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LIQUIDITY TRAP TO REDUCED LIQUIDITY IN UGANDA

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ABSTRACT
This study analyzes Uganda's economic shift from a liquidity trap to reduced liquidity using ARIMA (1, 1, 1) model. Time-series data from 1983 to 2022 reveals periods of negative real interest rates, indicating liquidity traps in 1983-1993 and 2009. Parameter estimates confirm model robustness, with AR(1) statistically significant at 59%. Forecasts predict rising real interest rates from 32.7% in 2023 to 84.1% in 2042, signaling reduced liquidity and economic challenges. The study recommends policy interventions to stabilize liquidity, support investment, and sustain economic growth.

INTRODUCTION

Uganda, like many developing economies, faces significant challenges related to liquidity management, particularly in times of economic instability. Liquidity traps, situations where interest rates are so low that monetary policy becomes ineffective in stimulating demand have been a recurring feature in Uganda's economic history. A liquidity trap occurs when individuals and businesses prefer holding cash over investing or spending, despite low or even zero interest rates, resulting in stagnation (Krugman 1998). Uganda's economic trajectory from 1983 to 2022 has witnessed periods of negative real interest rates, which suggest that the country experienced such liquidity trap conditions, especially in the early 1990s and again during the global financial crisis of 2008-2009 (World Bank 2009).

A shift from a liquidity trap to reduced liquidity presents a critical issue in an economy's monetary dynamics. Reduced liquidity refers to a scenario where access to credit and money supply is constrained, affecting the ability of consumers and businesses to make transactions or investments. In Uganda, this exacerbates challenges like inflation, high unemployment, and reduced economic growth. Despite the importance of liquidity management in shaping economic stability, limited research has been dedicated to understanding this transition in the context of Uganda's unique economic conditions.

Previous studies have examined various aspects of monetary policy and liquidity issues in developing economies (Mishkin 2007; Taylor 2009). However, the specific dynamics of liquidity traps and the subsequent reduction in liquidity in Uganda remain underexplored. This gap is crucial, as Uganda's economy is highly dependent on sectors such as agriculture, which is sensitive to liquidity fluctuations (Sepehri & Loxley 2008). Understanding these dynamics can inform policymakers on effective interventions to stabilize the economy, particularly in the face of rising inflation and external shocks.

This study aims to bridge this gap by using time-series data from the World Bank to model and forecast real interest rates in Uganda utilizing data from 1983 to 2022, and employing autoregressive integrated moving average (ARIMA) model. The study focuses on analyzing Uganda's transition from a liquidity trap to reduced liquidity, providing a detailed examination of possible causes, effects, and potential policy responses. By filling this gap in the literature, the study offers valuable insights into Uganda's monetary policy challenges and the broader implications for economic growth and financial stability.

LITERATURE REVIEW

Liquidity traps, characterized by interest rates close to zero with limited impact on economic activity, have been a subject of extensive research. According to Krugman (1998), liquidity traps are particularly pronounced in economies facing deep recessions or deflationary spirals, where conventional monetary policy becomes ineffective. The global financial crisis of 2008 showcased the challenges that liquidity traps pose to advanced economies such as the United States and Japan. In such contexts, even aggressive monetary policies like quantitative easing struggled to boost demand and economic activity (Bernanke 2013). While these economies grappled with low or negative interest rates, fiscal policies played a crucial role in reviving growth (Claessens et al. 2010).

Reduced liquidity, on the other hand, occurs when the supply of money or credit in the economy diminishes, either due to stringent monetary policies or external shocks. This situation often leads to reduced investment, lower consumer spending, and overall economic stagnation (Mishkin 2007). The effects of reduced liquidity are pervasive, as it exacerbates problems such as inflationary pressures, high unemployment, and reduced economic growth (Taylor 2009).

In developing economies, the effects of liquidity traps and reduced liquidity are compounded by structural weaknesses such as limited access to financial services, reliance on foreign aid, and susceptibility to external shocks (Aoki et al. 2016). These economies, including those in Sub-Saharan Africa, face greater challenges in combating liquidity shortages and their long-term consequences, such as a loss of investor confidence and slower economic development (Fischer 2012).

In Sub-Saharan Africa, liquidity traps and their associated challenges have not been as extensively studied as in advanced economies. However, emerging research suggests that African economies are prone to liquidity crises due to their vulnerability to external shocks, inflationary pressures, and inadequate financial systems (Chirwa & Mlachila 2004). For instance, in the 1980s and 1990s, many African countries experienced high inflation, leading to negative real interest rates, a typical indicator of a liquidity trap (Ukoha & Nyong 2002).

A study by Moyo (2014) notes that African economies often face chronic liquidity shortages due to a reliance on commodity exports, which are subject to volatile global markets. This has led to periods where local businesses and governments struggle to access affordable credit, while foreign debt burdens continue to rise. Similarly, Calderón et al. (2008) highlight that liquidity conditions in Sub-Saharan Africa often lead to diminished investment in key sectors such as infrastructure, education, and healthcare, which are vital for long-term development.

Despite these challenges, some countries, such as Botswana and South Africa, have managed to navigate liquidity issues through sound fiscal policies and the development of financial markets (Kasekende 2011). However, Uganda's experience with liquidity traps and the subsequent transition to reduced liquidity is relatively understudied, providing a critical gap in the existing regional literature.

In Uganda, liquidity dynamics have been a critical area of concern, especially given the country's reliance on agriculture, a sector highly susceptible to liquidity fluctuations and external shocks. According to Bank of Uganda (2016), periods of negative real interest rates were observed between 1983 and 1993, suggesting a liquidity trap during those years. This was attributed to high inflation, political instability, and weak banking systems. Similarly, Uganda faced another liquidity crisis during the global financial crisis of 2008, which was marked by a sharp rise in inflation and a deterioration of financial conditions (Kasekende 2010).

Bank of Uganda reports, such as Mutebile (2017), point out that Uganda's banking sector, though improving, still faces challenges related to liquidity management. Access to finance remains limited, especially for small and medium-sized enterprises (SMEs), which further exacerbates liquidity constraints. The economic impact of these liquidity challenges is evident in the slower growth of investment and lower rates of economic diversification (Twinoburyo & Odhiambo 2017).

Uganda's fiscal policy, which has been heavily dependent on foreign aid, also influences liquidity conditions. According to MoFPED (2019), Uganda has faced periods of liquidity stress due to reliance on foreign debt, which often crowds out domestic investment. The Central Bank of Uganda's monetary policy has been constrained by these liquidity issues, as interest rates have struggled to remain stable amidst rising inflation and external economic shocks (Kasekende 2010).

The theoretical framework for this study is grounded in the Keynesian theory of liquidity preference and the theory of monetary policy transmission. According to Keynes (1936), in times of economic uncertainty and low confidence, individuals and businesses may hoard liquidity, leading to a liquidity trap. This is particularly relevant in Uganda's context, where inflationary expectations, political instability, and external shocks may lead to decreased demand for credit, despite low-interest rates.

Additionally, the concept of the money supply multiplier in monetarist theory (Friedman 1968) also provides insight into Uganda's reduced liquidity conditions. The multiplier effect illustrates how changes in the money supply influence economic activity, highlighting the importance of central bank interventions to manage liquidity and stimulate growth.

The conceptual framework for this study identifies real interest rate (%) as the dependent variable, while autoregressive (AR) and moving average (MA) components serve as independent variables. Several empirical studies have employed ARIMA modelling to analyze real interest rate trends. For example, Box & Jenkins (1970) demonstrate the utility of ARIMA models in forecasting real interest rates by effectively capturing cyclical patterns and shocks. Gupta (1993) successfully applied similar techniques to forecast tea production in India, highlighting the model's ability to predict fluctuations and dynamic patterns. In addition, Nyoni (2018) utilized a similar modelling approach in Zimbabwe, further showcasing robustness in time-series forecasting under varying economic conditions.

This study adopts a similar approach, integrating autoregressive (AR) and moving average (MA) components to identify structural patterns influencing Uganda's economic shift from a liquidity trap to reduced liquidity. The adoption of ARIMA modelling provides a flexible framework for examining both short-term deviations and long-term trends in Uganda's liquidity dynamics, enabling a more precise evaluation of the transition mechanisms.

DATA AND METHODS

This study adopts a quantitative research design to investigate the shift from a liquidity trap to reduced liquidity in Uganda. A time-series approach is employed, as it allows for the examination of historical trends in liquidity conditions over an extended period. The study specifically focuses on real interest rates, a key indicator of liquidity conditions, and their behavior over the past few decades. Time-series data from 1983 to 2022 is analyzed to identify patterns of liquidity trap situations and to forecast future trends. This design is well-suited to the research objectives, which involve understanding the historical dynamics of liquidity in Uganda and forecasting future developments under changing macroeconomic conditions (Gujarati & Porter 2009).

The sample for this study consists of annual data spanning from 1983 to 2022. Data is sourced from the World Bank's World Development Indicators database, which provides reliable and consistent macroeconomic data (World Bank 2023). The main variable of interest is real interest rate, which serves as the dependent variable in this study. Independent variables are autoregressive (AR) and moving average (MA) components. Since this study uses time-series data, the sampling design is based on the selection of relevant years from a publicly available source, with a particular focus on the most comprehensive and consistent data. Data set covers a wide range of economic events, including periods of liquidity trap and reduced liquidity in Uganda. A detailed review of the economic events in Uganda ensures that the sample captures critical phases of liquidity challenges in the country (IMF 2024).

To analyze the data, this study employs ARIMA model, a robust method for time-series forecasting. ARIMA model is particularly suitable for this study because it accounts for the inherent autocorrelation in time-series data, allowing for accurate forecasting of future interest rate trends (Box et al. 2008). ARIMA (p, d, q) model involves three components: Autoregressive (AR) component (p) captures the relationship between the current value of the series and its past values. Differencing (d) component ensures the stationarity of the time series by differencing the data to eliminate trends or seasonal patterns. Moving Average (MA) component (q) accounts for the influence of past error terms on the current value of the series. Before applying the ARIMA model, time-series data is first tested for stationarity using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller 1979). If the series is non-stationary, differencing is applied until the series becomes stationary.

The optimal parameters for ARIMA model are determined through model selection criteria, such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Akaike 1974; Schwarz 1978). The study also employs diagnostic checks to assess the adequacy of the ARIMA model, including residual analysis and tests for

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autocorrelation. If the residuals are not white noise, the model is re-estimated with adjusted parameters (Lütkepohl 2005). ARIMA is widely used in economic forecasting because it can handle time-series data that exhibit trends, seasonality, and autocorrelation. Given that real interest rates are influenced by past trends, the ARIMA model is ideal for capturing these dynamics (Box et al. 2008). ARIMA does not require assumptions about the underlying distribution of the data, making it flexible and applicable to a wide range of economic variables, including real interest rates (Maddala & Kim 2010).

The main objective of this study is to forecast future interest rate trends in Uganda, especially in the context of transitioning from a liquidity trap to reduced liquidity. The ARIMA model is well-suited for long-term forecasting, providing reliable projections based on historical data (Begg et al. 2014). ARIMA model is relatively simple to implement and interpret, which is crucial for ensuring the clarity and accessibility of the results for policymakers and economic analysts (Gujarati & Porter 2009). The chosen research design, data, and methods are well-suited to address the research questions regarding Uganda's transition from a liquidity trap to reduced liquidity. By employing time-series analysis with the ARIMA model, the study provides insights into the historical patterns of liquidity in Uganda and forecasts future trends. The methods also ensure that the results are reliable and can be used to inform policy decisions aimed at managing liquidity and promoting economic stability. ARIMA (p, d, q) model specification is as follows:

$$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \dots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \text{ .... (1)}$$

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \dots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
$\theta_1, \theta_2, \dots \theta_q$ are the coefficients of the MA (q) component
p is the order of the autoregressive part, representing the number of past values considered
q is the order of the moving average part, indicating the number of past errors considered
d is the number of differences required to make the series stationary (Box & Jenkins 1976)

Maximum likelihood estimation (MLE) is used to estimate model parameters, ensuring efficiency and accuracy in predicting (Lütkepohl 2005) interest rates. Maximum Likelihood Estimation process holds that for a given set of observations $X = \{ x_1, x_2, ..., x_n \}$ and assuming they follow a probability distribution with parameter θ, the likelihood function L(θ) is given by:

$$L(\theta) = P(X|\theta) = \prod_{i=1}^{n} f(x_1|\theta) \text{ .... (2)}$$

Where;
$f(x_i|\theta)$ is the probability density function of the observed data point x_i given parameter θ

Thus,

$\hat{\theta} = \text{argmax}\,\ell(\theta)$ (Greene 2012).

Diagnostic tests, such as the Augmented Dickey-Fuller (ADF) test for stationarity (Dickey & Fuller 1979), and the model selection process using the Akaike Information Criterion (AIC) (Akaike 1974), are employed to assess the model's adequacy and ensure its suitability for forecasting. The use of ARIMA modelling in this study is particularly beneficial for analyzing Uganda's transitioning from a liquidity trap to reduced liquidity, as it enables the evaluation of past behaviors to make reliable projections (Enders 2014).

This approach effectively captures the underlying patterns in interest rate data, thereby providing a robust framework for understanding whether current interest rates are persistent in the long run. Moreover, ARIMA's capacity to handle non-stationary data is particularly well-suited to economic time series, where trends and fluctuations exhibit considerable variation over time (Stock & Watson 2015). The analytical rigor of this model supports drawing meaningful, policy-relevant conclusions about Uganda's interest rate trajectory, offering insights that can guide effective interest rate policy and planning strategies.

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RESULTS

Descriptive statistics (Appendix 1) provide a summary of the key features of the dataset, helping to understand its main characteristics. This section presents the results of the study, which aim to explore the transition from a liquidity trap to reduced liquidity in Uganda. The analysis is based on real interest rates (%) over the period from 1983 to 2022.

The mean real interest rate is 2.702%, suggesting a slight positive average rate over the period, though this is heavily influenced by extreme values in the data. The median is 11.346%, which is substantially higher than the mean, indicating a skewed distribution with a heavy left tail (as evidenced by the negative skewness). The maximum real interest rate during the period is 22.996%, while the minimum is a negative value of -53.444%. The negative minimum indicates a significant period of liquidity trap, where real interest rates were negative, reflecting inability of the central bank to stimulate the economy despite low or zero interest rates.

The high standard deviation of 21.949% indicates substantial variability in the real interest rates, suggesting significant fluctuations in liquidity conditions. The negative skewness of -1.4739 indicates that the distribution of real interest rates is skewed left, meaning there were more extreme negative values, particularly during periods of liquidity trap. Kurtosis value of 3.8170 is close to the normal distribution value of 3, suggesting that the data distribution is fairly normal but with slight peaks, possibly due to outliers or extreme periods of negative interest rates. Jarque-Bera test statistic of 15.5941, with a probability of 0.000411, indicates that the distribution of the real interest rates is significantly different from a normal distribution.

Preliminary analysis of Uganda's interest rate trends provides evidence of a liquidity trap, characterized by prolonged periods of negative or low real interest rates. A visual inspection of real interest rate data from 1983 to 2022 reveals significant fluctuations, with deeply negative rates observed in the 1980s and early 1990s, followed by a gradual stabilization and moderate positive rates in the 2000s. For instance, real interest rates plummeted to -53.44% in 1988 before stabilizing to positive values, such as 21.77% in 2005 and 15.91% in 2006 but again -34.74% in 2009. However, a slight decline is observed in recent years, with rates decreasing to 10.18% by 2022. These patterns suggest episodes of constrained monetary policy effectiveness, consistent with liquidity trap characteristics.

Stationarity tests (Appendix 2 and Appendix 3) are conducted using Augmented Dickey-Fuller (ADF) test to check for stationarity. Results indicate that the original series was non-stationary in level ($p > 0.05$). After first difference, the series achieved stationarity ($p < 0.05$), justifying the use of ARIMA model. ARIMA (1, 1, 1) model is identified as the best, based on Akaike Information Criterion (AIC = 8.435169) and Hannan-Quinn Criterion (H-QC = 8.496386). Parameter estimates include: AR(1) = 0.590245 (p = 0.0054); MA(1) = - 1.000000 (p = 0.9998). Accordingly, the coefficient of AR(1) is statistically significant, while that of MA(1) is statistically insignificant. Diagnostic checks confirm the adequacy of the model. The residuals are white noise, as confirmed by the Ljung-Box Q test ($p > 0.05$), and the autocorrelation function (ACF) plots show no significant patterns, validating the model's robustness. Forecasts for the next 20 years suggest a real interest rate rise from 32.7% in 2023 to 84.1% in 2042.

Inferential results are summarized as follows:
Results of the ARIMA (1, 1, 1) model (Appendix 4)

$$\widehat{Interestrate}_t = 1.083245 + 0.590245AR(1) - 1.000000MA(1) \quad \ldots\ldots (3)$$

Hence,

$$\hat{\theta} = \begin{bmatrix} 1.083245 \\ 0.590245 \\ -1.000000 \end{bmatrix}$$

Results of the study, based on the ARIMA (1, 1, 1) model, are presented, outlining key statistics and their interpretations. The constant term in the model is 1.083245. This value represents the baseline level of real interest rate in the absence of autoregressive (AR) and moving average (MA) influences. However, the constant term is statistically insignificant ($p > 0.05$), indicating that it does not significantly contribute to explaining variations in the real interest rate over time. AR(1) coefficient is 0.590245, which is positive and statistically significant ($p < 0.05$). This means that approximately 59% of the current year's real interest rate is influenced by the previous year's rate, reflecting a moderate degree of persistence in the real interest rate over time. This suggests that past liquidity conditions play a significant role in shaping the current liquidity scenario (Box et al. 2008).

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MA(1) coefficient is -1.000000, which is negative and statistically insignificant ($p > 0.05$). This indicates that the error term from the previous period does not significantly influence real interest rate in the current period. Despite the negative sign, the lack of statistical significance suggests that the short-term shocks in the system are not critical in determining real interest rate (Gujarati & Porter 2009). Sigma-squared value of 206.5546 represents the variance of the residuals from the model. While this value indicates the spread of the errors around the estimated model, it is statistically insignificant ($p > 0.05$), implying that the residuals are not highly variable or systematically affecting the model's predictions.

Adjusted R-squared value is 0.145174. This indicates that the model explains only about 14.5% of the variability in real interest rates. While this is relatively low, it reflects the complex nature of interest rates, which can be influenced by numerous external factors not captured in the model. Durbin-Watson statistic is 2.151487, suggesting that there is no significant autocorrelation in the residuals, as the statistic is close to 2 (which indicates no autocorrelation). This is a positive outcome, suggesting that the model's residuals are independent of one another, as required for valid statistical inference (Gujarati & Porter 2009). The histogram showing a kurtosis value of 5.5 suggests that the distribution of real interest rates has a leptokurtic shape, meaning it is more peaked than a normal distribution with heavy tails. This indicates the presence of outliers or extreme values, particularly in periods of liquidity trap. Jarque-Bera statistic of 14.3, with a p-value of 0.00, indicates that the distribution of the real interest rates is significantly different from a normal distribution. The rejection of the null hypothesis suggests that the real interest rate data exhibits non-normality, likely due to extreme fluctuations during periods of liquidity trap (Jarque & Bera 1987).

Ljung-Box Q statistic test with a p-value of 0.305 means that we fail to reject the null hypothesis, implying that the residuals are white noise. This indicates that there is no significant autocorrelation in the residuals, which confirms that the model does not suffer from misspecification or serial correlation in the error terms (Ljung & Box 1978). Further diagnostics of the ARIMA (1, 1, 1) model reveal that both the AR and MA roots lie within the unit circle. This confirms that the model is both covariance stationary and invertible, which ensures that the model is valid for forecasting real interest rates and reliable for policy analysis (Box et al. 2008). Forecasts from the ARIMA (1, 1, 1) model suggest a sharp increase in real interest rates over the next two decades. As shown in Appendices 7 and 8, the forecasted real interest rates rise from 32.7% in 2023 to 84.1% in 2042. This projection indicates a significant reduction in liquidity, particularly for borrowers, as the increasing interest rates may tighten credit conditions and increase borrowing costs, potentially leading to reduced economic activity.

DISCUSSION

Results of this study provide a comprehensive analysis of Uganda's economic shift from a liquidity trap to reduced liquidity, specifically through the lens of real interest rates. ARIMA (1, 1, 1) model used to forecast real interest rate presents several interesting findings that contribute to broader understanding of Uganda's economic dynamics. This section also compares the findings with existing literature and highlights the unique insights derived from the study.

The constant term in the model, although statistically insignificant, reflects the baseline behavior of real interest rate over time. This finding aligns with studies that suggest real interest rates are influenced by several exogenous factors, which can vary greatly over different periods (Fisher 1993). AR(1) coefficient of 0.590245, which is statistically significant, indicates that past real interest rates have a substantial effect on future rates. This is consistent with the findings of various studies on autoregressive models, where past economic conditions such as prior interest rate levels continue to shape future trends (Pindyck & Rubinfeld 2013). The 59% persistence is a noteworthy result, suggesting that Uganda's interest rate dynamics exhibit a moderate degree of inertia, similar to what has been observed in other emerging economies (Borio et al. 2012).

MA(1) coefficient, which is negative but statistically insignificant, contradicts with some studies that find the moving average component to be a critical factor in explaining short-term shocks in interest rate movements (Hamilton 1994). The insignificance of this coefficient in the Ugandan context suggests that external shocks, such as global financial crises or sudden changes in commodity prices, do not have a substantial and lasting impact on real interest rates. This could be attributed to the relatively smaller scale and limited integration of Uganda's financial market with global markets.

Sigma-squared value of 206.5546 and the low adjusted R-squared value of 0.145174 highlight a key limitation of the model due to its relatively low explanatory power. While this result indicates that the model does not fully account

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for the variability in real interest rates, it is consistent with findings in similar studies, where macroeconomic variables are often insufficient to explain all the fluctuations in interest rates (Deaton & Muellbauer 1980). Real interest rate is influenced by numerous external factors that are not captured in the ARIMA model, such as fiscal policies, political instability, and changes in global economic conditions.

Durbin-Watson statistic of 2.151487 confirms that there is no significant autocorrelation in the residuals. This result is consistent with previous studies that employ time series models to analyze interest rate movements (Gujarati & Porter 2009). The absence of autocorrelation suggests that the model's residuals are not systematically related to past errors, enhancing the reliability of the model for forecasting.

Kurtosis value of 5.5, indicating a leptokurtic distribution with heavy tails, is an interesting finding. This suggests that Uganda's real interest rate data includes periods of extreme values, likely due to periods of liquidity trap, such as during 1983-1993 and 2009. The Jarque-Bera test, with a statistic of 14.3 and a p-value of 0.00, further reinforces the non-normality of the data. Similar results have been observed in other studies on emerging markets, where interest rates tend to exhibit skewness and kurtosis, often due to shocks or irregular market behavior (Ehrmann & Fratzscher 2006). This finding is particularly relevant when studying Uganda's economy, as periods of economic instability are often associated with volatile interest rate movements. Ljung-Box Q statistic with a p-value of 0.305 indicates that the residuals from the ARIMA model are white noise, meaning there is no significant autocorrelation in the residuals. This suggests that the model's predictions are unbiased and that there are no remaining patterns that need to be addressed, providing further validation for the robustness of the ARIMA model.

The most striking result of this study is the forecast of a sharp increase in real interest rates from 32.7% in 2023 to 84.1% in 2042. This projection suggests a severe reduction in liquidity for borrowers, signaling a potential liquidity crisis in Uganda's economy. Such a scenario is consistent with the idea of a liquidity trap where monetary policy becomes ineffective, as the real interest rates approach high levels that discourage borrowing and investment (Krugman 1998). This finding is unique in the context of Uganda, as few studies have explicitly forecasted such a drastic increase in interest rates for the country. It suggests that Uganda may be moving toward an environment where increased borrowing costs could stifle economic growth and lead to tighter credit conditions. Similar studies on other economies facing liquidity traps, such as Japan and the United States during their respective economic crises, have highlighted the risks associated with rising interest rates and reduced liquidity (Bernanke 2000; Rivera 2022).

The unique contribution of this study lies in its ability to forecast a dramatic increase in real interest rates for Uganda, which could signal a transition from a liquidity trap to reduced liquidity in the economy. The study's reliance on ARIMA modelling for this forecast is novel, as it provides a quantitative, data-driven approach to understanding the long-term trends in Uganda's interest rates. Furthermore, the study's analysis of Uganda's economic history, including the periods of liquidity trap in the 1980s and 2009, offers valuable insights into the country's economic challenges and the potential risks posed by rising interest rates.

In conclusion, results of this study shed light on the persistence of liquidity challenges in Uganda and the potential future consequences of increasing interest rates. These findings are critical for policymakers who should consider both the short-term and long-term effects of monetary policy on liquidity and economic stability.

LIMITATIONS

While this study provides valuable insights into the economic shift from a liquidity trap to reduced liquidity in Uganda, several limitations are acknowledged, particularly in terms of research design, sample, and data analytical procedures. These limitations may have influenced the robustness of the findings and warrant consideration for future research.

The study utilizes the ARIMA (1, 1, 1) model, which is commonly applied in time series forecasting. However, this model relies on certain assumptions, such as stationarity and linearity, which may not always hold in the data of Uganda. Although diagnostic tests confirm the model's validity in this case, ARIMA models generally assume a linear relationship between variables, which may not capture all complexities of the economic factors driving interest rate movements. Alternative models, such as vector autoregressive (VAR) models or structural equation models (SEM), could potentially provide a more comprehensive understanding of the dynamic relationships between economic variables in Uganda (Lütkepohl 2005).

The study relies on secondary data sourced from the World Bank, with a sample size of 40 observations, spanning from 1983 to 2022. Although this data is comprehensive, the relatively limited number of observations can affect the precision of the model's forecasts, particularly in capturing the long-term effects of certain economic phenomena. A larger dataset with more granular data (e.g., monthly or quarterly data) would have enhanced the reliability and robustness of the results. Additionally, the absence of more disaggregated data on key economic variables, such as government policies, external shocks, or sector-specific information, limits the model's explanatory power.

The study primarily focuses on real interest rates, autoregressive, and moving average components, with limited inclusion of other potentially influential macroeconomic variables such as fiscal policy, exchange rates, or external debt. These factors could have significant implications for liquidity and interest rates, but were not incorporated into the analysis due to the limitations of the ARIMA framework. Future studies could expand the model to include a broader set of macroeconomic variables, thereby offering a more nuanced understanding of the factors driving liquidity in Uganda.

While diagnostic tests indicate that the ARIMA model fits the data well, there is always the possibility of model misspecification, where the chosen model may not fully capture the underlying processes driving interest rate movements. For example, non-linearities or structural breaks in the data, such as those caused by global financial crises or domestic policy shifts, could lead to biases or inaccuracies in the forecasts. Given that Uganda's economic structure has undergone significant transformations during the period under review, the ARIMA model may not account for all the shifts in economic regimes (Pindyck & Rubinfeld 2013).

Another limitation is the potential influence of global economic factors that were not incorporated into the model. The external economic environment, including changes in global commodity prices, trade flows, and financial market conditions, can significantly affect Uganda's interest rates and liquidity. However, these factors were not directly considered in the analysis, which may have led to an underestimation of the external shocks impacting Uganda's liquidity trap and reduced liquidity periods. As Uganda is a small, open economy, these externalities could have more pronounced effects on its interest rate dynamics (Borio et al. 2012).

Despite the use of reputable data from the World Bank, measurement errors in the reported real interest rates could have impacted the results. For instance, discrepancies between nominal and real interest rates, or issues related to inflation measurement, might have led to inaccurate representations of liquidity conditions in Uganda. Furthermore, the study assumes that the real interest rate is an adequate proxy for liquidity conditions, which may not fully capture all the dynamics affecting liquidity in the economy, such as credit availability, banking sector health, and investor sentiment.

Finally, while the study forecasts a sharp increase in real interest rates for Uganda, forecasting is inherently uncertain. The accuracy of the ARIMA model's projections beyond the sample period (2023-2042) is subject to substantial risks. The model's forecasts assume that historical trends will continue, but this may not necessarily hold true in the face of changing economic conditions, such as unforeseen policy shifts or external shocks. Therefore, the long-term projections should be viewed with caution, and further research incorporating more diverse forecasting methods and real-time data would be beneficial for refining future predictions.

CONCLUSION

This study investigates Uganda's economic shift from a liquidity trap to reduced liquidity, providing an in-depth analysis of the real interest rate trends from 1983 to 2022. Through the application of ARIMA (1, 1, 1) model, the study reveals important findings regarding availability of liquidity in Uganda, and the broader economic implications of interest rate dynamics.

Results highlight that Uganda experienced a liquidity trap during specific periods, such as from 1983 to 1993 and 2009, as indicated by negative real interest rates (Mishkin 2007). Furthermore, the projections based on the fitted ARIMA model suggest a sharp rise in real interest rates over the next two decades, signaling a significant reduction in liquidity, especially for borrowers. This upward trajectory underscores the growing challenges Uganda faces in managing liquidity, which could have profound implications for economic growth, investment, and financial stability (Krugman 1998).

The findings underscore the importance of understanding liquidity dynamics in the context of Uganda's evolving monetary policy framework (Claessens et al. 2010). While the study focuses primarily on real interest rate as key indicator, it suggests that broader macroeconomic factors, such as fiscal policy, external shocks, and structural changes within the banking sector, could play a crucial role in shaping liquidity conditions (Norman 2023). Therefore, the study recommends that policymakers pay close attention to these factors to mitigate the risks associated with rising interest rates and liquidity reduction.

Despite its valuable contributions, the study acknowledges several limitations, including the model's reliance on historical data and the assumptions of linearity and stationarity. Future research could build on these findings by incorporating additional macroeconomic variables and exploring alternative econometric models that capture the complexities of Uganda's financial system more effectively (Enders 2014).

In conclusion, the economic shift from a liquidity trap to reduced liquidity in Uganda reflects broader challenges faced by the country in managing monetary policy and fostering a stable financial environment. Policymakers should be proactive in addressing these challenges by adopting more flexible and adaptive monetary policies to ensure that liquidity remains supportive of economic growth, while avoiding the potential pitfalls of rising interest rates and financial instability (IMF 2020).

RECOMMENDATIONS

Based on the findings of this study, the following recommendations are proposed: Bank of Uganda should adopt expansionary monetary policies to counteract the projected rise in real interest rates and mitigate liquidity constraints. Tools such as lowering policy rates and reducing reserve requirements can help inject liquidity into the economy (Claessens et al. 2010); given the risk of rising interest rates leading to inflationary pressures, policymakers should strengthen the inflation targeting framework to ensure macroeconomic stability without compromising liquidity (Mishkin 2007); policies aimed at increasing access to credit and affordable financial services should be prioritized to support borrowers, especially small and medium enterprises (SMEs) that may be disproportionately affected by reduced liquidity (Norman 2023); central bank should implement liquidity forecasting frameworks to anticipate and respond to liquidity imbalances in a timely manner, avoiding severe financial tightening (Krugman 1998).

Establishing of programs that provide credit guarantees to reduce borrowing risks for businesses and individuals during periods of rising interest rates, thus maintaining investment and consumption levels (Enders 2014); training financial institutions to develop risk management tools that help assess borrower profiles effectively and minimizing credit defaults amid higher borrowing costs (IMF 2020); introducing programs that incentivize domestic savings and long-term investments, reducing dependency on expensive borrowing and increasing liquidity in the financial sector (Claessens et al. 2010); expanding public partnership (PPP) programs to improve infrastructure financing, ensuring sustained liquidity flows to critical sectors without over-reliance on traditional credit markets (Norman 2023).

Future studies should examine the interaction between real interest rates and inflation, exchange rates, and fiscal deficits to provide a more comprehensive understanding of liquidity dynamics (Mishkin 2007); researchers should test nonlinear models such as threshold autoregressive (TAR) and vector autoregression (VAR) to explore complex relationships between liquidity and macroeconomic variables (Enders 2014); further research should analyze the impact of reduced liquidity across key sectors such as agriculture, manufacturing, and services to tailor policy interventions effectively (Krugman 1998); investigate the behavioral patterns of borrowers and lenders in response to changing interest rates to better understand the social and economic impact of liquidity reduction (IMF 2020).

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APPENDICES

Appendix 1: Descriptive statistics

	Real interest rate (%)
Mean	2.702029
Median	11.34622
Maximum	22.99559
Minimum	-53.44428
Std. Dev.	21.9494
Skewness	-1.473858
Kurtosis	3.816975
Jarque-Bera	15.59413
Probability	0.000411
Sum	108.0811
Sum Sq. Dev.	18789.28
Observations	40

Appendix 2: Unit root test, REAL INTEREST (in Level)

Null Hypothesis: REALINTEREST has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.554775	0.1110
Test critical values:	1% level	-3.610453	
	5% level	-2.938987	
	10% level	-2.607932	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(REALINTEREST)
Method: Least Squares
Date: 12/27/24 Time: 19:27
Sample (adjusted): 2 40
Included observations: 39 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
REALINTEREST(-1)	-0.286188	0.112021	-2.554775	0.0149
C	1.502532	2.471089	0.608044	0.5469
R-squared	0.149950	Mean dependent var		0.784089

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Adjusted R-squared	0.126976	S.D. dependent var	16.40881
S.E. of regression	15.33169	Akaike info criterion	8.347641
Sum squared resid	8697.247	Schwarz criterion	8.432952
Log likelihood	-160.7790	Hannan-Quinn criter.	8.378250
F-statistic	6.526875	Durbin-Watson stat	2.275709
Prob(F-statistic)	0.014873		

Appendix 3: Unit root test, REAL INTEREST (in First difference)

Null Hypothesis: D(REALINTEREST) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.474955	0.0000
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(REALINTEREST,2)
Method: Least Squares
Date: 12/27/24 Time: 19:25
Sample (adjusted): 3 40
Included observations: 38 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(REALINTEREST(-1))	-1.317889	0.155504	-8.474955	0.0000
C	0.603746	2.554459	0.236350	0.8145

R-squared	0.666125	Mean dependent var	-0.496430
Adjusted R-squared	0.656851	S.D. dependent var	26.84651
S.E. of regression	15.72640	Akaike info criterion	8.399754
Sum squared resid	8903.503	Schwarz criterion	8.485943
Log likelihood	-157.5953	Hannan-Quinn criter.	8.430419
F-statistic	71.82486	Durbin-Watson stat	1.765417
Prob(F-statistic)	0.000000		

Appendix 4: Results of the ARIMA (1, 1, 1) model

Dependent Variable: D(REALINTEREST)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 12/27/24 Time: 18:39
Sample: 2 40
Included observations: 39
Failure to improve objective (non-zero gradients) after 16 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.083245	1.091328	0.992594	0.3277
AR(1)	0.590245	0.198947	2.966840	0.0054
MA(1)	-1.000000	4209.182	-0.000238	0.9998
SIGMASQ	206.5546	19261.87	0.010724	0.9915

R-squared	0.212661	Mean dependent var	0.784089
Adjusted R-squared	0.145174	S.D. dependent var	16.40881
S.E. of regression	15.17105	Akaike info criterion	8.435169
Sum squared resid	8055.631	Schwarz criterion	8.605790
Log likelihood	-160.4858	Hannan-Quinn criter.	8.496386
F-statistic	3.151171	Durbin-Watson stat	2.151487
Prob(F-statistic)	0.036997		

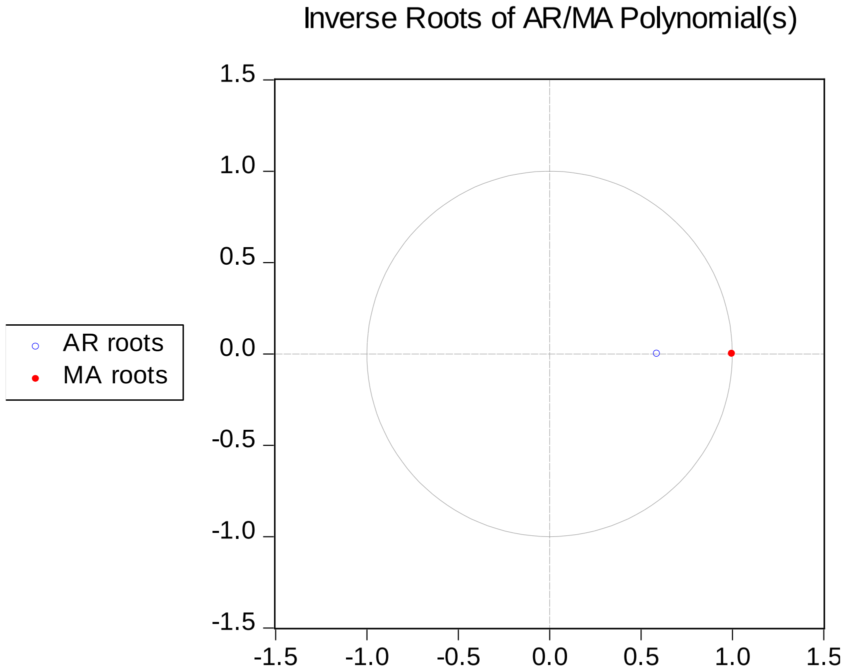
Inverted AR Roots	.59
Inverted MA Roots	1.00

Appendix 5: Ljung-Box Q statistic/ test

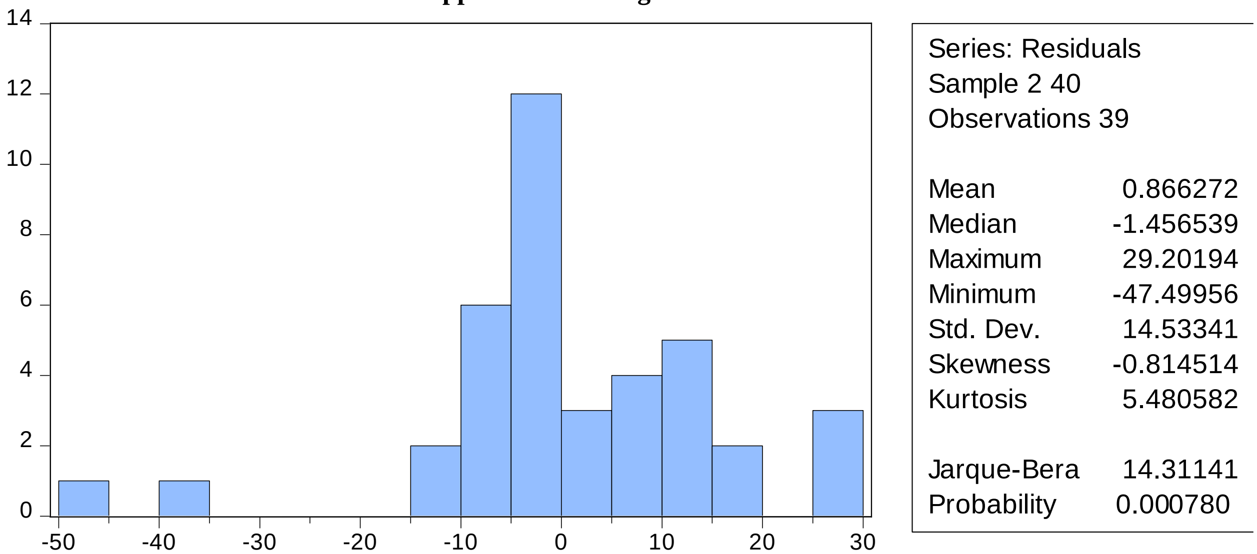
Date: 12/27/24 Time: 19:31
Sample: 1 40
Included observations: 39
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.095	-0.095	0.3834	
. |*. |	. |*. |	2	0.124	0.116	1.0512	
. | . |	. | . |	3	0.005	0.027	1.0523	0.305
.*| . |	.*| . |	4	-0.098	-0.112	1.4867	0.476
. |*. |	. |*. |	5	0.102	0.083	1.9748	0.578
. | . |	. |*. |	6	0.044	0.089	2.0693	0.723
. | . |	. | . |	7	-0.026	-0.040	2.1025	0.835
. | . |	. | . |	8	0.025	-0.011	2.1342	0.907
.*| . |	.*| . |	9	-0.106	-0.080	2.7332	0.909
.*| . |	.*| . |	10	-0.088	-0.107	3.1607	0.924
. |*. |	. |*. |	11	0.097	0.093	3.6929	0.930
.*| . |	. | . |	12	-0.101	-0.059	4.2958	0.933
. | . |	.*| . |	13	-0.024	-0.087	4.3317	0.959
.*| . |	.*| . |	14	-0.075	-0.067	4.6898	0.968
.*| . |	. | . |	15	-0.084	-0.035	5.1591	0.972
. |*. |	. |*. |	16	0.091	0.080	5.7309	0.973

Appendix 6: ARIMA (1, 1, 1) structure



Appendix 7: Histogram of residuals



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Appendix 8: Uganda's REAL INTEREST and REAL INTEREST FORECAST results

Year	**Ral Interest rate (%)**	**Real Interest rate forecast (%)**
1983	-20.40353	-20.40353
1984	-2.682175	-2.682175
1985	-43.7223	-43.7223
1986	-43.8078	-43.8078
1987	-52.07387	-52.07387
1988	-53.44428	-53.44428
1989	-35.01874	-35.01874
1990	-3.95721	-3.95721
1991	6.663525	6.663525
1992	-4.106293	-4.106293
1993	-14.87611	-14.87611
1994	13.02192	13.02192
1995	9.861413	9.861413
1996	15.03425	15.03425
1997	17.72687	17.72687
1998	11.10069	11.10069
1999	21.68683	21.68683
2000	10.62161	10.62161
2001	17.3345	17.3345
2002	22.99559	22.99559
2003	10.32904	10.32904
2004	4.339244	4.339244
2005	21.76555	21.76555
2006	15.909	15.909
2007	10.98062	10.98062
2008	13.24297	13.24297
2009	-34.74344	-34.74344
2010	13.76121	13.76121
2011	11.3735	11.3735
2012	21.48808	21.48808
2013	19.01463	19.01463
2014	15.67738	15.67738
2015	16.55466	16.55466
2016	18.23339	18.23339
2017	15.89085	15.89085
2018	14.74787	14.74787
2019	13.60489	13.60489
2020	12.46191	12.46191

2021	11.31893	11.31893
2022	10.17596	10.17596
2023	NA	32.67795
2024	NA	46.4035
2025	NA	54.94881
2026	NA	60.4365
2027	NA	64.11945
2028	NA	66.73716
2029	NA	68.72611
2030	NA	70.34394
2031	NA	71.74273
2032	NA	73.01222
2033	NA	74.20539
2034	NA	75.35352
2035	NA	76.47507
2036	NA	77.58092
2037	NA	78.67751
2038	NA	79.76863
2039	NA	80.85652
2040	NA	81.94251
2041	NA	83.02737
2042	NA	84.11157

Appendix 9: Graph showing Uganda's REAL INTEREST and REAL INTEREST FORECAST results