteria (Akan, 2007:60). With the advancement of risk measurement methods, the analysis of market risk and its impact on capital adequacy ratios has become crucial for banks.

Market risk is the risk that the value of an asset or portfolio of assets will decline due to changes in market prices. It is the most common type of risk faced by investors, and it can be difficult to manage. Market risk is the loss of commercial activity caused by several factors, including exchange rates, interest rates, commodity prices and stock prices, between the transaction object and financial institutions. Market risk can be measured in several different ways, including historical volatility, beta, value at risk, stress testing, and scenario analysis. In addition to the above, here are some other important concepts in market risk analysis: systematic risk, unsystematic risk, tail risk, and liquidity risk.

Market Risk Analysis with ML

Machine learning is a field of information and computer science that focuses on creating an automated algorithm to enhance management processes, making them more efficient and accurate. Market risk, or in common financial market risk, are the loss of a portfolio's activities in financial transactions. Scholars proved that a well-constructed portfolio could reduce the probability of risks (Markowitz, 1952). Figure 1 illustrates the development of market risk and the development of tail risk measurement techniques.

Figure 1. Revolution of Market Risk

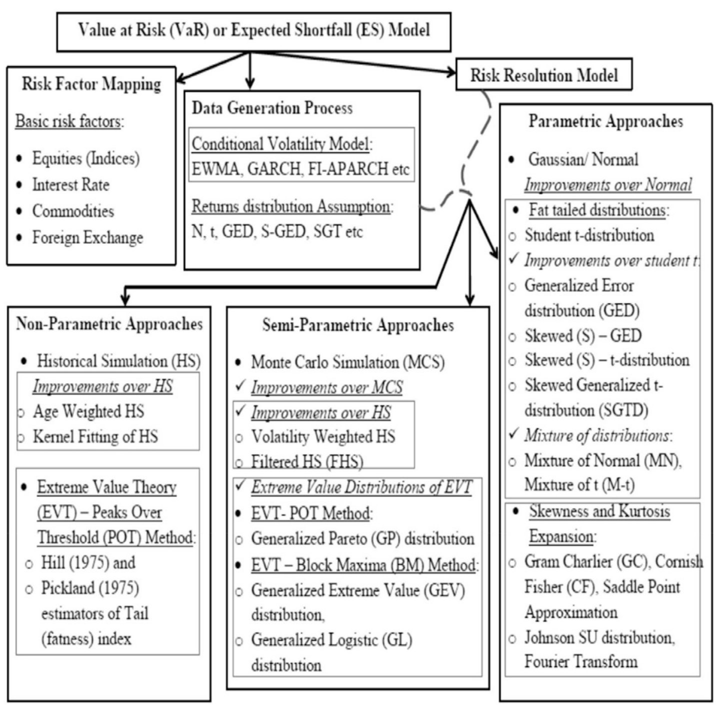


Source: *Chakraborty et al. (2021:3)*

AI and ML are used in various fields. Additionally, they are a useful tool for risk analysis. With the increasing utilization techniques, ML offers beneficial methods for risk measurement, classification, and analysis. In ML, data is divided into two parts, known as test and train data. Algorithm strives to enhance its consistency while learning from the train data. The results obtained through the most consistent iterations and then tested with the test data. This process aids in optimizing the algorithm. In scoring, in addition to the use of complex algorithms (Lessman et al., 2015:124), methods such as logistic regression, discriminant analysis, Bayes classifier, nearest neighborhood, classification trees, and artificial neural networks (Leo et al., 2019:8) have also been employed. Designing an early risk warning model using the SVM (Support Vector Machine) (Groth & Muntermenn, 2011:680) in ML algorithm and decision tree algorithms (Döpke et al., 2017:745) are other methods employed. Models have been trained with big data, and as a result, the consistency has been enhanced by increasing the size of the training data, as indicated by Chatzis et al. (2018:353). For example, Beutel et al. (2019:1) used ML algorithms to predict early warning systems with 45 years of data.

The various stages that market risk goes through (Figure 1) and the existence of many different VaR and ES (Expected Shortfall) models (Figure 2) increase diversity in risk analysis, especially when Machine Learning (ML) is used. Since there are numerous studies on this topic, it may not be useful to discuss each one individually. However, this study stands out for comparing 10-day forecasts with actual data, using four different models for VaR, constructing a portfolio with RF (Random Forest), improving the model, and employing RF algorithms for forecasting.

Figure 2. Classification of VaR and ES models



Source: Chakraborty et al. (2021:7)

Market Risk Determinants

Market risk determinants, also known as Factors or Sources of Market Risk, are events or variables that can affect the overall risk profile of financial markets. Market risk is the potential for a loss of value in an investment or portfolio due to a variety of market-related elements. These factors can influence the prices of stocks, bonds, and other financial instruments. There are different kind of risks and metrics that affect the market risk: interest rate risk, equity price risk, currency exchange risk, commodity price risk, credit risk, market volatility, liquidity risk, political or regulatory risk, economic indicators, geopolitical events, technological factors, market sentiment, global events, systemic risk, earnings and corporate events, supply and demand dynamics etc. On the other hand, these risks are not independent and related to each other factor. So, while analyzing market risk, one cannot take one of each variable as *ceterus paribus*. Though at some point we must do this prior condition to make a static evaluation. In this article we take some major determinants to analyze market risk: volatility index (VIX), F/X risk and commodity (gold and oil) risks. We use RF for weighting of these risks on the portfolio. Then we calculated VaR with different methods. This chapter makes a brief explanation of the risks and VaR methods that are evaluated in the analysis.

Volatility Index (VIX)

In today's global financial markets, volatility plays a crucial role in determining investment strategies and risk management. Volatility refers to the measure of fluctuations in the price of a financial asset and is of utmost importance for various stakeholders such as academics, policy makers, practitioners, and investors (Daniali et al., 2021:1). The VIX, also known as the Volatility Index, is a measure of market volatility and investor sentiment (Cainelli et al., 2021:285). The VIX index is often referred to as the "fear gauge" because it tends to rise when investors are fearful about the future of the stock market. Whaley (2000:14) found that the VIX index is a good predictor of future volatility, but it is not a perfect predictor. The VIX index tends to be more accurate at predicting short-term volatility than long-term volatility. Accurate volatility forecasting can help investors make informed decisions, manage risk effectively, and maximize potential profits (Russon & Vakil, 2017:200). Narasimhan and Viswanathan (2011:24) found that the VIX index can be used to identify market turning points. For example, the VIX index often spikes before a market crash. Furthermore, accurate evaluation of volatility index can assist policy makers in formulating effective policies and regulations to promote financial stability and mitigate systemic risks (Iskenderoglu & Akdağ, 2020:115). The use of machine learning algorithms in analyzing the VIX can provide valuable insights into market volatility (Shaikh & Padhi, 2015:44). This analysis can help predicting future market volatility and investor sentiment, which is crucial for managing market risk (Widhiarti et al., 2018:246).

Foreign Exchange (F/X) Risk

The potential loss caused by a decline in F/X rates is known as F/X risk, and it affects all exchange rate-related products with holdings valued in currencies other than the bank's reporting currency (Apostolik et al., 2009:234). According to Rupeika-Apoga (2005:151), F/X refers to the possibility for currency changes to alter the expected levels of volatility in the firm's future cash flows. Principles of hedging are essential to managing F/X risk. Foreign exchange risk hedging is a challenging problem. Hedging techniques including forward, futures, swap, options, and others are available to control currency exposures. The risk of unanticipated political, social, economic, and environmental changes affecting other countries is always present in the foreign currency market (Ahmed, 2015:117).

The three primary categories of exchange change risk were defined by Su (2018:530) as transaction, operation, and translation (accounting) risk. The volatility in the value of outstanding financial liabilities acquired before a change in exchange rates but not scheduled to be settled until after the change in exchange rates is calculated as transaction risk. According to Rupeika-Apoga (2005:151), operating risks are variations in the number of operating cash flows resulting from a company's future revenues and expenses and brought on by changes in the exchange rate. Operating risk, also referred to as "economic risk, competitive risk, or strategic risk", develops because of unanticipated exchange rate changes that alter a firm's expected future operating cash flows (Su, 2018:531).

Machine learning can be used to analyze historical exchange rate data and identify patterns and correlations with other economic factors (Deng et al., 2014:1). This analysis can help to predict future exchange rate movements and assess the potential impact on investments and transactions. By incorporating machine learning algorithms into foreign exchange risk analysis, financial institutions can enhance their ability to make informed decisions regarding currency hedging strategies, international trade decisions, and capital allocation in different currencies (Apergis & Papoulakos, 2013:1). Despite the F/X risk analysis, there is a lot of forecasting methods and articles for forex and stock prices with ML and DL (Hu et al., 2021; Sarangi et al., 2022; Ni et al., 2019; Zhang & Hamori, 2020). Standard risk analyzing techniques with ML and DL are subjected for F/X risks such as VaR, GARCH (Lu et al., 2022; Zhang et al., 2022), SVR (Höçük, 2022), stochastic models (Noorian & Leong, 2014; Simonella & Vazquez, 2023), ARMA-ARIMA.

Commodity Risk

Commodity risk is the potential loss due to an adverse change in commodity prices. There are different types of commodities including agricultural commodities (wheat, corn, soybeans), industrial (metals) and energy commodities (natural gas, crude oil). The value of commodities fluctuates a great deal due to changes in supply and demand (Apostolik et al., 2009:234). Since commodities are physical substances, the characteristic of commodity risk differs from other risk types. Commodities are being consumable, costly to produce and having variation in supply (Poitras, 2014:7). The commodity risk involves both price and quantity risk. There is uncertainty associated with the production, storage, and consumption decisions about specific commodities. The commodity risk management strategies pursued by firms involved in the production of commodities have substantive implications for valuing the equity securities of those firms.

Commodity supply and demand effects the global financial outcomes. For example, during the Covid-19 outbreak, oil consumption fell, and oil prices went down to its historical levels. During Russian-Ukraine war, price of grain and oil are affected. Price of these commodities have been volatile since the amount of supply decreases. Also, it affects the energy prices, especially for EU. There is a strong relationship between commodities and inter-sectorial connections (Foroni et al., 2022:3). During the crisis period, commodity price risk exposure appears for both financial and non-financial industries (Akhtaruzzaman et al., 2021:1).

Gold and oil have a larger volume compared to other commodities. During times of crisis, gold and oil have often been the first commodities to be affected. The perception of gold as a 'safe haven' has made it the preferred choice for investors during financial crises. In addition to periodic oil-related crises, in extreme situations such as the Ukraine-Russia conflict, oil is used as a significant geopolitical tool. The fact that oil plays a crucial role in energy supply makes it even more important. In addition to being needed in many sectors such as transportation, logistics, and manufacturing, oil also plays a crucial role in energy production, especially in petroleum and natural gas power plants. This grants a privilege to countries that extract oil. Due to the mentioned reasons, in this study, commodity risk is calculated by considering both oil and gold.

Value at Risk (VaR) and Analysis Methods

In April 1995, the Basel Committee on Banking Supervision declared that commercial banks' capital adequacy standards will be based on VaR. VaR quantifies the worst anticipated loss within a specified confidence interval over an objective horizon. VaR encapsulates in a single number the likelihood of unfavorable changes in financial variables and the world's exposure to market risks. The same units are used to measure risk at the bottom line (Jorion, 1996).

VaR has two basic parameters: (i) the significance level α, (ii) and the risk horizon, which is measured in trading days. Internal VaR models that evaluate capital risk requirements under the Basel II Accord must measure VaR with a 99% confidence level. Over various time frames, different risks are assessed. The VaR has a 10-day risk horizon, in accordance with Basel banking standards. The probability of the portfolio's insolvency or of defaulting on its commitments can be calculated using VaR. Regulators permit capital to be evaluated using an internal VaR model when certain qualitative criteria, including a 99% confidence level and a 2-week risk horizon, are also met. The market risk capital requirement is then calculated by multiplying this amount by a factor of between 3 and 4.

VaR models can be divided into three categories (Alexander, 2009:41):

- The parametric linear VaR model, which requires a linear portfolio and assumes that the distribution of risk factor returns is multivariate normal.
- The historical simulation model, which estimates VaR while making few assumptions on the risk factor return distribution. This model employs a significant amount of historical data.
- The Monte Carlo VaR model, which shares many of the same presumptions as the conventional linear VaR model in its most basic version.

The construction of this distribution is the primary explanation for why the three VaR models differ from one another. All three strategies might be developed and made more widespread.

The primary benefit of each strategy is as follows, in brief:

- The analytical tractability of the typical linear VaR model.
- Historical VaR does not assume the parametric shape of the distribution of the risk factors, which may be unrealistic.
- Because of its extreme adaptability, the Monte Carlo VaR model may be used to analyze any kind of position, including non-linear, path-dependent portfolios.

Parametric Linear VaR Model

Only portfolios with returns or Profit-Loss that are a linear function of the returns on their assets or risk factors qualify for use of the parametric linear VaR model. The model's most fundamental presumption is that risk factor returns are normally distributed and that their joint distribution is multivariate normal, therefore all that is necessary to capture the relationship between the risk factor returns is the covariance matrix of the risk factor returns.

Most of the time, VaR is measured over a narrow range of risk horizons, and it's reasonable to assume that excess return on your portfolio is equal to zero over that range. After that, the normal linear VAR formula takes on a very straightforward form. As a percentage of your portfolio's value, 100α%, normal linear VAR is simply the difference between the standard normal α

quantile and the standard deviations of the portfolio's returns over that range. If your portfolio is a linear one, the standard deviation can be represented as: The square root of the quadratic formula derived from the vector of your risk factors and the vector of the covariance matrix of your risk factors over the risk horizons.

Using the parametric linear model, we can calculate the (VaR) and Estimated Tail Loss (ETL) using analytic formulas that are based on the parametric distribution of the risk factor returns. When the portfolio value is just a linear function of the risk factors in the portfolio, we assume that the portfolio's returns are independent, and the returns are the same with the normal distribution. We can use this assumption to derive analytic formulas for the VAR and ETL for a linear portfolio. We can also use this assumption when the risk factor returns have the Student t distribution or a mix of normal and Student t distributions (Alexander, 2009:42).

Historical VaR Model

In the historical VaR model, all future variations are assumed to have occurred in the past and the historical simulated distribution is equal to the distribution over the forward-looking risk horizon. The historical scenarios on the contemporaneous movements of risk factors are employed to simulate a wide range of portfolio values over h days. To achieve this, the risk factor mapping must be applied to each of these simulated contemporaneous simulated risk factors returns. The sensitivities of the risk factors are assumed to remain constant at their present values. Historical data should be averaged at a daily frequency and extended over many years. This is because we need a large number of data points to compute the quantiles of the empirical distribution, particularly those in the ultra-low tail (which are necessary for high-confidence VaR estimates).

Historical VaR has one of the biggest advantages: it doesn't make a lot of distribution assumptions. There are no assumptions about the parametrical form of the return distribution of risk factors, at least not in the sense that there is any multivariate normality. The one distribution assumption that historical VaR make is that the multi-factor return distribution over a risk horizon is going to be the same as the multivariate return distribution over the past. Another big advantage of historical VaR is that risk factor dependencies are based on experience with risk factors and movements between them, rather than a parametrical model of their distribution (Alexander, 2009:43).

Monte Carlo Simulation

The most basic form of the Monte Carlo VaR model assumes of the normal linear VAR model, that the risk factors are independent and uniformly distributed with multivariate normal distributions. However, due to the robustness of the model, a wide range of multivariate distribution assumptions can be made. For example, in the independent and identically distributed multivariate normal VaR model, we simulate independent normal standard vectors and convert them to correlated normal vectors. We generate a very large number of simulations and employ methods to lower the error variance to reduce the sampling error. The normal linear VaR estimate and the normal Monte Carlo VaR estimate ought to be comparable. If it differs, it can only be because of not enough simulations being run. Applying normal Monte Carlo VaR to a linear portfolio is pointless because it only introduces sampling mistakes that are absent from the normal linear VaR model. The fact that the Monte Carlo VaR can be based on virtually any multivariate distribution for risk factor returns, as opposed to the fact that closed-form solutions for parametric linear VaR are only available for a small subset of distributions, makes it still worthwhile to use it to calculate the VaR for a linear portfolio (Alexander, 2009:45).

The similarity between probability and volume serves as the foundation for Monte Carlo methods. By linking an event with a set of outcomes and defining the probability of the event as its volume or measure relative to a universe of possible outcomes, the mathematics of measure formalizes the intuitive idea of probability. By understanding the volume of a set as a probability, Monte Carlo applies this identity backwards to determine the volume of a set (Glasserman, 2004).

Methodology

In this study, a portfolio has been created with the stocks of the four banks with the highest trading volume in the banking index of Borsa Istanbul (İş Bankası (ISCTR), Yapı Kredi (YKBNK), Akbank (AKBNK), Garanti (GARAN)). The selected stocks are also included in the BIST-30 index. The data consists of 5 years of daily closing prices, spanning from 2018 to 2023, comprising a total of 1264 days (25.06.2018 – 06.10.2023). The data was obtained from investing.com. The purpose of the study is to calculate the portfolio’s exposure to risk by using 10-day (work-day) periods and comparing it with the realized potential loss rates. Therefore, the portfolio’s diversification has been reconstructed for each 10-day time interval, and VaR has been recalculated. However, during these periods, no new stocks have been added or removed from the portfolio.

During the portfolio diversification process, stock prices have been considered as the dependent variable. The independent variables used in the analysis are the fear index (VIX), gold/TL exchange rate (XGOLD/TL), USD/TL exchange rate, and Brent oil prices. The impact of independent variables on the dependent variable has been calculated by using linear regression.

To determine the weighting of independent variables based on their impact on stocks, the RF method has been used. In the created RF model, the “n_estimators” (number of estimators) parameter has been set to 100. This quantity is sufficient to train the model. 'n_estimators' is a hyperparameter used in ensemble methods. Ensemble methods aim to create a more robust and general predictor by combining multiple learning models. In these methods, the primary goal is to use multiple learning models to achieve more reliable and stable results. The "n_estimators" hyperparameter is used in "forest" type models, which are a subset of ensemble methods. Thus, multiple learning models (decision trees) are combined to create a predictor. The "n_estimators" hyperparameter determines how many trees will be used to build this predictor. A higher "n_estimators" value means that more trees will contribute to forming the final prediction. The value of the "n_estimators" parameter depends on factors such as the dataset, its size, the number of features, and the complexity of the model. If you have more data and features, you typically choose a higher value for "n_estimators." The value of this hyperparameter is optimized using the test data performance. If the test performance is lower than the training performance, you should increase the "n_estimators" value and select a higher value.

Three different methods have been used for VaR calculation: historical simulation, parametric linear model, and Monte Carlo simulation. A confidence interval of 99% has been chosen. Models have been trained using 10-day periods (resulting in 126 separate VaR calculations), and then VaR calculations have been made for the next 10-day period.

Random Forest

Random forest is a type of supervised machine learning algorithm. It uses ensemble learning to build a model that is more robust and accurate. The random forest algorithm trains multiple decision trees on a subset of the data set. The predictions of the trees are then combined to form the final prediction. The random forest algorithm starts by randomly selecting a subset of all the features in the data set. It does this so that no single feature has too much effect on the model. Then, the random forest algorithm builds a decision tree based on that subset of features. The process is repeated many times, and the result is called a forest. The final prediction of random forest algorithm is calculated by taking the majority of the predictions from each tree. This reduces overfitting and improves the model's accuracy. Random forest is a general-purpose algorithm that can be applied to both classification and regression issues. It is easy to interpret and fine-tune, making it one of the most popular algorithms among machine learning experts[1].

While starting this article, we explored various ML models such as SVM, LSTM, KNN, RNN, and ANN. We analyzed and compared all error metrics and found that RF yielded the best results in terms of error metrics. Another

1 For more Random Forest (RF) imformation and mathematical formulation please see Jiang et al. (2017, p. 5643).

reason for choosing Random Forest is its ability to effectively explain the relationship between dependent and independent variables when constructing fundamental algorithms, and its capability to provide more realistic predictions compared to other models. Therefore, we opted for RF in our analysis. RF has been employed to assess the impact of risks, treated as independent variables, on portfolio weighting, as well as to train VaR models.

Findings

The analysis utilizes the four bank stocks with the highest trading volumes in BIST30 (ISCTR, YKBNK, AKBNK, GARAN). The combined market share of these selected stocks in the banking sector index has been calculated as 72%. The analysis covers the period from June 25, 2018, to October 6, 2023.

First, some fundamental data has been calculated. As a result of the calculations, the slopes and y-intercepts of the variables are provided in the table below.

Table 1. Slope and y-intercept of variables

	VIX	Gold/TL	USD/TL	Brent/TL
Slope	-0,1116	-0.0056	1.1710	-0.1178
Y- intercept	14,784	19,898	7,002	4,884

According to the provided data, USD/TL has a positive influence above the general trend, while the other variables have a negative impact. The calculated R-squared (R2) value, which is 0.89, indicates that the variables' fit to the model is reasonably high. Therefore, the model's performance is considered acceptable.

In the study, VIX, Gold/TL, USD/TL, and Brent/TL are used as variables. In multivariate regression models, machine learning techniques such as Ridge, Lasso, and Elastic Net are employed as regularization methods. These techniques help maintain the predictive power of the model while reducing its complexity and the risk of overfitting. Each of these techniques is used to measure the impact of each variable on the model.

Ridge regression reduces the complexity of a model by decreasing the coefficient values of variables. Its primary objective is to find the coefficients that minimize the sum of squared errors while applying a penalty (L2 norm) to these coefficients to resist overfitting. Ridge regression includes all variables in the model, does not remove irrelevant variables, but pushes their coefficients towards zero.

Lasso regression performs both variable selection and regularization to enhance the predictive accuracy and interpretability of the generated model. Like Ridge regression, its aim is to find coefficients that minimize the sum of squared errors while applying a penalty to these coefficients. However, Lasso regression sets the coefficients of irrelevant variables to zero.

Elastic Net regression is a combination of Ridge and Lasso regression techniques. Elastic Net reduces the model's complexity by both shrinking the coefficients of variables and removing variables from the model. In other words, it combines the penalization approach of Ridge regression with the variable selection approach of Lasso regression (Köseoğlu, 2020).

The reasons for using Ridge, Lasso, and Elastic Net are as follows:

1. Reducing the risk of overfitting: Multivariate regression models can be sensitive to overfitting, especially when there is an abundance of data. Ridge, Lasso, and Elastic Net, as regularization techniques, can help mitigate this risk, leading to improved predictions.
2. Decreasing model complexity: Multivariate regression models can involve a large number of variables, potentially increasing model complexity and diminishing predictive power. Ridge, Lasso, and Elastic Net, as regularization techniques, can reduce model complexity, thereby enhancing predictive performance.
3. Identifying the most important variables: Ridge, Lasso, and Elastic Net can assist in identifying the most important variables in the model by either shrinking the coefficients of less important variables or eliminating them. This can contribute to improved model interpretability.
4. Optimization Problems: A multi-dimensional input space can make the optimization process more challenging. This can lead to problems such as getting stuck in local minima or gradient vanishing occurring more frequently.

The choice of which regularization technique to use depends on the characteristics of the dataset and the target variable. Ridge regression generally provides better predictions than Lasso, but Lasso reduces model complexity to a greater extent. Elastic Net is a combination of Ridge and Lasso, offering the advantages of both techniques. It can be particularly useful when dealing with datasets that have many variables with varying levels of importance and multicollinearity.

Value at Risk (VaR) calculations can be performed for 1-day, 10-day, or 30-day periods. Basel criteria recommend conducting VaR calculations for a 10-day period. As a result, the chosen time frame has been divided into 126 10-day periods. Out of these periods, 122 of them, representing 70%, are used as training data, while the remaining 30% serve as test data. The calculations have been carried out for the last 4 periods. However, before the VaR analysis, it is necessary to explain the results of regression analyses conducted using machine learning to assess the impact of variables for these 4 periods.

First, Mean Square Error (MSE) has been calculated for the Ridge, Lasso, and Elastic Net regressions used. The lower the MSE, the more accurate the predictions. The MSE values are provided in the table below.

Table 2. MSE values of each regression method

	Ridge regression	Lasso Regression	Elastic Net regression
MSE	6,093	6,189	6,166

Based on the MSE data, the predictions of each method are at approximately the same level of accuracy. The table below contains the coefficients of each variable for the regression methods calculated for the specified periods.

Table 3. Effect of each regression model for each period

Ridge Regression

Periods	1st period	2nd period	3rd period	4th period
VIX	-0,1104	-0,0055	1,1699	-0,1189
USD/TL	-0,1579	-0,0084	1,9345	-0,1687
Gold/TL	-0,0774	-0,0030	0,8712	-0,0824
Brent/TL	-0,0587	-0,0020	0,7177	-0,0618

Lasso Regression

Periods	1st period	2nd period	3rd period	4th period
VIX	-0,0956	-0,0049	1,1032	-0,1016
USD/TL	-0,1430	-0,0078	1,8679	-0,1514
Gold/TL	-0,0625	-0,0024	0,8045	-0,0651
Brent/TL	-0,0438	-0,0014	0,6510	-0,0445

Elastic Net Regression

Periods	1st period	2nd period	3rd period	4th period
VIX	-0,0978	-0,0048	1,1041	-0,1097
USD/TL	-0,1418	-0,0074	1,8470	-0,1595
Gold/TL	-0,0661	-0,0024	0,8140	-0,0735
Brent/TL	-0,0481	-0,0015	0,6649	-0,0530

These values represent the coefficients that indicate the impact of each independent variable on the dependent variable. The sign of the coefficient signifies whether the independent variable increases or decreases the dependent variable. The magnitude of the coefficient indicates the magnitude of the independent variable's effect on the dependent variable. Considering these results, the following interpretations can be made:

For Ridge regression values:

- VIX reduces average stock prices by approximately 11.04%.
- USD/TL reduces average stock prices by approximately 15.79%.
- Gold/TL reduces average stock prices by approximately 7.74%.
- Brent/TL reduces average stock prices by approximately 5.87%.

For Lasso values:

- VIX reduces average stock prices by approximately 9.56%.
- USD/TL reduces average stock prices by approximately 14.30%.
- Gold/TL reduces average stock prices by approximately 6.25%.
- Brent/TL reduces average stock prices by approximately 4.38%.

For Elastic Net values:

- VIX reduces average stock prices by approximately 9.78%.
- USD/TL reduces average stock prices by approximately 14.18%.
- Gold/TL reduces average stock prices by approximately 6.61%.
- Brent/TL reduces average stock prices by approximately 4.81%.

These results indicate that all these variables have a negative impact on stock prices in the first period. In the third period, on the other hand, all variables are observed to have positive effects. The signs of the coefficients indicate whether the independent variables increase or decrease the dependent variable. In this case, all independent variables are shown to decrease the dependent variable, meaning that these variables have a negative impact on stock prices. Due to the explanations provided, ordinary least squares (OLS) regression was not performed, and the variables were analyzed separately.

In the next stage, VaR analyses were conducted using three different VaR calculation methods: parametric VaR, historical VaR, and VaR with Monte Carlo Simulation. Random Forest was utilized for both stock distribution estimation and VaR calculation in each of these methods. The stock distribution for each of the last 4 periods, for which VaR calculations were performed, varies depending on the methods. The table below illustrates the distribution of stock weights according to the methods:

Table 4. Diversification of stocks with VaR techniques

Parametric VaR	YKBNK	GARAN	AKBNK	ISCTR
1st period	31,2%	27,8%	26,8%	14,2%
2nd period	31,4%	27,7%	26,7%	14,2%
3rd period	31,5%	27,6%	26,6%	14,3%
4th period	31,7%	27,5%	26,5%	14,2%
Historical VaR	YKBNK	GARAN	AKBNK	ISCTR
1st period	31,8%	27,4%	26,4%	14,4%
2nd period	32,0%	27,3%	26,3%	14,5%
3rd period	25,2%	26,7%	28,0%	20,1%
4th period	25,4%	26,6%	27,9%	20,1%
Monte Carlo VaR	YKBNK	GARAN	AKBNK	ISCTR
1st period	25,5%	26,5%	27,8%	20,1%
2nd period	26,3%	25,8%	27,0%	21,0%
3rd period	26,4%	25,6%	26,9%	21,1%
4th period	26,5%	25,5%	26,8%	21,2%

When we examine the distributions above, it is evident that there are not significant changes in diversification for Parametric VaR and Monte Carlo Simulation VaR calculations. However, for Historical VaR, there are dramatic fluctuations. Historical VaR is calculated purely based on past data, while Parametric VaR involves regression analysis, and Monte Carlo VaR is simulation-based. Therefore, more abrupt changes occur in Historical VaR. Factors contributing to this include stock weights, closing values at the end of the day, and the explanatory power of variables.

The central focus of the research is the calculation of VaR for each period. Up to this stage, the significance of the variables and the weight distributions of the employed VaR methods have been calculated. Random Forest has been used in these distributions. In the final stage, VaR calculations have been performed for each method. The table below lists the VaR data.

Table 5. VaR of each method for periods

	1. period	2. period	3. period	4. period
Parametric VaR	-1,64%	-1,33%	-1,29%	-1,44%
Historical VaR	-1,20%	-2,25%	-2,59%	-2,31%
Monte Carlo VaR	-1,39%	-1,41%	-1,72%	-1,54%

According to the data provided above, in the first period, the parametric VaR method predicts the highest decrease, while for the other periods, the historical VaR method forecasts the highest decrease. In the final stage, it is necessary to calculate VaR using real data and compare it with the models' data. The table below provides the realized VaR values for the prepared portfolios.

Table 6. Realized VaR for each method

	1. period	2. period	3. period	4. period
Parametric VaR	-3.3%	-3.06%	-3.17%	-3.04%
Historical VaR	-3.27%	-3.66%	-3.93%	-3.4%
Monte Carlo VaR	-3.03%	-2,97%	-3.16%	-2.9%

To understand the deviation between the data, if we calculate percentage differences:

Table 7. Difference between Realized and Calculated

	1. period	2. period	3. period	4. period
Parametric VaR	50,30%	56,54%	59,31%	52,63%
Historical VaR	63,30%	38,52%	34,10%	32,06%
Monte Carlo VaR	54,13%	52,53%	45,57%	46,90%

Upon examining the results above, the Historical VaR method provides the highest deviation for the first period, while for the other periods, this method has yielded the best results. On the other hand, for the first period, all models have shown deviations exceeding 50%. Furthermore, when compared to realized VaR, all models have provided optimistic results. It can be observed that models, which involve various calculations and added variables, perform poorly in capturing reality.

Results and Discussion

Risk analysis is one of the most critical tasks for portfolio management and banks. Basel criteria have designated risk analysis as a major task and have mandated frequent VaR calculations. Risks are highly diverse, often interrelated, and their impact varies depending on the variables considered. Market risk, especially in stock market shares, is among the most significant risks that require careful attention. Predicting the exposure value of stock shares, which can change rapidly and react swiftly due to internal and external influences, holds great importance.

Machine learning based VaR calculation has been in use for some time. The method's utility, quick results, and its inclusion of a wide variety of techniques have a dual impact. There is no single "most accurate method," and the precision of the results obtained depends on the variables and the dataset used. As shown in Figure 2, various models can be established, ranging from parametric to non-parametric approaches. ML (Machine Learning) and DL (Deep Learning) methods are also available under numerous names and hybrids such as GARCH, E-GARCH, Knn, RNN, DT, RF, LSTM, GRU, XGBoost, and more. Additionally, factors such as the selection of dependent and independent variables, the number of these variables, and the time interval pose a probability aspect in the analyses. Therefore, focusing on a specific period, using explanatory variables with high explanatory power, having a dataset with sufficient inputs for machine learning, and selecting stocks that cover a specific sector would be a sensible approach to narrow down the possibilities.

The study involved conducting VaR analysis using three different methods to measure market risk. Each of the three methods has its own advantages. To achieve this, a portfolio was created with the four dominant stocks in the banking index, and a dataset consisting of five years of daily closing prices was used. The variables included VIX (fear index), USD/TL, Gold/TL, and Brent/TL. The fear index (VIX) was selected to understand general trends. USD/TL was chosen as it is the most effective currency in terms of F/X risk. Among commodities, gold and oil stand out, with gold having a distinct impact due to its tendency to move inversely.

Random Forest (RF) was utilized both to create portfolio weightings and to measure the impact weight of variables in the model. The functioning of RF is explained within the article. RF was chosen due to its ability to provide better results compared to other machine learning models such as Decision Trees (DT), Long Short-Term Memory (LSTM), and Support Vector Machines (SVM). To determine whether the variables were suitable for this model, regularization models of machine learning, namely Ridge, Lasso, and Elastic Net regression, were employed. The purpose of using these methods was to reduce both the complexity of the model and the risk of overfitting.

In each of the methods used for VaR analysis, the stock distribution for the 4 forecasted periods was calculated. This allowed for the calculation of VaR based on the determined distributions. These distributions and the resulting VaR results represent the most optimal values. For instance, in the Monte Carlo simulation, more than 10,000 iterations are performed to select the most suitable distribution. The goal here is to evaluate different VaR calculation methods using the selected variables and the created portfolio through the RF method.

When comparing realized data with forecast values, it is observed that the forecast data is optimistic. Furthermore, there is no approach with a deviation of less than 30% in any period where the deviation from realized values is high. The Historical VaR method, which provided the worst result in the first period, delivers the best result in other periods. Historical VaR solely relies on distribution and weighting based on past data. In comparison, other VaR models are more complex than Historical VaR. The reason for the optimism of the predictions can be attributed to the influence of past data. For instance, since a 5-year period is considered, the analysis suggests that bank stocks performed well in the first 3 years of this period, while in the last two years, the profitability of stocks decreased. Furthermore, the low performance of the models can also be explained by the portfolio composition. Since only stocks from a specific sector were selected, a high level of correlation was created, and all selected stocks were affected by sectoral influences. This finding can be considered as evidence of the necessity for diversification in stocks. The variables included in the model were not selected based on the stock market or index. This decision was made to avoid the impact of correlation. On the other hand, these choices, despite testing the consistency of the variables, can be seen as an explanation for the weakness in the models' performance. Another factor to consider is the sharp movements in the stock market during the last four periods. Indeed, during this period, significant movements were observed in the stock market, independent of the characteristics of individual stocks. In ongoing studies, the efficiency of VaR models can be investigated by working with variables that have high correlation, strong internal impact, and portfolios composed of different sectors.

In the academic literature, there are various analyses of stock markets in different countries using different indices, various machine learning methods, and different time intervals, with selected VaR methods. With so many diverse options, numerous unique studies can be conducted. What sets this study apart is the simultaneous use of RF for both portfolio creation and measuring the impact of variables. Additionally, it offers innovation by calculating three different VaR methods for multiple periods.

Almost every study emphasizes how "consistent" or "good" its findings are. However, in this study, the extent to which the results deviate from real results has been calculated. The results will vary depending on the selected stocks, stock distributions, portfolio construction, or the ML/DL model used. This variability is also possible for other studies. However, based on the obtained data, it has been observed that the RF model, despite efforts to ensure robustness, does not sufficiently approximate real data. The necessity of validating the results with real data rather than relying solely on error metrics has been an important inference for analysts interested in the subject.

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