Comparative Analysis of Exchange Rate Volatility Forecasting and Value at Risk Measurement Using GARCH-Type Models: An Empirical Study Based on Major Reserve Currency Pairs

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Abstract. This study compares the performance of GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) models in forecasting exchange rate volatility and estimating Value at Risk (VaR) for the major reserve currency pairs USD/EUR and USD/CNY. Using weekly return data from 2015 to 2025, the analysis shows that both series display fat tails, volatility clustering, and clear conditional heteroskedasticity. USD/CNY exhibits heavier tails and more persistent volatility. Based on maximum likelihood estimation and rolling-window forecasts, the asymmetric EGARCH and GJR-GARCH outperform the symmetric GARCH model. EGARCH delivers the most stable short-term volatility forecasts across both markets. Regarding distributional assumptions, the t-distribution improves the modelling of tail risks, especially for USD/CNY, although it introduces trade-offs for VaR stability during extreme events. Overall, the results highlight important differences between developed and emerging currency markets. They also provide practical guidance for selecting appropriate volatility models and distributional assumptions in exchange rate risk management.

Keywords: GARCH-type Mdels; Value at Risk; Prediction; Exchange Rate

1 Introduction

With the development of deepening global financial integration, exchange rates have become a linchpin of global economic connectivity, with their fluctuations constituting an essential factor influencing cross-border investment and risk management strategies in international trade. Given that USD/EUR and USD/CNY represent mature developed markets and emerging interventionist markets, respectively, this paper examines the suitability of GARCH-type models by comparing structural differences of these two markets, using these two major currency pairs as research subjects. GARCH models can effectively capture the clusteringof yield fluctuations yet, their symmetry assumption struggles to explain the 'leverage effect' (i.e. an asset's volatility tends to increase when its returns are negative and decrease when returns are positive) prevalent in

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exchange rate markets [1]. Consequently, beyond the foundational GARCH(1,1) model, this study introduces two asymmetric models: EGARCH(1,1) and GJR-GARCH(1,1). Dinga et al. (2023) show that conditional heteroscedastic models effectively capture and forecast exchange rate volatility, with both symmetric and asymmetric GARCH specifications—particularly EGARCH and GJR-GARCH—demonstrating strong predictive performance [2]. Further, Almisshal, B., & Emir, M. (2021) also show that both symmetric and asymmetric GARCH models, particularly EGARCH and GJR-GARCH, provide more accurate forecasts by capturing volatility clustering and the leverage effect [3]. Therefore, this paper examines whether the GJR-GARCH model has a comparative advantage in such markets .

Regarding residual distribution assumptions, prior research indicates that the normal distribution struggles to fit the fat-tailed characteristics of exchange rates, whereas the t-distribution performs better in fitting extreme tails [4]. Consequently, this paper examines the performance of models under different distribution assumptions—normal and t-distribution—in volatility forecasting and VaR measurement.

The study explores whether GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) exhibit significant differences in forecasting volatility accuracy for USD/EUR and USD/CNY exchange rates. It also studies whether the t-distribution enhance heavy-tail fitting capability and VaR reliability. In addition, this study investigates whether the leverage effect is consistent across developed and emerging market structures.

Therefore, this study employs maximum likelihood estimation to systematically fit the three models using weekly logarithmic return data for USD/EUR and USD/CNY from 2015 to 2025. Model performance is assessed across three dimensions: goodness-of-fit, short-term forecasting error in rolling windows, and VaR backtesting[2,5].

The significance of this research lies in: first, incorporating USD/EUR and USD/CNY into a unified framework to compare model fit across developed and emerging markets; second, testing model robustness under extreme scenarios such as the 2022 interest rate hikes; and third, contrasting normal and t-distributions to assess the impact of distribution assumptions on volatility modelling and VaR. In summary, this paper provides more reliable model selection criteria for exchange rate risk management under different market structures.

2 Literature Review

Modelling exchange rate volatility has been an important topic in international finance for many years. GARCH-type models are widely used because they can describe the clustering patterns often seen in exchange rate returns. Early studies showed that the variance of exchange rate series changes over time, which means that simple constant-variance models cannot capture real market movements [6]. You, Y., & Liu, X. compared several US dollar currency pairs and found that while GARCH models consistently capture the time-varying nature of volatility, their forecasting accuracy is higher for some currencies and market conditions than for other [7]. This encouraged later researchers to examine the robustness of these models in more depth.

As research progressed, scholars also noticed a key limitation of the basic GARCH model: it responds to positive and negative shocks symmetric. However, financial markets often show stronger reactions to negative news, a phenomenon known as the leverage effect.[8] Because of this, asymmetric models such as EGARCH and GJR-GARCH were introduced and applied to exchange rate data. Dritsaki studied the EUR/USD rate and found that EGARCH outperformed other models in capturing the asymmetric behavior of returns [9]. These findings highlight the importance of including asymmetric terms when modelling volatility in different market conditions.

Another important topic in recent literature is the choice of error-term distributions. Many studies argue that heavy-tailed distributions better match the real behavior of exchange rate returns. Charfi and Mselmi compared several distributional assumptions, including the normal and t-distributions, and found that heavy-tailed distributions better deacribe the tail features of returns [10]. Although the best distributional choice may vary across currency pairs, most research agrees that the normal distribution underestimates tail risks, while the t-distribution and its extensions offer more reliable results. Overall, the literature has examined model structures, distributional assumptions, and the effects of policy changes.

However, these researches show several limitations. First, many studies focus on a single currency pair and do not provide systematic comparisons across major reserve currencies. Second, a large part of the literature still assumes normally distributed residuals, even though exchange rate returns often display clear fat-tailed behavior. This mismatch may lead to weaker model performance. Third, most studies do not include major extreme events in long-term datasets, such as the Federal Reserve’s rapid interest rate hikes in 2022. To address these gaps, this study compares two major currency pairs, evaluates models under normal and t-distribution assumptions, and uses data over a decade to assess GARCH model performance in volatility forecasting and risk measurement.

Related evidence from portfolio allocation studies suggests that even advanced risk-based frameworks can suffer from severe out-of-sample instability when volatility or covariance structures are misspecified (Trucios, 2025) [11].

3 Research Methodology

3.1 Data Selection and Preprocessing

Selection of Currency Pairs and Rationale. This study aims to compare the rate pairs USD/EUR and USD/CNY, to evaluate the volatility forecasting and VaR measurement performance of three models, which are GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1).

These pairs cover key markets in Europe and East Asia, exhibit high liquidity and data availability, and reflect the characteristics of foreign exchange volatility between developed and emerging markets. The sample covers the period from January 2015 to January 2025, spanning ten years. This period includes extreme market conditions, such as the Federal Reserve's substantial interest rate hike cycle in 2022, which helps to assess the models’ performance in high-volatility environments.

Data preprocessing. Returns are presented in logarithmic form as

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

To facilitate subsequent model estimation and comparative analysis, logarithmic returns are multiplied by 100 and expressed as percentages in the descriptive discussion. To reduce the influence of potential data errors rather than genuine market extremes, a mild 3σ filtering rule is applied. The rule affects only a very small number of observations and does not materially alter the tail characteristics of the return distributions.

The weekly exchange rate data used in this study contain a few missing values. And most of them result from external factors such as market closures or delays in data-source synchronization. In this situation, methods such as linear interpolation or forward filling may create artificial smoothing effects, which can distort the volatility pattern of the return series. This distortion may further affect the conditional variance estimates in GARCH-type models, especially the ARCH term. Since the number of missing values is extremely small, their effect on sample size and statistical efficiency is small. Therefore, this study chooses to remove missing observations directly, preserving the original volatility structure of the data.

After pre-processing, an ARCH-LM test will be conducted to affirm whether the sequence exists a significant ARCH effect, to confirm the reasonability of employing a GARCH-type model.

3.2 Model Specification

This study employs three categories of GARCH-type models, among the most widely applied in research on exchange rate volatility. The main distinction between these models lies primarily in whether and how they characterize the "leverage effect". Furthermore, two residual distribution assumptions are considered simultaneously, thereby establishing a comprehensive framework for model comparison.

Specifically, the conditional variance equations for the three core models are set as follows.

First of all, The basic GARCH model was proposed by Engle and Bollerslev. Its mean equation is set as a constant term:

$$r_t=\mu+\varepsilon_t \quad \varepsilon_t=\sigma_t z_t \tag{2}$$

and its conditional variance equation is

$$\sigma_t^2=\omega+\alpha\varepsilon_{t-1}^2+\beta\sigma_{t-1}^2$$

Where

$$\omega>0,\ \alpha\geq 0,\ \beta\geq 0,\ \alpha+\beta<1 \tag{3}$$

when they are weakly stationary. Although the GARCH model captures volatility clustering and persistence, it assumes symmetrical market reactions to positive and negative shocks. To account for potential leverage effects in exchange rate markets, where negative unexpected shocks lead to greater volatility than equivalent positive shocks. Thus, this study introduces another two asymmetric models, EGARCH and GJR-GARCH.

EGARCH was proposed by Nelson to capture the "leverage effect" (negative impact amplification of volatility). Its logarithmic form ensures that σ_t^2 always remains positive:

$$\ln(\sigma_t^2)=\omega+\alpha|z_{t-1}|+\gamma z_{t-1}+\beta\ln(\sigma_{t-1}^2) \tag{4}$$

where $\gamma<0$ indicates the existence of leverage effects.

The GJR-GARCH model, proposed by Glosten et al., models the additional impact of negative returns by introducing an indicator variable I_{t-1} . The model is

$$\sigma_t^2=\omega+\alpha\varepsilon_{t-1}^2+\gamma\varepsilon_{t-1}^2 I_{t-1}+\beta\sigma_{t-1}^2 \text{ , Where } I_{(t-1)} = \begin{cases} 1, & \varepsilon_{t-1} <0 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where $\gamma>0$ implies the existence of leverage effects as well.

Moreover, as financial time series exist the characteristics of heavy tails with spikes, this study employs both normal and t-distributions as error distribution in each model estimation. The degrees of freedom parameter of the t-distribution can be utilized to further validate the presence of heavy tails.

3.3 Parameter Estimation and Test

All parameters are estimated via maximum likelihood estimation (MLE) using the R "rugarch" package.

Goodness-of-fit indicators are compared using: Akaike Information Criterion (AIC),Bayesian Information Criterion (BIC), and log-likelihood value (LL).

Among them, lower values of AIC and BIC indicate better model performance in balancing fit and complexity, while the higher log-likelihood values indicate the more effective the model is in explaining the sample data.

To ensure the model specification adequately captures the volatility structure of the return sequence, this study further conducted diagnostic tests on the estimated residuals.

Residual adequacy: The Ljung-Box test and the ARCH-LM are utilized to test for the presence of ARCH effects in the residuals. A p-value > 0.05 implies that the residual sequence of the model approaches white noise, suggesting the model successful extracts volatility characteristics from the sequence, and the estimation results are reliable.

3.4 Fluctuation Prediction and Accuracy Verification

To assess the forecasting performance of the GARCH models in a practical setting, this study uses a one-step-ahead forecasting approach with a 52-week rolling window. In each iteration, the model parameters are first estimated using the previous 52 weeks of data. These parameters are then used to forecast the conditional volatility for the next week. After the forecast is produced, the window moves forward by one week, and the same procedure is repeated until the end of the sample.

Once the full set of forecasts is obtained, predictive accuracy is evaluated using two measures: root mean square error (RMSE) and mean absolute error (MAE).

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

These metrics reflect how far the forecasted values deviate from the realised volatility, with lower values indicating better performance. To determine whether differences in forecast accuracy across models are statistically meaningful, the Diebold–Mariano (DM) test is applied. A significant DM test result suggests that one model consistently outperforms the others, providing a stronger basis for model selection.

3.5 VaR Calculation and Backtesting Verification

At the risk-measurement stage, VaR is calculated at the 95% and 99% confidence levels. The calculation is based on the conditional variance estimated by each model, along with their corresponding residual distribution. This approach allows the models to be evaluated on their ability to identify extreme loss risks.

After computing VaR, backtesting is carried out to assess its performance. The Kupiec test examines whether the observed failure rates match the theoretical confidence levels. The Christoffersen test further evaluates whether failure events occur independently over time, indicating whether the VaR measure captures risk consistently across different periods.

4 Results

4.1 Descriptive Statistics

Table 1. Descriptive Statisticsof Statistics of Weekly Returns

Pair	Min	Max	Mean	SD	Skew.	Kurtosis	JB_stat	JB p-val
USD/EUR	-3.418	3.360	-0.028	1.097	-0.100	3.801	14.805	6.096e-04
USD/CNY	-1.802	1.865	0.030	0.594	-0.024	4.625	57.508	3.253e-13

The descriptive statistics in Table 1 show that the mean weekly returns for both exchange rate pairs are close to zero. USD/EUR has an average return of about −0.028%, while USD/CNY shows around 0.03%, suggesting no clear long-term directional trend. This contrast can be partly attributed to differences in exchange rate regimes. While USD/EUR is largely market-determined, USD/CNY is subject to managed exchange rate policies, which tend to dampen short-term fluctuations.

Both series display high kurtosis, with values of approximately 3.80 and 4.63. These exceed the normal distribution benchmark of 3, indicating heavier tails. The Jarque–Bera test supports this conclusion. The p-values are far below 0.01, leading to a clear rejection of normality and confirming the presence of heavy-tailed and peaked return distributions.

Table 2. Results of the Augmented Dickey-Fuller (ADF) Test

Pair	ADF_stat	P_value
USD/EUR	-7.651168	0.01
USD/CNY	-6.368611	0.01

Table 2 reports the results of the ADF test. ADF test results confirm stationarity. The ADF test statistics are confirmed to be stationary, with ADF test statistics of -7.65 for USD/EUR and -6.37 for USD/CNY, both significant at the 1% level. Furthermore, the ARCH-LM test for conditional heteroskedasticity is highly significant ($p < 0.001$). These results show that the application of GARCH-type models is used to capture the volatility dynamics in the data.

4.2 Model Parameter Estimation Results

The sGARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) models were estimated separately on the training sample from 2015 to 2019 and evaluated under both normal and t-distribution assumptions.

For USD/EUR, the $\alpha+\beta$ sums in the sGARCH and GJR-GARCH models were close to, 1 (between 0.995 and 0.996), indicating strong volatility persistence while still satisfying the stationarity requirement. The estimated degrees of freedom for the t-distribution were high (near 100), suggesting that the t-distribution behaves similarly to the normal distribution for this mature currency pair.

For USD/CNY, the $\alpha+\beta$ values of sGARCH and GJR-GARCH also approached 1 (about 0.985 to 0.999), again reflecting high persistence. However, the degrees of freedom for the t-distribution were notably lower (around 2.1 to 2.2), showing clear fat-tailed behaviour in RMB returns. This implies that the t-distribution is more appropriate for capturing tail risk in this emerging market. The leverage terms in both EGARCH and GJR-GARCH were significantly different from zero in most cases, suggesting the presence of volatility asymmetry in both exchange rate series.

Diagnostic tests also support the adequacy of the models. The p-values from the Ljung–Box and ARCH-LM tests were generally above 0.05. This indicates that the conditional mean and variance equations captured most serial correlation and ARCH effects, and that the models fit the data reasonably well.

4.3 Model Comparison

As shown in Table 3, although the normal distribution occasionally yields slightly lower AIC/BIC values for the sGARCH specification, the Student-t distribution is retained in the main analysis due to its superior performance in capturing tail risk and Value-at-Risk measures.

Table 3. Model Comparison (AIC / BIC / Log-likelihood)

Pair	Model	AIC	BIC	Log-likelihood
USD/EUR	sGARCH_std	3.037	3.105	-389.806
USD/EUR	EGARCH_std	3.044	3.127	-389.763
USD/EUR	GJR-GARCH_std	3.039	3.121	-389.064
USD/CNY	sGARCH_std	1.517	1.585	-192.182
USD/CNY	EGARCH_std	1.510	1.592	-190.329
USD/CNY	GJR-GARCH_std	1.521	1.603	-191.667

*values are rounded to three decimal places

Information criteria provide further insight. For USD/EUR, differences in AIC and BIC across models were small, with the sGARCH model under the t distribution performing slightly better, although EGARCH and GJR-GARCH did not perform substantially worse. For USD/CNY, the EGARCH model with a t-distribution achieved the lowest AIC, outperforming other specifications. Considering the fat-tailed distribution and parameter estimates, the evidence suggests that for emerging market currency pairs, the EGARCH model with leverage effects and a t-distribution provides a better fit to the underlying data.

This finding is consistent with recent empirical evidence from high-frequency trading environments. Mbonigaba et al. (2025) show that asymmetric GARCH-type models, particularly EGARCH and GJR-GARCH, outperform the standard GARCH model in capturing volatility persistence and asymmetric responses to shocks [12]. Despite differences in data frequency, their conclusions are broadly consistent with the results observed in the exchange rate markets examined in this study.

4.4 Volatility Forecast Results Analysis

Table 4. Out-of-Sample Forecast Accuracy (RMSE / MAE)

Pair	Model	RMSE	MAE
USD/EUR	sGARCH_std	0.732	0.596
USD/EUR	EGARCH_std	0.720	0.581
USD/EUR	GJR-GARCH_std	0.724	0.587
USD/CNY	sGARCH_std	0.669	0.505
USD/CNY	EGARCH_std	0.609	0.474
USD/CNY	GJR-GARCH_std	0.690	0.521

*values are rounded to three decimal places

Out-of-sample conditional volatility forecasts for 2020–2024 were generated using a one-step-ahead rolling window, with 52 observations per year (shown in Table 4). Absolute returns were used as a proxy for realised volatility. The forecasting performance of the models was evaluated using the root mean square error (RMSE) and mean absolute error (MAE).

For the USD/EUR pair, the EGARCH_std model produced the smallest prediction errors. GJR-GARCH delivered the next-best results, while sGARCH performed slightly worse. For USD/CNY, EGARCH_std again achieved the lowest RMSE and MAE, whereas GJR-GARCH_std produced relatively larger errors.

Table 5. Out-of-Sample Diebold-Mariano Test

Pair	Model	DM_stat	P_value
USD/EUR	EGARCH_std	-2.32	0.021
USD/EUR	GJR-GARCH_std	-1.85	0.018
USD/CNY	EGARCH_std	-3.33	0.001
USD/CNY	GJR-GARCH_std	-1.43	0.153

* values are rounded to three decimal places

The Diebold–Mariano test was conducted using sGARCH_std as the benchmark (shown in Table 5). The DM test p-values for EGARCH_std were below 0.05, implying that EGARCH provides a statistically significant improvement in short-term volatility forecasting. For USD/EUR, GJR-GARCH also performed significantly better than sGARCH. However, for USD/CNY, the performance difference between GJR-GARCH and sGARCH was not statistically significant.

Overall, these results suggest that models incorporating asymmetry tend to improve forecasting accuracy for both currency pairs. Among them, EGARCH demonstrates the most consistent and robust advantage.

4.5 Out-of-Sample Value-at-Risk Estimates

Table 6. Out-of-sample mean Value at Risk

Pair	Model	95% Confidence Level	99% Confidence Level
USD/EUR	sGARCH_norm	-2.038	-2.672
USD/EUR	sGARCH_std	-2.079	-2.756
USD/EUR	EGARCH_norm	-1.997	-2.619
USD/EUR	EGARCH_std	-2.059	-2.740
USD/EUR	GJR-GARCH_norm	-2.043	-2.676
USD/EUR	GJR-GARCH_std	-2.091	-2.776
USD/CNY	sGARCH_norm	-1.136	-1.496
USD/CNY	sGARCH_std	-3.305	-6.623
USD/CNY	EGARCH_norm	-1.118	-1.472
USD/CNY	EGARCH_std	-4.008	-8.362
USD/CNY	GJR-GARCH_norm	-1.113	-1.468
USD/CNY	GJR-GARCH_std	-3.493	-7.059

*CIs are rounded to three decimal places

In the VaR analysis, estimates were generated at the 95% and 99% confidence levels for out-of-sample periods. As expected, the VaR at the 99% level is much larger than at the 95% level, reflecting the more conservative nature of higher confidence thresholds (Table 6). For USD/CNY, the t-distributed models is exceptionally high VaR estimates (e.g., -8.362% for EGARCH_std at the 99% level), which appear disproportionately large relative to observed return volatility, indicating that tail risk may be overstated. In the case of USD/EUR, the sGARCH_std and EGARCH_std models produce mean VaR estimates of around −2% at the 95% level and about −3% at the 99% level.

4.6 VaR Backtesting Results

Table 7. VaR Backtesting Results

Pair	Model	95% Confidence Level			99% Confidence Level		
		Actual rate	Kupiec p-value	Christoffersen p-value	Actual rate	Kupiec p-value	Christoffersen p-value
USD/EUR	sGARCH_norm	0.076	0.069	0.926	0.019	0.189	NA
USD/EUR	sGARCH_std	0.065	0.290	0.710	0.019	0.189	NA
USD/EUR	EGARCH_norm	0.084	0.021	0.993	0.038	0.001	0.138
USD/EUR	EGARCH_std	0.073	0.116	0.866	0.027	0.129	0.842
USD/EUR	GJR-GARCH_norm	0.075	0.069	0.923	0.027	0.0243	0.382
USD/EUR	GJR-GARCH_std	0.065	0.290	0.710	0.019	0.189	0.198
USD/CNY	sGARCH_norm	0.065	0.290	0.262	0.042	0.001	0.771
USD/CNY	sGARCH_std	0.008	0.001	NA	0.004	0.245	NA
USD/CNY	EGARCH_norm	0.080	0.039	0.968	0.034	0.002	NA
USD/CNY	EGARCH_std	0.008	0.001	NA	0.000	NA	NA
USD/CNY	GJR-GARCH_norm	0.076	0.069	0.178	0.038	0.001	0.681
USD/CNY	GJR-GARCH_std	0.008	0.001	NA	0.004	0.250	NA

*Expected failure rates are 5% and 1% for the 95% and 99% confidence levels, respectively.

*NA indicates cases where likelihood ratio tests are not applicable due to zero or insufficient violations.

*p-values are rounded to three decimal places

The backtesting results are summarized in Table 7. For USD/EUR, the Kupiec and Christoffersen tests show that the normal-distribution models deviate from the expected failure rates in some cases. By contrast, the t-distributed EGARCH and GJR-GARCH models produce more reasonable failure frequencies at the 95% level, with several specifications passing both tests. At the 99% level, however, all models occasionally over- or under-report failures, suggesting that extreme tail events remain difficult to model accurately. For USD/CNY, the normal-distribution specification consistently overpredicts failures at both confidence levels, with extremely small p-values, indicating a systematic underestimation of risk. The t-distributed models for USD/CNY produce substantially lower failure rates than the theoretical benchmark, indicating that VaR estimates are conservative. These results highlight that VaR performance for emerging-market currency pairs is highly sensitive to model structure and distributional assumptions, making it difficult to identify a single model that performs reliably across all conditions.

5 Discussion

5.1 Findings

By combining the results from model fit, forecasting accuracy, and VaR backtesting, several empirical patterns emerge. First, both currency pairs show fat tails, volatility clustering, and strong conditional heteroskedasticity, with USD/CNY displaying heavier tails and more persistent volatility. Second, extended EGARCH and GJR-GARCH models generally outperform the basic GARCH in fitting and forecasting, and EGARCH delivers the most stable short-term volatility forecasts across both currencies. Third, the t-distribution provides clear benefits for the heavily-tailed RMB series, although its higher tail sensitivity leads to a trade-off in VaR performance.

Another critical finding is the distributional dilemma appeared in VaR estimation for USD/CNY. Considering the out-of-sample period, the models generate implausibly high VaR estimates. Consequently, these models produce too few violations and are statistically rejected by backtests. Similar sensitivity of Value-at-Risk to distributional assumptions has also been documented in recent empirical studies. Using high-frequency data, Contreras-Valdez et al. (2024) show that VaR effectiveness can deteriorate substantially in the presence of heavy or semi-heavy tails, highlighting the inherent fragility of parametric VaR under tail misspecification [13]. GARCH-family models have a key limitation: the unconditional extrapolation of in-sample tail properties, which can lead to structural bias. Recent evidence further suggests that ignoring structural breaks can substantially undermine the forecasting performance of GARCH models. Hasanov et al. (2024) show that GARCH specifications accounting for structural breaks consistently outperform single-regime models in out-of-sample exchange rate volatility forecasting, highlighting the importance of regime instability in volatility dynamics [14]. As a result, risk measures may be either underestimated under the normal distribution or severely overestimated under a static t-distribution when the tail risk regime is unstable over time. Recent advances address this issue by incorporating high-frequency realized measures and time-varying leverage structures. For example, Lin et al. (2025) show that allowing leverage effects to vary over time within a realized GARCH framework improves volatility modelling and risk prediction. Although such approaches rely on high-frequency data and are beyond the scope of this study, they point to important directions for enhancing the robustness of volatility and VaR modelling [15].

5.2 Implications

According to the results, for risk managers, they should balance volatility forecasting of currencies with asymmetric dynamics. What's more, for VaR calculations of managed currencies like the RMB, standard GARCH models with parametric distributions exhibit clear limitations and should be replaced with more robust alternatives.

6 Conclusion

This paper compares the performance of GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) models in forecasting exchange rate volatility and measuring VaR, using USD/EUR and USD/CNY as case studies. The results show clear volatility clustering and fat-tail behaviour in both currency pairs, with USD/CNY displaying heavier tails and stronger volatility persistence. In out-of-sample volatility forecasting, particularly for USD/CNY, models that account for asymmetric shocks (EGARCH and GJR-GARCH) generally outperform the basic GARCH framework. Among them, EGARCH provides the most stable fit and the strongest short-term forecasting ability. The t-distribution also captures the tail risks of RMB returns more effectively than the normal distribution, although its higher sensitivity reduces VaR robustness under certain extreme conditions.

However, this study has several limitations. It analyses only two currency pairs, which restricts generalisability. Forecasts rely on a one-step rolling window, without assessing multi-step horizons. In addition, more advanced GARCH extensions and machine learning methods were not examined. Future work could incorporate APARCH models to capture volatility asymmetry and apply LSTM-based approaches to improve long-term forecasts. Further research might also integrate macroeconomic or policy variables into the modelling framework, or compare performance using higher-frequency intraday data.

References

1. Chalissery, N., Anagreh, S., Nishad, M. T., & Tabash, M. I. (2022). Mapping the trend, application and forecasting performance of asymmetric GARCH models: A review based on bibliometric analysis. Journal of Risk and Financial Management, 15(9), 406.
2. Dinga, B., Claver, J. H., Cletus, K. K., & Che, S. F. (2023). Modeling and predicting exchange rate volatility: Application of symmetric GARCH and asymmetric EGARCH and GJR-GARCH models. Journal of the Cameroon Academy of Sciences, 19(2), 155–178.
3. Almisshal, B., & Emir, M. (2021). Modeling exchange rate volatility using GARCH models. GJEBD: Global Journal of Economics and Business, 7(1), 1–16.
4. Obeng, C. (2021). Measuring value at risk using GARCH model – Evidence from the cryptocurrency market. International Journal of Entrepreneurial Knowledge, 9(2), 63–84.
5. Wang, Y., Xiang, Y., & Zhang, H. (2022). Comparison and forecasting of VaR models for measuring financial risk: Evidence from China. Discrete Dynamics in Nature and Society, 2022, 5510721.
6. Iseringhausen, M. (2020). The time-varying asymmetry of exchange rate returns: A stochastic volatility – stochastic skewness model. Journal of Empirical Finance, 58, 275–292.
7. You, Y., & Liu, X. (2020). Forecasting short-run exchange rate volatility with monetary fundamentals: A GARCH-MIDAS approach. Journal of Banking & Finance, 116, 105849.
8. Yu, M. (2019). Forecasting bitcoin volatility: The role of leverage effect and uncertainty. *Physica A: Statistical Mechanics and its Applications, 533*, 100-108.

9. Dritsaki, C. (2019). Modelling and forecasting exchange rate volatility of the EUR/USD: A comparison of GARCH-type models. Journal of Risk and Financial Management, 12(3), 133.
10. Charfi, S., & Mselmi, N. (2022). Exchange rate volatility modelling using heavy-tailed distributions: An empirical assessment. Journal of Applied Economics, 25(1), 45–62.
11. Trucios, C. (2025). *Hierarchical risk clustering versus traditional risk-based portfolios: An empirical out-of-sample comparison*. Available at SSRN.
12. Mbonigaba, C., Vasuki, M., Kumar, A. D., & Asamoah, P. J. (2025). *Applications of GARCH models for volatility forecasting in high-frequency trading environments*. International Journal of Applied and Advanced Scientific Research, 10(1), 12–21.
13. Contreras-Valdez, M. I., Sahu, S., Núñez-Mora, J. A., & Santillán-Salgado, R. J. (2024). Value-at-Risk effectiveness: A high-frequency data approach with semi-heavy tails. Risks, 12(3), 50.
14. Hasanov, A. S., Brooks, R., Abrorov, S., & Burkhanov, A. U. (2024). Structural breaks and GARCH models of exchange rate volatility: Re-examination and extension. Journal of Applied Econometrics, 39(7), 1403–1407.
15. Lin, J., Mao, Y., Hao, H., & Liu, G. (2025). Semiparametric estimation and application of realized GARCH model with time-varying leverage effect. Mathematics, 13(9), 1506.