Robust Value-at-Risk Currency Portfolio Optimization for Net Open Position (NOP) Hedging

Abstract

This article presents a comprehensive study on "Robust Value-at-Risk Currency Portfolio Optimization for Net Open Position (NOP) Hedging," specifically focusing on the effectiveness of value-at-risk models, including VaR, Copula VaR, and Copula Conditional Value-at-Risk (CVaR), in optimizing currency portfolios. The research utilizes quantitative analysis and time-series observations of daily logarithmic returns of four major and commonly traded currencies, namely USD, EUR, AED, and CNY, from April 6, 2013, to September 21, 2021. For the out-of-sample evaluation, the dataset is limited to a one-month period from May 21, 2021, to June 21, 2021, using Sepah Bank's historical data. All calculations in this study are performed using the open-source software R 4.2.1. The results indicate that the Copula GARCH VaR model outperforms both Copula GARCH - CVaR and GARCH VaR methods in terms of Sharpe ratio. Additionally, the research highlights the significant role of the USD as an independent currency compared to others, making it an essential component in all three optimization methods used in the study. On the other hand, due to relatively strong and positive conditional correlations among the EUR, AED, and CNY currencies, minimizing the allocation of any one of these currencies is favored to reduce risk as much as possible. Consequently, in the GARCH VaR and Copula-GARCH VaR methods, higher realized returns are achieved compared to the Copula GARCH - CVaR model.

Key word: Net Open Position, Currency Portfolio Optimization, Bank

1. INRODUCTION

In the dynamic global financial landscape, banks face a myriad of challenges when it comes to managing their currency portfolios effectively(Gololo, 2018). One critical aspect of this task is the optimization of currency portfolios to minimize risk and maximize returns(Hrytsiuk et al., 2019). A key risk that banks encounter is the Net Open Position (NOP), which arises from imbalances between their foreign currency assets and liabilities(Liao & Zhang, 2020). To effectively mitigate the NOP risk and enhance risk management practices, banks must incorporate a strong Value at Risk (VaR) framework. This essay aims to explore the significance of optimizing currency portfolios with a focus on the USD, EUR, AED, and CNY while utilizing VaR as a robust tool to cover the risk of NOP.

Currency portfolio optimization refers to the process of allocating funds across different currencies to maximize returns while minimizing risk(Ma et al., 2020). Financial institutions, such as Sepah Bank, often maintain exposure to multiple currencies due to their international operations and client requirements. However, uncontrolled exposure can lead to vulnerabilities, especially when faced with fluctuating exchange rates and geopolitical uncertainties. By optimizing their currency portfolios, banks can strike a balance between generating profits and mitigating potential losses(Musavi et al., 2016). NOP refers to the overall imbalance in a bank's foreign currency assets and liabilities. It represents the difference between a bank's long and short positions in various currencies (Demirkılıç, 2021; Kustiningsih et al., 2020). The NOP risk arises from the potential adverse impact of exchange rate movements on a bank's assets and liabilities denominated in different currencies(Pradita & Geraldina, 2019; Yang, 2023). A substantial NOP can expose Sepah Bank to significant financial losses if the exchange rates move unfavorably. Value at Risk (VaR) is a widely adopted risk management tool that quantifies potential losses within a specified confidence level and time horizon. VaR provides an estimate of the maximum loss a bank can expect to incur under normal market conditions. By utilizing VaR, Sepah Bank can assess the potential downside risk associated with its currency portfolio and make informed decisions about capital allocation and hedging strategies. therefore, Integrating VaR into Sepah Bank's risk management framework can provide valuable insights into the potential impact of exchange rate fluctuations on its currency portfolio. VaR calculations can be performed using historical data, Monte Carlo simulations, or advanced models like DCC-MAGARCH. By monitoring VaR at regular intervals, Sepah Bank can ensure that the risk associated with its NOP stays within acceptable limits. It can be stated that Implementing a currency portfolio optimization strategy backed by VaR offers several benefits to Sepah Bank. Firstly, it helps reduce the NOP risk exposure, thus safeguarding the bank's financial health. Secondly, it allows for effective risk diversification by allocating funds across currencies with low correlation. Thirdly, it facilitates informed decision-making by quantifying potential losses and aiding the evaluation of hedging strategies. Given the importance and practicality of the results of this research in assisting managers to make better decisions in the complex policy-making environment, ultimately, it provides a model for daily optimization of a currency portfolio in a bank based on four currencies: USD, EUR, AED, and CNY. In the following, in the second part, we present the METHOD AND DATA COLLECTION TOOL, then in the third section, we delve into the ANALYSES, and finally, in the fourth section, we address the Evaluation and Conclusion.

2. METHOD AND DATA COLLECTION TOOL

The purpose of this research is to extract model factors for the daily optimization of a currency portfolio in a bank based on four currencies: USD, EUR, AED, and CNY. Specifically, we aim to investigate the effectiveness of risk value models, including VaR (Value at Risk), Copula VaR, and Copula CVaR, in optimizing the currency portfolio. In this research, a quantitative approach is employed, and the observations are in the form of time series data of the daily logarithmic return's percentage of four main and commonly traded currencies in the country, including the USD, EUR, AED, and CNY. The data from 27 March 2013 to the end of September 2021. From this time domain, the one-month period from 21 June 2021 to 21 July 2021 is selected as an out-of-sample dataset for the final evaluation. The overall approach of this research consists of three main parts. Firstly, in the first part, after preparing the data, descriptive analysis along with an examination of the fundamental assumptions of the statistical models used in the study have been presented. Secondly, the second part focuses on modeling the value at risk based on the conditional multivariate heteroscedasticity model (DCC-MGARCH) with vector autoregressive (VAR) mean model. Lastly, in the third part, the expected returns are simulated using the Copula function based on the Monte Carlo method. The optimization of portfolios and determination of their efficiency boundary are performed using the Sharpe ratio as the criterion, followed by the final evaluation for an out-of-sample one-month period. All the necessary calculations for this research have been conducted using the open-source software R 4.2.1.

3. ANALAYSES

3.1. data preparation, and descriptive statistics.

First, in this research, we start by using formula (1) to calculate the percentage of returns.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \tag{1}$$

In the above formula, P_t represents the exchange rate of the currency on day t, and P_{t-1}represents the exchange rate of the currency on the previous day.In order to gain a better understanding of the variables under study, descriptive statistics related to the daily percentage returns of the four currencies used in the research are presented in Table (1).

Table (1): Descriptive Statistics of Daily Percentage Returns for Four Exchange Rates

Currency	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
USD	0.0801	1.5815	-11.4072	18.3799	1.0399	20.505
EUR	0.0752	2.6329	-33.0806	33.114	-0.5788	39.5871
AED	0.0788	2.6471	-36.6288	38.2733	-0.6795	51.1225
CNY	0.0782	2.6737	-36.3626	37.6663	0.7869-	46.7849

Based on the results from Table (1), we can analyze the concentration measures (mean and median) and observe that the average return of the USD compared to the other currencies under study is slightly higher (approximately 0.005 to 0.002). However, the average daily return of the price index for all selected currencies within the given time period is positive, indicating an overall upward trend for all selected currencies during the study period. On the other hand, by examining the values of standard deviation, we can see that the USD has a lower deviation compared to the other three currencies. This implies that the fluctuation of the USD's exchange rate compared to its own average is lower than that of the other currencies. Furthermore, with the positive skewness of the USD, it can be concluded that the data is more concentrated towards the right side, while for the other currencies, the negative skewness indicates a concentration towards the left side. Additionally, considering the positive and larger kurtosis value (greater than 3), we find that the peak of the distribution is sharper and more pronounced compared to a normal distribution. Hence, due to the non-zero skewness and significantly high kurtosis values of the returns, it can be inferred that the distribution of returns for all four currencies does not follow a normal distribution.

In the next step, using Shapiro-Wilk normality tests, the augmented Dickey-Fuller unit root test, ARCH, and Ljung-Box effects on the normality test, validity, variance heterogeneity, independence, and autocorrelation of the data have been examined prior to modeling.

Table (2) shows the results of preliminary tests conducted prior to modeling to examine the basic assumptions.

Currencies	**The Shapiro-Wilk test.**		**The augmented Dickey-Fuller test.**		**The ARCH effects test.**		**The Ljung-Box test.**	
	Significant value.	**Statistic.**	**Significant value.**	**Statistic.**	**Significant value.**	**Statistic.**	**Significant value.**	**Statistic.**
USD	0.8317	0.01>	13.253-	0.01>	630.078	0.01>	1.5532	0.2126
EUR	0.7217	0.01>	17.367-	0.01>	251.908	0.01>	0.0108	0.9169
AED	0.7317	0.01>	17.849-	0.01>	280.392	0.01>	0.1417	0.7065
CNY	0.7457	0.01>	17.961-	0.01>	272.603	0.01>	0.9614	0.3268

The intuitive results from Table (2) show the test statistic values for the Shapiro-Wilk normality test for the currencies: USD (0.8317), EUR (0.7217), AED (0.7317), and CNY (0.7457). Since the p-values for each currency are less than 0.01, the assumption of normality for the time series of the currencies is rejected. Therefore, in this study, we will use the t-student distribution for modeling. To examine the assumption of stationarity in currency returns, the augmented Dickey-Fuller unit root test has been employed. The test statistic values obtained for the USD, EUR, AED, and CNY are -13.253, -17.367, -17.849, and -17.961, respectively. The p-values for all four currencies are less than 0.01, indicating the acceptance of the stationarity assumption for the returns of all four currencies.Looking at the results of the variance heterogeneity test (ARCH effects) in Table (2), the test statistic values obtained for the USD, EUR, AED, and CNY are 630.078, 251.908, 280.392, and 272.603, respectively. Considering the significance values less than 0.01 for each currency, the hypothesis of the presence of ARCH effects or variance heterogeneity in the returns of each currency is accepted. Finally, to examine the presence of serial autocorrelation patterns, the Ljung-Box test has been utilized. The test statistic values obtained for the USD, EUR, AED, and CNY are 1.5532, 0.0108, 0.1417, and 0.9614, respectively. Additionally, the significance values for each currency are greater than 0.05. Therefore, the null hypothesis of no serial autocorrelation is accepted based on the Ljung-Box test. Consequently, there is no autocorrelation in the returns of the currencies according to the Ljung-Box test. (Significance values less than 0.05 indicate the significance of the test. In the table below, values that are less than 0.01 are indicated as 0.01>)

3.2. Modeling risk exposure for currencies using the VAR-MGARCH

After identifying the appropriate lags in the Vector Autoregression (VAR) model, the results are presented in Table (3). Based on the minimum value of the Akaike Information Criterion (AIC), a lag of 10 has been identified. The reason for using the AIC criterion is the relatively high number of observations in the time series of the currencies.

Table (3) Identification of lags in the Vector Autoregression (VAR) model.

lags:	**AIC**
lag 1	2.456685
Lag 2	2.429633
Lag 3	2.417866
Lag 4	2.411811
Lag 5	2.405272
Lag 6	2.368767
Lag 7	2.288745
Lag 8	2.257865
Lag 9	2.256208
Lag 10	2.252028

Interpreting the coefficients of a Vector Autoregression (VAR) model can be challenging due to the presence of endogeneity. Therefore, the analysis of shocks through impulse response functions in the VAR model is more commonly emphasized. Additionally, Table (4) provides the residual correlation matrix obtained from the VAR model.

Table (4) - Residual Correlation Matrix of the VAR model.

Currencies	**USD**	**EUR**	**AED**	**CNY**
USD	**1**	**0.047606**	**0.033296**	**0.047264**
EUR	0.047606	1	0.808882	0.80712
AED	0.033296	0.808882	1	0.908163
CNY	0.047264	0.80712	0.908163	1

Based on Table (4), a relatively strong and positive correlation is observed among the residuals of the three currencies, EUR, AED, and CNY. Before analyzing shocks, the stability of the fitted Vector Autoregression (VAR) model will be assessed. To examine the stability, a structural stability test is used to determine the stability of the model and identify the presence or absence of structural breaks. The Cumulative Sum of Squares (CUSUM) test is employed for this purpose. Two upper and lower critical bounds are shown at a significance level of 5%. If the obtained statistical plot falls within the range of these bounds and does not cross them, it can be claimed with 95% confidence that the model is stable, and the null hypothesis of no structural break is not rejected.

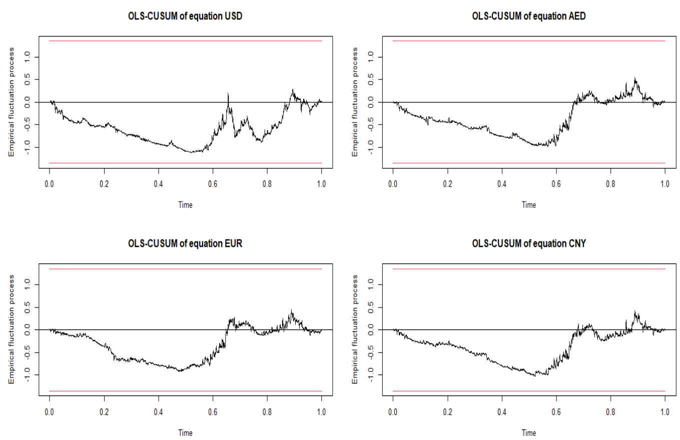


Figure (1) - Structural Stability Plot of the Vector Autoregression (VAR) model.

In continuation, we proceed with modeling the currency returns using the Multivariate GARCH (MGARCH) model, specifically the Dynamic Conditional Correlation (DCC) approach, with a multivariate t-student distribution. In this context, a GARCH (1,1) model is utilized as a univariate GARCH model to estimate the conditional variance matrices of the returns, which are then employed in the DCC model. Essentially, the input for the DCC model is the standardized returns obtained through the conditional variances from the GARCH model on the return time series. Significant results of the GARCH component coefficients and conditional correlation parameters can be observed from Table (5). The objective of this approach is to extract volatility or conditional variances in order to measure the exposure to risk. Additionally, the obtained conditional variance-covariance matrix is utilized for portfolio optimization purposes.

Table (5) Estimated Coefficients of Dynamic Conditional Correlation.

parameters		estimated coefficient	SD	t-statistic	SIG value
	omega	0.00805	0.00262	3.06613	0.01>
	alpha1	0.20225	0.02200	9.19111	0.01>

USD	beta1	0.79674	0.02612	30.49833	0.01>
	shape	4.30839	0.2349	18.34138	0.01>
EUR	[EUR]. omega	0.01334	0.00701	1.90057	0.057357
	[EUR]. alpha1	0.04997	0.00927	5.36636	0.01>
	[EUR]. beta1	0.94920	0.01368	69.35548	0.01>
	[EUR]. shape	2.61735	0.07167	36.51602	0.01>
AED	[AED]. omega	0.01279	0.00880	1.45251	0.146359
	[AED]. alpha1	0.08665	0.02558	3.38648	0.01>
	[AED]. beta1	0.91234	0.03524	25.88376	0.01>
	[AED]. shape	2.76633	0.14226	19.44479	0.01>
CNY	[CNY]. omega	0.01219	0.00630	1.93382	0.053135
	[CNY]. alpha1	0.07460	0.01538	4.85024	0.01>
	[CNY]. beta1	0.92439	0.02092	44.17566	0.01>
	[CNY]. shape	2.76020	0.09782	28.21562	0.01>
conditional correlation parameters	**[Joint]dcc_ a**	0.04063	0.00449	9.04847	0.01>
	[Joint]dcc_ b	0.95847	0.00462	207.4501	0.01>
	[Joint]mshape	4	0.13556	29.5065	0.01>

According to Table (5), it can be observed that the parameter "omega" in the GARCH model is statistically significant only for the USD exchange rate. In all cases, the sum of alpha1 and beta1 is greater than 0.9, indicating a high degree of conditional variance stability in the time series of these currencies' returns. Additionally, in all cases, the sum of these two parameters is less than one, indicating finite conditional variance and strong persistence. Furthermore, based on the results obtained from estimating the DCC model, it is observed that the parameters "a" and "b" are statistically significant, non-negative, and their sum is less than one. This suggests that the conditional correlation model that allows for time-varying correlations is more appropriate than models assuming constant correlation over time. The positive value of parameter "a" indicates that following a shock in the return series, an increase in conditional correlation can be expected for the next period. The parameter "b" in the DCC model represents the effect of the conditional correlation in the previous period on the conditional correlation in the current period. The closer this parameter is to 1, the expectation is that the conditional correlations in the current period will be close to the conditional correlations in the previous period for each pair of calculated correlation

$$h_{11t} = 0.00805 + 0.20225\ \epsilon_{1,t-1}^2 + 0.79674\ h_{11,t-1}$$

$$h_{22t} = 0.01334 + 0.04997\ \epsilon_{2,t-1}^2 + 0.94920\ h_{22,t-1}$$

$$h_{33t} = 0.01279 + 0.08665\ \epsilon_{3,t-1}^2 + 0.91234\ h_{33,t-1}$$

$$h_{44t} = 0.01219 + 0.07460\ \epsilon_{4,t-1}^2 + 0.92439\ h_{44,t-1}$$

$$Q_t = (1 - 0.04063 - 0.95847)\,.\,\bar{Q} + 0.04063\ \epsilon_{t-1}\epsilon_{t-1}' + 0.95847\ Q_{t-1}$$

Regarding the results of the estimated dynamic conditional correlations in the mentioned model, it should be noted that the estimated conditional correlation plots between the desired variables are often used to interpret the results of the DCC model estimation. Therefore, Figures (2) to (7), which encompass the dynamic conditional correlation trends between the daily returns of the USD, EUR, AED, and CNY, are presented below. As evident from the figures, the correlation exhibits different values over time under the influence of various factors, indicating the need to consider dynamics in the model. By observing the movement of these plots, we can make judgments about the magnitude of changes in conditional correlation between variables or, in other words, monitor the propagation of effects and shocks of one variable on the others. The correlation between all pairs of the examined currencies is mostly positive in most periods. However, in some periods, the correlation values show negative correlations. This indicates that not only does the magnitude of correlation change in different periods, but this change can also alter the type of correlation, whether positive or negative. Another important point to note, as observed in the plots, is that the level of correlation remains relatively constant in the long-term period under examination. However, in short-term periods, it exhibits significant fluctuations that should not be overlooked, as ignoring them could lead to considerable errors in calculations requiring correlation values.

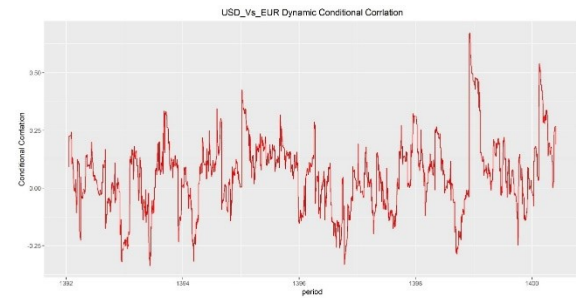


Figure 2. The dynamic conditional correlation trend between the daily returns of the USD and EUR.

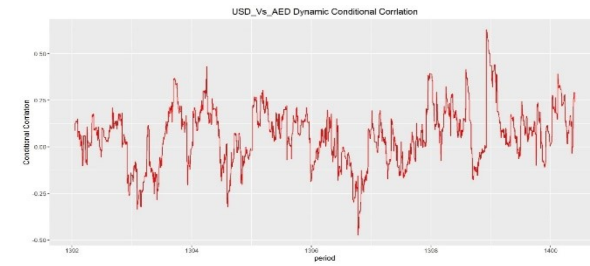


Figure 3. The dynamic conditional correlation trend between the daily returns of the USD and AED.

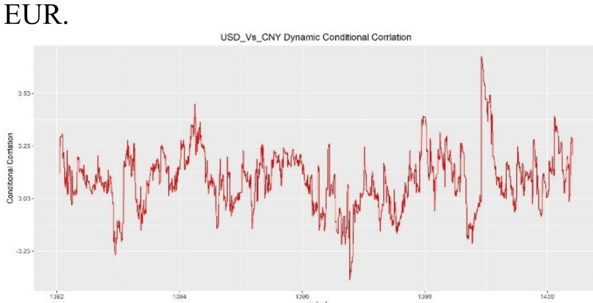


Figure 4. The dynamic conditional correlation trend between the daily returns of the USD and CNY.

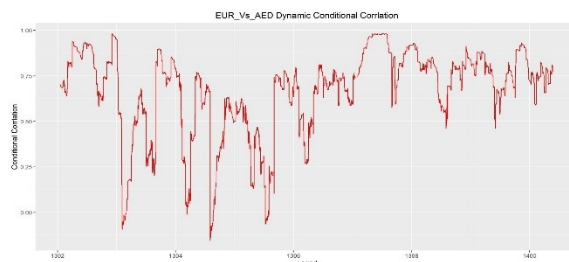


Figure 5. The dynamic conditional correlation trend between the daily returns of the EUR and AED.

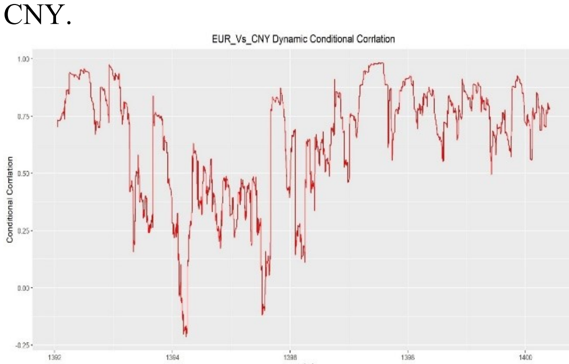


Figure 6. The dynamic conditional correlation trend between the daily returns of the EUR and CNY.

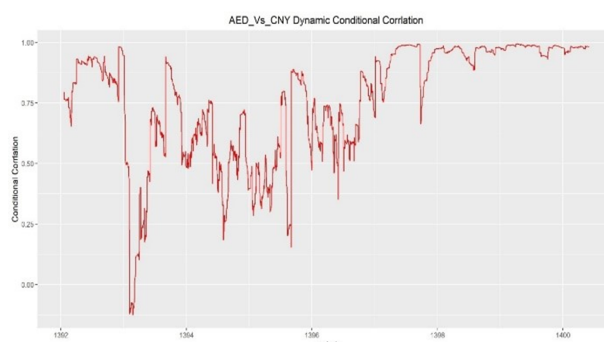


Figure 7. The dynamic conditional correlation trend between the daily returns of AED and CNY.

If we analyze the above figures, it can be observed that the conditional correlation between the EUR and the EUR, and AED, as well as the USD and AED, exhibits more negative values compared to the conditional correlations in other cases, indicating a fluctuating nature of conditional correlation between these currency pairs. The noteworthy point is that the dynamic conditional correlation trend has been consistently positive and strong in all cases in the last year. However, it can be said that the dynamic conditional correlation between AED and CNY has remained consistently positive, and in the last year, it has exhibited a relatively stable trend. This trend somewhat encompasses the conditional correlation between the EUR and AED, as well as the EUR and CNY. The range of variation for these correlations is usually between 0.25 and 0.5, indicating a higher frequency of dynamic conditional correlation values between 0 and 0.5. Table (6) displays the level of conditional correlation among the currencies on the last day of the training set. As mentioned in the interpretation of the above figures, the conditional correlation between AED and CNY is relatively higher compared to the other currencies. EUR and CNY, as well as EUR and AED, exhibit similar patterns in terms of the level of conditional correlation. The conditional correlation of the USD with other currencies also shows oscillations ranging from 0.1 to 0.24.

Table (6) shows the level of conditional correlation among the currencies on the day of August 22, 2021.

Currencies	**USD**	**EUR**	**AED**	**CNY**
USD	1	0.187764	0.237891	0.206665
EUR	0.187764	1	0.779621	0.787974
AED	0.237891	0.779621	1	0.979887
CNY	0.206665	0.787974	0.979887	1

The implications of these results for investors regarding the allocation of a currency basket among the desired currencies can be expressed as follows: the presence of a very high correlation between AED and CNY can partially offset the benefits of diversification. On the other hand, the low correlation between the USD and other currencies suggests that considering a currency basket as a suitable alternative investment against AED and CNY, EUR and AED, and EUR and CNY could be more favorable.

3.3. Testing the models and selecting an appropriate level of risk.

One useful method for assessing the performance of value at risk (VaR) in the face of calculated risk is back testing, which involves using quantitative methods to evaluate the consistency of model predictions with the assumptions on which the model is based. In this study, we employed two well-known tests: the unconditional coverage test (Kupiec test) and the conditional coverage test (Christoffersen test), the results of which are available in Tables (7) and (8). As observed from the table below, the backtests at the 99% confidence level demonstrate a high level of confidence. Therefore, we can rely on the obtained value at risk and use it for portfolio optimization purposes.

Table (7) presents the results of back testing the calculated value at risk at 95% and 99% risk levels**.**

Currencies	test	at the 99% confidence level		at the 95% confidence level	
		Statistically significant value	Statistic	Statistically significant value	Statistic
USD	The Kupiec test	0.164	1.934395	0.01>	14.22548
	The Christoffersen test:	0.33	2.217646	0.01>	14.68927
EUR	The Kupiec test	0.107	2.596946	0.01>	38.588773

	The Christoffersen test:	0.24	2.851066	0.01>	41.01244
AED	The Kupiec test	0.587	0.2948948	0.01>	37.22090
	The Christoffersen test:	0.7	0.7106175	0.01>	44.09008
CNY	The Kupiec test	0.24	1.377939	0.01>	24.11815
	The Christoffersen test:	0.175	3.481457	0.01>	39.27597

Table (8) presents the results of back testing the calculated conditional value at risk at 95% and 99% risk levels

Currencies	**test**	**Statistically significant at the 95% confidence level.**	**Statistically significant at the 99% confidence level.**
USD	McNemar-Freedman (bootstrapping)	0.01>	0.01>
EUR	McNemar-Freedman(bootstrapping)	0.01>	0.01>
AED	McNemar-Freedman(bootstrapping)	0.01>	0.01>
CNY	McNemar-Freedman(bootstrapping)	0.01>	0.01>

3.4. Estimation of parameters using the Student's t Copula and simulation of returns.

After obtaining the volatility of each currency's returns and standardizing them to estimate the parameters of the Copula function, we utilize the Student's t Copula function with marginal normal distributions, for which we have the information from the following tables. Once the parameters of the Student's t Copula function are estimated using a Monte Carlo simulation approach with 10,000 repetitions, we simulate the expected returns for the currencies and employ them in optimizing the currency portfolio.

Table (9) Estimation of parameters for the Student's t Copula function.

Copula Function	**Estimating Copula Parameters**	**Degrees of freedom**
T student	0.3628902	4

Table (10) Estimated parameters for the marginal distribution of the Copula function.

Currencies	The estimated marginal distributions for each currency in the .Student's t Copula function
USD	The normal distribution with a mean of 0.08014426 and a standard deviation of 1.581481.

EUR	The normal distribution with a mean of 0.0751911 and a standard deviation of 2.632933.
AED	The normal distribution with a mean of 0.07878386 and a standard deviation of 2.647144.
CNY	The normal distribution with a mean of 0.07818758 and a standard deviation of 2.673654.

Figure (8) also illustrates the scatter plot of actual currency returns and simulated currency returns using the estimated Copula function. This plot also shows the type and intensity of the correlation between the currency returns. By examining these plots, similar to the results obtained from the conditional correlation analysis, we observe a strong positive linear correlation between the EUR, AED and CNY. However, on the other hand, the Dollar appears to be almost independent of the other currencies.

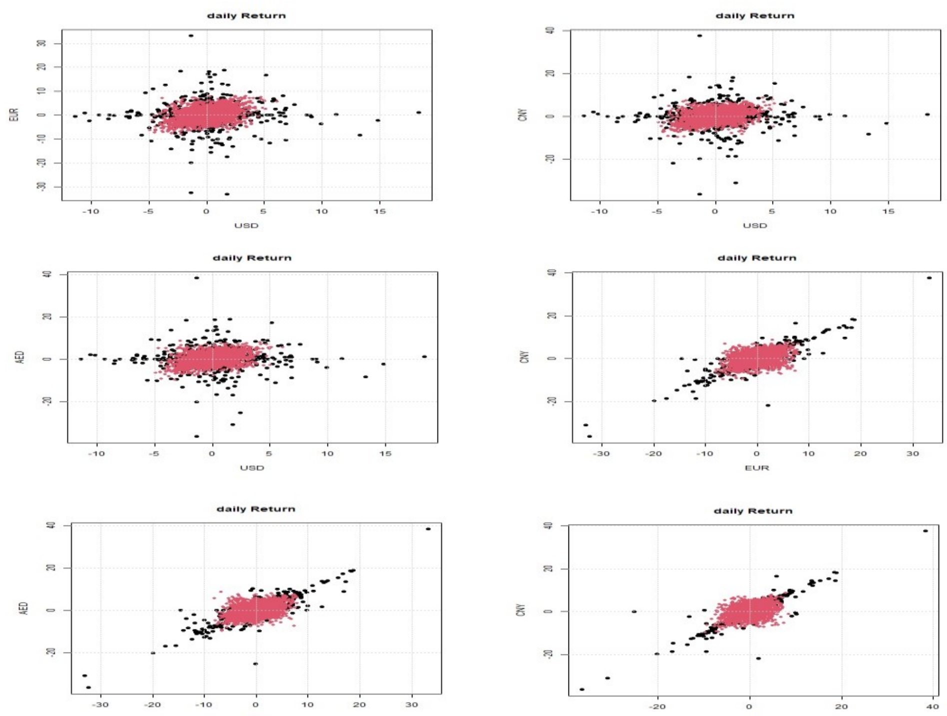
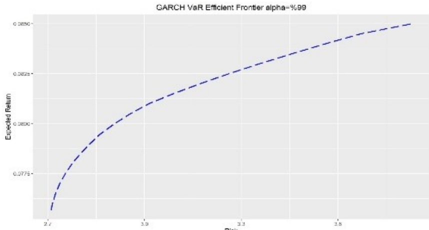


Figure 8. Scatter plot of the pairwise dispersion between actual and simulated currency returns.

3.5. Estimation of parameters using the Student's t Copula and simulation of returns.

In this research, to determine the efficiency frontier and compare three risk-based portfolio optimization methods, the Sharpe ratio has been used as the criterion. Figures (9), (10), and (11) illustrate the efficiency frontier of the employed methods in this study, which enables the identification of efficient portfolios.



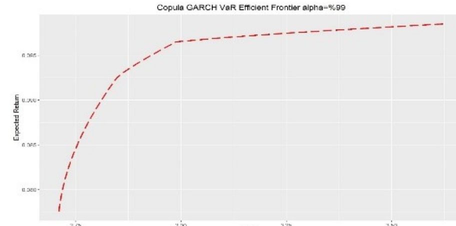


Figure 9. Efficiency Frontier of the DCC-MGARCH VaR Method.

Figure 10. Efficiency Frontier of the Copula DCC-MGARCH VaR Method.

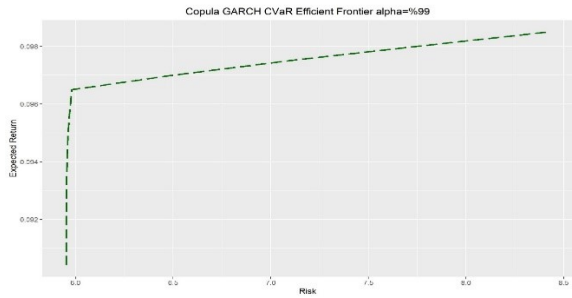


Figure 11. Efficiency Frontier of the Copula GARCH CVaR Method.

Table (11) also presents the results of the selected efficient portfolios based on these three methods, showing that the Copula GARCH VaR model has a higher Sharpe ratio compared to the other two methods.

Table (11). Results of the Selected Efficient Portfolios

Optimization Methods	The expected portfolio returns.	The portfolio risk.	The Sharpe ratio.
GARCH VaR	0.0775	2.754	0.0281
Copula GARCH VaR	0.0930	2.860	0.0325
Copula GARCH CVaR	0.0965	5.981	0.0161

On the other hand, to compare the three proposed methods more effectively, the Kruskal-Wallis test has been employed, and the results are provided in Table (12). The purpose of this test is to compare the mean Sharpe ratios obtained from the efficient portfolios among the three methods. Based on the obtained values, we observe a statistically significant difference at a 95% confidence level in the mean Sharpe ratios among the three proposed methods. Furthermore, the test reveals that the Copula GARCH VaR model holds a higher rank, indicating its superior performance in comparison to the other methods.

Table (12). Results of the Kruskal-Wallis Test for Mean Comparison at 95% Confidence Level

The variable	The statistic.	Degrees of Freedom.	Significance Value.
Sharpe Ratio	64.723	2	0.01>

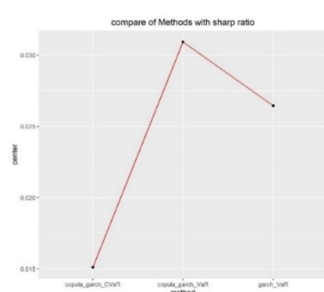


Figure 12. Comparison of the Mean Sharpe Ratios of Efficient Portfolios among Three Different Methods.

This text presents Table (13), which shows the optimal weights obtained for each of the currencies included in the basket. It should be noted that during the optimization, the constraint of open position limitation in the positive state has been taken into account. According to this constraint, only 35% of the total capital base is allocated to the entire basket, and in addition, the share of each currency in the basket is limited to a maximum of 15% of the total capital base. Therefore, all the results obtained in the above table and the following figures are based on this fundamental condition set by the central bank. The weights obtained have been rounded to three decimal places.

Table (13). displays the optimal weights obtained for each method presented separately.

Currencies	GARCH VaR	Copula GARCH VaR	Copula GARCH CVaR
USD	0.43	0.43	0.43
EUR	0.31	0.13	0.00
AED	0.00	0.43	0.43
CNY	0.26	0.01	0.14

The evident point in the obtained results is the significant role of the dollar in the currency basket. As we mentioned earlier, the USD exhibits a relatively independent nature compared to other currencies; therefore, in all three optimization methods used in this research, the dollar is included as the main currency in the basket. On the other hand, due to the relatively strong and positive conditional correlation between the three currencies (EUR, AED, and CNY), in order to minimize the risk as much as possible, the allocation percentage for any one of these currencies is kept very minimal, nearly approaching zero. Next, we will proceed with evaluating the performance of these three optimization methods during a one-month out-of-sample period.

4. Evaluation and Conclusion

In this article, we delved into the optimization of a currency portfolio consisting of USD, EUR, AED, and CNY with a strong focus on Value at Risk (VaR) to cover the risk of the NOP of Sepah Bank. The objective was to effectively manage the currency basket while minimizing risks and maximizing returns. Through a rigorous analysis of the data, we observed that the USD played a crucial role in the portfolio due to its relatively independent nature compared to the other currencies. As a result, in all three optimization methods applied, the dollar was included as the primary currency in the basket. Furthermore, we encountered a significant positive conditional correlation among EUR, AED, and CNY, prompting us to limit the allocation percentage for each of these currencies to minimize potential risks. The optimization methods - GARCH VaR and Copula-GARCH VaR - outperformed other models, yielding higher realized returns compared to the expected daily rate of return.

For the final empirical evaluation, a one-month out-of-sample period has been considered, starting from 23 / 8 / 2021 to 22 / 9 / 2021, comprising 27 working days. The evaluation criterion is based on the average capital growth, and its formula is provided below:

$$TER = A_0 \times (1 + r)^n \tag{2}$$

In the above formula, A_0 represents the initial allocated capital to the basket, r denotes the expected rate of return, and n is the total number of periods under consideration. For example, if the daily expected rate of return is 0.075%, and the initial allocated capital is \$1000, the expected final capital at the end of the 27-day period can be calculated as follows:

$$1000 \times (1 + 0.00075)^{27} = 1020.449 \tag{3}$$

In other words, the expected rate of return for this period is approximately 2.05%. Accordingly, we perform the currency basket optimization for these 27 working days using the Monte Carlo method, and the results are presented in Table (14) and Figure (13).

Table (14). presents the results obtained from the out-of-sample evaluation for 27 working days.

Optimization Methods	GARCH VaR	Copula- GARCH VaR	Copula GARCH - CVaR
Achieved Return Percentage	%2.43	%2.14	%0.79

As observed, both the GARCH VaR and Copula-GARCH VaR optimization methods have achieved higher realized returns compared to the other model. Additionally, by examining the charts in Figure (13), we can see that the realized returns from these two methods have been higher than the expected daily rate of return. Another noteworthy point from the figures is the variation in the capital base throughout the 27-day period. The maximum loss value was approximately 0.5%, indicating effective control over the maximum portfolio risk. However, despite this, the obtained return has been positive and higher than the initial expected value.

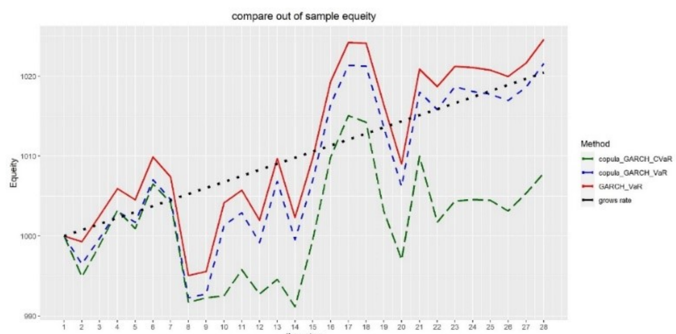


Figure (13). displays the capital growth charts for each of the different optimization methods separately.

In conclusion, the study presented comprehensive insights into the optimization of the currency portfolio for Sepah Bank. By employing strong VaR techniques and carefully managing the allocation of different currencies, Sepah Bank can achieve a balanced and risk-averse portfolio while ensuring competitive returns. This research provides valuable guidelines for financial institutions seeking to enhance their currency portfolio management and mitigate currency-related risks effectively.

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