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-RESEARCH ARTICLE-

THE IMPACT OF ECONOMIC AND FINANCIAL INSTABILITIES ON FORECASTING INTEREST RATES

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—Abstract—

The study forecasts interest rates amid economic and financial instabilities using data sourced from South Africa. Interest rates are a crucial financial instrument used by central banks to manage the economy. Monthly data was used spanning from 2000 – 2022 using time series regression techniques of autoregressive conditionally heteroscedastic (ARCH) to measure volatility and be able to test forecasting ability. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) technique and the Threshold GARCH were used to cater for symmetry and asymmetry

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assumptions. Economic instabilities have a significant impact on interest rates, and failing to account for them in forecasting models can lead to inaccurate predictions. Interest rate forecasting is essential for various patrons, which include financial institutions, financial markets investors, and policymakers. Accurate interest rate forecasts can assist policymakers make good decisions regarding monetary policy, while investors can use them to make investment decisions. Instabilities were inherent within the series, as empirically shown form the results. With occurrences like the global COVID-19 crisis, widespread protests, and the 2008 global financial crises, instabilities were more pronounced around 2009, and between 2016 and 2020. Results showed that the normal error distribution supposition is the best performing hypothesis across all three series (interest rates, treasury bill rate, and government bonds rate. The results point to the need for better macroeconomic policy management to reduce instabilities and have better predictable trends to allow investors planning.

Keywords: Interest rates, GARCH model, Economic and financial instabilities, repurchase rate, treasury bill rate, and government bond rate.

INTRODUCTION

Interest rates are a reward or price of capital that determines money creation and money in circulation, expressed as a percentage calculated annually, quarterly, or monthly. Any interest rate is one of the foremost imperative factors of the economic system. They play a significant role in affecting the returns on savings and the expenses associated with borrowing money, making them a critical element in the overall profitability of various investments. Furthermore, specific interest rates present insights into potential economic and financial market trends v(Bollerslev et al., 2016). Interest rates are a crucial tool for central banks in managing their countries' economies. In South Africa, the Reserve Bank uses interest rates to control inflation and promote economic growth (Takawira & Javangwe, 2024). However, forecasting interest rates can be a challenging task, particularly in the presence of instabilities in the economy.

Projecting interest rates is tough due to their daily fluctuations, which complicates the task of linking them with economic fundamentals like monetary or fiscal policies. Nevertheless, macroeconomics can offer valuable insights, as the long-term drift in interest rates is determined by the trend of real interest rates and inflation. The ability to forecast changes in interest rates holds significance for a range of stakeholders, including professional forecasters, policymakers, and academics, as these rates influence government debt, business financing costs, and the overall economic well-being of a country (Bauer & Hamilton, 2016). By making forecasts regarding interest rates, economists can predict interest rate shifts and relay this information to regulatory bodies and investment managers. Such predictions enable markets to proactively adapt to evolving conditions (Staff, 2014).

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Forecast instability refers to a situation where the predicted performance of a particular forecasting model either significantly deteriorates or improves compared to its historical performance. This would necessitate a revision of the forecasting model when the forecaster becomes aware of the occurrence of such instability (Casini, 2018). Instabilities are widespread in economic time series and were predominant during the Great Recession (Rossi, 2021). These economic instabilities can originate from various sources, including external shocks like fluctuations in global commodity prices or shifts in investor sentiment. Internal aspects, such as changes in economic policies and political uncertainty, can also contribute to economic instability (Javangwe & Takawira, 2022).

In time series economically, instabilities are predominant. For example, a simple observation points to the significant reduction in the volatility of various macroeconomic indicators around the mid-1980s, ushering in the era known as the "Great Moderation." However, this was followed by a major economic crisis a few years later, the "Great Recession," during which the relationships among macroeconomic variables underwent abrupt changes. More recently, we have witnessed the COVID-19 crisis (Rossi, 2021). The problem of projecting interest rates in South Africa is complex due to several factors. First, South Africa's economy is characterized by high volatility levels and instability, particularly in the political sphere. Second, the country has a history of fiscal and monetary policy changes that can make it difficult to identify stable long-term trends in the data. Third, the global economic environment can also have a significant impact on South African interest rates, particularly given the country's position as a commodity exporter (Nowak, 2005).

Interest rates are the driving force behind the economic activity of a nation. They have a significant impact on a wide range of economic processes, including consumer borrowing, investment, inflation, and unemployment management. Reserve banks use interest rates as a key tool to manage the complex combination of inflation and growth targets. In a market economy, like South Africa’s, interest rates have the power to influence investment, consumption, and saving levels. Central banks can increase or decrease the availability of credit by interest rate adjustments to reduce inflation pressures or to stimulate economic activity when needed. Furthermore, interest rates affect capital inflows and foreign exchange rates. The economy of South African features several distinct forms of interest rates, each serving specific purposes and affecting different economic activities and sectors. The SARB administers and sets interest rates to accomplish its twofold obligation of maintaining stability of prices and advancing economic growth in the long-term.

The repo rate or repurchase rate is the interest rate used by the SARB to extend loans to commercial banks. Modifications of repo rates absolutely influence banks’ borrowing costs, which, consecutively, has a ripple effect on the interest rates charged

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to businesses, households and consumers. The performance of the South African repo rate between 2000 and 2022 is closely tied to inflation dynamics and reflects the efforts of the South African Reserve Bank (SARB) to sustain price stability while fostering economic growth (Bank, 2021a). Figure 1 depicts a graphical representation of the South African repo rate starting from 2000 to 2022, offering a broad viewpoint of the country's monetary policy development. During this period, the repo rate has demonstrated various significant changes, presenting a glance of the trend of the South Africa's economy.

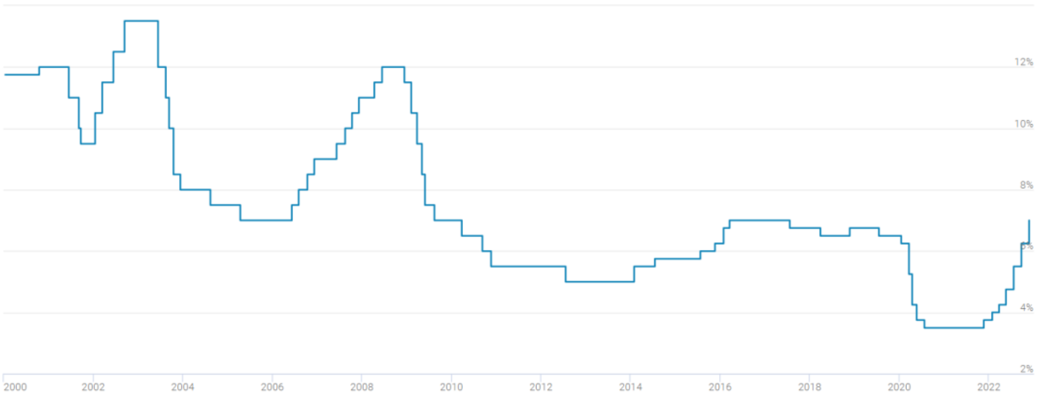

Figure 1: Repurchase (Repo) Rate Movement
Source: Global Rates (2023)

Government debt is financed by government bonds. The yields on these government bonds, called benchmark bond yields, induce interest rates across the market. Higher benchmark bond yields can transform into higher interest rates for borrowers in the private sector, as they reflect the perceived risk-free rate of return. These yields are closely monitored by investors and can be affected by various factors, including changes in economic conditions, monetary policy, and investor sentiment.

Foreign interest rates are not set by the SARB but have a significant impact on the South African market, particularly due to its open and interconnected nature. Higher interest rates in foreign countries can attract capital flows, affecting the value of the South African rand. The performance of the USD-ZAR exchange rate from 2001 to 2021 exhibited a dynamic trajectory influenced by various economic, geopolitical, and market factors. Over this period, the exchange rate experienced notable fluctuations, reflecting changing investor sentiment, economic conditions, and global events.

The early 2000s saw the USD-ZAR exchange rate averaging around 8 ZAR to 1 USD, induced by domestic factors such as South Africa's economic reforms and political transition. Figure 2 represents the USD/ZAR exchange rate from 2000 to 2022. The graph shows the currency market's variations and significant trends over this extended period. The Rand showed sizable depreciation against the US Dollar in the early

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2000s due to economic uncertainties, followed by periods of relative stability. There was a sharp spike in the exchange rate during the emerging market currency crisis of 2015-2016, demonstrating the effect of domestic, regional and global economic factors on the USD/ZAR exchange rate.

Figure 2: USD/ZAR Exchange Rate Movement
Source: Trading Economics (2023)

The global economic landscape is prone to periods of volatility, such as market sentiment changes, unexpected shocks, and swings in key economic indicators, which can have a significant impact on monetary policy decisions. Previous research has shown that interest rates and monetary policies are heavily influenced by economic shocks. These dynamics are particularly evident in South Africa, a country prone to domestic and global shocks. A prime example of this is the period preceding the global financial crisis in 2008. The collapse of the US financial institution, Lehman Brothers, and the resulting global economic crisis forced the SARB to rapidly adjust its interest rates amid heightened uncertainty, as the Reserve Bank Governor observed in 2010.

In the South African economy shocks, such as those seen in commodity prices around the world, are a major determinant of South Africa's export earnings. The country's heavy reliance on coal, in particular, makes it vulnerable to supply shocks and energy price volatility. Political instability and governance issues can also affect investor sentiment and inflows and outflows of capital. Exchange rate movements, which are driven by global economic conditions and investor sentiment, affect the cost of import prices, inflation, and the trade balance. These various forms of economic instability highlight the challenges South Africa faces in achieving long-term economic growth and stability.

In September 2001 the Monetary Policy Committee evaluated the monetary policy stance and issued a statement. Following a thorough examination of the prevailing economic conditions and anticipated price trends, the committee decided to decrease the repurchase rate by 50 basis points to 9.5%. The tragic events of September 11, 2001, in the United States overshadowed the international economic outlook. At the time of the statement, the long-term effect of these events was still uncertain. In the immediate aftermath of the attacks and the resulting global economic uncertainty, central banks around the world, including SARB, adopted accommodative monetary policies. To encourage economic activity and enhance investor confidence, the SARB initially reduced interest rates. Due to the uncertainties in global markets, the South African Rand's currency rate fluctuated. The South African rand experienced a 26% nominal depreciation against the US dollar. However, during this period, short-term interest rates remained constant, long-term bond yields rose by less than 100 basis points, and the spreads on sovereign US dollar-denominated bonds decreased by approximately 40 basis points (Bhundia & Ricci, 2005).

In 2018, a decrease in inflationary pressures led to a reduction in policy rates since inflation remained comfortably within the target range of the South African Reserve Bank (Bank, 2021a). The inflation rate for consumer prices dropped from 6.6 percent in January 2017 to 4.4 percent in January 2018, and subsequently to 4 percent in February. Numerous factors contributed to this decline. Notably, lower inflation in food and fuel prices had a substantial impact, especially as the country was recovering from the effects of the 2015 drought, which still had lingering repercussions in 2016. Another significant factor contributing to the improved inflation outlook was the strengthening of the South African Rand, driven by robust commodity prices, alongside a recovery in investor confidence and capital inflows following the ANC elective conference in December 2017 (Bank, 2021b). This study aims to forecast interest rates under economic instabilities which will assist investors in making appropriate investment decisions and policymakers formulating effective policies that guard citizens against adverse movements in interest rates.

LITERATURE REVIEW

The section illustrates a narration of the theoretical literature review and empirical literature review of this study.

Theoretical Literature Review

The first concept of interest rates is the classical theory which is also known as the "real theory of interest." Interest rates are determined by the intersection of investment demand and saving intentions, according to this classical theory (Hansen, 1951). Interest rates in the products market are influenced by the meeting point of savings and investment supply and demand. Interest rates change to balance the economy through investment and saving. (Pal, 2018). Figure 3 shows how the classical theory of interest rates determines interest rates. Figure 3 shows interest rate on the vertical

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axis and investment and saving on the horizontal axis. Line R1 represents the equilibrium interest rate, often known as the natural rate of interest in the products market. This rate is determined by the intersection of saving and investing at point E. When the market interest rate (R2) is greater than the natural interest rate (R1), as seen at point A in Figure 3, savings surpass investment. The interest rate will decrease until it reaches the equilibrium interest rate. Contrarily, savings will be lower (see point C), and investment will be higher when the market interest rate (i.e., R) is lower than the natural interest rate (see point D). As a result, the interest rate will rise until it reaches its equilibrium level.

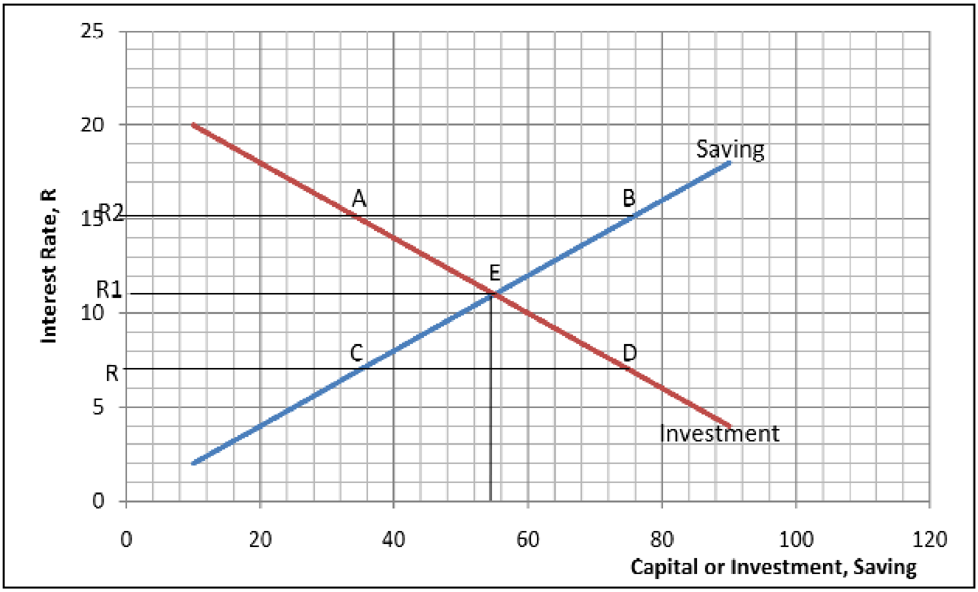

Figure 3: Classical theory - Determination of interest rates
Source: Pal (2018)

The loanable funds theory is an extension of the classical interest rate theory (savings and investment) hence also referred to as neo-classical theory of interest. Loanable funds account, for both non-monetary and monetary factors for saving and investments.

Keynes contradicts the classical theory of interest rates. Keynes contended that interest rates are primarily a monetary phenomenon, serving as compensation for lending out liquidity. The theory, known as the theory of liquidity preference, is based on the idea that interest rates are decided in the short run. According to this theory, interest rates, liquidity preferences, and the amount or availability of money are related. This suggests that the general population would want to store more money than the money that is readily available if interest rates were low. The opposite is also true: If interest rates are low, there will be more money available since people will not want to store any cash. As a result, the amount of money will be another factor in

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determining interest rates.

Alvin H. Hansen and John R. Hicks developed the modern theory of interest rates by building on the classical theory of interest rates and Keynes' liquidity preference theory. This theory is sometimes referred to as the Neo-Keynesian theory of interest because it identifies shortcomings in Keynes' theory, particularly in dealing with income uncertainty, rendering it inconclusive. Figure 4 represents how interest rates are determined in the modern theory of interest rates. The LM curve indicates the different interest rates associated with various income levels, considering the family of liquidity preference curves and the money supply. When combined with the investment-demand schedule, this leads to the creation of the IS curve. The IS curve reveals the different income levels associated with varying interest rates, considering the saving schedules and investment-demand schedules.

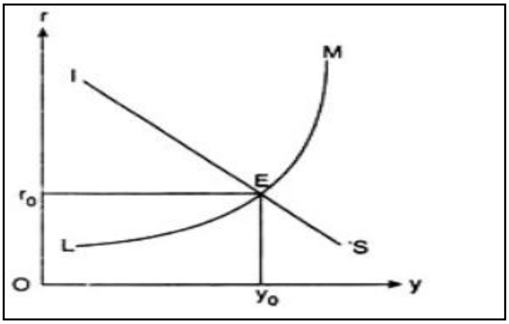

Figure 4: Equilibrium in the IS-LM model
Source: Boianovsky (2004)

In Figure 4, at the crossing point of these two curves, denoted as point E in Figure 4, both income and interest rates are calculated concurrently. At point E, income and interest rates are coupled in such a way that: (1) investment and savings are balanced, suggesting that actual savings match intended savings; and (2) the demand for money aligns with the supply of money, indicating that the desired quantity of money equals the actual money supply. This means that at point E, the goods and the money market would simultaneously be in equilibrium if the economy's level of income and interest rate were y_o and r_o.

Empirical literature review

To improve our proficiency in predicting outcomes in the face of the inherent volatility of financial markets, the empirical literature on predicting interest rates in the presence of instabilities is a crucial area of economic research. Others have explored the potential of dynamic factor models to effectively incorporate multiple sources of information and their changing relevance in volatile environments. Studies on forecasting interest rates have evolved. Through progression, authors have done studies to strengthen forecasting models to provide accurate results. In 2021, Rossi

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offered valuable insights into assessing the forecasting abilities of models under conditions of instability and improving their precision.

Rossi (2021) emphasized the importance of understanding and identifying instabilities in the data before implementing forecasting models. Rossi (2021) explores various approaches to evaluate model performance in the presence of instabilities in her study. It discusses methods to detect structural breaks or regime changes in the data, which can help in understanding when and why the forecasting accuracy may be affected. Furthermore, the paper discusses the relevance of robust forecasting techniques that can provide reliable predictions even when dealing with unstable data. These techniques aim to minimize the adverse effects of outliers or extreme observations on model forecasts. Rossi suggests combining forecasting methods, exploring different techniques for combining forecasts, such as optimal weights, and Bayesian model averaging. By recognizing instabilities, researchers, and practitioners can gain valuable insights into model shortcomings and potential biases.

In another study, Ilu (2020) examined Nigerian interest rates for the period 1997 to 2017 using Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) modelling. The study looked at monthly interest rate data and looked for AutoRegressive Conditional Heteroskedasticity (ARCH) effects. The research paper compared symmetric GARCH models, specifically GARCH (1,1) and GARCH-M (1,1), to asymmetric models, which included EGARCH and TGARCH, and concluded that results produced by asymmetric models were more suitable in generalized error distributional assumptions than results produced by symmetric models. The study refers to Black (1976) who showed the negative correlation between stock market returns and change in volatility returns meaning that in reaction to bad news, volatility tends to rise and fall in reaction to good news. On the contrary, the GARCH model does not take into account whether the volatility return is positive or negative but rather assumes that the conditional variance of financial returns can be forecasted based on historical information. The GARCH model assumes symmetry in the market's reaction to negative and positive shocks and that there is no difference in how volatility evolves after positive or negative events. Asymmetric GARCH models do not only consider the size of the volatility return but also the different reactions to positive and negative shocks.

These instabilities have significantly affected economic stability, causing inflationary pressures, exchange rate volatility, and fluctuations in interest rates. Existing studies, like Ahmed and Huo (2020), indicate that predicting interest rates in the face of instabilities is complex and affects policy decisions. While some studies have attempted to predict South African interest rates using different models, such as time-varying parameter vector autoregression (VAR) and linear or nonlinear models, there remains a gap in the literature regarding the accuracy and reliability of these forecasting models. Numerous studies have used a limited set of economic indicators,

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like inflation and GDP, to forecast interest rates, but these may not encompass all the relevant factors influencing interest rate movements, such as global economic conditions, exchange rates, and political events. Emenogu et al. (2020) focused on the modelling of interest rates in Nigeria using the GARCH model, comparing the symmetric and asymmetric GARCH performance in modelling interest rates. The current study aims to examine South African interest rates.

Reserve banks employ monetary policy to control the money supply within the economy in pursuit of their objectives. In the case of the South African Reserve Bank (SARB), it utilises interest rates as a means to influence the inflation rate (Monetary Policy n.d.). The need for research on forecasting South African interest rates in the presence of economic instabilities is justified for several reasons. Firstly, economic instabilities have a significant impact on interest rates, and failing to account for them in forecasting models can lead to inaccurate predictions. Furthermore, South Africa's economy is heavily dependent on commodity prices, which are subject to global economic conditions. Accurate interest rate forecasts can help policymakers make informed decisions regarding monetary policy, while investors can use them to make investment decisions. Financial institutions can use them to manage their risk exposure, which can significantly impact on their profitability.

These studies showed that incorporating asymmetric responses to extreme events is another essential strength as symmetric models tend to underestimate the lasting impact of volatility, potentially leading to inaccurate forecasts. Financial crises, policy surprises, or unexpected economic releases can trigger disproportionate market reactions. Asymmetric models acknowledge these instances by responding more sensitively to negative shocks, producing forecasts that better align with actual market behaviour. Symmetric models, on the other hand, lack to distinguish such asymmetry, potentially leading to suboptimal forecasts during economic instability.

METHODOLOGY

Models

Existing literature introduces several approaches to capture and model volatility, with the most leading ones being the autoregressive conditional heteroskedasticity (ARCH) and the generalized autoregressive conditional heteroskedasticity (GARCH) models (Moffat & Akpan, 2020). Literature of late has shown the relevance of both symmetric and asymmetric patterns, demonstrating it is not yet a settled debate. Asymmetry implies that unexpected news affects conditional volatility at different magnitudes. This led to the development of other techniques to cater to the asymmetries (Nelson, 1991) such as the threshold GARCH (TGARCH) approach, considering the negativity or positivity of the shock over and above the general magnitude.

In general forecasting is akin to predicting likely values of the series, based on good past data, implying that the longer the available series is, the better the forecasting (Raicharoen et al., 2003). The accuracy of the forecasting can be determined by observing actual values in the future and see how close they are to the forecasted values. However, waiting for the future is not necessary as in sample forecasting can be done. This is forecasting a period that already has data, as if it has not- then compare with the data that exist. In that regard, a successful time series forecasting on data quality and having appropriate techniques applied. Table 1 below illustrates the variables, definition and their sources.

Table 1: Relationship between variables and instability outcomes

Variable and Proxies	Definition	Data Source	A priori expectation
Repurchase (Repo) Rate (INT)	"The South African repo rate is the benchmark interest rate set by the South African Reserve Bank (SARB) at which it lends money to commercial banks, influencing the overall cost of borrowing and economic activity in the country," Javangwe and Takawira (2022).	SARB	During an economic recession, the repo rate is expected to decrease to stimulate financial sector activity by making borrowing cheaper and encouraging spending and investment. Conversely, during economic expansion, the repo rate is expected to rise to cool off inflationary pressures and prevent the economy from overheating by making borrowing more expensive.
Government Bond Rate (BOND)	The South African government bond rate refers to the interest rate paid by the South African government on its issued bonds, reflecting the cost of borrowing for the government.	SARB	During an economic recession, the South African government bond rates are expected to decrease as investors seek safer assets, driving up demand for government bonds and lowering their yields. Conversely, in an economic expansion, government bond rates are expected to rise due to increased optimism, higher inflation expectations, and a shift of funds toward riskier assets.
Treasury Bill (BILL)	The South African Treasury Bill rate refers to the interest rate set by the government on short-term debt securities, typically with maturities of less than one year.	SARB	During an economic recession, the South African Treasury Bill rate may decline as investors seek safe-haven assets, leading to increased demand for these short-term government securities. Conversely, in an economic expansion, the Treasury Bill rate may rise due to improved economic outlook, higher inflation expectations, and a shift towards riskier investments.

Source: Author (2023)

Monthly interest rate data from the South African Reserve Bank online, ranging from 2000 to 2022 was used. The monetary policy framework of inflation targeting started in 2001, with the interest rate being the prime monetary policy tool used by the central bank. Three indicators, repo rate (central bank rate), treasury bill rate (bill rate), and government bond rates (bond rate) have been used for robustness. The preliminary test

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in estimating GARCH models, like any other time series estimation, is the unit root test (Francq et al., 2016; Ghani & Rahim, 2019). Both informal (graphical) and informal tests were conducted for all three series.

According to Brooks (2008), the ARCH model permits conditional variance of the error term, σ_t^2, to depend on recent historical values of squared error with ARCH (1), adopting the form:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

where σ_t^2 is conditional variance of the error term and $\alpha_1 u_{t-1}^2$ represents a lagged value of the squared error.

According to Alam et al. (2013), the ARCH (q) model takes the following form, where error variance depends on q delays of squared errors:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_q u_{t-q}^2 \quad \ldots\ldots\ldots(2)$$

Bollerslev (1986) developed the ARCH model into the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to improve its effectiveness. In the GARCH model, Zt is presumed to have the same structure as in the ARCH model, and the GARCH (1, 1) model is defined as follows:

$$h_{t+1}^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

All the model factors must possess positive values, and the sum of the coefficients (α + β) offers a quantitative measure of the impact of volatility shocks. The GARCH (1, 1) model, which plays a crucial role in predicting volatility, functions by estimating future volatility through a weighted combination of factors: the constant long-term variance denoted as ω, the prior forecasted variance, and past volatility represented by squared 'news' about returns. This formulation elegantly captures the phenomenon of volatility clustering, wherein forecasts of volatility increase following significant returns in either direction.

In line with Bollerslev (1986) a GARCH model is specified as follows:

$$\mathrm{IRt} = \omega + \alpha\varepsilon_{t-1}^2 + \beta IR_{t-1} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots \quad (4)$$

In this context, IR_t signifies the predicted variance of the monthly interest rate, utilizing three proxies (the central bank rate, treasury bill rate, and government bond rate). Conversely, ω represents the constant, long-term, or average variance. IR_{t-1} reflects the past predicted variance, and ε_{t-1}^2accounts for the previous volatility, which involves squared 'new information.' The summation of the alpha and beta coefficients, as mentioned earlier, quantifies the persistence of volatility shocks. Additionally, ε_{t-1}^2 indicates that volatility forecasts increase following substantial news, whether positive or negative. A *priori*, all parameters are expected to be positive, demonstrating symmetry.

EMPIRICAL FINDINGS

This section presents results obtained after employing the techniques discussed in the methodology section.

Unit Root Tests

The Dickey-Fuller test is among the most frequently utilized tests for assessing stationarity. The series is assumed to have a unit root under the null hypothesis, implying non-stationarity with an underlying trend. The graphical unit root tests are shown in the Appendix section A.1 and A2. The table 2 below illustrates the unit root test results.

Table 2: Stationarity tests results

Variable	ADF t-statistic	Critical t (1%)	Critical t (5%)	Critical t (10%)	MacKinnon approximate p-value for Z(t)	H_0 = There is no unit root (underlying trend)
INT	-2.259	-3.459	-2.879	-2.570	0.1855	Fail to reject
INT_D	-5.368	-3.459	-2.879	-2.570	0.0000	Reject
BILL	-2.543	-3.459	-2.879	-2.570	0.1053	Fail to reject
BILL_D	-4.793	-3.459	-2.879	-2.570	0.0001	Reject
BOND	-3.609	-3.459	-2.879	-2.570	0.0056	Fail to reject at 1% and 5%
BOND_D	7.046	-3.459	-2.879	-2.570	0.0000	Reject

Source: Own computation in Stata, using data from SARB

As presented in Table 2 above, the Augmented Dickey-Fuller (ADF) test was performed with a constant term, and the ADF results indicate that the series only becomes stationary after the first (1^{st}) differencing.

GARCH Model Results

The GARCH (1,1) model was estimated, and the results are presented in this section. Regarding the parameters governing the conditional variance process, the tested models effectively demonstrate patterns of volatility persistence. This is evident from the positive and statistically significant estimated parameters, as indicated in Tables 3 to 6. Furthermore, when we sum the parameters α (L.arch) and β (L.garch) for the GARCH models, considering different assumptions about the distribution of errors we get approximately 1, confirming the random walk hypothesis (Ahmed et al., 2018; Engle, 1982). These coefficients are the results of interest, in terms of their sign and

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the sum of α (L.arch) and β (L.garch) being not different from I. Table 3 – table 6 presents results in segments depending on the variable used to measure interest rate (bank interest rate = INT or treasury bill rate = Bill or bond yield rate = Bond) and error distribution assumptions (normal, student t, and GED).

Table 3 has α = 0.198 and β = 0.760 totaling 0.966~1, thus confirming the presence of random walk in the series interest rate under the normal distribution assumption of the error. When the t-distribution of the errors is assumed, the total of the coefficients is 0.869, which is lower than 1, while the GED assumption was not compatible with this variable. The results confirm volatility persistence in the series as the coefficients are positive.

Table 3: GARCH regression results of bank interest rate

ARCH family regression – normal

INT_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	-.006	.019	-0.34	.733	-.043	.031	
A	.198	.026	7.62	0	.147	.249	***
B	.768	.016	49.55	0	.738	.798	***
Constant	.007	.001	10.53	0	.006	.008	***
Mean dependent var		-0.023	SD dependent var			0.327	
Number of obs		271	Chi-square			.	
Prob > chi2		.	Akaike crit. (AIC)			73.091	

ARCH family regression – t-distribution

INT_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	.003	.014	0.19	.85	-.025	.031	
A	.199	.029	6.76	0	.141	.256	***
B	.67	.026	25.75	0	.619	.721	***
Constant	.004	.001	7.05	0	.003	.005	***
Mean dependent var		-0.023	SD dependent var			0.327	
Number of obs		271	Chi-square			.	
Prob > chi2		.	Akaike crit. (AIC)			-25.466	

Source: Authors' Compilation

Table 4 present the results for the variable, treasury bill rate (Bill). The beta coefficient is not statistically significant under the normal error distribution assumption, but significant under the t-distribution and GED assumptions. Important to note however, that the totals are approximately one (1) under the student t-distribution assumptions, as for normal and GED distributions the totals are above 1 indicative of explosive volatility, a departure from random walk assumptions in the series. Persistence in volatility is however confirmed across all assumptions given the positive sign of the coefficients.

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Table 4: GARCH regression results of Treasury bill rate ARCH family regression – normal

Bill_D1	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
Constant	.027	.011	2.46	.014	.006	.049	**
A	1.203	.168	7.18	0	.874	1.531	***
B	.018	.041	0.45	.654	-.061	.098	
Constant	.026	.003	8.65	0	.02	.032	***
Mean dependent var		-0.016	SD dependent var			0.271	
Number of obs		271	Chi-square			.	
Prob > chi2		.	Akaike crit. (AIC)			0.700	

ARCH family regression – t distribution

Bill_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	.001	.009	0.08	.936	-.017	.018	
A	.409	.073	5.57	0	.265	.553	***
B	.613	.034	18.16	0	.547	.679	***
Constant	.002	.001	3.09	.002	.001	.004	***
Mean dependent var		-0.016	SD dependent var			0.271	
Number of obs		271	Chi-square			.	
Prob > chi2		.	Akaike crit. (AIC)			-71.933	

ARCH family regression – GED

Bill_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	0	.001	0.00	1	-.002	.002	
A	.712	.261	2.73	.006	.201	1.222	***
B	.546	.085	6.43	0	.379	.712	***
Constant	.003	.002	1.44	.149	-.001	.008	
Constant	-.253	.103	-2.46	.014	-.455	-.051	**
Mean dependent var		-0.016	SD dependent var			0.271	
Number of obs		271	Chi-square			.	
Prob > chi2		.	Akaike crit. (AIC)			-110.289	

Source: Authors' Compilation

Although persistence can be confirmed with bond series, the random walk cannot be confirmed as the sum of coefficients is less than 1 in all error distribution assumptions (see Table 5). In essence, across the three series used to proxy interest rates, it is shown that bank rates show persistence in volatility across all assumptions, in random walk base both normal and t-distribution, while treasury bill rates show persistence and random walk under student t-distribution.

Table 5: GARCH regression results of Government bond rate ARCH family regression – normal

Bond_D1	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
Constant	-.012	.021	-0.59	.558	-.053	.028	
A	.22	.089	2.48	.013	.046	.395	**
B	.283	.178	1.59	.111	-.065	.632	
Constant	.061	.016	3.72	0	.029	.093	***

Mean dependent var	-0.010	SD dependent var	0.341
Number of obs	271	Chi-square	.
Prob > chi2	.	Akaike crit. (AIC)	184.812

ARCH family regression – t-distribution

Bond_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	-.017	.02	-0.87	.382	-.055	.021	
A	.154	.082	1.88	.06	-.007	.314	*
B	.444	.252	1.77	.077	-.049	.937	*
Constant	.042	.021	1.98	.048	0	.083	**
Mean dependent var		-0.010	SD dependent var			0.341	
Number of obs		271	Chi-square			.	
Prob > chi2		.	Akaike crit. (AIC)			164.241	

ARCH family regression – GED

Bond_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	-.011	.017	-0.67	.506	-.045	.022	
A	.149	.108	1.38	.167	-.062	.359	
B	.445	.356	1.25	.211	-.252	1.143	
Constant	.047	.033	1.42	.156	-.018	.112	
Constant	.203	.102	1.98	.048	.002	.403	**
Mean dependent var		-0.010	SD dependent var			0.341	
Number of obs		271	Chi-square			.	
Prob > chi2		.	Akaike crit. (AIC)			163.671	
*** *p<.01*, ** *p<.05*, * *p<.1*							

Source: Authors' Compilation

TGARCH Model Results

In addition to the above GARCH (basic model) and, to accommodate the reality of asymmetric response to information, TGARCH (see Table 6) is applied which captures the asymmetric. For decision-making based on the results, when the sum of the parameters α and β for the TGARCH model is greater than 1, volatility is explosive as in Sarkar et al. (2006) given the non-stationarity. In this study, for all the series, in most cases as was the case under the GARCH presented above the sum of α and β is not greater than 1, therefore series are stationary, and volatility is not explosive. For the TGARCH, the Gamma γ parameter is positive and significant except for the Bond series under t-distribution which has a gamma of -0.934.

A positive and substantial GARCH coefficient suggests that the rate of decay in volatility is prolonged, indicating a long memory effect, as noted by Adewale et al. (2016). Specifically, in the context of the TGARCH model, when considering different assumptions for error distributions (normal, t-distribution, and general), the GARCH coefficients for Treasury bill rates show values like 0.903 and 0.914 under normal and t-distribution assumptions. Similarly, they exhibit values of 0.39, 0.934, and 0.585 under normal, t, and general distributions, respectively. These findings indicate a persistent, long-memory pattern in volatility. In simpler terms, the current

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level of volatility significantly influences future volatility.

Table 6: TGARCH Results ARCH family regression - normal

Bill_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	0	.007	0.00	1	-.014	.014	
A	.142	.053	2.70	.007	.039	.246	***
B	.626	.076	8.29	0	.478	.775	***
Γ	.903	.025	35.73	0	.854	.953	***
Constant	-.282	.079	-3.57	0	-.436	-.127	***

Mean dependent var	-0.016	SD dependent var	0.271
Number of obs	271	Chi-square	.
Prob > chi2	.	Akaike crit. (AIC)	-82.525

ARCH family regression - student t-distribution

Bill_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	0	.005	0.00	1	-.01	.01	
A	.168	.109	1.54	.124	-.046	.383	
B	.755	.179	4.22	0	.404	1.106	***
Γ	.914	.041	22.54	0	.834	.993	***
Constant	-.152	.119	-1.28	.202	-.386	.081	
Constant	-.212	.101	-2.10	.035	-.41	-.014	**

Mean dependent var	-0.016	SD dependent var	0.271
Number of obs	271	Chi-square	.
Prob > chi2	.	Akaike crit. (AIC)	-116.120

ARCH family regression - normal

Bond_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	-.015	.022	-0.70	.483	-.058	.027	
A	-.014	.063	-0.22	.823	-.138	.11	
B	.475	.115	4.12	0	.249	.701	***
Γ	.39	.136	2.87	.004	.124	.655	***
Constant	-1.306	.315	-4.14	0	-1.924	-.688	***

Mean dependent var	-0.010	SD dependent var	0.341
Number of obs	271	Chi-square	.
Prob > chi2	.	Akaike crit. (AIC)	185.540

ARCH family regression - student t-distribution

Bond_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	-.02	.02	-1.00	.316	-.058	.019	
A	.038	.046	0.83	.408	-.052	.129	
B	.009	.042	0.21	.832	-.073	.09	
Γ	-.934	.168	-5.56	0	-1.263	-.605	***
Constant	-4.402	.436	-10.10	0	-5.256	-3.548	***

Mean dependent var	-0.010	SD dependent var	0.341
Number of obs	271	Chi-square	.
Prob > chi2	.	Akaike crit. (AIC)	172.771

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ARCH family regression

Bond_D1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	-.013	.017	-0.74	.457	-.047	.021	
A	.007	.087	0.08	.94	-.164	.178	
B	.302	.171	1.76	.078	-.033	.637	*
Γ	.585	.333	1.76	.079	-.067	1.237	*
Constant	-.898	.754	-1.19	.233	-2.376	.579	
Constant	.204	.109	1.88	.061	-.009	.417	*
Mean dependent var	-0.010	SD dependent var	0.341				
Number of obs	271	Chi-square	.				
Prob > chi2	.	Akaike crit. (AIC)	165.755				
*** *p<.01*, ** *p<.05*, * *p<.1*							

Source: Authors' Compilation

Overall, the results under the TGARCH test show mixed outcomes, as in most of the cases some of the coefficients were not statistically significant. It is only under TGARCH normal, that the three coefficients of α, β, and γ are statistically significant and positive. In this way, the basic GARCH managed to identify persistence in volatility and random walk within the series, more than the TGARCH. Results for the diagnostic tests are presented in the appendix section. All diagnostics tests show the existence of arch effects, and normality of residuals and no auto correlations as depicted in Figures A.3-A.10 in the appendix section.

Forecasting

In-sample forecasting was performed on all series using the error distribution assumptions of normal, t-distribution, and generalized error distribution, in that sequence. Important to note here is that for central bank policy rate, t-distribution assumption was not converging. For all the three series used to proxy interest rates, the in-sample forecasting proved to be powerful as the forecast mirror closely the realized (observed) values, especially for treasury bill and government bonds rate, not so for the interest rate. This is shown in Figure 5. (interest rate), Figure 6. (treasury bill) and Figure 7. (bond rate) below.

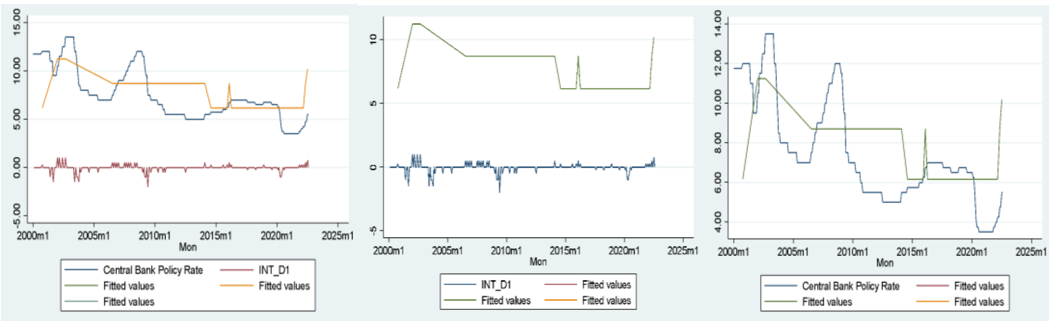

Figure 5: Forecasting INT rate under the three assumptions

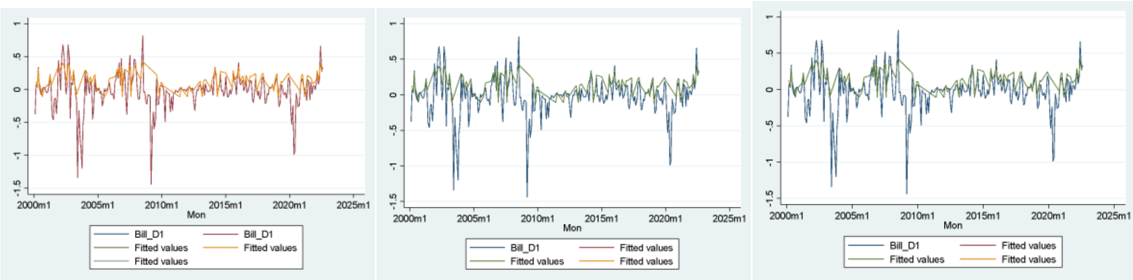

Figure 6: Forecasting Treasury bill rate under the three assumptions

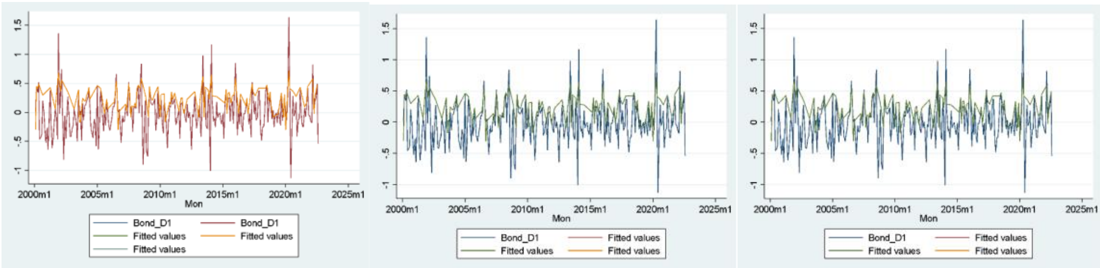

Figure 7: Forecasting Government bond rate under the three assumptions

In this regard, Giacomini and Rossi (2010) test is used to assess the prediction accuracy of competing models. In contrast, the examination employs Rossi and Sekhposyan (2016) evaluation to examine the fairness and rationality of forecasts. In this study, the results of Giacomini and Rossi (2010) innovative fluctuation test, which takes into account instabilities when comparing two competing models, are compared to the traditional Diebold and Mariano (1995) test results.

Relative Forecasting Performance tests

This test considers instabilities as predicated in literature that are inherent in any economy.

According to the data presented in Table 7, when considering models that accommodate instabilities, all other error distribution assumptions are consistently outperformed by the t-distribution error assumption. This indicates that when the t-distribution assumption is used, all the models perform well. In contrast, the general error distribution assumptions outperform the normal distribution version, indicating that the normal distribution is the least effective choice.

The calculations show that the normal error distribution assumption is the best performing assumption, given better forecasting than the counterparts, across all three series. It was evident that instabilities are inherent within the series, more pronounced around 2009, and between 2016-2020. The finding that any instabilities in the broader economy get incorporated into the interest rate shows the seriousness of the matter. Results showed that the normal error distribution assumption is the best performing

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postulation across all three series (interest rates, treasury bill rate, and government bonds rate).

Table 7: Relative comparison (distribution vs distribution)

			Accounting for instabilities: Giacomini and Rossi (2010)test			Traditional tests: Diebold & Mariano (2010) test					
	Competing Models		t-statistic	Critical value	Conclusion on the hypothesis	MSE criterion	MSE criterion	difference	S(1)	P-value	Conclusion
	Model 1	Model 2				Model 1	Model 2				
INT	$Garch_t$	$Garch_{normal}$	4.8391	3.393	We Reject H_0	0.1465	0.1655	-0.01897	-2.019	0.0434	GARCHt is the better forecast
Bill	$Garch_{tb}$	Garchnorb	3.9481	3.393	We reject H_0	0.1278	0.2097	-0.08187	-1.865	0.0622	GARCHtb is the better forecast
	Garchtb	Garchgedb	3.9481	4.6912	We fail to H_0	0.1278	0.1813	-0.05351	-1.796	0.0724	GARCHtb is the better forecast
	Garchgedb	Garchnorb	4.6912	3.393	We reject H0	0.1813	0.2097	-0.02835	-1.776	0.0757	GARCHgedb is the better forecast
Bond	GARCHtboo	GARCHnorbo	3.8903	3.0041	We reject H0	.1321	.136	-.003877	-4.123	0.0000	GARCHtboo is the better forecast
	GARCHtboo	GARCHgedbo	3.8903	3.3930	We reject H0	.1321	.134	-.001934	-5.193	0.0000	GARCHtboo is the better forecast
	GARCHgedbo	GARCHnorbo	3.3930	3.0041	We reject H0	.134	.136	-.001943	-2.147	0.0318	GARCHgedbo is the better forecast

CONCLUSION

Assuming instabilities are present and that they are affecting forecasting ability has been vindicated by the tests conducted. When comparing models that account for instabilities, the t-distribution error assumption outperforms all other error distribution assumptions. T-distribution is therefore a favoured error distribution assumption under both specifications. According to the Rossi-Sekhposyan test, compelling evidence against projected rationality appears to be especially prominent around 2009, as well as during the period from 2016 to 2020, across all models. This data substantially supports the assumption that, in the presence of instabilities, fluctuation tests outperform standard approaches significantly. They not only offer a robust statistical measure but also visually depict moments when predictive accuracy either emerges or deteriorates within the dataset. Essentially, these tests go beyond mere numerical outcomes. They also provide a dynamic insight into the patterns of predictive ability, pinpointing specific periods of strength or weakness in the data. By offering this nuanced understanding, fluctuation tests become invaluable tools in analyzing and interpreting the performance of forecasting models in volatile environments. Our findings confirm the results by (Rossi, 2021) who provides techniques of predicting in the presence of instabilities and leaves a gap to explore suitable forecasting models for interest rates in the presence of such instabilities.

As confirmed from the results, the study concludes that there is volatility in South African interest rates, therefore the study rejects the null hypothesis (H0: There is no volatility in interest rates). In addition, assuming instabilities were justified as it was found that instabilities influence interest rate forecasting, without controlling instabilities the results will be distorted. For the second hypothesis, the study rejects the null hypothesis (H0: Instabilities have no effect on interest rate forecasts) and concludes that the effect exists as confirmed in this study. Instabilities identified were most political events and crises (global financial crisis and the pandemic). Our results agree with the findings of (Olasehinde-Williams et al., 2024). The outcomes point to the need for better macroeconomic policy management to reduce instabilities and have better predictable trends to allow investors planning. The study leaves room for future students to consider other variations in GARCH models such as EGARCH, IGARCH, and APARCH to have a wide range of comparisons.

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APPENDIX

Informal/ graphical tests

The three series are presented in Figure A.1 below at levels, as can be seen there is an underlying trend in each series - implying presence of unit root (non-stationarity).

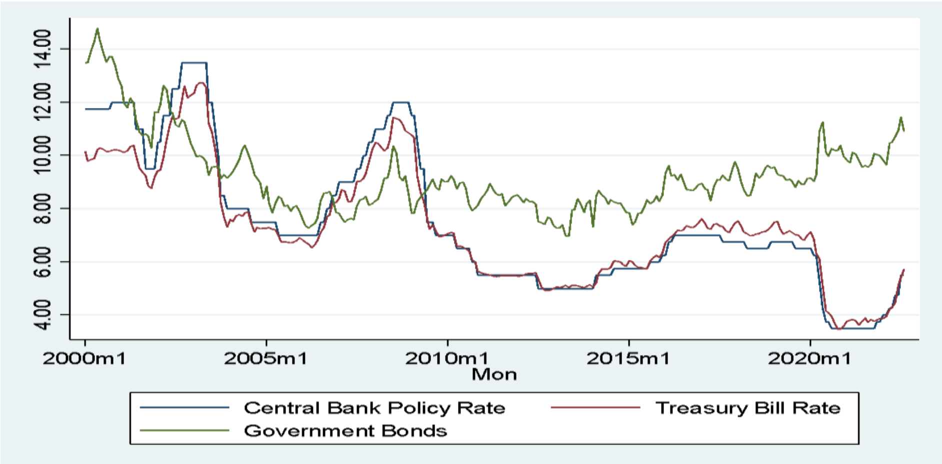

Figure A.1: Graphical Unit Root Test at Levels

Figure A.1 shows a downward trend, implying the mean of the interest rate has been declining over time, thus it is non-stationary. This aligns with economic theory, indicating that asset prices, like stocks or returns, adhere to a random walk pattern, signifying their nonstationary nature (Gujarati, 2003). After applying first-order differencing to the series, the same analysis is conducted and is depicted in Figure A.2. Following this differencing process, all the series exhibit stationarity (reverting around zero mean).

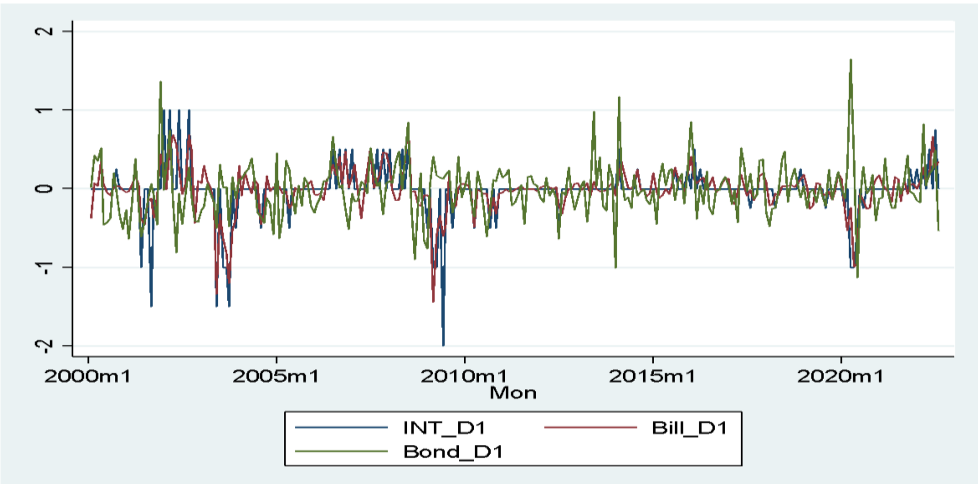

Figure A.2: Graphical Unit Root Test at First Difference

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Having established series that show persistence in volatility, and random weakness under the different assumptions, the study then presents the diagnosis of these analysis to enable inference with confidence.

Volatility Estimation Diagnostic Test Results

Figure A.3 shows clustering of volatility on the top left-hand corner, while autocorrelation checks full (top right corner) or partial (bottom right corner) indicate lack of serial autocorrelation as the series are hovering around the mean zero (0). The p-values are also around 0, although one outline in the first lag existing with a higher than 0.10 p value, leading to failure to reject the null hypothesis of ‘no serial correlation’.

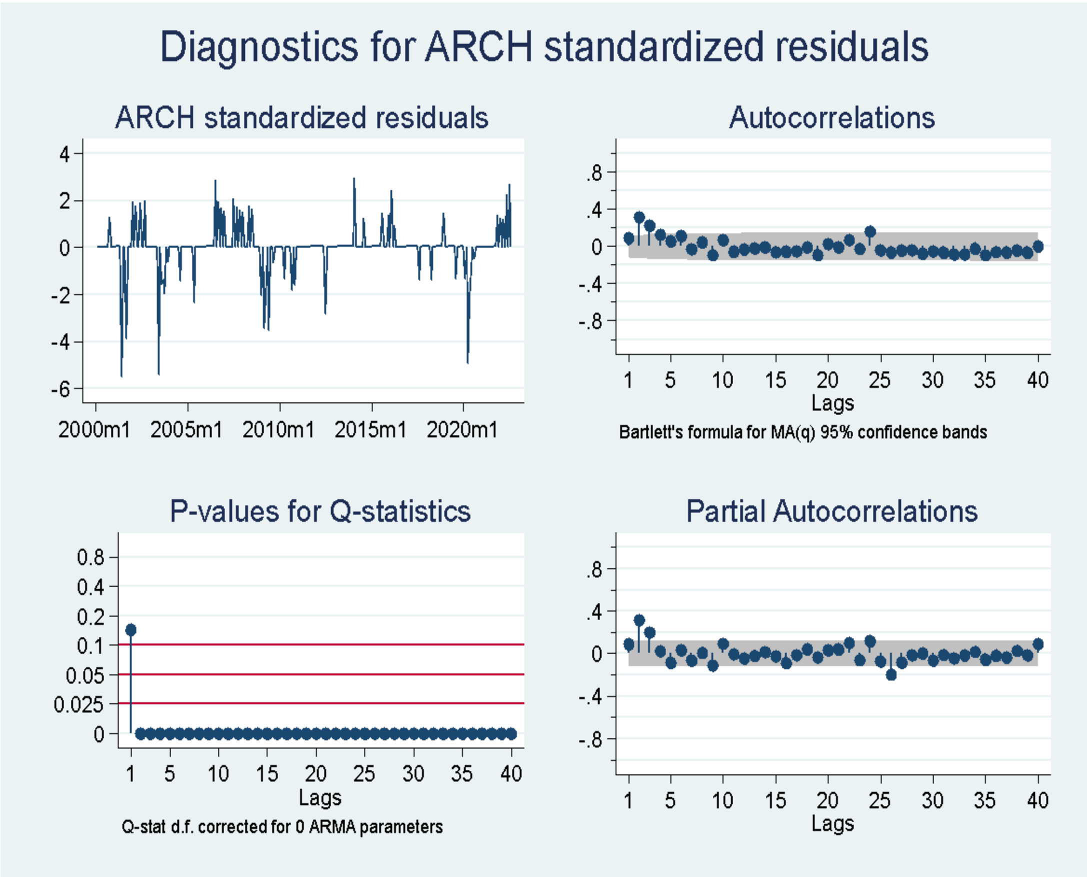

FIGURE A.3: Diagnostics of ARCH standardized residences – INT under normal error distribution assumption

Figure A.4 below shows the same results as Figure A.3, confirming volatility clustering and lack of serial correlation. Volatility clustering is seen from the series in top left corner, revolving around the zero-mean.

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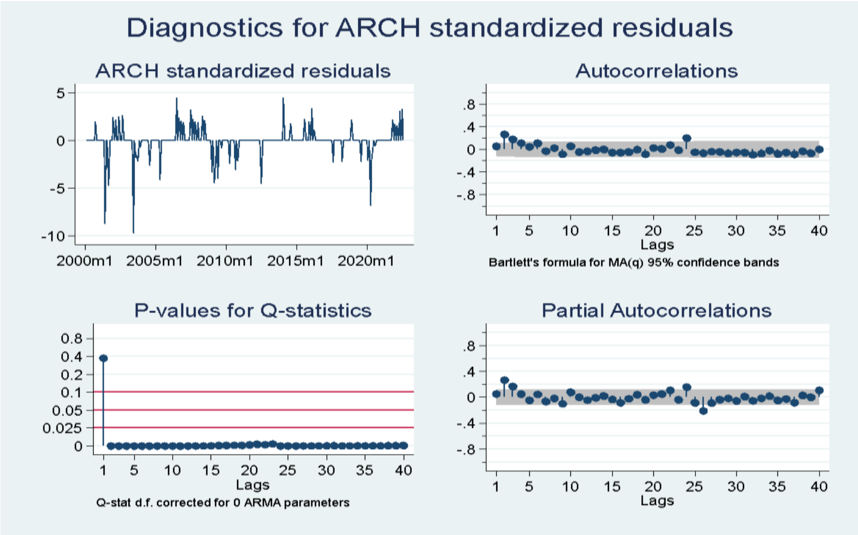

Figure A.4: Diagnostics of ARCH standardized residences – INT under student t distribution assumption

For the bill rate, Figures A.5, A.6 and A.7 present the results. It is observable that although there is some clustering of volatility, sharp and isolated peaks exist; and the p-values are close to zero across all lags. This leads to rejection of the null and concluding that the series have serial autocorrelation. This is true under all assumptions- the normal, student t- distribution and GED.

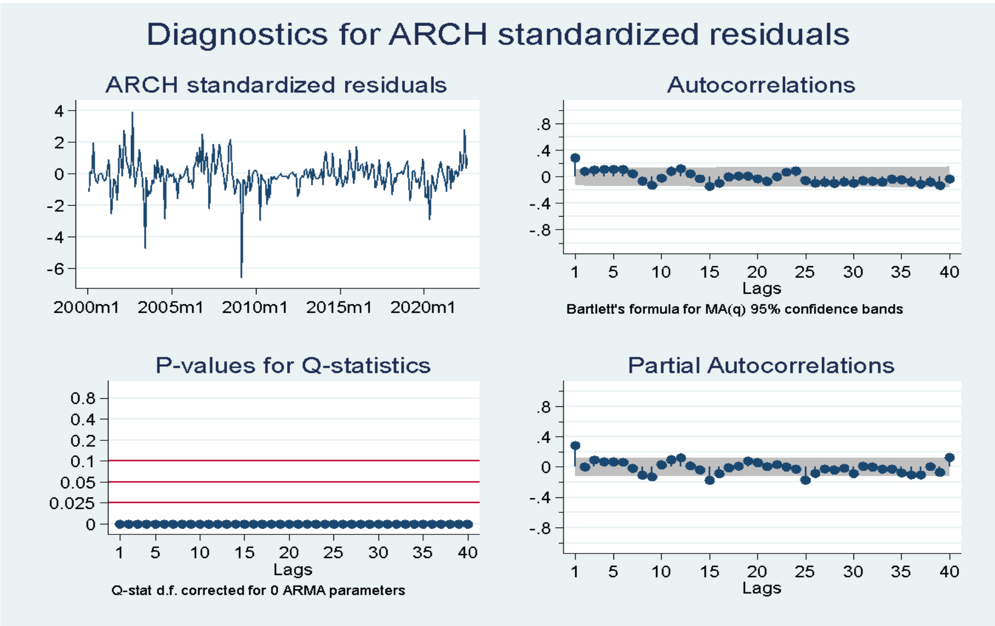

Figure A.5: Diagnostics of ARCH standardized residences – Bill rate under normal error distribution assumption

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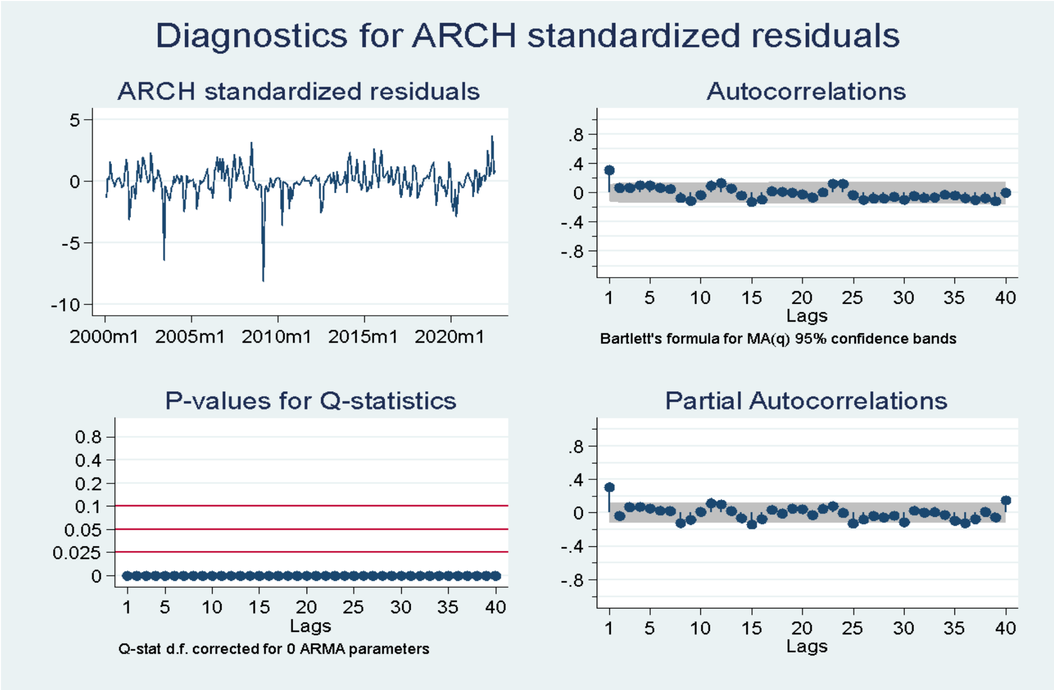

Figure A.6: Diagnostics of ARCH standardized residences – Bill rate under student t error distribution assumption

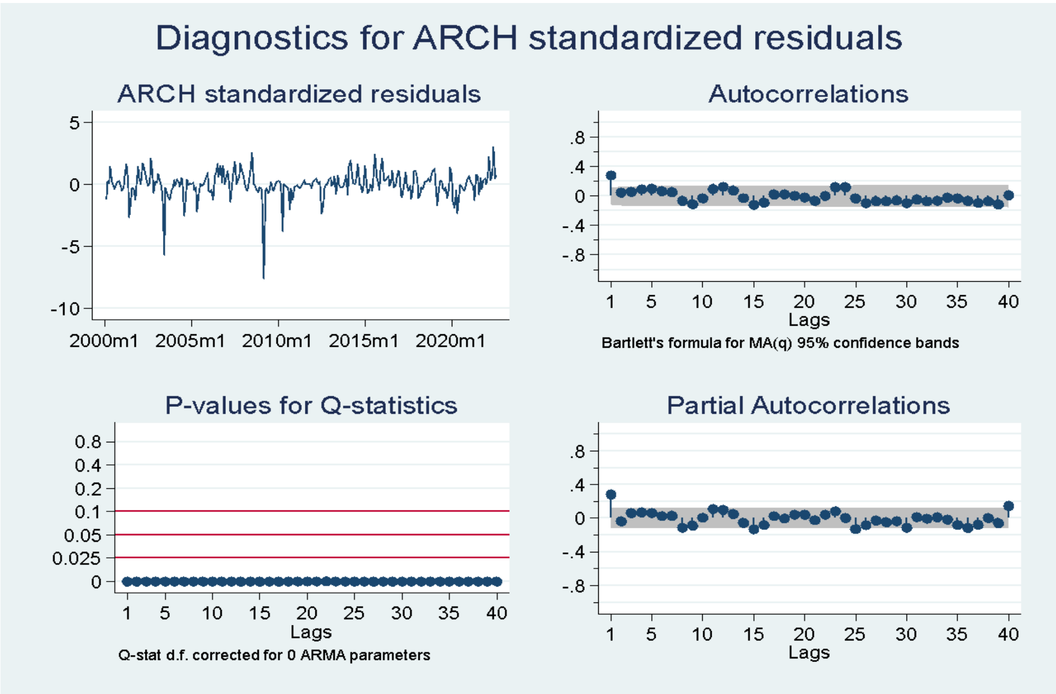

Figure A.7: Diagnostics of ARCH standardized residences –Bill under GED error distribution assumption

Volatility clustering is confirmed centrally to the bill rate with the bond rate, and the hypothesis of no serial autocorrelation cannot be excluded because the p-values are greater than 0.10 in the majority of the instances. This is the case for results depicted in Figures A.8, A.9 and a.10 below.

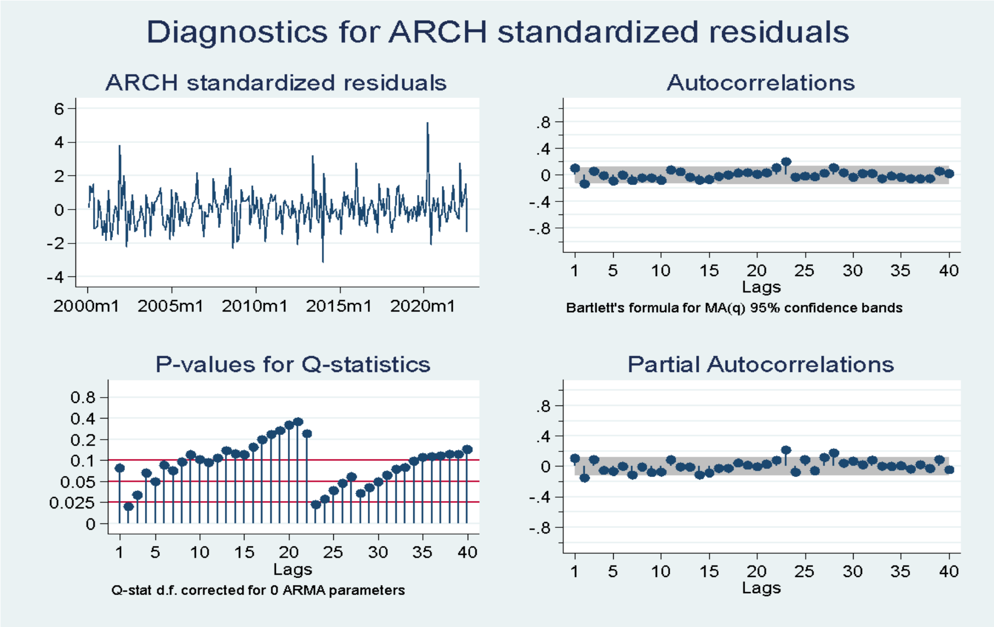

Figure A.8: Diagnostics of ARCH standardized residences – Bond under normal error distribution assumption

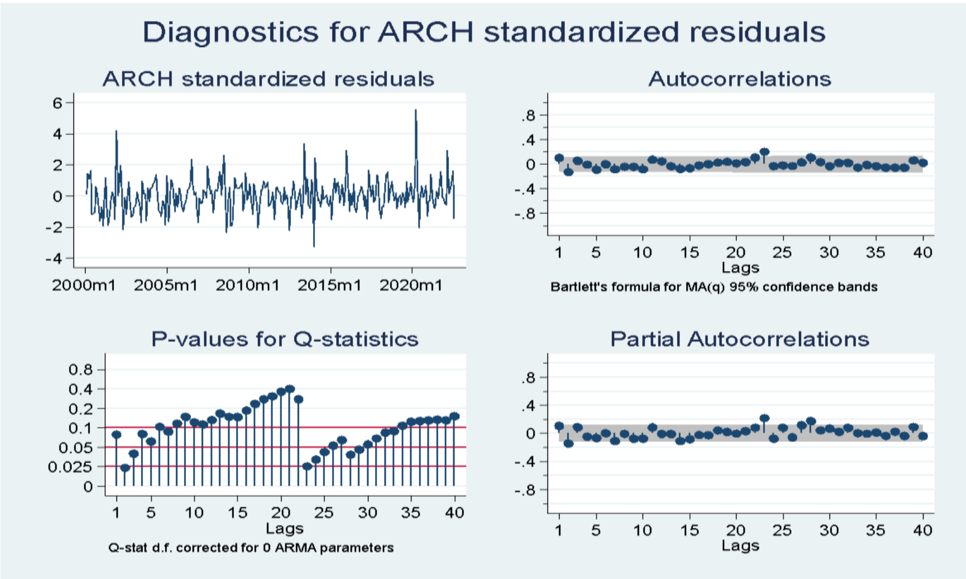

Figure A.9: Diagnostics of ARCH standardized residences – Bond under student t error distribution assumption

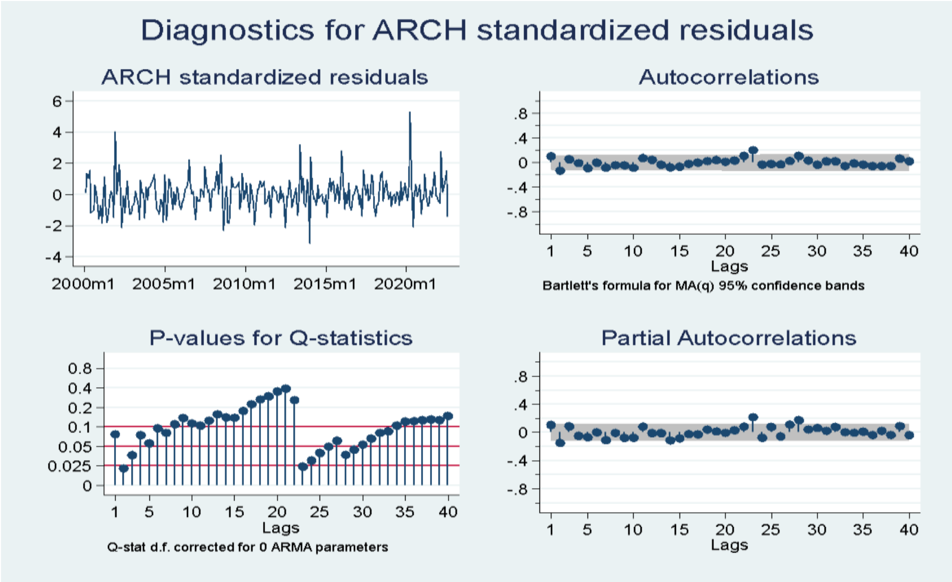

Figure A.10: Diagnostics of ARCH standardized residences – Bond under GED error distribution assumption

In addition to the plots above, Table A.6 presents the Shapiro Wilk W test for normality showing non normality in the series distribution as p-value is less than 0.001, this needs to be considered when interpreting results and making any generalization. The study’s primary focus is on volatility and forecasting, which are not influenced much by skewness and kurtosis. For all the three measures of interest rates, the null hypothesis of ‘series is normally distributed’ is rejected, concluding therefore that each of the series has some skewness.

Table A.6: Shapiro-Wilk W test for normal data

Variable	Obs	W	V	z	Prob>z
INT	272	0.931	13.384	6.060	0.000
Bill	272	0.957	8.437	4.982	0.000
Bond	272	0.882	23.017	7.327	0.000