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Modeling Exchange Rate Volatility of the Papua New Guinea Kina Against the US Dollar Using GARCH-Type Models

Ambrose Tuckayo[1*], Chris Wilkins[2], Boaz Andrews[3] & Mohsen Aghaeiboorkheili[4]
[1, 2, 3, 4] School of Mathematics and Computer Science, Papua New Guinea University of Technology, Lae, Morobe Province, Papua New Guinea
[*]Corresponding Author Email: mohsen.aghaeiboorkheili@pnguot.ac.pg

ABSTRACT
Volatility in the exchange rate is a vital consideration in macroeconomic policy-making and financial decision-making, especially in emerging nations such as Papua New Guinea, where empirical research is still lacking. This paper focuses on investigating the exchange rate volatility of Papua New Guinea Kina (PGK/USD) within the 2024 to 2026 exchange rate reform period based on the GARCH models. The daily exchange rate data collected from Bank of Papua New Guinea was converted into logarithmic returns and used in the GARCH (1,1) and EGARCH (1,1) models for analysis. Tests for stationarity, non-normality, fat tails, and volatility clustering proved that the series was characterized by these factors. Results revealed skewness of 9.2839 and kurtosis of 125.0649, implying the series has high levels of leptokurticity. For the GARCH model, the coefficient of volatility persistence was found to be 0.6620 while that for the EGARCH was 0.8866, which has an asymmetry parameter of -0.0442 implying depreciation shocks have more effect on volatility than appreciation shocks.

Keywords:
Exchange Rate Volatility,
GARCH,
EGARCH,
Papua New Guinea,
Kina,
Time Series Analysis

INTRODUCTION

For Papua New Guinea (PNG) as a developing country, exchange rate volatility has become a major issue in macroeconomic management During the last couple of decades, the movement of the exchange rate across different countries of the world has piqued the interest many researchers, ranging financial economists to government policy makers especially after the end of the Bretton Woods Agreement (Abdalla, 2012).

Following the global shift from fixed to flexible exchange rates regimes, exchange rates have shown significant fluctuations characterized by uncertainty and instability. These changes affect trade, inflation and investment decisions.

Between 2024 and 2026, Papua New Guinea as a nation underwent notable exchange rate reforms all aimed at reducing market imbalances and improving foreign exchange (FOREX) market efficiency. But reforms like this often create short term volatility in the currency market. Understanding and modelling this volatility is important for effective policy formulation.

Time series data such as exchange rates often tend to have properties like volatility clustering, persistence, non-normality, and asymmetry. Linear models are generally ineffective at modelling such data sets, thus necessitating the use of GARCH-type models that are more appropriate for modelling financial volatility.

The GARCH model works well for modelling volatility persistence, whereas the EGARCH model can be used to model volatility asymmetries where shocks have different impacts on volatility depending on whether they are positive or negative.

A number of empirical studies have utilized GARCH-type models in exchange rate volatility models. For example, Abdalla (2012) showed that there is high persistence in exchange rate volatility through the use of GARCH models. Epaphra (2016) showed that asymmetric volatility effects exist in GARCH and EGARCH models while Chong et al. (2002) showed the usefulness of GARCH models in predicting exchange rate risks. Even though there is significant evidence from the above empirical studies, there is inadequate research on volatility in the exchange rates in Papua New Guinea especially during the exchange rate reform period 2024 to 2026.

In this regard, this research paper contributes to the existing body of knowledge on exchange rate volatility modeling in Papua New Guinea by employing both GARCH (1,1) and EGARCH (1,1) models to analyze the persistence and asymmetric effects in the PGK/USD exchange rate volatility. Contrary to most of the research carried out in large economies, this research will focus on the PNG foreign exchange market during the period of exchange rate reforms.

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Problem Statement
Even though exchange rate stability is important in PNG, there is limited research on modeling the volatility of the Kina exchange rate, especially during the recent 2024–2026 exchange rate reform period**.** Government officials and policy makers may have difficulty effectively predicting and managing exchange rate risks without proper modeling.

Project Aims and Objectives
Aim:
The aim of this paper is to utilize the different GARCH type models to model and analyze the Papua New Guinea Kina (USD/PGK) during exchange rate reform period (2024-2026).

Objectives:
- To evaluate the exchange rate returns and their statistical properties.
- To test the volatility clustering and heteroscedasticity.
- To estimate both the GARCH model and the EGARCH model.
- To analyze volatility persistence and the effects of asymmetry.
- To provide policy relevant insights.

Scope and Limitations
This study focuses on daily exchange rate data for the Papua New Guinea Kina against the US Dollar obtained from the Bank of Papua New Guinea covering the period 2024–2026**.** The analysis is largely limited to univariate GARCH-type models. It does not incorporate macroeconomics variables or multivariate frameworks.
This paper is arranged into four sections: Introduction, Methodology, Results and Discussion, and Conclusion.

MATERIALS AND METHODS
Data
In this paper, we used daily exchange rates of the Papua New Guinea Kina to United States Dollar (PGK/USD) exchange rate taken from the Bank of Papua New Guinea (BPNG). The exchange rate data comprised the period from January 2024 to February 2026 during the recently reformed exchange rates of Papua New Guinea. There were 647 observations for the dataset collected from the official documents released by the Bank of Papua New Guinea. The exchange rate was converted into logarithmic returns before estimation to eliminate variance and make the time series stationary.
The logarithmic returns were calculated as:

$$r_t = \ln\left(\frac{S_t}{S_{t-1}}\right) \quad (1)$$

Where r_t stands for the daily logarithmic return at period t, S_t refers to the exchange rate at the current period, and S_{t-1} refers to the exchange rate at the previous period.

The reason for choosing the GARCH (1,1) model and EGARCH (1,1) is due to the fact that the aforementioned models are commonly applied when it comes to volatility persistence and asymmetry in finance. It is evident from earlier researches that GARCH (1,1) model is usually enough when it comes to exchange rate volatility modelling, whereas EGARCH captures leverage effects(Girgin, 2023).

Preliminary Analysis
The preliminary analysis involves turning the exchange rate series into returns and conducting statistical tests on the resulting series. Since exchange rate levels are not usually stationary (non-stationary), the data are converted into logarithmic returns after which GARCH type models are applied. The preliminary analysis includes the following:
Stationarity tests: Augmented Dickey-Fuller
- Normality test: Jarque-Bera
- ARCH test: to detect heteroscedasticity

I. **Convert Exchange Rate to Logarithmic Returns.**
The following is used to change the exchange rates into log returns:

$$r_t = \ln\left(\frac{E_t}{E_{t-1}}\right) \times 100 \quad (2)$$

II. **Descriptive Statistics**
To examine the basic properties of the PGK/USD return series, the Descriptive Statistics are computed. The mean return gives the average daily change and the standard deviation measures volatility. Skewness indicates whether the distribution is symmetric whereas kurtosis indicates whether the return series exhibits fat tails.

III. **Plotting Exchange and Returns**
The plots for exchange rate show the movement of the Kina Value against the US Dollar value over a given time period. This is used to show volatility clustering during periods of large changes are followed by more are changes and similarly small changes are followed by small changes.

IV. **Unit Root Test or Stationery Test.**
Before applying GARCH Models, the return series has to be stationary. In this paper we will be using the Augmented Dickey-Fuller (ADF) test (May & Farrell, 2018). In our analysis the ADF test was used to check for stationarity in the PGK/USD value return series. The null hypothesis states that the series contains a unit root. The null hypothesis is rejected if the p-value is below 0.05 which indicates the return series to be stationary and suitable for GARCH modeling.

V. Normality Test

Financial returns are rarely normally distributed. In this paper we use the Jarque-Bera test to check whether the returns have a normal distribution. In our analysis the Jarque-Bera test was used to check whether the PNG/USD return series has a normal distribution. A p-value that is below 0.05 shows non-normality. Non-normality is common in series such as this financial series and supports the use of GARCH-type models (Pilbeam & Langeland, 2015).

VI. ARCH Effect Test

To check whether volatility changes over time the ARCH-LM test is used. This is a very important test to use before using the GARCH models. In our analysis the ARCH-LM test was used to detect conditional heteroscedastic in the return series. When the past shocks influence current volatility, it makes the test significant and justifies the use of GARCH type models.

VII. Autocorrelation Test

In this paper to test whether returns or squared returns are autocorrelated we use The Ljung-Box test. It is used it test serial correlation in the return the squared return series. If we have significant autocorrelation, it suggests that there is volatility clustering which than supports the application of GARCH models.

GARCH Model

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (3)$$

EGARCH Model

$$ln(\sigma_t^2) = \omega + \beta ln(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + \alpha\left|\frac{\epsilon_{t-1}}{\delta_{t-1}}\right| \quad (4)$$

Estimation Technique

The Models in this paper are calculated and estimated using Maximum Likelihood Estimation (MLE) implemented in the **R** statistical software environment**.**

RESULTS AND DISCUSSION

In this chapter we see the empirical results of the analysis done for the PGK/USD exchange rate volatility for the period of January 2024 to February 2026. The overall analysis was done using data that was obtained from the Bank of Papua New Guinea. The USD currency exchange rate was converted into PGK per USD, and a calculation of the daily logarithmic returns was calculated before the GARCH and EGARCH models were estimated.

Preliminary Findings

The final dataset consisted of 647 observations covering the period from January 2024 to February 2026. The PGK/USD exchange rate ranged from a minimum of 3.7299 PGK/USD to a maximum of 4.2974 PGK/USD during the study period. The results clearly show that the PNG Kina has dropped in value against the US dollar over the reform period.

The estimated mean return of the Kina was a 0.0219% while its standard deviation was 0.0409%. This shows that the average daily movement was small even though some periods experienced higher exchange rates.

A big feature if that the major dataset was the presence of 344 zero returns, which represents a little over 53.17% of the observations. This shows that on during more than half of the trading days, the exchange rate did not change. This is very important as GARCH Type models depend on changes that occur in the series to detect volatility.

I. Convert Exchange Rate to Logarithmic Returns.

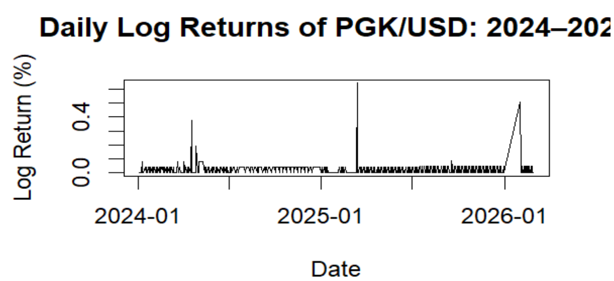

Figure 1. Daily logarithmic returns of the PGK/USD exchange rate from January 2024 to February 2026.

The daily returns were computed and the output graphed using R.

Descriptive Statistics

II. Descriptive Statistics.

The descriptive statistics were computed using R and the following are the outputs.

Table 1 Descriptive Statistics Using R Software

Descriptive Statistic	Computed
Mean	0.02188717
Standard Deviation	0.04091721
Min	0
Max	0.6454238
Skewness	9.283875

Kurtosis	125.0649

The value of the skewness which is 9.2839 as stated in the table shows that the distribution of the return is greatly positively skewed. This is an indication that large positive changes happen more often than large negative changes in the PGK/USD returns.
The value of the Kurtosis which is 125.0649 is significantly greater than 3 which tells that the distribution of the return is highly leptokurtic which means that the distribution has a higher and sharper peak with fatter tails as opposed to normal distribution.

III. Plotting Exchange and Returns

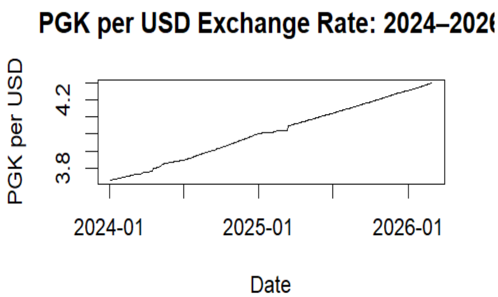

Figure 2. Daily PGK/USD exchange rate movements from January 2024 to February 2026.

The daily exchange rate of the PGK/USD returns were computed and the output graphed using R.

Unit Root Test or Stationery Test.

In this paper The Augmented Dickey-Fuller test is utilized to test whether the return series is stationary or not.

Table 2 Unit Root Test

Test	P-Value or Static Value
Static ADF	-8.5400
P-Value ADF	0.0000

Since the p-value of the ADF test is less than 0.05, the null hypothesis of the unit root is rejected which means the PGK/USD return series is found to be stationary and makes the series suitable for modelling using GARCH type models.

Normality Test

To test whether the return series has a normal distribution or not we utilize The Jarque-Bera test.

Table 3 Normality Test

Test	P-Value or Static Value
Static Jarque-Bera	410968.8083
P-Value Jarque-Bera	0.0000

From the findings the null hypothesis is rejected because the p-value is less than 0.05. This tells that there is no normal distribution in the return series. This is a common type of result in financial time series and confirms that volatility models like GARCH and EGARCH.

Autocorrelation Test and ARCH Effect

In this paper the ARCH-LM test is used to test for the existence of heteroscedasticity in the return series.

Table 4 Autocorrelation Test

Test	P-Value
ARCH-LM with (df=12)	1.0000
Ljung-Box Test for returns (df=12)	0.1495
Ljung-Box Test for Squared Returns (df = 12)	1.0000

The results from the ARCH-LM test suggest that there is lack of the detection of Strong ARCH effect in the return series because it has a p-value of 1.0000. With that there was also no strong autocorrelation in the series volatility as suggested by the results of the Ljung-Box test on the squared returns.
This is most probably a result due to the existence of a large number of unchanged daily exchange rate values in the dataset that was collected. The signal was weak because 53.17% of the returns were in fact zero values and this makes the volatility signal weaker than anticipated.
With that GARCH type models were computed for comparison the return series did not have a normal distribution, was fat tailed and was linked to a period of reform of the exchange rates.

GARCH (1,1) results.

To estimate whether or not current volatility is dependent upon past shocks and past volatility we use the GARCH (1,1) Model.

Table 5 Volatility Test

Parameters	Calculated
Mu (μ)	0.0186
Omega (ω)	0.000214
Alpha1 (α_1)	0.0000
Beta1 (β_1)	0.6620
Nu(ν)	6.8986
Log-Likelihood	1477.8932
$A\|C$	-2945.7863
$B\|C$	-2923.4246

As per the results of the GARCH Model the ARCH Coefficient α_1, approximately 0.234729, suggests that immediate past shocks had very little influence on the current volatility. The

Other GARCH coefficient $\beta_1$computed was approximately 0.000000 suggest there is moderate volatility persistence.

The persistence value calculated is:

$$\alpha_1 + \beta_1 = 0.234729 + 0.00000 = 0.2347 \quad (5)$$

Because the value of persistence is less than 1 the process of volatility is mean reverting which means there is no indefinite persistence of exchange rate volatility.

EGARCH Results.

To determine whether shocks in the series have different effects either positive or negative on volatility we utilize the EGARCH Model.

Following are results from R Studio.

Table 6 Results from R

Parameters	Calculated
Mu (μ)	0.0191
Omega (ω)	-0.8422
Alpha1 (α_1)	0.0847
Gamma (γ_1)	-0.0442
Beta1 (β_1)	0.8866
Nu (v)	7.2310
Log-likelihood	1480.1636
$A\|C$	-2948.3272
$B\|C$	-2921.4931

From the results of computation of the dataset using the EGARCH Model it is seen that β_1 has a value of 0.8866, suggesting the EGARCH Model has a stronger volatility persistence than that of the standard GARCH Model. It means over a period of time the volatility shocks will die out or decay slowly.

The γ_1 parameter is negative at -0.0442 which suggests that there is presence of an asymmetric effect or in other words types of shocks like depreciation can increase volatility even more than the appreciation shocks that have similar size.

These are very important results because they suggest that the PNG Kina exchange rate can respond to market movements both positive and negative differently in times of reform.

Comparing Models

Table 7 Comparing Results

Model Type	Log-likelihood	A|C	B|C
GARCH (1,1)	1477.8932	-2945.7863	-2923.4246
EGARCH (1,1)	1480.1636	-2948.3272	-2921.4931

The comparison of models was performed based on the criteria of Akaike Information Criteria (AIC), Bayesian Information Criterion (BIC), and Log-Likelihood. EGARCH (1,1) model generated a smaller value of AIC than the standard GARCH (1,1) model; hence it can be argued that the EGARCH model had slightly better results in explaining the series of exchange rate returns. Furthermore, it was possible to observe the effect of asymmetric volatility in the EGARCH model due to the generation of a negative gamma parameter; however, it was not possible in the standard GARCH model.

Log-likelihood results also showed that both models had a good fit to the exchange rate returns data. It should be noted however that the EGARCH model had slightly better results than the other model in explaining this data. That said the GARCH Model does have a smaller B\C vale meaning that even though EGARCH is ideal for the data, GARCH is more frugal.

Both Models have their advances EGARCH being more useful when determining asymmetric behaviors of the exchange rate volatility during times of reform.

Interpretation and Discussion.

From the results obtained in this study, it can be noted that the PGK/USD exchange rate return series possess key features associated with financial time series data, such as non-normality, persistence of volatilities, asymmetries, and fatter tails. These results are supported by other researchers such as Abdalla (2012), Epaphra (2016), and Chong et al. (2002), who found the same volatility pattern in the exchange rates using GARCH family models.

From the descriptive statistics analysis, it was seen that the kurtosis and skewness were very high and positive, suggesting that there existed extremely large fluctuations in exchange rates and non-normal distribution. This implies that the sudden changes in the PNG Kina exchange rate are likely to take place much more frequently compared to normal scenarios.

The results of the GARCH (1,1) model indicated a moderate degree of persistence, while those of the EGARCH model revealed a higher degree of persistence along with asymmetric impacts. The negative gamma found using the EGARCH model means that the effects of depreciation shocks tend to be greater than those of appreciation shocks on exchange rate volatility. In an economic perspective, shocks associated with depreciation would cause more uncertainty in the foreign exchange market of PNG than positive shocks. Such results are significant to the policymaker since a depreciating exchange rate could mean an increase in inflation and the cost of imports.

Even though the ARCH-LM test failed to establish a significant ARCH effect, such a result can mostly be attributed to the structure of the dataset. Over half of the returns were observed to be zeros, which indicated that the exchange rate had not changed for several days. The

presence of zero return made the time series less volatile and therefore could explain why the existence of an ARCH effect was not detected. This result indicates that the PNG foreign exchange market in the reform era might be partially managed.
Notwithstanding the above shortcomings, the results obtained from applying EGARCH models to study the asymmetry in exchange rates and volatility persistence during the reforms were nevertheless informative. Consequently, the study concludes that the GARCH-type models are relevant when conducting research on exchange rate risk in PNG.

Summary of Chapter.

In this chapter the exchange rate returns taken from January 2024 through to February 2026 were analyzed. The results tells that the series of return was stationary but did not have a normal distribution. It also consists of a large number of entries having the value zero which had made the ARCH effect.
The GARCH (1,1) model showed an average Prescence of volatility and the EGARCH (1,1) Model shows a stronger presence of volatility and asymmetric effects. It was found based on the A|C that the EGARCH model gave a better result, even though the difference was small. To conclude the EGARCH model is a far better tool for capturing the behavior of the rate of the exchange of the volatility of the PNG Kina during times of reform.

CONCLUSION

In summary, this research assessed the volatility characteristics of the Papua New Guinea Kina (PGK/USD) in the exchange rate reform years between 2024 and 2026, using the GARCH (1,1) and EGARCH (1,1) approaches. As a result, it was observed that the return series is stationary, highly non-normal, positively skewed, and leptokurtic. Therefore, there were signs of high volatility, with extreme movement and uncertainty within the exchange rates during the period.
The GARCH model estimated the volatility persistence to be low and the EGARCH model revealed higher volatility persistence and asymmetry such that the effect of depreciation shocks on volatility was larger than appreciation shocks. In addition, the analysis reveals that more than half of the return series had zero values. Consequently, the existence of strong ARCH effects and volatility clustering becomes less detectable, hence implying partial management within the foreign exchange market of PNG in those years.
Overall, the EGARCH model was chosen as having the slightly better model fit based on AIC, BIC, and log-likelihood values. Thus, it can be said that this model captures the exchange rate return series characteristics better since it accounts for volatility asymmetry better compared to GARCH.
One disadvantage associated with this research is the high percentage of stable exchange rates, which might weaken the effectiveness of volatility estimation. Further researches could consider the application of multivariate GARCH models, macroeconomic indicators, or higher frequency exchange rates for a better volatility modeling and forecasting.

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Conflict of Interest

The authors declares that there is no conflict of interest regarding the publication of this paper.

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