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Assessing the Effectiveness of the Garch Model in Forecasting Volatility of Headline Inflation in Namibia

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Abstract: This study assesses the effectiveness of various volatility models, the GARCH(1,1), TGARCH, and EGARCH in forecasting inflation volatility in Namibia, using data from January 2003 to December 2024. Our finding shows that headline inflation volatility in Namibia exhibits persistence and mean-reversion, which is a common feature of volatility. Employing multiple metrics and in-sample criteria such as AIC and Schwarz, the GARCH(1,1) model emerged as the preferred choice for in-sample estimation. However, diagnostic tests revealed persistent serial correlation in residuals across all models, indicating possible limitations of using univariate models to explain inflation volatility. Out-of-sample forecast evaluation from October to December 2024 identified the EGARCH model as the most accurate, with superior performance across RMSE, MAE, and MAPE metrics. Further, this study shows that recent inflation shocks significantly impact volatility, with little evidence of asymmetric effects from positive or negative shocks. The research highlights the importance of ongoing model monitoring and evaluation. Volatility models designed for short-term forecasting need to be adjusted so that their parameters accurately reflect the relevant dynamic structure of the variable predicted by that model. Further investigation into the serial correlation issue offers valuable insights about how this can be accurately captured, thereby designing a model for policymakers aiming to stabilise inflation and manage it effectively, and mitigate the risks.

Keywords: Inflation, Inflation Volatility, Grach, Uncertainty

1. Introduction and Background

Price stability and financial stability are essential goals for macroeconomic stability, and they are conditions necessary for a healthy, sustainable economic development and economic wellbeing [18]. When price stability is achieved and maintained, monetary policy makers have done their job well [43]. Central banks play a crucial role in maintaining this macroeconomic stability; however, they need tools and a solid understanding of how to enhance their ability to achieve it. One of the central bank's primary functions is to control inflation, anchor inflation expectations, and conduct monetary policy in a manner that reduces inflation volatility within the economy. We are of the view that this is easier said than done, as argued by [37], who said that "fundamental economic relationships, such as that between unemployment and inflation, have become muddier, making decisions much more difficult to take". Despite this challenge, these objectives (i.e. price and financial stability in the presence of uncertainty) are crucial because they impact household consumption, investment decisions, and overall economic well-being [5, 28]. To achieve economic benefits from macroeconomic stability, central banks need tools to manage economic uncertainty, evaluate inflation forecasts, and understand the risks associated with the inflation outlook as indicated by inflation volatility.

Unfortunately, macroeconomic management's pursuit of macro stability in the presence of uncertainty is dogged by a lack of precise measures of inflation uncertainty[1] and the challenge of bi-causality between inflation and inflation

[1] Measures of inflation volatility vary; there are those that are survey-based and model-based measures. Typically, survey-based measures are difficult to apply because they demand more resources to construct and are dogged by issues of reliability and validity.

volatility. Historical uncertainty, also known as unconditional volatility, can be inferred from historical standard deviations. Domestic factors and global factors drive it; however, future volatility is uncertain, as the future is uncertain. Despite these challenges, decision-makers are expected to make judgments about the risks associated with upside and downside inflation movements, the expected path of inflation and the uncertainty around that path. This paper evaluates how good techniques such as GARCH, EGARCH, and TGARCH are in forecasting inflation volatility to inform judgements during monetary policy decisions. Inflation is typically measured by two important indicators: headline inflation, which shows the overall pace and shift in the level of prices, and core inflation, a growth rate derived from the Consumer Price Index (CPI), which does not include volatile elements like the price of food and energy. Headline inflation reflects the overall consumer price developments in the economy, while core inflation provides a reliable indicator of underlying pricing pressures, excluding the volatile components. Accurate forecasts of these indicators' volatility were mostly used in financial markets. However, the applications of inflation volatility are now far beyond that. For example, the assessment of risks and uncertainty is an essential part of monetary policy decision-making for assessing both the downside and upside risks of the forecasted inflation path ahead. This is important in improving risk control and developing efficient strategies, especially in economies that aim to stabilise inflation around the target.

In statistics, volatility is commonly defined as the variance or dispersion of a variable from its mean. Volatility regarding inflation refers to the fluctuations or instability in inflation rates around its normal level. Economic literature has extensively examined this concept. [30, 41], and [34] assert that inflation volatility is a significant factor in economic research because the world is concerned with uncertainty. [8] assert that for macroeconomists, the fluctuation of inflation is frequently more significant than its magnitude in comprehending economic stability. Hence, in central banks, it is not enough to achieve the target but also to minimise the severe price movements around the target.

Traditional time series models, such as ARIMA or structural models, assume that the conditional variance is constant. This has been proven long ago not to be the case in many empirical studies [19]. However, many models find it challenging to accurately represent the time-varying volatility inherent in actual inflation data [19]. Most economic and financial time series data exhibit heteroskedasticity (non-constant variance). This means that time-series models based on the idea of constant variance often don't work well with data that doesn't have constant variance. Hence, they also give wrong statistical conclusions about the uncertainty around the forecasts.

There are additional techniques to determine the volatility of inflation, including the logarithm of the standard deviation of monthly inflation rates [3] and the conditional variance of inflation shocks derived from various GARCH parameters [40]. However, [44] argue that the generalised autoregressive conditional heteroskedasticity (GARCH) model, proposed by [11], has become one of the most effective methods for modelling and predicting time-varying volatility. ARCH and the GARCH variants models are very proficient for time series data that demonstrate volatility clustering. [21] and [33] observed that volatility clustering is characteristic of most heteroscedastic processes in finance and economics, wherein large changes of either sign typically succeed large changes, while small changes generally follow small changes.

1.1. Problem Statement

Neglecting asymmetric factors such as the direction (positive or negative), magnitude, and source (demand- or supply-driven) of shocks undermines efforts to model volatility accurately. This can lead to either over- or under-prediction of volatility levels depending on the nature of the prevailing shocks. Grasping volatility is crucial in portfolio management, yet it has received less attention in the monetary policy decision-making process, while this process involves an assessment of the risks associated with the swings in inflation ahead. This may be due to the absence of concentrated efforts to evaluate how effective the tools, such as GARCH, EGARCH and TGARCH, are. However, this issue might be less pronounced if the variables do not exhibit high frequency and, therefore, do not demonstrate clear clustered variance, as commonly seen in financial market indicators. Nonetheless, we argue that for many countries like Namibia, the variance of inflation is not constant; periods of high volatility tend to follow periods of high volatility before eventually transitioning to low volatility. In light of this challenge, which volatility model most accurately captures the dynamics of inflation volatility and effectively forecasts it within the short-term horizon for Namibia? This paper aims to address this gap by extending the application of GARCH models to forecast the volatility of headline inflation in Namibia.

1.2. The Main Objective

The primary objective of this paper is to assess the effectiveness of the GARCH model and its related variants (i.e. the Threshold-GARCH (TGARCH) and Exponential-GARCH (EGARCH) models) in estimating historical volatility and forecasting future volatility over a three-month horizon. The study uses monthly headline inflation data to analyse the time-varying volatility of month-on-month and annual inflation from January 2003 to December 2024. We aimed to achieve our goal by closely:

1. examining a symmetric GARCH model and two asymmetric extensions, the TGARCH and EGARCH models, to evaluate their effectiveness in capturing volatility.
2. identifying the best-performing model using the forecast accuracy information criterion.

This study aims to contribute to knowledge by providing empirical evidence of effective techniques for assessing inflation volatility, which can inform monetary policy decisions in Namibia.

Our study provides empirical evidence that inflation and its volatility in Namibia exhibit mean-reverting behaviour, which is a common characteristic of volatility. Our analysis indicates that the EGARCH model is effective for accurately forecasting headline inflation volatility over a short-term horizon. However, we did not find any evidence of asymmetry, meaning that large fluctuations are not typically followed by similarly large fluctuations, nor are periods of low volatility followed by low volatility before returning to a normal state.

The rest of the paper is structured as follows: Section 2 reviews the literature on inflation volatility and GARCH models. Section 3 outlines the methodology, including data sources and model specifications. Section 4 presents the data, results and discussion, while Section 5 summarises the key findings and offers recommendations.

2. Literature Review

Inflation volatility poses a significant challenge to economic stability, primarily due to the uncertainties and risks faced by economic agents. Despite considerable efforts to reduce inflation levels globally, particularly in advanced economies, many countries in sub-Saharan Africa (SSA) continue to experience high inflation. This region also demonstrates significant inflation volatility, complicating the implementation of monetary policy and general monetary policy management [15].

Existing literature underscores the importance of estimating inflation volatility [11] and generally agrees on the relationship between inflation and its volatility. However, there is a lack of consensus regarding the direction of causality. [25] propose that rising inflation leads to increased inflation uncertainty, constrains investment decisions, increases the cost of hedging in financial markets and hampers economic growth. While evidence for Autoregressive Conditional Heteroskedasticity (ARCH) effects varies internationally, substantial research indicates that countries experiencing high inflation tend to display significantly greater levels of inflation volatility on average [16]. Additionally, [16] argue that central banks are likely to create inflation surprises when confronted with high inflation uncertainty.

Numerous financial studies indicate that asymmetric GARCH models produce superior results compared to symmetric GARCH models. This was demonstrated by [1], a study which analysed inflation models across several Asian countries, including Indonesia, by contrasting symmetric and asymmetric GARCH models. The set of literatures include [30] for the UK; [39] for Pakistan; [14] for the annualized US inflation rate; and [24] for G7 countries; [27] for Mexican inflation; and [32] for inflation in Chile.

The primary limitation of typical ARCH and GARCH models is their assumption of a symmetric response of conditional variance (volatility) to both positive and negative shocks. However, it has been suggested that inflation volatility behaves asymmetrically rather than symmetrically. Researchers such as [13, 23, 24], and [6] argue that positive inflation shocks have a significantly greater impact on volatility than negative inflation shocks.

Recent studies have enhanced the understanding of inflation volatility, although not in relation to monetary policy management. For instance, [36] utilised three models from the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) family to provide a concise analysis of Nigeria's inflation volatility dynamics from 1996 to 2011. They found that the asymmetric TGARCH (1,1) model was most suitable for explaining the dynamics of both headline and core Consumer Price Index (CPI) volatilities in Nigeria. In contrast, the symmetric GARCH (1,1) model was adequate for modelling the food CPI.

Additionally, [22] discovered that positive news about price changes tends to increase volatility more significantly than negative news. Their findings further assert that core inflation is more persistent in its volatility compared to headline inflation. When evaluating the different volatility models, they concluded that symmetric models (GARCH and GARCH-M) are less effective in capturing inflation volatility than asymmetric models (EGARCH and TGARCH). However, EGARCH offered the best fit for capturing inflation dynamics and its volatility.

Additionally, [46] employed the GARCH model to estimate headline inflation volatility and examined its impacts on foreign direct investment between 1970 and 2005, using annual data. Similarly, [2] fitted a symmetric GARCH (1,1) model to provide volatility estimates for Nigeria's headline CPI using annual data for the period 1970-2001. These studies assumed a symmetric response of inflation volatility to positive and negative shocks, as implied by the basic GARCH model. However, such a symmetric restriction in the GARCH model has been rejected by several empirical studies as inflation volatility was more sensitive to positive inflation shocks than negative shocks [13].

In conclusion, time-varying inflation volatility has decreased in many economies due to consistent monetary action policies that have successfully anchored inflation expectations. Although the analyses aimed at understanding inflation volatility are well established in many countries, we did not find research studies on this topic conducted in Namibia to forecast the volatility of anticipated inflation.

3. Methodology

3.1. Methodology

The paper uses three GARCH models (GARCH, TGARCH, and EGARCH) to evaluate which of the three models is effective at estimating and forecasting inflation volatility. We applied these methods to estimate annual headline inflation and monthly inflation volatility in Namibia. In examining this, this paper reviews GARCH models derived from the Autoregressive Conditional Heteroscedasticity (ARCH) model proposed by [19]. In laying out the procedures for estimating volatility, firstly, we introduced the ARCH model, then extended it to the symmetric GARCH and the asymmetric variants of GARCH, i.e TGARCH and EGARCH models.

3.2. Models

ARCH model, historically, volatility in financial markets is estimated with a simple autoregressive conditional heteroscedasticity (ARCH) model. The Autoregressive Conditional Heteroscedasticity (ARCH) model, introduced by [19], was the first to present a systematic framework for predicting time-varying conditional variance. The ARCH(q) model is defined thereby:

$$\sigma_t{}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}{}^2 \tag{1}$$

$$, where \varepsilon_t = \sigma_t z_t \tag{2}$$

$z_t \sim I.I.D.(0,1),\ \alpha_0 > 0, \alpha_i > 0, i > 0$

The "(1)" $\sigma_t{}^2$ is the conditional variance, and ε_t denotes the error terms (return residuals, with respect to a mean process). The error terms ε_t are split into a stochastic piece: z_t is a white noise term and a time-dependent standard deviation σ_t.

The α_0 , α_i in "(1)" represent coefficients, with restrictions applied to prevent negative variance. The ARCH model can handle conditional variance that changes over time based on past errors, which is a useful way to show volatility clustering and leptokurtosis. Some weaknesses include the necessity for numerous parameters and a high order of the ARCH term q to capture the dynamic behaviours of conditional variance effectively. Additionally, it tends to overpredict volatility due to its slow response to isolated shocks in returns and does not adequately account for the leverage effect [45]. To account for this, other models that are extensions of the ARCH framework were proposed.

GARCH Model: [11] introduced a generalised ARCH model, creating the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model. The GARCH model facilitates a more flexible lag structure through the imposition of non-linear restrictions, consequently reducing the number of parameters required in the model. The GARCH (p, q) model "(3)" is expressed using the following formula:

$$\sigma^2{}_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon^2{}_{t-i} + \sum_{j=1}^{p} \beta_j \sigma^2{}_{t-j} \tag{3}$$

Where σ_t^2 denotes the conditional variance at time t, with $q > 0$, $p \geq 0$, $\alpha_0 > 0$, $\alpha_i \geq 0$ for $i = 1, \ldots, q$, $\beta_j \geq 0$ for $j = 1, \ldots, p$.

The α_0, α_i, and β_j are parameters to be estimated. The q denotes the order of the ARCH terms, while p signifies the order of the GARCH terms. To guarantee a positive conditional variance σ_t^2 for all t, the constraints α_0, α_i, and β_j are enforced. When $p = 0$, the GARCH(p, q) model simplifies to an ARCH(q) process. The conditional variance in ARCH is defined solely as a linear function of past sample values, while GARCH incorporates lagged conditional variance into the model as well.

Therefore, the GARCH(1,1) model was then used in the study to account for headline and core inflation, and the model is given as:

$$\sigma_t^2 = a_0 + a_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{4}$$

In a GARCH(1,1) process, the current conditional variance σ_t^2 is influenced by the prior shock ϵ_{t-1}^2, similar to the ARCH model, as well as by the conditional variance from the previous day, σ_{t-1}^2. As illustrated by Equation 4, the fundamental GARCH model posits that volatility is determined by previous squared returns and historical volatility. While this approach is fundamentally sound, it fails to account for the possibility that positive and negative shocks may have distinct effects on volatility.

The Threshold GARCH Model: The TGARCH model, as proposed by [26], incorporates asymmetric effects in volatility modelling. The TGARCH model presents a significant advantage over the GARCH model by analysing the differential responses of financial market volatility to positive and negative shocks. It emphasises that adverse news tends to provoke a more substantial increase in volatility than positive news of equivalent magnitude. [26] augmented the GARCH model by incorporating an additional term γ to account for potential asymmetries in the data. They specified the TGARCH model as follows:

$$\sigma_t^2 = a_0 + a\epsilon_{t-1}^2 + \gamma h_{t-1}\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

Here, h_{t-1} is an indicator function that equals 1 if $\epsilon_{t-1} < 0$ and 0 otherwise; γ is the asymmetric parameter, while α and β are described in Equation (3). Positive shocks occur when $\epsilon_{t-1} > 0$, whereas negative shocks arise when $\epsilon_{t-1} < 0$. Positive news influences the conditional variance by α, but negative news affects it by $\alpha + \gamma$. If $\gamma \neq 0$, the impact of news is asymmetric; if $\gamma > 0$, a leveraging effect exists, wherein negative shocks elevate volatility more than an equivalent quantity of positive shocks. The TGARCH model simplifies to the fundamental GARCH model when the asymmetry parameter (γ) equals zero.

The Exponential GARCH Model [35] introduced the Exponential Generalised Autoregressive Conditional Heteroscedasticity (EGARCH) model to address the limitations of symmetric models, specifically the leverage effect. [35] utilised the natural logarithm of the conditional variance, $\log(\sigma_t^2)$, to ensure a nonnegative conditional variance rather than imposing constraints.

$$\log(\sigma_t^2) = c_0 + a\left(\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right|\right) + \gamma\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right) + \beta\log(\sigma_{t-1}^2) \tag{6}$$

Where α, β, and γ are defined in equations (3) and (5). The left-hand side of equation (6) represents the logarithm of the conditional variance, indicating that the leverage effect is exponential rather than quadratic. Consequently, forecasts of the conditional variance must be non-negative. The parameter γ captures the asymmetric effect of past shocks. If $\gamma \neq 0$, the news impact is asymmetric; if $\gamma < 0$, a leverage effect is present. The influence of conditional shocks on the conditional variance is quantified by α. A positive shock in a given period results in an effect of $\alpha + \gamma$ on the conditional variance, while a negative shock results in an effect of $\alpha - \gamma$.

3.3. Diagnostic Tests

Numerous criteria exist in the literature for model selection. This work aims to evaluate the GARCH models' sufficiency and forecast capability of inflation volatility in Namibia. This work utilises the Akaike Information Criterion (AIC) to balance the model fit and complexity trade-offs as described in '(7)' below. It is defined as:

$$\mathrm{AIC} = -2\left(\frac{L}{N}\right) + 2\left(\frac{K}{N}\right) \tag{7}$$

whereby L denotes the log-likelihood function value, K represents the number of estimated parameters, and N signifies the number of observations. Various models are fitted within each model class, and the model with the lowest AIC value is deemed the optimal choice for that class. Before the estimations, unit root tests for stationarity will be performed using the augmented Dickey-Fuller (ADF) test, the most prevalent in the literature.

3.4. Forecast Evaluation

Statistical loss functions assess the accuracy of out-of-sample volatility forecasts by measuring the alignment between predictions and actual data. This method allows for the evaluation of out-of-sample forecast accuracy, as the minimal divergence from zero indicates the most precise forecast. [17] and [31] argue that choosing the most suitable loss function is not straightforward, as various loss functions impose different penalties depending on the measure's equation.

This paper evaluates the forecasts using four distinct metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) as proposed by [14] and [38], and Mean Absolute Error (MAE) as suggested by [29]. Using multiple metrics facilitates the identification of the optimal forecasting model [4]. The model exhibiting the lowest value of loss functions is deemed the most effective for predicting inflation volatility.

4. Results and Analysis

4.1. Data: Headline Inflation Trends

This study uses data on the Namibian Consumer Price Index (NCPI) to derive both annual and monthly headline inflation. The NCPI was obtained from the Namibia Statistics Agency and encompasses the sample from January 2003 to December 2024. Figure 1 below shows the month-on-month inflation rate alongside the 15-month moving average standard deviation of monthly inflation. The observed volatility in monthly inflation demonstrates persistence, characterised by significant fluctuations in both upward and downward directions. The monthly standard deviation indicates that positive shocks to volatility are likely to result in sustained increases in volatility until a directional shift occurs, a common stylised feature associated with volatility. In contrast, negative shocks tend to lead to extended periods of negative volatility prior to a change in direction. This indicates that today's volatility shocks will influence future volatility expectations over multiple periods (see [20]). Moreover, the second row of Figure 1 provides an overview of annual headline inflation in conjunction with its corresponding moving average standard deviation. Unconditional inflation volatility, measured by standard deviation, exhibits mean reversion towards a constant of approximately 0.3 for monthly inflation and 1.0 for annual inflation volatility.

Table 1. *Summary of Statistics.*

Variable	Mean	Std. Dev.	Maximum	Minimum	Coef. of Variation (CV)
Annual Inflation	5.352	2.168	12.914	0.943	40.5
Monthly Inflation	0.421	0.505	3.228	-1.362	119.9

Table 1 above presents summary statistics for Namibia's headline inflation. On average, annual inflation was 5.35%, which indicates that consumer prices rose by roughly 5.35% annually. With inflation ranging from a low of 0.94% (showing stable prices) to a high of 12.91% (representing considerable price increases), the standard deviation of 2.17 shows moderate fluctuation. On the other hand, monthly inflation averaged 0.42%, indicating that monthly price increases were generally less than 0.5 percent. It's higher relative standard deviation (0.51), however, indicates more short-term volatility, with monthly movements ranging from 3.23% (rapid price increases) to -1.36% (deflation). The use of time-varying volatility models, such as the ARCH family, to capture these dynamics is justified by the fact that these numbers represent times of both inflationary pressure and price contractions.

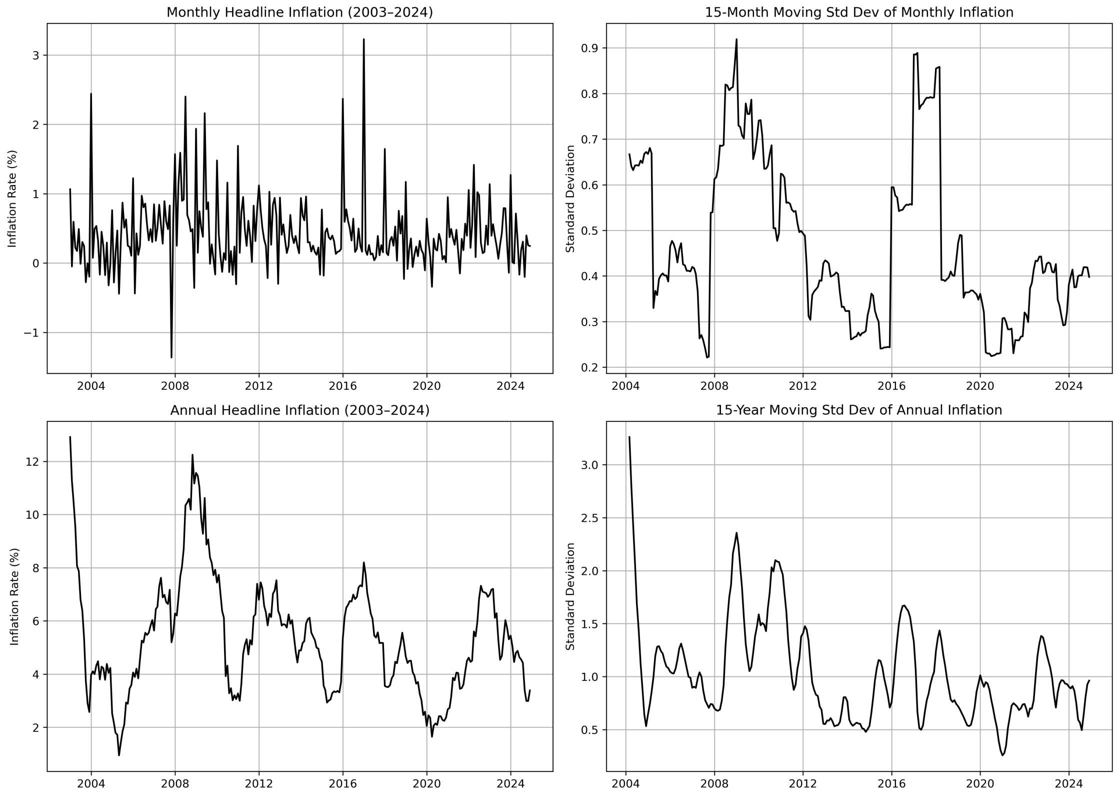

Figure 1. *Annual Headline Inflation, Monthly Inflation (2003 - 2024) and Unconditional 15-Period Moving Standard Deviations: Monthly and Annual (2003 - 2024).*

4.2. Unit Root Tests

In Table 2, we present the unit root test, which evaluates the stationarity of the time series annual headline inflation and monthly headline inflation. Using the Augmented Dickey-Fuller (ADF) test, the hypothesis evaluated is H_0: The series is non-stationary against H_1: The series is stationary.

Table 2. *ADF Test Results.*

	t-Statistic	Probability
Monthly Inflation	-2.990	0.037**
Annual Inflation	-3.195	0.021**

Note: ** indicate significance at 5 per cent, respectively.

The ADF test results in Table 2 show that no unit root exists in both the monthly and annual headline inflation data. The p-values of 0.037 and 0.021 are both below the 0.05 significance level. Therefore, the null hypothesis of a unit root is rejected, indicating that the data do not exhibit a unit root problem and that both monthly and annual headline inflation are stationary.

4.3. Test for ARCH Effects

Before estimating an Autoregression Conditional Heteroscedasticity (ARCH) family model, the prerequisite is to determine if there are any ARCH effects in the data series (see Table 3 below). ARCH represent the simplest form of models for estimating volatility in financial markets. Stylised facts show that periods of low volatility tend to be followed by periods of low volatility for a prolonged period, and similarly, period of high volatility is followed by periods of high volatility for a prolonged period, and when this happens to residual, then there is a justification to run the ARCH family [19]. However, if the series' residuals do not exhibit any ARCH effects, the ARCH family model is superfluous and incorrectly provided. The hypotheses for the ARCH test: H_0 : No ARCH effects (constant variance) H_1 : ARCH effects present (time-varying volatility).

Table 3. *Heteroskedasticity Test: ARCH.*

	Obs*R-squared	Probability
Monthly Inflation	0.131	0.717**
Annual Inflation	214.612	0.000**

Note: ** indicate significance at 5 per cent, respectively.

Table 3 above presents the results of the ARCH test for both monthly and annual inflation. For monthly inflation, we fail to reject the null hypothesis, as the obs*R-squared value has a p-value of 0.717, which is greater than the 0.05 significance level. Therefore, there is no evidence of an ARCH effect in the monthly headline inflation, and the study will not proceed with the ARCH family model using monthly data. In contrast, for annual inflation, the test statistic obs*R-squared value has a p-value of 0.000, which is below the 0.05 significance level. As a result, we reject the null hypothesis and accept the alternative hypothesis. This indicates the presence of an ARCH effect, and we can proceed with running the ARCH family model for the annual data.

4.4. Estimations of the GARCH Family Models

Table 4 below presents the estimation results for the GARCH(1,1), TGARCH, and EGARCH models. For GARCH(1,1), the constant, which represents the baseline level of the conditional variance, has a coefficient of 0.270 and a p-value of 0.011, which is statistically significant at the 5% level. This implies that, even in the absence of recent shocks or past volatility, the inflation rate exhibits a non-zero level of expected volatility.

The ARCH term, $\text{RESID}(-1)^2$, which measures the impact of the previous period's squared error (i.e., the shock) on the current period's volatility, has a coefficient of 0.946 and is statistically significant (p-value of 0.002). This suggests that past shocks to inflation have a strong and immediate influence on today's inflation volatility; a large shock yesterday translates into significantly higher expected volatility today.

Table 4. *Estimation results for GARCH(1,1), TARCH and EGARCH.*

	GARCH(1,1)	**TGARCH**	**EGARCH**
Parameter	**Coeff. (p-value)**	**Coeff. (p-value)**	**Coeff. (p-value)**
α_0(Constant)	0.270 (0.011**)	0.271 (0.012**)	-1.244 (0.001**)
α_1(RESID(-1)^2)	0.946 (0.002**)	0.956 (0.014**)	1.563 (0.000**)
γ(RESID(-1)^2(RESID(-1)<0))		-0.023 (0.959)	
γ(RESID(-1)/$\sqrt{\text{GARCH}(-1)}$)			0.053 (0.777)
β(GARCH(-1) / LOG(GARCH(-1)))	-0.003 (0.986)	-0.003 (0.982)	0.750 (0.000**)
AIC/Schwarz	3.607 / 3.661	3.614 / 3.682	3.638 / 3.705

In contrast, the GARCH term, $\text{GARCH}(-1)$, has a coefficient of -0.003 and is statistically insignificant at the 5% level. This indicates that past volatility itself does not have a substantial direct impact on current volatility after accounting for the effect of recent shocks. This could possibly be undermined by the fact that the GRACH(1,1) model did not fully eliminate the systematic correlation effects in the residuals. Overall, the GARCH(1,1) model results in Table 4 suggest that volatility in Namibia's headline inflation is primarily driven by recent shocks. When there is a significant unexpected change in inflation, it leads to a notable increase in the uncertainty and fluctuations surrounding future inflation. Hence, it is important for monetary policy makers to anchor inflation expectations and forward concerted efforts to stabilise inflation, which will further contribute to lower inflation outcomes. However, the persistence of this volatility (independent of new shocks) appears to be very weak or non-existent. Once the effect of a past shock has been accounted for, the level of volatility does not seem to linger on its own. In the absence of new shocks, volatility tends to revert to its baseline level relatively quickly.

In the Threshold GARCH (TGARCH) model, the constant term (0.271) remains statistically significant, indicating a baseline level of inflation volatility. The ARCH term, $\text{RESID}(-1)^2$, continues to be highly significant (0.956), confirming the strong impact of past squared errors (shocks) on current volatility. The main addition in the TGARCH model is the asymmetric term, $\text{RESID}(-1)^2 \times (\text{RESID}(-1) < 0)$, which captures the differential impact of negative shocks compared to positive shocks of the same magnitude. However, this coefficient (-0.0235) is statistically insignificant, suggesting that in the case of Namibian headline inflation, negative shocks do not appear to have a significantly different effect on subsequent volatility compared to positive shocks. Lastly, the GARCH term, $\text{GARCH}(-1)$, remains small and statistically insignificant (-0.003), consistent with the GARCH(1,1) results, indicating a lack of persistence in volatility beyond the impact of current shocks.

The EGARCH model reveals a statistically significant constant term (-1.244) in the log of the conditional variance. Consistent with the significant constant terms found in the *GARCH(1,1)* and TGARCH models, the magnitude of past standardised shocks (ARCH = 1.562) also significantly influences current volatility in the EGARCH framework. Notably, the coefficient capturing the leverage effect ($\gamma = 0.053$) is statistically insignificant, indicating no evidence of a differential impact of negative versus positive inflation shocks on subsequent volatility.

Furthermore, the statistically significant coefficient (0.750) on the lagged log of the conditional variance, $\log(\text{GARCH}(-1))$, in the EGARCH model - unlike in the GARCH(1,1) and TGARCH models, where this term was insignificant - indicates a substantial degree of persistence in conditional variance. This suggests that past volatility levels strongly influence current volatility, specifically within the EGARCH framework. Therefore, the insignificance of the leverage terms in both the TGARCH and EGARCH models suggests that there is no strong evidence of an asymmetric effect whereby negative inflation shocks lead to significantly higher volatility than positive shocks of the same magnitude in Namibian headline inflation.

Table 5. *Model Selection Criteria.*

Models	AIC	Schwarz
GARCH (1,1)	3.607	3.661
TGARCH	3.614	3.682
EGARCH	3.638	3.705

The GARCH(1,1) model has the lowest AIC (3.607) and Schwarz (3.661) criteria compared to TGARCH and EGARCH. Therefore, based on these information criteria, GARCH(1,1) is the preferred and best-fitting model for the volatility of Namibian headline inflation among the three considered.

4.5. Diagnostics Check: Residual Diagnostic Tests

Before continuing to forecast with the preferred model (the best model, GARCH(1,1)), the model should undergo diagnostic checks. Table 6 below presents the diagnostic results on the Correlogram Q-stat test, Jarque-Bera test, and ARCH test. In this study, the diagnostic checks are applied to all three models to evaluate whether the residuals from the models do not suffer from serial correlation, non-normality, or the presence of any arch effects.

Table 6. *Diagnostic Test Results.*

Models	Q-Stat/p-value	Jarque-Bera Statistics/p-value	ARCH Test/p-value
GARCH (1,1)	0.000**	14.743/0.001**	0.153/0.696
TGARCH	0.000**	14.807/0.010**	0.161/0.688
EGARCH	0.000**	13.506/0.001**	0.684/0.408

Note: ** indicate significance at 5 per cent, respectively.

To evaluate for the presence of serial correlation in residuals, the *Correlogram Square Residual Test (Q-Stat)* shows a p-value of 0.000 for all three models, which is highly statistically significant. This leads to a rejection of the null hypothesis of no serial correlation in the squared residuals. The results suggest that there are still predictable patterns in the squared errors that the models have failed to account for. The presence of persistent serial correlation in the squared residuals is a concern, and the consideration of alternative model specifications may be necessary. It is our belief that several methodologies may be employed to address the issue of serial correlation in the residuals of GARCH models. These include increasing lag lengths, utilising a difference model, implementing a regression model with an intercept, or adopting an autoregressive distributed lag (ARDL) model. However, it is important to note that a multivariate GARCH model with a high dimensionality is likely better suited to capture systematic effects that may not be adequately accommodated by the aforementioned approaches. Furthermore, transforming variables, adjusting standard errors, or employing diagnostic tests such as the Breusch-Pagan test may prove beneficial in enhancing the model's robustness. Regarding the normality *Jarque-Bera statistics*, the p-values (0.001 for GARCH(1,1), 0.010 for TGARCH, and 0.001 for EGARCH) are all below the 5% significance level. This leads to a rejection of the null hypothesis of normally distributed residuals for all three models, indicating that the error terms deviate significantly from a normal distribution.

Lastly, to evaluate the presence of ARCH effects, the *ARCH LM Test* provides a different picture. The p-values for GARCH(1,1) (0.696), TGARCH (0.688), and EGARCH (0.408) are all well above the 5% significance level. This means we fail to reject the null hypothesis of no ARCH effect in the residuals of any of the models. Therefore, we conclude that these GARCH-type models have successfully captured the time-varying volatility clustering that is characteristic of ARCH effects.

4.6. Forecasting Inflation Volatility at 3-month Horizon

The GARCH, TGARCH, and EGARCH models were employed to forecast headline inflation volatility out-of-sample (from July 2024 to December 2024) to determine the most effective forecasting model. The forecasts are assessed with the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) to identify the optimal forecasting model at three three-month horizon. The model with the lowest value is chosen as optimal for forecasting inflation volatility at a three-month horizon. Table 7 below presents the forecast accuracy of the three models.

Table 7. *Out-of-Sample Forecast Evaluation.*

	GARCH (1,1)	TGARCH	EGARCH
	Forecasts (2024M10 - 2024M12)		
RMSE	1.825	1.824	1.748
MAE	1.815	1.814	1.738
MAPE	58.686	58.659	56.212

The forecast evaluation for the period October to December 2024 reveals that the EGARCH model outperforms both the GARCH(1,1) and TGARCH models across all considered forecast error metrics. Specifically, the EGARCH model exhibits the lowest Root Mean Squared Error (RMSE = 1.748), Mean Absolute Error (MAE = 1.738), and Mean Absolute Percentage Error (MAPE = 56.21%). Therefore, these results indicate that the EGARCH model provides more accurate forecasts of inflation volatility for the specified forecast horizon. We show that if you want to evaluate the outlook of inflation volatility in Namibia over a short-term horizon, the EGARCH model will provide more accurate out-of-sample forecast results than other models. Despite in-sample results that some models were not able to purge the serial correlation from the residual, the out-of-sample results for the EGARCH model show consistency with low forecast errors.

5. Conclusion and Recommendations

5.1. Conclusion

The study modelled and forecast headline inflation volatility in Namibia using GARCH(1,1), TGARCH, and EGARCH models with data spanning from January 2003 to December 2024. Inflation volatility in Namibia shows persistent characteristics and some mean reversion, which are common traits associated with volatility. Based on the in-sample model selection criteria (AIC and Schwarz), the GARCH(1,1) model appeared as the preferred model for estimation. However, diagnostic checks revealed a significant issue of serial correlation in the squared residuals for all three models, including the GARCH(1,1), suggesting an incomplete capture of volatility dynamics. This may be because the models estimated in this paper are univariate; however, inflation volatility does not fully evolve independently of some macro factors, so future research could extend this analysis to techniques such as GARCH-M to include exogenous factors. In this study, we did not extend the analysis to GARCH-M because forecast generations from this technique further complicate how to assess forecast accuracy in the results. Furthermore, all models exhibited non-normally distributed residuals. Despite these issues, the ARCH LM test indicated that all models successfully eliminated the ARCH effect in their residuals.

In contrast to the in-sample preference, the out-of-sample forecast evaluation for the period October to December 2024 demonstrated a clear superiority of the EGARCH model in forecasting annual headline inflation volatility at a three-month horizon. The EGARCH model consistently yielded the lowest values for RMSE, MAE, and MAPE, indicating its better accuracy in predicting future inflation volatility compared to both GARCH(1,1) and TGARCH. However, EGARCH did exhibit the same serial correlation issues found in the other models during the estimation phase. The insignificant leverage terms in both the TGARCH and EGARCH models also point towards a symmetric response of headline inflation volatility to positive and negative shocks in Namibia.

5.2. Recommendations

1. Further investigate serial correlation: While EGARCH shows promise for forecasting, the presence of serial correlation in the squared residuals of the estimated models warrants further investigation. Future research could explore: Considering alternative GARCH specifications (e.g., GARCH-M, higher order models, FIGARCH) or investigating potential structural breaks or exogenous variables that might be contributing to the serial correlation.
2. The consistent insignificance of the leverage effect in the asymmetric models (TGARCH and EGARCH) suggests that, for the studied period, positive and negative inflation shocks have a similar impact on subsequent volatility. This finding can inform the understanding of how the Namibian economy responds to inflationary pressures and deflationary tendencies.
3. Continuous model evaluation: Uncertainty remains a persistent concern in the global economy. Consequently, it is essential for monetary policy to consistently assess the forecasting performance of various volatility models and other potential methodologies as new data emerges. Regular backtesting and comparative analysis against alternative forecasting techniques are vital for ensuring the robustness and accuracy of inflation volatility predictions derived from these models.

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Abbreviations

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
ARIMA	Autoregressive Integrated Moving Average
EGARCH	Exponetial Generalized Autoregressive Heteroskedasticity
FIGARCH	Fractional Integrated Generalized Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GARCH-M	Generalized Autoregressive Conditional Heteroskedasticity in Mean
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
TGARCH	Threshold-Generalized Autoregressive Conditional Heteroskedasticity

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Conflicts of Interest

The authors declare no conflicts of interest.

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