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Analyzing Stock Performance in the Banking Sector: Unveiling Value-at-Risk and Conditional Value-at-Risk Strategies

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Abstract

This study explores stock ranking in the banking sector using Value at Risk (VaR) and Conditional Value at Risk (CVaR). The research focuses on bank stocks and employs the Normal Exponential Weighted Moving Average (EWMA) method for volatility calculation and the Historical Simulation Approach for model generation. Data from the Thai stock market's banking sector, specifically the SET Finance index, is analyzed from January 1, 2017, to December 31, 2021, with confidence levels set at 95 % and 99 %. Model quality is assessed through the Violation Ratio, Three-zone Approach, and Normalized CVaR testing. The findings facilitate stock ranking and aid investors in risk estimation. Results reveal the ranking of banks based on VaR and CVaR, with Bank A identified as the highest-risk bank and Bank B as the lowest-risk bank. Two models, VaR using the Normal EWMA method at the 99% confidence level and CVaR using the Historical Simulation Approach at the 95% and 99% confidence levels, pass the model quality testing and provide valuable insights for stock ranking.

Keywords: Value at risk, conditional value at risk, historical simulation approach, normal exponential weighted moving average.

1. Introduction

The banking sector is crucial for economic growth, and competition among banks is intense. To stay competitive, banks need to undergo restructuring and enhance various aspects of their operations. This includes implementing effective marketing strategies, modernizing their image, improving customer accessibility, embracing technology advancements for efficient and secure services, and developing innovative products to meet customer demands and expand their client base. In addition to providing savings and loan services, facilitating currency exchange, and offering consumer credit options, banks play a significant role in Thailand's economy and financial policies. Therefore, risk management and governance are vital in the banking industry, especially during economic crises. Market risk refers to the potential losses incurred due to market price volatility. It can be categorized into direct risk and indirect risk. Direct risk involves losses resulting from fluctuations in financial variables such as security prices, interest rates, and exchange rates. On the other hand, indirect risk arises from factors like basis risk, which stems from differences in interest rates between assets and liabilities. The Basel Accord Amendment of 1996 introduced two methods for measuring market risk: maximum loss estimation in different scenarios and Conditional Value at Risk (CVaR), which calculates the probability-weighted average of potential losses. CVaR is particularly suitable for non-normal distributions and accounts for tail risk. Another commonly used measurement is Value at Risk (VaR), which provides a single number to summarize market risk. VaR is a straightforward measure that uses statistical techniques to analyze variables of interest. Understanding expected returns and risk helps investors make informed decisions and allocate assets efficiently. It also aids in risk management by effectively managing investment portfolios within acceptable risk levels. While VaR is widely used, its accuracy depends on the chosen confidence level for calculation. In certain cases, VaR may underestimate the actual risk if the confidence level is too low. In 1997, CVaR was introduced as a risk measure suitable for non-normal distributions, particularly for heavy-tailed distributions. CVaR considers diversification benefits but requires more complex calculations and back-testing to assess model quality. Although VaR is recommended by international institutions for measuring market risk, calculating VaR for investments in multiple assets or portfolios may increase measured risk due to the diversification effect. Therefore, caution should be exercised when using VaR. This research proposes using CVaR alongside VaR to enhance investment decision-making. The study aims to measure and evaluate risk in the banking sector using these methodologies. The results serve as a basis for ranking securities and informing bank management and investors.

This research analyzes market risk in the banking sector by examining two risk measures: VaR and CVaR. The primary objective is to rank the stocks of each bank based on their respective risk levels. The specific goals of the study are as follows: 1) To assess the suitability of VaR to evaluate investment risk within the banking sector. 2) To investigate using CVaR to measure the average value of risks exceeding the VaR threshold at a specific confidence level. 3) To compare the effectiveness of VaR and CVaR in describing stock risk within the banking sector, utilizing calculations and model performance evaluations. The aim is to employ these measures to facilitate stock ranking decisions. This research aims to gain a deeper understanding of market risk in the banking industry and provide valuable insights for risk management and investment strategies. The ranking of stocks within the banking sector is aimed to be achieved in this research by utilizing VaR and CVaR. Different calculation methods are employed to compare the effectiveness of various models in predicting the risk of each stock. The study includes 10 banks: Krung Thai Bank (BAY), Bangkok Bank (BBL), Kasikornbank (KBANK), Kiatnakin Phatra Bank (KKP), Krungthai Bank (KTB), LH Financial Group (LHFG), Siam Commercial Bank (SCB), Thanachart Capital (TCAP), TISCO Bank (TISCO), and Thai Military Bank (TTB). The risk assessment uses the Normal Exponentially Weighted Moving Average (Normal EWMA) method for measuring volatility and the Historical Simulation Approach based on historical data. Confidence levels of 95% and 99% are considered, and the quality of the models is evaluated through Back-testing using the Violation Ratio and Three-zone Approach. The research solely focuses on market risk, specifically the measurement of price volatility. To conduct the study, the research utilizes the closing stock price data of the selected banks and the SET Finance index, covering the period from January 1, 2017, to December 31, 2021.

2. Literature Review

Several research studies have been conducted on the topic of VaR and CVaR. These studies provide valuable insights into risk measurement and its applications. Rockafellar and Uryasev (2002) compared different risk evaluation models and found that CVaR can measure risk beyond the normal VaR. This aligns with Yamai and Yoshiba (2005) findings, who used Extreme Value Theory and copulas to compare VaR and CVaR. They concluded that CVaR is superior, especially for non-normal distributions and tail risks. Taamouti (2009) also explored VaR and CVaR estimation using Gaussian and Regime-Switching Models, finding similar results. Jorion (2002) examined VaR as a monetary measure, highlighting its importance for financial institutions in reporting income volatility. Varnananda (2013) studied the use of VaR and CVaR for assessing exchange rate and security risks in various countries, favoring the Historical Simulation Approach. Prapinmongkolkarn (2008) used CVaR to construct portfolios, resulting in lower loss dispersion and higher maximum returns than VaR and market index portfolios. Busarin Homwichian (2011) focused on the accuracy of VaR estimation models, concluding that a 95% confidence level provided better alignment with actual losses than a 99% level. Additionally, studies examined the relationship between economic factors and stock prices in the Thai banking sector. Pattiphan Surit-chot (2005) found a significant long-term relationship between Thai bank stock prices and international bank stock prices in Asia. Umaphorn Thaijaruen (2005) identified economic factors that influenced changes in Thai bank stock prices. These studies contribute to understanding risk measurement methodologies and their practical applications in finance.

3. Market Risk and Risk Assessment Models

Market risk is the uncertainty associated with fluctuations in the prices or values of financial positions, including assets, liabilities, and commitments. It results from varying market factors influencing these prices or values, such as exchange rates, interest rates, and political events. However, this risk can be mitigated through diversification by investing in a wide range of securities. Two popular approaches are employed to measure market risk, which stems from the potential losses due to price volatility: 1) utilizing standard deviation as a measure of risk and 2) employing VaR as a measure of risk. This research focuses on the second approach, specifically using Value at Risk and CVaR to assess market risk. A brief overview of these models is provided below.

3.1. Value at risk models

The Value at Risk model is an essential risk management tool that assesses the greatest potential loss a financial position or portfolio could experience within a defined time period and confidence level. Quantifying the worst-case scenario empowers investors and risk managers to understand and handle risk exposure effectively. VaR gauges the probability and magnitude of losses under typical market conditions while considering rare, extreme occurrences. The model calculates the maximum potential loss at a given confidence level, which can be represented as:

$$P\left(L > VaR\right) \leq 1 - \alpha, \tag{1}$$

where L is a random variable representing the loss or damage value, α is the confidence level, and P represents the probability measure. Various methods exist for calculating VaR, and this research employs a widely accepted, accurate approach favored by analysts. This method uses a normal distribution combined with an Exponentially Weighted Moving Average (Normal EWMA) to determine the variance. Alternatively, the Historical Simulation Approach calculates Value at Risk by constructing a model based on historical data.

3.1.1 Normal distribution method with exponentially weighted moving average (Normal EWMA)

The Normal EWMA method calculates the variance and risk of a financial position by combining a normal distribution with an Exponentially Weighted Moving Average. This approach responds more to recent market fluctuations, enabling better risk management decisions. However, it may not be suitable during extreme market events or when returns exhibit non-normal behavior. To calculate Value at Risk using the normal distribution method with an Exponentially Weighted Moving Average (EWMA), the following formula can be used:

$$VaR = -\mu_r + \sigma_r Z_\alpha, \tag{2}$$

where μ_r represents the average rate of return, Z_α represents the standard score at a certain confidence level $1 - \alpha$ and σ_r represents the standard deviation of the rate of return. The key assumption of the EWMA model is that the rate of return must have a normal distribution, and the standard deviation can measure the risk of a security group. An example of calculating Value at Risk using the normal distribution method with exponentially weighted moving average variance is shown in Figure1.

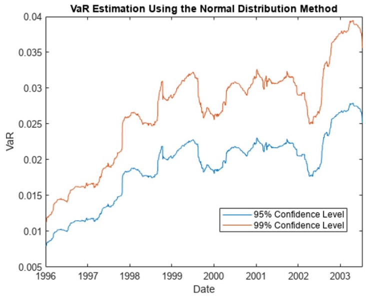

Figure 1 Calculating value at risk using the normal distribution method with exponentially weighted moving average variance.

3.1.2 Historical simulation approach

The Historical Simulation Approach for VaR estimation utilizes historical data to calculate potential losses. It involves sorting returns in ascending order and identifying the value at a specified confidence level's percentile. This method is advantageous because it doesn't require assumptions about return distribution but may be less accurate if historical data isn't representative or insufficient. The VaR using the Historical Simulation Approach can be calculated as:

$$VaR_\alpha = R_r^{p_\alpha}, \tag{3}$$

where $R_r^{p_\alpha}$ is the percentile of the total data at the confidence level $1-\alpha$. A key assumption of the VaR calculation using the Historical Simulation Approach is that the various factors determining market returns remain unchanged and consistent. An example of VaR estimation using the historical simulation approach is shown in Figure 2.

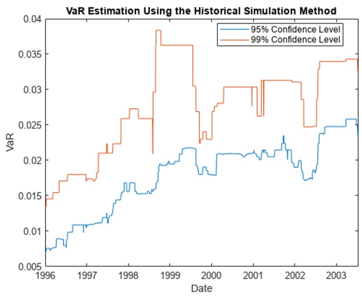

Figure 2 Value at risk using the historical simulation approach.

3.2. Conditional value at risk models

Conditional Value at Risk or CVaR extends the VaR concept by assessing tail risk beyond a specified confidence level. It calculates the average of all losses exceeding the VaR level, providing a more accurate representation of potential losses during extreme market events. This helps investors and risk managers better understand and prepare for the impact of severe market fluctuations.

3.2.1 Normal distribution method with exponentially weighted moving average (Normal EWMA)

CVaR, or Expected Shortfall, measures extreme losses beyond VaR. Calculated using Normal EWMA, it offers a comprehensive view of tail risk. CVaR is vital for assessing the impact of extreme events and enables more informed risk management decisions. By considering average losses beyond VaR, CVaR provides valuable insights for mitigating tail risk. The CVaR at time t, denoted as $CVaR_t$, can be calculated using the formula:

$$CVaR_t = -\mu_r + \frac{\sigma_r \phi Z_\alpha}{1-\alpha}, \tag{4}$$

where μ_r represents the average rate of return, Z_α represents the standard score at a certain confidence level$1-\alpha$, σ_r represents the standard deviation of the rate of return, and ϕ represents the standard deviation of the standard normal distribution.

3.2.2 Historical Simulation Approach

The CVaR using the historical simulation approach can be calculated by examining past data and considering all average return values below the risk's negative value from historical data. The formula can represent this:

$$CVaR_\alpha(X) = -E\left[X \mid X < -VaR_\alpha(X)\right], \tag{5}$$

where X is a random variable denoting the loss level. The measuring of risk using VaR and CVaR is shown in Figure 3.

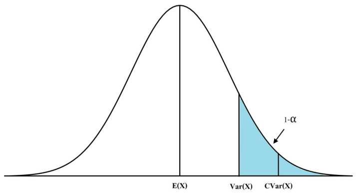

Figure 3 Measuring risk using CVaR.

3.3. Back-testing

Back-testing is crucial to validate VaR models by comparing calculated values with historical losses. Excessive VaR limits may hinder investments, while low limits may lead to unexpected losses. Ideally, during a 100-day period, there should be < 5 exception dates where actual losses exceed calculated VaR and CVaR values at 95% confidence. Similarly, at 99% confidence, there should be < 1 exception date for reliable risk assessment.

3.3.1 Quality Evaluation of Value at Risk Models

The quality evaluation of VaR models used in this research includes the following methods:

1) Violation Ratio (VR): Danielsson (2011) proposed using the Violation Ratio to assess model quality. An appropriate range for the Violation Ratio is between 0.8 and 1.2. If the Violation Ratio exceeds 1.5 or is below 0.5, the model is considered inaccurate. Exception Dates occur when the actual losses exceed the VaR calculated by the model,

$$VR = \frac{E}{N(1-\alpha)}, \tag{6}$$

under a confidence level of $1-\alpha$, where E represents the number of Exception Dates and N is the number of data points used for VaR forecasting. However, this method has limitations and may not be a reliable indicator of model adequacy. Thus, the three-zone approach, based on BIS criteria, is used for model validation. A high-quality model should provide sufficiently large VaR values and effectively capture actual losses.

2) Three-Zone Approach: The three-zone approach, based on criteria established by the Bank for International Settlements (BIS), assesses the quality of VaR models. A reliable VaR model should meet three criteria: providing sufficiently large VaR values for adequate risk coverage, accurately capturing real-world losses, and encompassing a broad range of potential losses, including extreme events. The three-zone approach is a valuable tool for evaluating the accuracy and dependability of VaR models in measuring and managing risk. The probability of having fewer or equal to n exception dates can be represented as $P\left(k \leq n \mid N, p\right)$ and calculated using,

$$P\left(k \leq n \mid N, p\right) = \sum_{k=1}^{n} \binom{N}{n} p^{k} (1-p)^{N-k}. \tag{7}$$

By categorizing into zones based on cumulative probabilities:
- The red zone represents the minimum number of days with a cumulative probability $\geq 99.99\%$. Model rejection is possible in this zone.
- The yellow zone starts from the number of days with a cumulative probability $\geq 95\%$ but $< 99.99\%$. It includes one exception date but is insufficient for model rejection.
- The green zone covers the remaining cumulative probability range, indicating no significant model quality concerns.

The categorization into 3 zones based on cumulative probabilities is shown in Figure4.

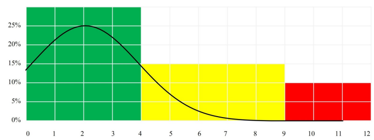

Figure 4 Probability that the number of abnormal days is less than or equal to n times, separated by zones according to cumulative probability.

3) Verification of conditional value at risk model quality: Verification of CVaR model quality involves assessing the accuracy and reliability of a CVaR model used to measure financial risk. Key steps include model validation, data quality assessment, backtesting, sensitivity analysis, benchmarking, and ongoing monitoring. This process helps ensure the model accurately represents risk exposure, leading to informed decision-making and effective risk management practices. For testing CVaR, we examine whether the average return rate on the exception date, when the Value at Risk exceeds the acceptable level, differs from the average of the CVaR calculated using the model on that day. Calculate the ratio between the average return rate on the day the Value at Risk exceeds the acceptable level and the conditional risk value on day t,

$$nCVaR = \frac{y_t}{CVaR_t}, \tag{8}$$

where $CVaR_t$ is the conditional risk value on day t and y_t is the average return rate on the day the Value at Risk exceeds the acceptable level. In hypothesis testing, the T-Test method is used by comparing the return rate on the exception date, when the value at risk exceeds the acceptable level, divided by the conditional value at risk calculated from the model on that day, to see if it significantly differs from 1 at a 0.05 significance level. The main hypothesis is $H_0: \overline{nCVaR} = 1$ and the alternative hypothesis is $H_1: \overline{nCVaR} \neq 1$.

4. Methodology and Procedures

The work process of the research is divided into 6 steps as follows:

Step1) Data collection. In this research, daily closing prices of the SET finance index are collected and set as the benchmark. The closing prices of stocks in the banking group, including Krungsri Ayudhya (BAY), Bangkok Bank (BBL), Kasikornbank (KBANK), Kiatnakin Phatra (KKP), Krung Thai Bank (KTB), Siam Commercial Bank (SCB), LH Financial Group (LHFG), Thanachart Capital (TCAP), TISCO Bank (TISCO), and TMBThanachart Bank (TTB) are used. The data covers the period from January 1, 2017, to December 31, 2021. Next, the closing price data is used to calculate daily return rates. The daily return rate for day t can be calculated as:

$$R_t^k = \frac{P_t^k - P_{t-1}^k}{P_{t-1}^k}, \tag{9}$$

where R_t^k represents the return rate of security k and P_t^k represents the price on day t of security k.

Step2) Analyze the statistical characteristics of the data. Use data set 1 in the form of daily return rates to analyze the statistical characteristics by calculating the mean, median, and standard deviation (SD %).

Step3) Calculate the frequency distribution of daily returns. Use the daily return rate data to calculate the frequency distribution of returns and present it in a data table format.

Step4) Calculate risk values. Calculate risk values at a 95% confidence level and a 99% confidence level, with a risk measurement period of 1 day, using different models and methods as follows:

1) VaR (%) using the Normal EWMA method
2) VaR (%) using the Historical simulation method
3) CVaR (%) using the Normal EWMA method, and
4) CVaR (%) using the Historical simulation method

Step5) Verify the quality of the model. Verify the quality of risk value measurement models from the results in Step 4 using the following methods:

1) Violation Ratio: VR
2) Three-zone Approach
3) Verification of conditional value at risk model quality

Step6) Rank the rating of stocks in the bank group. Utilize the findings to arrange the stocks of the banking group according to their investment rating criteria, as detailed in Table 1, following the principles of score distribution.

The overall workflow from data collection to ranking bank stocks based on investment criteria can be summarized as shown in Figure 5.

Table 1 presents the criteria for measuring investment rating levels using the TRIS and FITCH rating systems. It categorizes stocks into two main groups: Attractive Investing Stocks and Speculative Stock Investments. Each group is further divided into rating levels, with corresponding definitions indicating the level of risk and stability associated with the investment. This table is useful for analyzing market risk in the banking sector by categorizing stocks based on their risk and stability, which can facilitate stock ranking decisions and provide insights for risk management and investment strategies.

5. Results of the Quantitative Risk Value Analysis

From the work process in Section 4, the results are as follows:

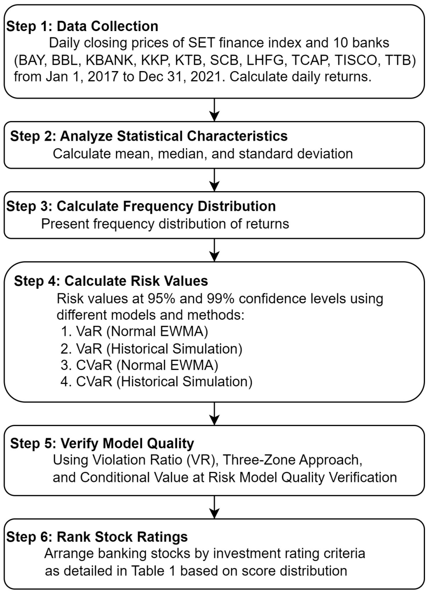

Figure 5 A visual representation of the 6-step methodology and procedures for the research.

Table 1 Criteria for measuring investment rating (Rating) levels.

Investment Rating	Rating Level	TRIS&FITCH	Definition
Attractive Investing Stocks	Maximum	AAA	Investment rating with low risk. Companies have high stability.
	High	AA+	Investment rating with low risk. Companies have high stability.
		AA	
		AA-	
	Medium-High	A+	Investment rating with medium risk. Companies have moderate stability.
		A	
		A-	
	Low-Medium	BBB+	Investment rating with high risk. Companies have low stability.
		BBB	
		BBB-	
Speculative Stock Investments	Low	BB+	Investment rating with high risk. Companies have low stability.
		BB	
		BB-	
	Medium-Low	B+	Not recommended for investment. Companies have low stability.
		B	
		B-	
		CCC+	
		CCC	
		CCC-	
		CC	
		C	
		D	

5.1. Results of statistical analysis

From step 2, the results of the statistical analysis are presented in Table 2. From Table 2, TISCO Bank has the highest average daily return (0.03207%), while Kiatnakin Phatra Bank (KKP) has the lowest (0.00174%). Thai Military Bank (TTB) has the highest volatility at 2.22489% per day, and LH Financial Group Limited (LHFG) has the lowest at 1.59193%. Investing in TTB appears to be high-risk but offers a high average return compared to Set Finance.

Table 2 Results of statistical analysis of SET finance index and individual stocks in the banking group

Bank	Mean (%)	Median (%)	SD (%)
BAY	0.00981	0.00000	1.83342
BBL	0.02416	0.00000	1.66791
KBANK	0.02041	0.00000	2.07678
KKP	0.00174	0.00000	1.74970
KTB	0.02551	0.00000	1.62364
SCB	0.01718	0.00000	1.95513
LHFG	0.02040	0.00000	1.59193
TCAP	0.01399	0.00000	1.75994
TISCO	0.03207	0.00000	1.66323
TTB	0.03165	0.00000	2.22489
SET Finance (Benchmark)	0.00418	0.00535	1.30504

5.2. Results of VaR and CVaR calculations

1) The average VaR and CVaR at a 95% confidence level and a 1-day risk measurement period are shown in Table 3. From Table 3, at a 95% confidence level, the bank with the highest VaR is TTB at 3.69127% and 3.04592% per day using Normal EWMA and Historical Simulation Approach, respectively. The bank with the highest CVaR is TTB at 4.62096% and 5.48696% per day using the same methods, due to the highest volatility of 2.22489% per day. The bank with the lowest VaR is LHFG at 2.63888% and 2.00007% per day, and the lowest CVaR is LHFG at 3.30408% and 3.44928% per day, due to the lowest volatility of 1.59193% per day.

Table 3 Average VaR and CVaR at a 95% confidence level and a 1-day risk measurement period

Bank	SD (%)	Normal EWMA VaR (%)	Historical Simulation VaR (%)	Normal EWMA CVaR (%)	Historical Simulation CVaR (%)
BAY	1.83342	3.02552	2.48460	3.79163	3.89252
BBL	1.66791	2.76763	2.42273	3.46458	4.15545
KBANK	2.07678	3.43641	2.93061	4.30421	4.79169
KKP	1.74970	2.87626	2.46926	3.60738	4.21415
KTB	1.62364	2.69615	2.02027	3.37460	3.83585
SCB	1.95513	3.23308	2.56424	4.05005	4.46162
LHFG	1.59193	2.63888	2.00007	3.30408	3.44928
TCAP	1.75994	2.90884	2.39055	3.64424	4.04565
TISCO	1.66323	2.70370	2.22231	3.39869	4.08562
TTB	2.22489	3.69127	3.04592	4.62096	5.48696
Set Finance (Benchmark)	1.30504	2.15077	1.73214	2.69610	3.23965

2) The average VaR and CVaR at a 99% confidence level and a 1-day risk measurement period are shown in Table 4. From Table 4, at a 99% confidence level, the bank with the highest VaR

is TTB at 5.20752% and 6.80535% per day using Normal EWMA and Historical Simulation Approach, respectively. TTB also has the highest CVaR at 5.96147% and 11.19225% per day using the same methods. This is due to the highest volatility of 2.22489% per day. The bank with the lowest VaR is LHFG at 3.72377% and 4.34851% per day using the same methods, while the lowest CVaR is also LHFG at 4.26322% and 6.51605% per day, resulting from the lowest volatility of 1.59193% per day.

Table 4 Average VaR and CVaR at a 99% confidence level and a 1-day risk measurement period

Bank	SD (%)	Normal EWMA VaR (%)	Historical Simulation VaR (%)	Normal EWMA CVaR (%)	Historical Simulation CVaR (%)
BAY	1.83342	4.27498	4.81192	4.89627	6.58033
BBL	1.66791	3.90430	5.68874	4.46950	7.63402
KBANK	2.07678	4.85173	6.48606	5.55548	9.16025
KKP	1.74970	4.06866	5.58098	4.66158	9.06688
KTB	1.62364	3.80265	4.65200	4.35285	7.88938
SCB	1.95513	4.56549	6.03957	5.22802	9.21371
LHFG	1.59193	3.72377	4.34851	4.26322	6.51605
TCAP	1.75994	4.10823	4.50237	4.70461	8.23542
TISCO	1.66323	3.83718	5.24258	4.40079	8.47776
TTB	2.22489	5.20752	6.80535	5.96147	11.19225
Set Finance (Benchmark)	1.30504	3.04015	3.73471	3.48238	6.98334

5.3. Results of VaR model validation

1) VaR model validation results using the violation ratio are shown in Table 5. From Table 5, at a 99% confidence level, the normal EWMA method is the most widely accepted model for VaR, with BBL, KTB, and TISCO having appropriate violation ratios. However, KBANK, SCB, and TTB can reject the model quality. In contrast, the Historical Simulation Approach can reject the model quality for all banks, requiring further inspection. Comparing the VaR from Table 4 at a 95% confidence level, the normal EWMA method rejects the model quality for all banks except LHFG and TISCO. In contrast, the historical simulation method rejects the model quality for all banks except LHFG and TCAP, which cannot reject the model's accuracy.

2) Quality assessment of models using the Three-zone approach for VaR at a 99% confidence level is shown in Table 6. From Table 6, the quality testing results of the three-zone approach model for VaR at a 99% confidence level are shown. The normal EWMA and historical simulation methods passed the testing, indicating good quality with no indication of poor performance. However, at a 95% confidence level, both methods failed the testing, as they had a significant number of exception dates, suggesting poor model quality.

5.4. Quality testing of CVaR models

The testing results for nCVaR (Normalized CVaR) and hypothesis testing utilize the T-Test method, comparing the daily return rates where Value at Risk exceeds the acceptable level (Exception Date) divided by the Conditional Value at Risk calculated from the model on that specific day. The test examines whether there is a significant difference from 1 at a significance level of 0.05, with the null hypothesis being $H_0: \overline{nCVaR} = 1$ and the alternative hypothesis being $H_1: \overline{nCVaR} \neq 1$. The results align with Table 7.

Table 5 Violation ratio test results for VaR at 95% and 99% confidence levels

Bank	95% confidence level		99% confidence level	
	Normal EWMA VaR	Historical Simulation VaR	Normal EWMA VaR	Historical Simulation VaR
BAY	2.02303	2.13816	1.41447	3.04276
BBL	1.79276	2.05592	1.16776	2.96053
KBANK	2.68092	2.79605	1.77632	4.52303
KKP	1.74342	2.05592	1.29934	2.96053
KTB	1.54605	1.64474	0.88816	2.30263
SCB	2.23684	2.13816	1.51316	2.87829
LHFG	1.33224	1.23355	0.78947	1.64474
TCAP	1.95724	1.31579	1.29934	2.54934
TISCO	1.48026	1.72697	1.08553	2.38487
TTB	2.50000	2.79605	1.82566	5.01645

Table 6 Exception dates and quality testing of the three-zone approach model for VaR at 95% and 99% confidence levels

Bank	95% Normal EWMA VaR	95% Historical Simulation VaR	99% Normal EWMA VaR	99% Historical Simulation VaR
BAY	86 (Red)	123 (Red)	37 (Green)	26 (Green)
BBL	71 (Red)	109 (Red)	36 (Green)	25 (Green)
KBANK	108 (Red)	163 (Red)	55 (Green)	34 (Green)
KKP	79 (Red)	106 (Red)	36 (Green)	25 (Green)
KTB	54 (Red)	94 (Red)	28 (Green)	20 (Green)
SCB	92 (Red)	136 (Red)	35 (Green)	26 (Green)
LHFG	48 (Red)	81 (Red)	20 (Green)	15 (Green)
TCAP	79 (Red)	119 (Red)	31 (Green)	16 (Green)
TISCO	66 (Red)	90 (Red)	29 (Green)	21 (Green)
TTB	111 (Red)	152 (Red)	61 (Green)	34 (Green)

Table 7 Number of exception dates for CVaR at 95% and 99% confidence levels

Bank	95% confidence level		99% confidence level	
	Normal EWMA CVaR	Historical Simulation CVaR	Normal EWMA CVaR	Historical Simulation CVaR
BAY	48	32	29	3
BBL	52	34	28	5
KBANK	71	48	39	11
KKP	45	34	27	6
KTB	37	25	22	5
SCB	51	32	27	9
LHFG	33	18	18	5
TCAP	51	26	22	5
TISCO	38	24	22	8
TTB	73	57	43	11

The CVaR measured at the 95% confidence level, using the Historical Simulation Approach, is the only model that has passed the quality testing for daily return data of the Set Finance index, as shown in Table 8. It confirms the primary hypothesis that $\overline{nCVaR} = 1$.

Table 8 The outcomes of computing the normalized CVaR values for CVaR at the 95% and 99% confidence levels

Bank	95% confidence level		99% confidence level	
	Normal EWMA CVaR	Historical Simulation CVaR	Normal EWMA CVaR	Historical Simulation CVaR
BAY	2.06	0.91	1.89	0.74
BBL	2.26	0.99	2.05	0.83
KBANK	2.53	0.97	2.37	0.85
KKP	2.60	1.04	2.52	0.91
KTB	2.52	0.96	2.35	0.89
SCB	2.49	0.97	2.48	0.93
LHFG	2.41	0.94	2.23	0.88
TCAP	2.67	0.94	2.74	1.00
TISCO	2.49	1.04	2.23	0.94
TTB	2.78	1.10	2.36	1.01

The risk rankings of each bank based on VaR and CVaR calculations are summarized in Table 9. Using the Normal EWMA method, TTB, KBANK, and SCB are identified as the highest-risk banks, while LHFG, KTB, and TISCO are the lowest-risk. However, with the Historical Simulation Approach, TTB and KBANK remain the highest risk, and LHFG and KTB are the lowest risks. The rankings vary depending on the calculation method employed.

Table 9 Summarizing the ranking of risks from low to high obtained from each model and the confidence levels of each bank

	Lowest-risk								Highest-risk	
Model	1	2	3	4	5	6	7	8	9	10
95% Normal EWMA VaR	LHFG	KTB	TISCO	BBL	KKP	TCAP	BAY	SCB	KBANK	TTB
99% Normal EWMA VaR	LHFG	KTB	TISCO	BBL	KKP	TCAP	BAY	SCB	KBANK	TTB
95% Historical Simulation VaR	LHFG	KTB	TISCO	TCAP	BBL	KKP	BAY	SCB	KBANK	TTB
99% Historical Simulation VaR	LHFG	TCAP	KTB	BAY	TISCO	KKP	BBL	SCB	KBANK	TTB
95% Normal EWMA CVaR	LHFG	KTB	TISCO	BBL	KKP	TCAP	BAY	SCB	KBANK	TTB
99% Normal EWMA CVaR	LHFG	KTB	TISCO	BBL	KKP	TCAP	BAY	SCB	KBANK	TTB
95% Historical Simulation CVaR	LHFG	KTB	BAY	TCAP	TISCO	BBL	KKP	SCB	KBANK	TTB
99% Historical Simulation CVaR	LHFG	BAY	BBL	KTB	TCAP	TISCO	KKP	KBANK	SCB	TTB

6. Application and Conclusion

Applying the findings for stock ranking and overall conclusions, the primary model demonstrating good quality for estimating VaR is the normal EWMA method at a 99% confidence level. This model has been rigorously tested using both the violation ratio and the three-zone approach. The preferred approach for assessing CVaR is the historical simulation method at a 95% confidence level, which effectively evaluates risk within the desired confidence level without excessive risk exposure. However, it's important to note that TCAP and TTB did not pass the hypothesis testing for Exception Dates, suggesting a significant deviation from the estimated values. Users may opt to use the 99% confidence level model instead, considering whether the calculated risk is unreasonably high. A comprehensive summary of the results can be found in Table 10.

Table 10 Summary of the top-performing models in evaluating VaR and CVaR across banks

Bank	Value at Risk	Conditional Value at Risk
BAY	99% Normal EWMA VaR	95% Historical Simulation CVaR
BBL	99% Normal EWMA VaR	95% Historical Simulation CVaR
KBANK	99% Normal EWMA VaR	95% Historical Simulation CVaR
KKP	99% Normal EWMA VaR	95% Historical Simulation CVaR
KTB	99% Normal EWMA VaR	95% Historical Simulation CVaR
SCB	99% Normal EWMA VaR	95% Historical Simulation CVaR
LHFG	99% Normal EWMA VaR	95% Historical Simulation CVaR
TCAP	99% Normal EWMA VaR	99% Historical Simulation CVaR
TISCO	99% Normal EWMA VaR	95% Historical Simulation CVaR
TTB	99% Normal EWMA VaR	99% Historical Simulation CVaR

The overall scores obtained by averaging the combined ratings in each model are summarized in Table 11. These ratings are based on the investment risk measured using Value at Risk and Conditional Value at Risk at 95% and 99% confidence levels. Subsequently, the average overall scores are calculated using a standard criterion to determine the rankings of the investment ratings. This information is valuable for future investment decisions.

Table 11 Summary of the rating rankings based on VaR at the 95% and 99% confidence levels

Bank	95% confidence level		99% confidence level	
	Normal EWMA VaR	Historical Simulation VaR	Normal EWMA VaR	Historical Simulation VaR
BAY	BBB+	BBB-	BBB+	AA-
BBL	AA	BBB	AA	BB
KBANK	B-	CCC-	B-	CCC-
KKP	AA-	BBB-	A+	BBB-
KTB	AA+	AAA	AA+	AA
SCB	BB	BB	BB	B
LHFG	AAA	AAA	AAA	AAA
TCAP	A	BBB+	A	AA+
TISCO	AA+	A+	AA+	BBB+
TTB	C	C	C	C

The study presents a comprehensive analysis revealing significant variations in the effectiveness of Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) models across the banks listed in Tables 12, 13, and 14. Consequently, a summarized rating for each bank, based on the performance of these risk assessment models, is outlined as follows:

BAY: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (BBB+ rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (A+ rating). Overall, BAY has an A- investment suitability rating.

Table 12 Summary of the rating rankings based on CVaR at the 95% and 99% confidence levels

Bank	95% confidence level Normal EWMA CVaR	Historical Simulation CVaR	99% confidence level Normal EWMA CVaR	Historical Simulation CVaR
BAY	BBB+	A+	BBB+	AAA
BBL	AA	BBB+	AA	A+
KBANK	B-	B+	B-	BB
KKP	A+	BBB+	A+	BB+
KTB	AA+	AA-	AA+	A-
SCB	BB	BB+	BB	BB
LHFG	AAA	AAA	AAA	AAA
TCAP	A	A-	A	BBB+
TISCO	AA+	A-	AA+	BBB
TTB	C	C	C	C

Table 13 Summary of the overall scores using the average rating across all models

	VaR				CVaR				
BANK	EWMA (95%)	HSA (95%)	EWMA (99%)	HSA (99%)	EWMA (95%)	HSA (95%)	EWMA (99%)	HSA (99%)	Total score
BAY	26	24	26	30	26	29	26	34	27.63
BBL	31	25	31	22	31	26	31	29	28.25
KBANK	18	15	18	15	18	20	18	22	18.00
KKP	30	24	29	24	29	26	29	23	26.75
KTB	32	34	32	31	32	30	32	27	31.25
SCB	22	22	22	19	22	23	22	22	21.75
LHFG	34	34	34	34	34	34	34	34	34.00
TCAP	28	26	28	32	28	27	28	26	27.88
TISCO	32	29	32	26	32	27	32	25	29.38
TTB	10	10	10	10	10	10	10	10	10.00

Table 14 Summary of investment rating rankings using the criterion of averaging ratings across each model

No.	Bank	Average Rating
1	BAY	A-
2	BBL	A
3	KBANK	B-
4	KKP	BBB+
5	KTB	AA-
6	SCB	BB-
7	LHFG	AAA
8	TCAP	A-
9	TISCO	A+
10	TTB	C

BBL: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (AA rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (BBB+ rating). Overall, BBL has an A investment suitability rating.

KBANK: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (B- rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (B+ rating). Overall, KBANK has a B investment suitability rating.

KKP: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (A+ rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (BBB+ rating). Overall, KKP has a BBB+ investment suitability rating.

KTB: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (AA+ rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (AA- rating). Overall, KTB has an AA- investment suitability rating.

SCB: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (BB rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (BB+ rating). Overall, SCB has a BB- investment suitability rating.

LHFG: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (AAA rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (AAA rating). Overall, LHFG has an AAA investment suitability rating.

TCAP: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (A rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (A- rating). Overall, TCAP has an A- investment suitability rating.

TISCO: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (AA+ rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (A- rating). Overall, TISCO has an A+ investment suitability rating.

TTB: The study found that using Normal EWMA for VaR at a 99% confidence level yielded the highest quality model (C rating). Using the Historical Simulation Approach for CVaR at a 95% confidence level also yielded the highest quality model (C rating). Overall, TTB has a C investment suitability rating.

This study explores the ranking of stocks within the banking sector using the powerful tools of VaR and CVaR. By collecting daily data and analyzing various models, we aim to find the most accurate representations of risk. These models are then thoroughly evaluated to determine their quality and provide investment suitability ratings. We recommend expanding the stock sample for a broader perspective to enhance the decision-making process. While challenges may arise, our dedicated team is committed to conducting meticulous research, studying trends, and gathering reliable data. This study will greatly benefit individuals and investors, equipping them with the knowledge to make well-informed investment decisions and ultimately paving the way for future success.

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