Forecasting GDP using Inflation in Selected AFRITAC West 2 Member Countries: An ADL-MIDAS Approach

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Abstract- This paper investigates the contribution of inflation in forecasting output in selected AFRITAC West 2 member countries using an Autoregressive Distributed Lag-Mixed Data Sampling (ADL-MIDAS) approach. The study contributes to the literature of inflation-output nexus in three manifolds. First, we use the ADL MIDAS to test the effectiveness of predicting output that is often in low frequency using high frequency inflation data in its original form. Second, we use an in-sample predictability and out-of-sample forecast analysis to examine the performance of the ADL-MIDAS model against the traditional Autoregressive (AR) model. Third, we shed light on the dynamic relationship between inflation and output, accounting for the impact of exchange rate to ascertain the sensitivity of the model. The results show that inflation significantly predicts output, and accounting for exchange rate improves the predictability of the ADL MIDAS model. Furthermore, both the in-sample and out-of-sample forecasting outcomes significantly favor the ADL-MIDAS compared to AR model. The paper recommends adopting a holistic approach to monetary policy and highlight the importance of incorporating exchange rate in modelling inflation-output nexus, as well as using inflation in its original form when predicting output.

Indexed Terms- Inflation, Gross Domestic Product, Exchange Rate, ADL-MIDAS

I. INTRODUCTION

The study of inflation and economic growth is as old as mankind. The monetary and fiscal policy authorities consider these variables significant indicators for monitoring the operation of the macroeconomy. Theoretically and empirically, the relationship between inflation and output has been a topic of considerable study among scholars, given its importance to monetary policy decisions (Seleteng et al., 2013; Ibarra & Trupkin, 2016; Ndoricimpa, 2017; Nene et al., 2022). Consequently, policymakers often forecast GDP to project the implications of policy decisions for setting policy targets. Similarly, investors used GDP predictions to make informed decisions. However, the challenge often faced by analysts is that GDP numbers are low frequency, whereas inflation is high frequency. The researchers usually aggregate high-frequency inflation into low-frequency inflation to make predictions. This act leads to a loss of information. Hence, the use of variables in their original frequency for prediction has been gaining momentum in recent times (Salisu & Egbonna, 2019; Umar et al., 2024).

Instability in the movement of prices is a major concern for countries, specifically in the context of African countries (Umar et al., 2024), with the African Regional Technical Assistance Centre in the West (AFRITAC West 2) region not being exempt. These economies are being characterised by rising foreign exchange and continued fluctuations in the prices of goods and services as a result of the COVID-19 pandemic, ongoing Russia's invasion of Ukraine, the Israel-Gaza war, and increasing geoeconomic fragmentation (World Economic Outlook, October 2023, and Jawo et al., 2023). After the global shocks and structural imbalances, the West 2 region remains subdued amidst high inflation and sluggish economic growth. As a result, the average output growth in the region was projected to grow 3.7 per cent in 2023, a decline from 4.8 per cent in 2022, while inflation would increase from 17.5 per cent in 2022 to 21.0 per cent in 2023 (WEO October 2023).

Historically, the region has experienced 6 consecutive year-on-year rising double-digit inflation and two episodes of economic recession in (2015 and 2022), since its exception in 2013. Notably, similar inflationary trends have been observed in all the member countries (Cabo Verde, The Gambia, Liberia, Nigeria and Sierra Leone). However, growth across member countries, such as The Gambia's economy contracted by 1.4 per cent, while Ghana and Nigeria grew by 2.9 and by 6.3 per cent in 2014, respectively. Inflation in The Gambia, Ghana, and Nigeria has experienced an uptick from 6.3, 15.5, and 8.0 per cent in 2014 to 17.0, 42.2, and 25.1 per cent in 2023 compared to 11.5, 31.9. 18.8 percent in 2022, respectively. Hence, this causes a continuous decline in the performance of the domestic currencies and the corresponding rise in the foreign exchange rate, of Naira, Ghana Cedi, and Dalasi to US Dollar ($) (Enu and Havi 20214). The GDP of Nigeria stood at US$535.34 billion in 2022, which accounted for an average of 84.6 percent of output growth in AFRITAC West 2 member countries and was over eight times larger compared to the US$68.00 billion GDP of Ghana. Over 291 times bigger compared to The Gambia's economy, which stood at US$1.84 billion in 2022 (World Bank, 2023).

The relationship between inflation and economic growth from a theoretical point of view could be either positive or negative depending on the findings (see Seleteng et al., 2013; Vinayagathasan, 2013; Thanh, 2015; Ibarra and Trupkin, 2016; Ndoricimpa, 2017; Nyoni & Mutongi, 2019; Nene et al., 2022; Lubeniqi et al., 2022; Woblesseh et al., 2022; Adebanjo et al., 2022; Mandeya & Ho, 2023; Nkwatoh & Mallum, 2023; Achiyaale et al., 2023; Osei, 2023; Havi, 2023; Amoah et al., 2023; Jawo el at., 2023). High inflation is harmful to the economy due to its undesirable re-distributional and welfare effects (see Eggoh & Muhammad, 2014; Jawo et al., 2023). Although proposed by Friedman (1969), negative inflation has never been considered as a policy agenda since a certain magnitude of inflation is necessary to 'grease the wheels' of the economy (Seleteng et al., 2013). This was buttressed by various theoretical frameworks such as Taylor (2019), Okun (1971), Friedman (1977), Cukierman and Meltzer (1986), Pourgerami and Maskus (1987), Ungar and Zilberfarb (1993), Holland (1995) among others who established the inflation-growth nexus. Okun (1971) and Friedman (1977) argue that inflation uncertainty is harmful to real economic activity.

Additionally, empirical findings reveal a non-linear relationship between inflation and economic growth in Africa with threshold values of 6.7, 9.0 and 6.5 percent for the whole sample, and sub-sample of low-income and middle-income countries (Ndoricimpa, 2017). On the contrary, Amoah et al. (2023) show that output has a favourable short-term impact on inflation in Ghana's economy. The findings from Jawo et al., (2023) reveal that inflation positively and negatively affects economic growth in The Gambia. The empirical evidence on the inflation-output nexus has been studied using different methodologies, data sets, and sample periods. One of the challenges in estimating the inflation-output nexus is the choice of the appropriate econometric model that can capture the dynamic and nonlinear features of the data. A common approach is to use autoregressive distributed lag (ARDL) models, which allow for short-run and long-run effects of inflation on output. However, ARDL models have some limitations, such as the assumption of constant parameters, the difficulty of handling high-frequency data, and the lack of flexibility in modelling the lag structure.

To overcome these limitations, this study proposes to use a novel approach based on the ADL-MIDAS model, which combines the ARDL model with the mixed data sampling (MIDAS) technique. The objective of this paper is to analyse the predictability of inflation and output nexus in Ghana, The Gambia and Nigeria economies. We adopt a two-comprehensive econometric approach known as the Autoregressive Distributed Lag-Mixed Data Sampling (ADL-MIDAS) and Autoregressive (AR) framework proposed by Ghysels et al. (2002, 2006, 2007; Andreou et al., 2010; Salisu et al., 2019).

The objective of this paper is to analyse how inflation predicts output in Ghana, The Gambia and Nigeria mixing low-frequency GDP data and high-frequency inflation data. The authors adopt a two-comprehensive econometric approach known as the Autoregressive Distributed Lag-Mixed Data Sampling (ADL-MIDAS) and Autoregressive (AR) framework proposed by Ghysels et al. (2002). The ADL-MIDAS method permits the utilization of data with mixed frequencies (annual and monthly), enabling the examination of the interaction between a high-frequency predictor variable (such as inflation) and a low-frequency predicted variable (like output) in elucidating the dynamics between inflation and output. Additionally, it facilitates the incorporation of diverse parameters, nonlinear impacts, and adaptable lag selection. The novelty of this paper contributes to the literature by considering both the in-sample and out-of-sample forecasts evaluation, to the best of our knowledge, no study considers the three member countries of AFRITAC West 2 which account for 98.2 per cent of the total gross domestic product (GDP) of the 6 member countries. More so, the current study differs from Umar et al., (2024) and others, in methodology by using the Autoregressive Distributed Lag-Mixed Data Sampling (ADL-MIDAS) approach and AR (1) model. Several studies focus only on non-linearities in the inflation–output nexus in Africa, the output-inflation nexus in 17 selected African countries, inflation targeting policy on inflation uncertainty and economic growth in African and European countries among others (see Nene et al., 2022; Lubeniqi et al., 2022; Woblesseh et al., 2022; Adebanjo et al., 2022; Mandeya and Ho, 2023; Nkwatoh and Mallum, 2023; Achiyaale et al., 2023; Osei, 2023; Havi, 2023; Amoah et al., 2023; Jawo el at., 2023 and Umar et al., 2024).

This study is driven by three distinct objectives. Firstly, we explore the significance of inflation in influencing output within the region. Secondly, we conduct robustness tests utilizing exchange rates to assess the model's sensitivity. Lastly, we evaluate the most competitive model to enhance forecast accuracy. The implications of this research extend beyond theoretical comprehension. By uncovering the relationship between inflation and output in Ghana, The Gambia, and Nigeria, monetary and fiscal authorities along with policymakers can gain crucial insights into the factors impacting inflation and their repercussions on macroeconomic stability. This knowledge can facilitate the formulation of appropriate policies aimed at fostering consistent output growth while effectively managing inflationary pressures. The remainder of the paper is structured as follows: Section 2 presents the data and stylised facts; Section 3 focuses on the methodology; Section 4 reports the empirical results including the in-sample and out-of-sample forecast evaluation; and Section 5 contains the conclusion and policy implications.

II. DATA AND STYLISED FACTS

The paper used an annual series of gross domestic product (GDP) and a monthly series of inflation rates for Ghana, The Gambia and Nigeria spanning from 1980 to 2022 and 1981M1 to 2022M12 for the monthly frequency. The paper uses time series data from three member countries of the African Regional Technical Assistance Centre in West Africa (AFRITAC West 2), which are Ghana, The Gambia and Nigeria. The intent was to examine the six member countries but historical data for Cabo Verde, Liberia and Sierra Leone was not up to 30 observations for proper alignment with the central limit theorem. Furthermore, the three-member countries selected to account for 98.3 per cent of the total GDP of the member countries[1]. Hence, the selected member countries provide an interesting case to be studied. GDP (constant 2015 US$) and monthly headline consumer price index (CPI) were obtained from the World Development Indicators (WDI) database and cross-country database of inflation archived by the World Bank Group as a database of inflation and Exchange Rate (Official exchange rate (LCU per US$, period average) are sourced from WDI of the World Bank. The data on inflation (Average of the monthly headline consumer price index) is obtained from (Ha et al., 2023) cross-country database of inflation archived by the World Bank Group[2].

Descriptive Statistics

Table 1: Descriptive Statistics

	Annual Frequencies						Monthly Frequencies					
	GDPGH	GDPGM	GDPNG	EXRGH	EXRGM	EXRNG	CPIGH	INFGH	CPIGM	INFGM	CPING	INFNG
Mean	28.5853	1.0312	275.3203	1.4637	22.1816	115.6556	80.35986	26.2690	75.45642	8.9766	80.81045	19.02473
Std. Dev.	18.2819	0.3773	148.8533	2.0276	16.5092	119.1827	110.0358	26.9633	55.53824	9.8174	104.0167	16.8725
Skewness	0.82390	0.4092	0.5334	1.6294	0.5414	1.0253	1.591649	2.76059	0.825786	3.7811	1.615597	1.7983
Kurtosis	2.32361	2.1260	1.6543	4.8773	1.9498	3.2301	4.907474	11.1692	2.829624	20.9584	4.960635	5.9921

Jarque-Bera	5.5523*	2.5088	5.1611*	24.7519***	3.9820	7.4520**	296.0946***	2041.6070	59.26939******	7973.5810***	307.1210***	459.6356
Observations	43	43	43	43	43	43	516	516	516	516	516	516

Note: GDPGH, GDPGM and GDPNG stand for the GDP of Ghana, The Gambia and Nigeria, respectively. EXRGH, EXRGM and EXRNG denote exchange rates for Ghana, The Gambia and Nigeria, respectively. CPIGH, INFGH, CPIGM, INFGM and CPING INFNG are for consumer price index (CPI) with their correspondence inflation rate of Ghana, The Gambia and Nigeria, respectively. The GDP figures are measured in Billion US$. *, ** and *** signifies significance level at 10%, 5% and 1%, respectively.

Table 1 presents descriptive statistics of the average GDP for Ghana, The Gambia and Nigeria at 28.59 billion USD, 1.03 billion USD and 275.32 billion USD. The standard deviations for the countries stood at 18.28, 0.38 and 148.85. This indicates a higher deviation of GDP for The Gambia, compared to Ghana and Nigeria. The GDP figures reveal significant disparities among the three countries. While Nigeria boasts of the highest average GDP, The Gambia displays the lowest average GDP with a higher deviation, suggesting a possible level of economic instability compared to Ghana and Nigeria. The average values of exchange rate are 1.46, 22.18 and 115.66 for Ghana, The Gambia and Nigeria, respectively. For the exchange rate, Nigeria experienced less volatility evidenced by the lowest standard deviation at 119.18. This relative stability in the exchange rate could be attributed to managed foreign exchange rate policy in the period under review.

The average consumer price index (CPI) for Ghana and Nigeria are almost the same. The Gambia on the flip side recorded the lowest mean value, which shows that The Gambia has a relatively lower CPI than Ghana and Nigeria between 1980 and 2022. All the variables are positively skewed. The exchange rates of Ghana and Nigeria and the CPI are leptokurtic.

Fig. 1: Trends in Inflation and GDP in Ghana (1981- 2022)

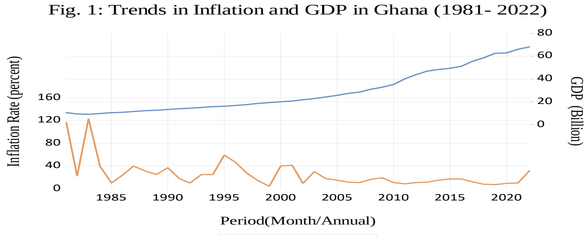


Fig. 2: Trends in Inflation and GDP in Gambia (1981- 2022)

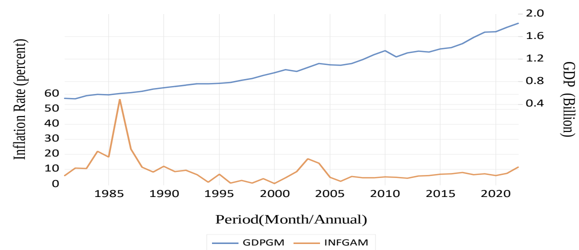
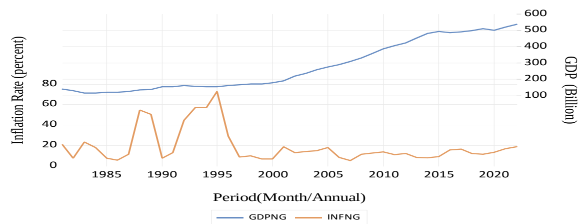


Fig. 3: Trends in Inflation and GDP in Nigeria (1981- 2022)



We supplement our analysis with visual representations to elucidate the dynamics of the series. Figure 1 to 3 illustrates the relationship between the GDP of each country and its corresponding inflation series. As anticipated, the GDP exhibits a discernible upward trend across all countries, indicating positive growth. Conversely, inflation exhibits fluctuations, with notable disparities among nations. Particularly, Nigeria exhibits markedly higher volatility in its inflation rates compared to Ghana and The Gambia, a trend that is consistent with the descriptive statistics (Table 1).

We observed a pattern of elevated and erratic inflation rates for all countries, particularly in the 1980s. This coincides with periods of depressed GDP figures. This observed trend implies a potential correlation between inflation and output fluctuations. This insight not only underscores the interplay between inflation and output but also suggests avenues for further investigation into the underlying mechanisms driving inflation dynamics and their predictability of economic performance.

III. METHODOLOGY

This paper adopts the Autoregressive Distributed Lag-Mixed Data Sampling (ADL-MIDAS) technique. The MIDAS approach is structured based on the framework introduced by Ghysels et al. (2002) and further improved by Andreou et al. (2010), which incorporates data with varying degrees of frequencies into a unified regression analysis. The rationale behind employing this technique lies in its capability to seamlessly integrate information from higher-frequency data into lower-frequency regressions The basic MIDAS takes the form of a distributed lag, as the predicted series in each period is influenced by multiple lags of the higher-frequency regressor.

The annual frequency serves as the dependent variable, whereas the independent variable is measured monthly. This shows that a dependent variable, $\{yt\}$, available once between time t and $\mathrm{t}-1$, the independent variable, $x\_t\hat{}m$, is observed $\mathrm{m}=12$ times in the same period. Consequently, the dynamic relationship is between y_t and $x\_t\hat{}m$. The distributed lag relation exists when the left-hand variable y_t is forecasted based on a sequence of past observations of $x\_\{t-f/m\}\hat{}m$. The superscript on $x\_\{t-f/m\}\hat{}m$ indicates a higher sampling frequency, with the precise timing lag expressed as a fraction of the unit interval between $\mathrm{t}-1$ and t. Thus, f varies from 1 to 12 between $\mathrm{t}-1$ and t, generating four coefficients for the relationship between the dependent and the independent variables in one year. A simple MIDAS model is

$y\_t = \backslash beta\_0 + \backslash beta\_1\mathrm{B}\backslash\mathrm{left}(L\hat{}\backslash\mathrm{frac}\{1\}\{m\};\backslash theta\backslash\mathrm{right})x\_t\hat{}\{(m)\} + \backslash varepsilon\_t\hat{}m$ (1)

For $\mathrm{t}=1,\backslash\mathrm{ldots},\mathrm{T}$, where $\mathrm{B}(L\hat{}\backslash\mathrm{frac}\{1\}\{m\};\theta)=\sum_{k=0}^{K} B(k;\theta)L^{\frac{k}{m}}$, and $L^{\frac{1}{m}}$ is a lag operator such that $L^{1/m}x_t^{(m)}=x_{t-1/m}^{(m)}$; the lag coefficients in $B(k;\theta)$ of the corresponding lag operator $L^{k/m}$ are parameterized as a function of a small dimensional vector of parameters θ. Finally, the parameter β_1 captures the overall impact of lagged $x_t^{(m)}$'s on y_t. This is identified by normalizing the function $B\left(L^{\frac{1}{m}};\theta\right)$ to sum to unity (see Ghysels et al., 2007).

Equation (1) has been adjusted to incorporate an autoregressive version of the dependent variable. This modification aims to account for the possible persistence in the level of real GDP. Therefore, the MIDAS model can be represented as

$$y_{t+1}=\beta_0+\gamma y_t+\beta_1 B\left(L^{\frac{1}{m}};\theta\right)x_t^{(m)}+\varepsilon_{t+1} \quad (2)$$

Where γ represents the degree of continuity in the GDP level, while the other variables retain their previously established definitions.

In this study, the MIDAS-GETS estimation method is employed. Unlike traditional approaches that rely on a weighting scheme to diminish the variable count, MIDAS-GETS addresses the challenge posed by the large number of variables in a dataset by employing the Auto-Search/GETS variable selection algorithm. This algorithm decides which high-frequency variables should be incorporated into the regression. Notably, the Auto-Search/GETS algorithm, utilized in E-Views' indicator saturation detection routines, is also integrated into MIDAS-GETS. Consequently, MIDAS-GETS can automatically include indicator variables, facilitating the accommodation of outliers and structural changes in the model. This inclusion significantly enhances the forecasting performance. Additionally, the Auto/GETS weighting scheme, an extension of U-MIDAS, utilizes variable selection to decrease the number of individual coefficients by excluding insignificant lags.

The U-MIDAS method incorporates each higher frequency component as a regressor in the lower frequency regression. Specifically, the U-MIDAS weighting method is essentially the application of the individual coefficients technique outlined in equation (3):

$$y_t=X_t'\beta+\sum_{\tau=0}^{S-1}X_{(t-\tau)/S}^{H}{}'\theta_\tau+\varepsilon_t \qquad (3)$$

Thus, the ADL-MIDAS specification for inflation-output nexus in this study is presented in equation (4):

$$lngdp_{t+1}^{A}=\lambda+\sum_{i=1}^{P_{GDP}^{A}-1}\alpha_i lngdp_{t-i}^{A}+\left[\sum_{\tau=0}^{S-1}X_{(t-\tau)/S}^{H}{}'\theta_\tau\right]\sum_{i=0}^{q_{inf}^{M}-1}lncpi_{N_{M-\tau,t-i}}^{M}+\varepsilon_{t+1} \quad (4)$$

The dependent variable, represented as $lngdp$, is log of GDP and the independent variable $lncpi$ is inflation. The superscripts/subscripts M and A signify monthly and annual frequencies, respectively. $\left[\sum_{\tau=0}^{S-1}X_{(t-\tau)/S}^{H}{}'\theta_\tau\right]$ denotes the coefficient of the U-MIDAS regression as extracted from the EViews 12 user's guide. Despite its high flexibility, U-MIDAS necessitates the estimation of a substantial number of coefficients. While it doesn't mitigate the challenge of requiring numerous coefficients, U-MIDAS is applicable in scenarios where only a few lags are necessary, making it commonly employed for comparative analysis.

While Equation (4) lacks control variables, we formulate an additional model to consider the influence of pertinent factors, such as the real exchange rate. (See also, Salisu et al., 2017, 2019).

3.1 The inherent Rules of the ADL-MIDAS Model.
The Autoregressive Distributed Lag-Mixed Data Sampling (ADL-MIDAS) specification of inflation based predictive model for Ghana, The Gambia and Nigeria output is predicted on the following assumption:

Inflation has a major impact on GDP through its effect on the components. This assumption relies on Inflation being classified into demand-pull and cost-push. Demand-pull inflation occurs when aggregate demand exceeds aggregate supply, often leading to increased GDP and rising prices. On the other hand, cost-push inflation is caused by increases in production costs, which may not necessarily be associated with increased GDP. This assumption is important for policy makers to understand the source of effect of inflation on GDP

The model assumes that regressand is of low data frequency, while the regressor is of high data frequency. This hypothesis permits us to use the data in its original form rather than aggregating the latter to suit the former since most inflation is in high frequency.

In relation to equation (2), we additionally posit that the ADL-MIDAS is expected to yield superior forecast accuracy compared to other competing models that solely handle uniform data frequency. This is premised on the fact that by aggregating data in order to make the frequency uniform for all the variables in a predictive model may conceal some salient features inherent in the high frequency series and by extension reduces the precision of the forecasts. Thus, the ADL-MIDAS approach that allows for mixed data frequency of the relevant series will enhance the accuracy of the forecast results.

3.2 Forecast Evaluation Measures
(Clark & West, 2007) introduced the Clark and West test, which is approximately asymptotically normally distributed when applied to nested models. The C.W. statistic is obtained through the following derivation: Where $\hat{y}_f$ is the model forecasts of interest, and $\hat{y}_{rw}$ is the random walk forecasts, while y is the realized values. The Clark West statistic tests against the null hypothesis of equal root mean square errors (RMSE):

$$H_0: RMSE_f = RMSE_{rw-adj} \quad (5)$$

$$H_1: RMSE_f < RMSE_{rw-adj} \quad (6)$$

Where,

$RMSE_f = \sum(y_t - \hat{y}_{f,t})^2$ and,

$RMSE_{rw-adj} = \sum(y_t - \hat{y}_{rw,t})^2 - \sum(\hat{y}_{f,t} - \hat{y}_{rw,t})^2$

Rejection of the null hypothesis indicates that the forecasting model's mean squared prediction error is lower than that of the random walk, which can be interpreted as out-performance of the random walk by the forecasting model (Heidinger el al., 2018).

This study examines out-of-sample forecasts evaluation spanning from 1980 to 2022. The out-of-sample forecast for horizon τ pertains to the period concluding in 2022 + τ – 1. Based on the findings, we recursively generate out-of-sample forecasts using model (5&6). After accounting for initial observations reserved for data differencing and lag determination, the forecast relies on models estimated with data from 1980 + τ – 1. As the forecasting progresses over time, the models' parameters are recalculated, incorporating additional data that becomes available. From recursively estimated models, we obtain two sequences of forecast errors, $\hat{u}_{ADL,t+\tau}$ and $\hat{u}_{AR,t+\tau}$. With the specifications of the sample, we have a total of 43 - τ – 1 forecast for horizon τ. Subsequently, we calculate the RSMEs for these forecasts.

$$RSME_{ADL} = \sqrt{P^{-1}\sum_{t=R}^{R+P-1}\hat{u}_{ADL,t+\tau}^2}, \qquad RSME_{AR} = \sqrt{P^{-1}\sum_{t=R}^{R+P-1}\hat{u}_{AR,t+\tau}^2} \quad (7)$$

Where P denotes the count of τ-step ahead forecasts considered during the sample period, covering observations from $R+\tau$ to $R+\tau+P-1$, and R represents the last observation employed in the regression estimates that form the basis for the initial forecast within the specified period (Clark & McCracken 2006).

IV. RESULTS

This section presents and discusses how inflation predict output in three selected member countries of AFRITAC West 2. The ADL-MIDAS results the data analysis are presented in Table 1, which are based on two competing models – ADL-MIDAS and the AR (1) for both in-sample predictability and out-of-sample forecast with three forecast horizon (h) such as 1- year out-of-sample forecast (h = 1) as the short-run forecast, the 2- years out-of-sample forecast (h = 2) representing medium-term forecast and 4-years out-of-sample forecast (h =4) as the long-term forecast (Salisu and Ogbonna, 2019). The AR (1) is estimated to compare the relevance of including exchange rate in the model. Our results are discussed in three distinct parts, which include the in-sample predictability by comparing the model without control variables and with control variables, assessing the in-sample and out-of-sample forecasts evaluation with and without control variable.

Table 1
Estimate of the ADL-MIDAS for the inflation-output Nexus

Market	Constant	Lag	LCPI	R^2
Without Control				
Nigeria	25.5055*** (0.0633)	Lag 2	0.2172*** (0.0184)	0.7897
Ghana	23.08858*** (0.0605)	Lag 2	5.1510*** (0.0039)	0.9221
Gambia	19.1262*** (0.0685)	Lag 2	0.3826*** (0.0173)	0.9210
With Control				
Nigeria	25.5875*** (0.0768)	Lag 2	0.3494*** (0.0764)	0.8067
Ghana	22.41843*** (0.2194)	Lag 2	3.7777** (1.5883)	0.9393
		Lag 3	-3.3579** (1.5963)	
Gambia	19.1262*** (0.0685)	Lag 2	0.3826** (0.0173)	0.9210
		Lag 3	-2.7146** (1.3931)	

*Note: This table presents the ADL-MIDAS results for the inflation on real GDP growth nexus in Nigeria, Ghana and Gambia, with and without control variable (exchange rate). To control for problem of dimensionality, ADL MIDAS is estimated with AutoGET. The chosen lag length is determined to be the most suitable for the independent variable. By converting the variables into log form, the analysis allows for the calculation of elasticity estimates. Standard errors for each coefficient are shown within parentheses. The symbols ***, **, and * denote levels of statistical significance at 1%, 5%, and 10%, respectively.*

4.1 In-sample Predictability

The results are presented in Table 1 to test the power of the predictor (inflation) in influencing output. Numerous studies have already established a significant link between inflation and economic growth using various methodologies (Seleteng et al., 2013; Ibarra & Trupkin 2016; Ndoricimpa, 2017; Nene et al., 2022 & Umar et al., 2024), our focus diverges to investigate the applicability of ADL-MIDAS in establishing the inflation-output nexus in 3 selected countries member of AFRITAC West 2, as this has not been extensively explored in existing literature. This technique offers a fresh perspective in the field of inflation and growth studies.

The model is estimated with the Auto GETS weighting scheme at lag 3 to drop the insignificant lags. The model is also estimated with and without control variables to test for coefficient stability (Tumala et al., 2022). Thus, if the ADL-MIDAS model incorporating a control variable proves to be statistically significant, it will be chosen as the preferred model. The efficacy of each model is assessed through statistical tool such as R^2, with the ideal model showcasing a higher R^2 value, indicating a coefficient of determination that approaches 1, reflecting superior predictive accuracy. Notably, the result in Table 1 indicates that in Nigeria for the model with no control variable, inflation has a positive and significant effect on the GDP, showing that a one percent increase in inflation will lead to 21.7 percent increase in GDP. This is in line with apriori expectations and the result of Seleteng et al., (2013), but however contrary to the result of Nkwatoh and Mallum (2023), who asserts that a rise in inflation can restrict growth. The findings also remain consistent when including control variables in the model, indicating the robustness of the results across different model types, whether they are bivariate or multivariate. This consistency supports the reliability of the outcome regardless of the model choice. The relationship between inflation and GDP is invariably so because higher prices can lead to increased profits for businesses, potentially allowing them to invest in expansion, creating jobs and further stimulating the economy. Also, when prices rise, consumers may feel the need to purchase goods and services before they become even more expensive, leading to a boost in demand.

In the case of Ghana and the Gambia, there is a positive and significant relationship between inflation and GDP in the model with control variable, indicating that real GDP grows on an average of 5.2 and 38.3 percent, respectively, on account of an increase in inflation by one percent. However, the results seem to vary in the model where exchange rate is introduced as a control variable. The relationship between real GDP and inflation in this case is non-linear and significant, indicating that the impact of inflation on real GDP for Ghana and Gambia could change by intensity, direction or behaviour at different levels of inflation. For example, a small amount of inflation might positively impact growth up to a certain point, but beyond that, additional inflation could be detrimental to growth (see Eggoh & Muhammad, 2014; Ndoricimpa 2017). The results corroborate with theory and validates the study of Jawo et al., (2023) who notes a nonlinear relationship in the growth inflation nexus.

Conversely, the result differs with that of Nigeria and Ghana including Gambia. This might be attributed to the latter two countries' longstanding adoption of more stringent inflation-targeting policies by their Central Banks. These policies likely make Ghana and Gambia more reactive to inflationary trends, possibly dampening the positive short-term relationship between inflation- GDP. Additionally, Gambia's economy, being smaller and less diverse, may exhibit greater sensitivity to external disturbances and policy changes leading to variations in the growth-inflation relationship.

Table 2:
In-Sample Forecast Evaluation using Clark and West test statistic.

Market	Model Without Control versus AR	Model With Control versus AR	Model without Control versus Model with Control
Nigeria	0.4627***	0.4712***	0.0083*
Ghana	1.3699***	1.3808***	0.0108***
Gambia	0.8625***	0.9054***	0.0043**

*Note: ADL-MIDAS model is unrestricted model in the Clark and West test reported in the table, while AR (1) are the restricted model. The column compares ADL MIDAS with the AR (1) model. Without control/ with control compares the in sample of the model of without control variable to the model with control variable. A positive value suggests that the model without restrictions outperforms the competing model, while a negative value indicates the opposite scenario. The symbols ***, **, and * denote levels of statistical significance at 1%, 5%, and 10%, respectively.*

4.2 In-sample forecast evaluation

After presenting the result of the predictability of inflation on output in the 3 countries examined using AR as a baseline and ADL-MIDAS with control and without control, the paper evaluates the in-sample forecast using Clark and West (CW) (2007) test statistic. The CW test was chosen because our model is a nested model and the test unlike other forecast evaluation techniques shows the level of significance. The result presented in Table 3 indicates that the ADL-MIDAS model without control predicts output better than the AR (1). This is evidenced by the positive and significant statistic across the three countries. In the same vein, the ADL-MIDAS with control variable outperforms the AR (1) model. We also evaluate the in-sample forecast performance between the ALD-MIDAS model without control variable and the model that controls for exchange rate. The statistic is positive and significant, implying that ADL-MIDAS with a control variable predicts better than the one without a control variable. This means that although inflation predicts output, it is advisable to control for exchange rate as it increases the predictability of output (see for instance Clark & McCracken 2006) and Salisu et al., 2019).

Table 3
Out-of-Sample Forecast Evaluation using Clark and West test statistics.

Market	Model Without Control versus AR			Model With Control versus AR			Model without Control versus Model with Control		
	AR(1)			AR(1)					
	h = 1	*h = 2*	*h = 4*	*h = 1*	*h = 2*	*h = 4*	*h = 1*	*h = 2*	*h = 4*
Nigeria	0.4942***	0.5246***	0.5900***	0.5052***	0.5378***	0.6087***	0.0087**	0.0089**	0.0094**
Ghana	1.4542***	1.5348***	1.7430***	1.4670***	1.5504***	1.7554***	0.0110***	0.0113***	0.0115***
Gambia	0.9020***	0.9409***	1.0247***	0.9452***	0.9836***	1.0653***	0.0043**	0.0043**	0.0043**

*Note: Each cell contains the Clark and West test value, which compares ADL MIDAS with the AR (1) models in each column, The column Without control/ with control is the comparison between the without control variable model and the with control variable model A positive value suggests that the model without restrictions outperforms the competing model, while a negative value indicates the opposite scenario. Statistical significance of the test values at 1%, 5% and 10% are represented by ***, ** and *, respectively.*

4.3 Out-of-sample forecast evaluation

This study aims to evaluate future economic trends in Nigeria, Ghana, and Gambia using the out-of-sample forecast, we compare two forecasting models: the ADL-MIDAS and the AR (1). The aim is to assess the accuracy of each model in predicting output, peering not just one step ahead into the near future, but also two and four steps for robustness. The Clark and West (2007) test are employed to compare the forecasting performance of different models. In particular, it assesses how well an autoregressive model AR (1) with a certain specification performs against an alternative model, in this case the ADL-MIDAS. The results consistently favours the ADL-MIDAS model across all three countries and all timeframe horizons. This means that the ADL-MIDAS model, considering not only past data but also various economic factors, forecasts the horizon 1, 2 and 4 more effectively than the AR (1).

Additionally, when comparing the model without control and with control using the ADL MIDAS, the model with control (exchange rate) is better off than the model without control in the three countries and for the one-year, two years and four-year forecasts. This suggests that exchange rate has a significant effect on the predictability of inflation on GDP nexus in the countries of focus. Overall, the combination of the performance of the ADL-MIDAS in the case of the in-sample and out-of-sample outweighs the performance of the baseline model of AR (1) and gives validation to the inflation-GDP nexus. The paper also affirms the importance of the MIDAS-based model for improved forecast accuracy of the inflation predictor in the model.

CONCLUSION

This paper investigates the inflation-output nexus in selected AFRITAC West 2 member countries using an Autoregressive Distributed Lag-Mixed Data Sampling (ADL-MIDAS) approach. The results of our analysis reveal nuanced insights into the inflation-output dynamics in Nigeria, Ghana, and Gambia. While a positive relationship between inflation and GDP is observed across all countries, the impact varies depending on accounting for exchange rate. In Nigeria, inflation appears to stimulate economic growth with or without accounting for exchange rate. In Ghana and Gambia, the relationship is more complex, influenced by exchange rate movements. These findings emphasis the need for tailored policy responses that consider country-specific economic conditions and external factors. The study also compares the liner time series AR model with the ADL MIDAS model with both in-sample and out-of-sample forecast using different forecast horizons. The study concludes that the ADL MIDAS model was a better model in predicting output using inflation.

Policy Implication

Nigeria: Given the positive relationship between inflation and GDP, policymakers may consider adopting accommodative monetary policies to stimulate economic growth. However, careful monitoring is necessary to prevent overheating of the economy.

Ghana and The Gambia: In these countries, the impact of inflation on GDP is more nuanced, hence, policymakers should adopt a cautious approach to monetary policy, considering the potential adverse effects of inflation on economic stability. This may involve keeping an eye on exchange rate while implementing the inflation-targeting policies to ensure price stability while promoting sustainable growth.

Ghana and The Gambia: The inclusion of exchange rate as a control variable highlights its significance in shaping the inflation-output relationship. Policymakers should prioritize measures to strengthen exchange rate management, including interventions to enhance exchange rate stability and mitigate the impact of external shocks on the economy.

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