Revisiting the accuracy of inflation forecasts in Nigeria: The oil price-exchange rate-asymmetry perspectives

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Abstract

Motivated by the distinctive paradoxical nature of the Nigerian economy as the only OPEC oil-exporting economy that yet depends heavily on the importation of gasoline, we are compelled to re-examine the accuracy of the oil-based augmented Philips curve model in the predictability of inflation. Using quarterly data from 1970 to 2020, we investigate whether including the exchange rate into the oil price-based augmented Phillips curve improves the accuracy of forecasting inflation for the Nigerian economy. We rely on the outcomes of our preliminary analysis to account for the presence of endogeneity, persistence, and conditional heteroscedasticity in the predictability of inflation following the Westerlund & Narayan (2015) procedure. We find the extended variant of the oil price-based Phillips curve model that includes the exchange rate pass-through as most accurate for improving inflation forecasts in Nigeria. Given the robustness of our results from several models, we conclude that the exchange rate channel through which shocks to the oil price transmit into the economy is essential for forecasting inflation.

JEL Classification: E53, E31, E37

Keywords: Nigeria, Inflation forecasts, Phillips curve, Oil price-exchange rate asymmetry

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1 Introduction

Low and stable inflation remains a key objective of monetary policy in most countries across the globe. But achieving this objective can be quite challenging in the absence of a reliable inflation forecasting framework. Since monetary policy and its ultimate success in achieving price stability depends, among others, on the likely path of inflation, the quest for more accurate and reliable inflation forecasts cannot be overemphasized. At least not for developing economies whose inflation dynamics are relatively more complex than those of advanced economies (see Kapur, 2013). Essentially, there have been increasing efforts to improve inflation forecasts, both in terms of methodology and efficiency of the predictors. However, while the Phillips curve remains the workhorse of many predictive models in forecasting inflation, its restrictiveness to a single approach of forecasting inflation has continued to fuel doubt on its usefulness to do so accurately. Confirming this position is the submission by Atkeson & Ohanian (2001) that the Phillips curve-based forecast tends to give larger out-of-sample prediction errors than a simple random walk forecast of inflation (see also Cecchetti *et al.*, 2000; Stock & Watson, 1999, 2001, 2002).

Motivated by the assertion that the problem with the Phillips curve is due to the simplicity of its specification, Stock & Watson (2003) and Brave & Fisher (2004) extend the analysis to include additional activity predictors. Findings from these studies confirm the dominance of the autoregressive random walk model as the most appropriate to forecast inflation (see, for example, Ang, Bekaert & Wei, 2007; Canova, 2007; Matheson, 2006; Stock & Watson, 2007). It is in this light, among others, that Stock & Watson (2008) questioned the usefulness of the Phillips curve or the activity-based predictive model in forecasting inflation (see Banbura & Mirza, 2013; Diron & Mojon, 2008). For instance, the actual inflation movements are influenced not only by demand-side pressures but also by supply-side shocks. Consequently, much research effort has recently been directed towards understanding the extent to which supply-side shocks such as changes in oil price matters in the Phillips curve predictability of inflation (see Adelakun & Ngalawa, 2020; Brown & Cronin, 2010; Chen *et al.*, 2014; Ciner, 2011; Fernandez, 2014; Frankel, 2013; Gelos & Ustyugova, 2016; Kagraoka, 2015; Karlsson & Karlsson, 2016;Richards *et al.*, 2012; Salisu *et al.*, 2018; Salisu & Isah, 2018; Tule *et al.*, 2020).

Notwithstanding the above, most of the aforementioned studies are rooted mainly on the cost-push side of inflation, where oil is seen as an input to production. This raises yet another concern on whether their findings of improved inflation forecasts are sensitive to the oil-importing/oil-exporting peculiarity of the cases investigated. For example, in oil-importing economies where oil is seen as an important input in the production process, an upward trend in oil price movements is expected to increase the general price level through higher production costs. For oil-exporting economies on the other hand, particularly those relying on oil earnings to finance government expenditure, shocks to the oil price will first and foremost affect their economies through fiscal channels and then the general price level through exchange rate pass-through.

From the preceding discussion, it is clear that the impact of an oil price change for inflation forecasting purposes cannot be isolated from the channels through which such shocks transmit to the economy. Thus, while acknowledging that there has been growing efforts to evaluate the accuracy of the oil price-based augmented Phillips curve [henceforth OP-APC] in the forecasting of inflation (see Adelakun & Ngalawa, 2020; Tule *et al.*, 2020), it is instructive that these extant studies have continued to ignore some key insights in their methodological approach such as the perspective of oil-exporting versus oil-importing economies. Beyond extending the Phillips curve to include oil price-based supply-side shocks, it is not clear the extent to which the non-consideration of the channel through which shocks to oil price transmits into the economy is likely to undermine the accuracy of the inflation forecast. In this study, we thus evaluate the role of the exchange rate in the accuracy of OP-APC inflation predictability model.

The rest of the paper is structured as follows: Section 2 discusses the contribution of the study to the literature and the motivation for choosing the economy under investigation. The next section presents the estimation model, including the forecast performance measures. The data used in the study and some other some preliminary information are then outlined in Section 4. The pen-ultimate section presents and discusses the empirical results, while the last part concludes the study.

2 Motivation for the Study and Contribution to the Literature

As indicated to previously, we choose the Nigerian economy as our case-study becuase it remains one of the few top oil-producing countries that yet depends so heavily on the importation of gasoline. In other words, Nigeria is the only OPEC member that relies on proceeds from oil exports mainly to ensure a constant supply of foreign exchange to meet her high gasoline import bills. Unlike Tule *et al.* (2020) whose study mainly identifies with changes in the oil price as the potential for enhancing the accuracy of inflation forecasting in Nigeria; this study rests on the oil-exporting–fuel-importing paradox feature of the Nigerian economy to hypothesise as follows: it is incorrect to treat all changes in the dollar-price of oil as exogenous in a predictive model without taking cognizance of the channel through which oil price shocks transmits into the economy.

Theoretically, the terms of trade channel linking the oil price and the exchange rate posit that a depreciation of currencies will follow an oil price increase in countries with large oil dependence in the tradable sector (Amano & van Norden, 1998; Benassy-Quere *et al.*, 2007). There are then also the wealth and portfolio channels, which assert that when the oil price rises, wealth is transferred to oil-exporting countries, and this is reflected in an improvement in the current account balance. With oil-exporting countries' currencies likely to appreciate, the reverse is expected for oil-importing economies (Golub, 1983;

Buetzer *et al.*, 2016; Krugman, 1983; Turhan *et al.*, 2014;). Based on this theoretical position, it thus emerges that the exclusion of exchange rate in any empirical analysis of the impact of oil supply shocks might lead to incorrect estimates of the impact of such shocks since the exchange rate has been proven to be *the* channel through which shocks to the oil price transmits into the economy (see Ahmad & Hernandez, 2013; Aloui *et al.*, 2013; Atems *et al.*, 2015; Bal & Rath, 2015; Bouoiyour *et al.*, 2015; Chen, 2016; Chou & Tseng, 2015; Fowowe, 2014; Jiang & Gu, 2016; Le & Chang, 2011; Park & Ratti, 2008; Roberodo, 2012; Turhan *et al.*, 2014; Yang *et al.*, 2017).

One of the main contributions of this present study is to test whether the augmented oil price-based Phillips curve model that includes the exchange rate as the channel through which shocks to the oil price transmits into the economy will render better inflation forecasts. Secondly, in addition to the inclusion of this factor, there has been an emerging debate on whether the nexus between the oil price and the exchange rate is linear or nonlinear. Indeed, this concern has been given considerable attention in the literature, with several of the extant studies affirming that there are asymmetries in the nexus.[1] However, while many previous studies forecast inflation using nonlinear models (see Ascari & Marrocu, 2003; Marcellino, 2008; Moshiri & Cameron, 2000), to our knowledge, little attention has been paid to the sensitivity of the role of the exchange rate in the oil-price forecast of inflation to the linear or nonlinear channels of exchange rate pass-through.

In view of the above, including the exchange rate for enhancing the forecast accuracy of the OP-APC model in predicting inflation may yet also muddle whether the shock is trasmitted in a linear (symmetric) or nonlinear (asymmetric) fashion. To accommodate for this concern, we further disaggregate the exchange rate channel in the proposed modified OP-APC model into positive and negative changes in exchange rates, which equally depicts currency depreciation and appreciation, respectively. Methodologically, the predictive models considered in this context are constructed to accommodate the statistical features of the considered series (see Table 1). Finally, we test the robustness of our findings by comparing the forecast performance of our preferred augmented Phillips curve predictive model to several conventional time-series predictive models used previously in the literature.

3 Model and Estimation Procedure

3.1 The model

As a starting point to our proposed modified OP-APC predictive model to include the role of exchange rate pass-through, the traditional demand-side-based Phillips curve model (TPC) is specified in equation (1) as follows:.

$$\pi_t = \alpha + \beta\pi_{t-1} + \lambda(InY - In\bar{Y}) + \varepsilon_t^s \tag{E1}$$

[1] See Alqaralleh (2020) for an extensive review on the asymmetric response of the exchange rate to an oil price shock.

where $\pi_t \equiv \ln P_t - \ln P_{t-1}$ is inflation and $(\ln Y_t - \ln \bar{Y}_t)$ is the output gap (yg) such that Y_t is the actual output and $\bar{Y}_t$ is the potential output that is being measured using the Hodrick Prescott (henceforth HP) filter, while the ε_t^s term is the aggregate supply curve. But as highlighted by Phillips & Shi (2019), the HP filter suffers from the same criticism as the linear trend method since it is mechanical and not based on economic theory. Notwitstanding these limitations, the HP filter has the advantage (over the linear trend method) of making the output gap stationary over a wide range of smoothing values, in addition to allowing the output trend to change over time.

Theoretically, inflation is expected to rise when actual output is greater than expected output; hence we predict a positive relationship between the output gap and inflation. To augment the Phillips curve model in equation (1) with a supply-side oil price-based shock, we follow the Çatik & Önder (2011) approach to rewrite the backward-looking Phillips curve equation as:

$$\pi_t = \alpha + \beta(L)\pi_t + \lambda(L)\, yg_t + \delta(L)op_t + \varepsilon_t^s. \tag{E2}$$

Equation (2) is the OP-APC predictive model where $\beta(L)$, $\lambda(yg)$, and $\delta(op)$are the polynomial in the lag operator of inflation rate, the output gap, and changes in the oil price, respectively. However, while the estimated coefficients of all parameters, for instance, $\beta, \lambda$and$\delta$are predicted to be positive, it is instructive that the magnitude of the parameter δmight be sensitive to the structure of the economy under consideration (see Çatik & Önder, 2011; Marquez, 1984; Salisu *et al.*, 2017). For the probable effects of changes in the relative price associated with the country's importation of oil-related intermediates, we capture these via the exchange rate pass-through as

$$\pi_t = \alpha + \beta(L)\pi_t + \lambda(L)\, yg_t + \delta(L)op_t + \psi(L)er_t + \varepsilon_t^s. \tag{E3}$$

Equation (3) is the proposed extended version of the OP-APC predictive model that includes the role of exchange rage rate pass-through. However, pertinent to this study is whether shocks to the oil price transmission into the economy via the exchange rate pass-through matter for the forecast accuracy of inflation in Nigeria. Hence, to ensure that the exchange rate in equation (3) does not merely imply the addition of a regressor in the equation, we further re-represent the oil price exchange rate mechanism in the specification in an interactive form as

$$\pi_t = \alpha + \beta(L)\pi_t + \lambda(L)\, yg_t + \delta(L)op_t + \psi(L)er_t + \Phi(L)op_t * er_t + \varepsilon_t^s \tag{E4}$$

The emphasis in equation (4) is on the statistical significance of the interaction coefficient, and whether the forecasting power of oil price-based supply-side shock is more accurate when captured via the exchange rate pass-through. To evaluate whether asymmetries matter in the role of exchange rate pass-through for enhancing the forecasting accuracy of the oil-based augmented Phillips curve model, we partition the exchange rate pass-through into positive and negative changes in the exchange rate as

$$\pi_t \;=\; \alpha + \beta(L)\pi_t \;+\; \lambda\,(L)\,yg_t \;+\; \delta(L)op_t \;+\; \psi^+(L)er_t^+ \;+\; \psi^-(L)er_t^- \\ +\; \Phi^+(L)op_t * er_t^+ \;+\; \Phi^-(L)op_t * er_t^- + \varepsilon_t^s \tag{E5}$$

where er_t^+ and er_t^- are, respectively, the positive and negative partial sum of exchange rate pass-through, defined as below following the Shin *et al.* (2014) procedure. $er_t^+ = \sum_{j=1}^{t} \Delta er_j^+ = \sum_{j=1}^{t} \max(\Delta er_j,\, 0)$ and $er_t^- = \sum_{j=1}^{t} \Delta er_j^- = \sum_{j=1}^{t} \min(\Delta er_j,\, 0)$

The intuition behind equations (5) & (6) is to determine whether the transmission of oil price shocks via the exchange rate varies for an exchange rate depreciation (positive change in the exchange rate) compared to an exchange rate appreciation (negative change in the exchange rate). If they do, then the exchange rate role in the oil price-inflation forecast is likely to be asymmetrical. And, if otherwise, then incorporating such asymmetries is likely to produce less optimal results when compared to the symmetric variant.

3.2 Estimation Technique - The Westerlund & Narayan Procedure

As reported in Section 4 below, there is evidence of a mixed order of integration of the data series; conditional heteroscedasticity (becuase of the high-frequency of the data); endogeneity bias (due to the exclusion of some important predictors), and lastly, persistence due to the dynamic behaviour of economic agents. Thus, estimating the predictive model(s) in equations (1) through to (5) with the conventional OLS is likely to be biased to some, if not all, of these statistical features, as exhibited both by the predicting and predictor series (see Table 1).

In view of the above, we adjust the predictive models in line with the Westerlund & Narayan (2012, 2015) procedure, particularly to account for the inherent statistical features of the series. This procedure has been consistently validated empirically in the literature as reliable when forecasting with historical and high-frequency data (see Devpura *et al.*, 2018; Isah & Raheem, 2019; Narayan & Bannigidadmath, 2015; Narayan & Gupta, 2015; Salisu *et al.*, 2019; Salisu & Isah, 2018; Tule *et al.*, 2020). Our adjusted predictive model to forecast inflation in Nigeria is therefore as follows:

$$\pi_t = \alpha + \beta^{Adj} x_{t-1} + \delta\,(x_t - \rho x_{t-1}) + \eta_t \tag{E6}$$

where π_t remained as previously defined and x_t is a potential predictor of inflation (π_t) which is output gap (yg_t) in the case of bivariate traditional Phillips curve (TPC) model in equation (1). Correspondingly, the x_t in the case of the multivariate predictive model of equations 2, 3, 4 & 5 includes not onlyyg_t but op_t & ex_t, as well as the asymmetric feature as in the case of equation 5.

The above procedure, known as the Lewellen (2004) approach, adjusts for the probable biasedness in the OLS estimator of β. But this Lewellen estimator mainly captures (only) endogeneity and persistence effects (including any inherent unit root problem in the predictor series), whereas the Feasible Quasi Generalized Least Squares (FQGLS) estimator of Westerlund & Narayan (2015) captures these effects and, additionally, information on any conditional heteroscedasticity.

The FQGLS estimator assumes that the regression error, i.e. η_t, follows an autoregressive conditional heteroscedasticity (ARCH) structure $\hat{\sigma}^2_{\eta,t} = \mu + \sum_{i=1}^{q} \varphi_i \hat{\eta}^2_{t-i}$, so that the resulting $\hat{\sigma}^2_{\eta,t}$ may then be used as a weight in the predictive model (see Devpura *et al.*, 2018; Isah & Raheem, 2019; Narayan & Bannigidadmath, 2015; Narayan & Gupta, 2015; Salisu *et al.*, 2019, 2020; Salisu & Isah, 2018; Tule *et al.*, 2020). Basically, the GLS-based t-statistic for testing $\beta = 0$ is given as below (see Westerlund & Narayan, 2015):

$$t_{FQGLS} = \frac{\sum_{t=q_m+2}^{T} \tau_t^2 x_{t-1}^d r_t^d}{\sqrt{\sum_{t=q_m+2}^{T} \tau_t^2 \left(x_{t-1}^d\right)^2}} \tag{E7}$$

where $\tau_t = 1/\sigma_{\eta,t}$ is used in weighting all data in the predictive model and $x_t^d = x_t - \sum_{s=2}^{T} x_t/T$.

For the purpose of our analyses, we consider the following pair of predictors:

$$\pi_t = \alpha + \beta yg_{t-1} + \delta\left(yg_t - \rho yg_{t-1}\right) + \eta_t \tag{E8a}$$

$$\begin{aligned}\pi_t = \alpha + \beta_{yg} yg_{t-1} + \beta_{op} op_{t-1} + \delta_{yg}\left(yg_t - \rho_{yg} yg_{t-1}\right) \\ + \delta_{op}\left(op_t - \rho_{op} op_{t-1}\right) + \eta_t\end{aligned} \tag{E8b}$$

$$\begin{aligned}\pi_t = \alpha + \beta_{yg} yg_{t-1} + \beta_{op} op_{t-1} + \beta_{er} er_{t-1} + \beta_{op*er} op * er_{t-1} \\ + \delta_{yg}\left(yg_t - \rho_{yg} yg_{t-1}\right) + \delta_{op}\left(op_t - \rho_{op} op_{t-1}\right) + \delta_{er}\left(er_t - \rho_{er} er_{t-1}\right) \\ + \delta_{op*er}\left(op * er_t - \rho_{op*er} op * er_{t-1}\right) + \eta_t\end{aligned} \tag{E8c}$$

$$\begin{aligned}\pi_t = \alpha + \beta_{yg} yg_{t-1} + \beta_{op} op_{t-1} + \beta_{er^+} er_{t-1}^+ + \beta_{er^-} er_{t-1}^- + \beta_{op*er^+} op * er_{t-1}^+ \\ + \beta_{op*er^-} op * er_{t-1}^- + \delta_{yg}\left(yg_t - \rho_{yg} yg_{t-1}\right) + \delta_{er^+}\left(er_t^+ - \rho_{er^+} er_{t-1}^+\right) \\ + \delta_{er^-}\left(er_t^- - \rho_{er^-} er_{t-1}^-\right) + \delta_{op*er^+}\left(op * er_t^+ - \rho_{op*er^+} op * er_{t-1}^+\right) \\ + \delta_{op*er^-}\left(op * er_t^- - \rho_{op*er^-} op * er_{t-1}^-\right) + \eta_t\end{aligned} \tag{E8d}$$

Equation (8a) represents the traditional Phillips curve (TPC), while its augmented variant (OP-APC), capturing the supply-side shock via changes in oil prices, is expressed in equation (8b). The proposed extended variant of equation (8b) that includes the role of exchange rate pass-through (OP-APC-ER) is represented in equation (8c). And lastly, equation (8d) is OP-APC-ASY:ER i.e. the asymmetric variant of equation (8c), where the pass-through of the exchange rate is captured in a nonlinear form via a partial sum of positive and negative changes in the exchange rate.

3.3 Forecast Performance Evaluation Measures

Since in-sample forecasts are insufficient to assume out-of-sample forecast gains, the forecast power of the predictive models will be evaluated for both the in-sample and out-of-sample periods. Taking cognizance o;f the time-varying feature of both the predicted and predicting series, we explore a recursive window approach to generate the forecast results. To evaluate the forecast performance, the accuracy of each model is measured separately [using the Root Mean Square Error (RMSE), Mean Square Error (MSE) and Mean Absolute Error (MAE) measures] and these are then complemented using the pairwise method of Campbell–Thompson (2008) and Clark & West (2007).

Mathematically, the Campbell-Thompson statistic [henceforth; C-T test], often described as the out-of-sample R-squared (OOS_R^2) is computed as $OOS\_R^2 = 1-(M[ERR : macc : iOp = 0x0311]E_2/M[ERR : macc : iOp = 0x0311]E_1)$, where $M[ERR : macc : iOp = 0x0311]E_2$ and $M[ERR : macc : iOp = 0x0311]E_1$ are the mean square errors associated with the out-of-sample forecast based on TPC, OP-APC and OP-APC*ER, and OP-APC-ASY:ER, respectively. When comparing the TPC and OP-APC, the latter is the unrestricted model because it is nested off the former. Contrarily, when the OP-APC and OP-APC-ER are compared, the OP-APC will be the restricted model because it is nested within the former. Lastly, for a comparison between the OP-APC-ER and the OP-APC-ASY: ER, the latter, reflecting a non-linear (asymmetric) exchange rate will be regarded as the unrestricted predictive model, with the former linear one being nested within it

Given the above, a positive C-T statistic will suggest that the OP-APC outperforms the TPC model, and vice versa if negative. Likewise, it will also imply that including the exchange rate in the augmented oil price-based Phillips curve model will be more accurate for forecasting inflation in Nigeria. Finally, when the comparison is between the predictive models with an asymmetric exchange rate (OP-APC-ASY:ER) and the ones without (OP-APC-ER), then a positive C-T statistic hypothetically implies the predictive model with asymmetry is the most accurate at forecasting inflation.

To further enhance the C-T test for the purposes of evaluating of nested models, we complement it with the Clark and West (2007) test [henceforth C-W]. This is done to further ascertain the *statistical* significance of the forecast evaluation results. The underlying procedure for the C-W test involves calculating the following:

$$\hat{\pi}_{t+k} = \left(\pi_{t+j} - \hat{\pi}_{1t,t+j}\right)^2 - \left[\left(\pi_{t+j} - \hat{\pi}_{2t,t+j}\right)^2 - \left(\hat{\pi}_{1t,t+j} - \hat{\pi}_{2t,t+j}\right)^2\right] \tag{E9}$$

where j is the forecasting period; $\left(\hat{\pi}_{t+j} - \hat{\pi}_{1t,t+j}\right)^2$ is the squared error for the restricted model and $\left(\pi_{t+j} - \hat{\pi}_{2t,t+j}\right)^2$ for the unrestricted model, respectively, depending on the comparison of interest.

The $\left(\hat{\pi}_{1t,t+j} - \hat{\pi}_{2t,t+j}\right)^2$ in equation (9) is the adjusted squared error introduced by C-W to correct for any noise associated with the larger model's forecast. Thus, the sample average of $\hat{f}_{t+k}$ can be expressed as: $MSE_1 -$

$(MSE_2 - adj)$ and each term is computed as:

$$MSE_1 = N^{-1} \sum (\pi_{t+j} - \hat{\pi}_{1t,t+j})^2;$$

$$MSE_2 = N^{-1} \sum (\pi_{t+j} - \hat{\pi}_{2t,t+j})^2; and$$

$$adj. = N^{-1} \sum (\hat{\pi}_{1t,t+j} - \hat{\pi}_{2t,t+j})^2.$$

To test for the equality of forecast performance between the restricted and unrestricted models, the $\hat{f}_{t+k}$ is regressed on a constant only. The resulting t-statistic is then used to draw the correct inference for the null hypothesis predicting equality of the MSEs.

4 Data and Preliminary Analyses

The highest accessible frequency for the output gap (YG)series for Nigeria, measured as the log of the difference between the actual output and the potential output, is at a quarterly interval. Hence, we restrict all other variables to quarterly frequency even though some are available in monthly frequency. Essentially, the log of the first difference of the consumer price index is used to proxy for inflation (π), while the supply-side component of the Phillips curve is proxied using the log of the West Texas Intermediate (WTI) crude oil prices. The exchange rate (er) is measured against the United States Dollar (USD) as the reference currency, for instance, the log of Naira/USD. Data for all the variables of interest were obtained from International Financial Statistics (IFS), but the oil price was sourced from the US Energy Administration Information (EIA).

The starting date for the sourced data is the first quarter of 1970, and its end date is the first quarter of 2020, totaling 201 observations. Not in line with any theoretical guidance though, researchers typically used 25%, 50% or 75% of the full sample as the in-sample period for estimation, and the balance for the out-of-sample forecast periods (see Narayan & Gupta, 2015; Salisu *et al.*, 2018; Salisu & Isah; 2018, Tule *et al.*, 2020). However, our preference for the 50% of total observations as sufficient for the in-sample period is motivated by our relatively large sample size when compared to the number of observations used in other studies (e.g. Tule *et al.*, 2020). In addition, we also consider multiple out-of-sample forecast horizons such as two-quarter $(h = 2)$, four-quarter $(h = 4)$, and six-quarter $(h = 6)$ periods ahead forecasts.

We offer some preliminary analyses on the statistical features of the series as depicted in Table 1, as justification for the choice of methodology adopted in this study. Starting with the descriptive statistics, the standard deviation portrays all the series as highly volatile, the only notable exception being the output gap series. The skewness statistic is non-zero, and together with the fat tail in the kurtosis statistic, corroborating this tendency of high dispersion in both the predicted and predictors series. Part A of Table 1 also reports the stochastic property of the series using the ADF unit root test. The predicting series (i.e.

the inflation rate) is stationary at level, but otherwise for the various predictors under consideration. This is not surprising, however, since the inflation rate is first differenced and therefore expected to be stationary. The predictors, on the other hand, are all logged in their respective levels, clarifying why they are become stationary only after first differencing.

Notwithstanding the mixed order of integration of the series, the stochastic behaviour of both the predicting and predictor series aligns with the chosen methodology. For example, in Table 1B, the pre-estimation results for autocorrelation and conditional heteroscedasticity using the Ljung-Box and ARCH-LM tests, respectively, are presented. Irrespective of lag lengths, serial dependence and conditional heteroscedasticity are found in all the series at the conventional levels of significance. There is likewise evidence of a high degree of persistence and endogeneity bias in the predictor series (see Table 1C). These outcomes though, are not unexpected for series that are integrated of higher order (see unit root testing results). But ignoring them can undermine the forecasting power of these predictors of inflation and therefore validates our preference for the Westerlund & Narayan (2012, 2015) procedure as the most appropriate estimator to accommodate these underlying statistical features.

5 Empirical Results and Discussion of Findings

5.1 Predictability Test Results

The broad objective of this study is to examine the extent to which inclusion of the exchange rate pass-through to the oil price–based augmented Phillips curve improves the accuracy of inflation forecasts in Nigeria. We begin by testing the predictability of the predictors. Table 2 presents the bias-adjusted GLS estimates for each of the predictors across both the single-factor and multiple-factors-based predictive models under consideration.

Starting with the TPC model, we find a positive and significant impact of the output gap (yg) on inflation which conforms with our *apriori* expectation and findings in previous studies (see Salisu *et al.*, 2018, Salisu & Isah, 2018; Tule *et al.*, 2020). Furthermore, the positive sign on the coefficient on changes in the oil price in the OP-APC predictive model supports the hypothesis of a positive relationship between the oil price and inflation. However, unlike in Tule at al. (2020), the significance of the inflationary impact of changes in the oil price is statistically relatively more significant when the oil price is interacted with the exchange rate in the extended OP-APC predictive model (i.e. OP-APC-ER). This, among others, supports the trade channel link between the oil price and the exchange rate. Thus, ignoring the exchange rate as the channel through which shocks to the oil price transmits into the economy may bias the accuracy of the Phillips curve forecast of inflation.

On whether asymmetries matter in the exchange rate predictability of inflation, we find the coefficient on positive changes in exchange rates (i.e., an exchange rate depreciation) to be positively signed and statistically significant.

On the other hand, however, the coefficient on negative changes in exchange rates (i.e., an exchange rate appreciations) is negatively signed but statistically *in*significant. This further strengthens our hypothesis that asymmetries matter on the extent to which the exchange rate is capable of enhancing the forecasting power of oil prices in the predictability of inflation. Complementing our predictability test results is the graphical illustration of the actual and predicted inflation series across the various Phillips curve models under consideration. Figures 1.1 and 1.2 present the actual and predicted inflation series obtained from the TPC and OP-APC predictive models, respectively. Similarly, Figures 2.1 and 2.2 present the actual and predicted inflation series obtained from the OP-APC-ER and OP-APC-ASY:ER predictive models, respectively. Compared to Figure 1, the predicted inflation series in Figure 2 appears to have tracked the actual inflation series relatively better. Moreover, in addition to extending the OP-APC predictive models to include the exchange rate pass-through, the model with a nonlinear (asymmetric) exchange rate pass-through (Fig. 2.2) tends to track the actual inflation series far better. This supports our hypothesis that nonlinearity (i.e. asymmetries) in the exchange rate pass-through matters for improving the exchange rate's forecasting power of inflation.

5.2 Forecast Performance Results

It is evident from the preceding section that there is overwhelming evidence for the rejection of the null hypothesis of no predictability, particularly when the oil price-based augmented Phillips curve is extended to include the exchange rate. Hence, the innovation here is to determine which variant of the predictive models under consideration is the most accurate in terms of the predictability of inflation in Nigeria. In this regard, Table 3 presents the in-sample and out-of-sample forecast performances of the respective predictive models under consideration.

As in Tule *et al.* (2020), we find the RMSE, MSE and MAE values to be smaller for the OP-APC when compared to the TPC. Moreover, a further look at Table 3 indicates that these are relatively even smaller for the Phillips curve model that includes not only the oil price but also the exchange rate simultaneously. Thus, unlike Tule *et al.*'s (2020) study, which primarily augments the Phillips curve model with the oil price only, the current study is innovative in that interacting the oil price with the exchange rate is critical to improving the accuracy of the inflation forecast in Nigeria.We find this position particularly pronounced when the exchange rate in the predicive model is captured in a nonlinear form to account for the role of asymmetries.

We conclude, based on our consistent findings for both in-sample and out-of-sample forecasts, that, in addition to the oil price, accounting for exchange rate and its asymmetric feature is important for ensuring the accuracy of inflation forecasts. This suggests that combining the Phillips curve model with not only the oil price but also the exchange rate and its asymmetries is the most accurate predictive model (i.e., OP-APC-ASY: ER) from among those tested for forecasting inflation in Nigeria.

To ascertain the reliability of our preference for the OP-APC-ASY:ER, we further complement the RMSE, MSE, and MAE approaches to forecast performance evaluation with the pairwise-methods of the C-T and C-W tests, respectively. Starting with the former, since the C-T test statistics in Table 4 are all positive it suggests that whilst the OP-APC-ER is better than the OP-APC, the OP-APC-ASY: ER is still overall the most preferred model. For the significance or otherwise of these C-T test results, the C-W test is then employed.

The underlying intuition is to determine whether the difference between the forecast errors of two nested models (i.e., OP-APC-ER and OP-APC-ASY:ER) is statistically significant. A non-rejection of the null of the C-W test implies identical forecasting accuracy between the two models, whilst a rejection favours the OP-APC-ER against OP-APC, and the OP-APC-ASY: ER against the OP-APC-ER. Since the results are statistically significant (at the 5% level), we again find support for the earlier inference that the model that includes both the oil price and exchange rate simultaneously (OP-APC-ER) outperforms the model that includes the oil price only. Likewise, these results also confirm the superiority of the model that included asymmetries in the exchange rate as the most accurate, overall, in the predictability of inflation in Nigeria.

5.3 Robustness Check

To further ascertain the reliability of our preferred model (OP-APC-ASY:ER) as the most accurate for inflation forecasts in Nigeria, we further test its robustness relative to forecasts based on time-series models. The time-series models considered in the context of this study are the Historical Average (HA), the Autoregressive Integrated Moving Average (ARIMA), and the Autoregressive Fractional Integrated Moving Average (ARFIMA). However, while the HA model only required a reduced form of equation (6) such that;

$$\pi_t = \alpha + \varepsilon_t^s \tag{E10}$$

the generalised specification for ARIMA (p,d,q) is as given below.

$$\left(1 - \sum_{i=1}^{p} \rho_i B^i\right) (1 - B)^d (c_t - \psi) = \left(1 + \sum_{i=1}^{q} \theta_i B^i\right) \varepsilon_t \tag{E11}$$

where ψ is the drift parameter, $(1 - B)^d$ denotes the difference operator, p and q are the maximum lags for c_t and ε_t respectively. The order of integration is d, that is, the number of times c_t is differenced to obtain stationarity. However, since c_t is integrated of order 1, a simple representation of equation (11) which is an ARIMA(1,1,1) is considered and it is specified as:

$$\Delta c_t = \psi + \varepsilon_t + \theta_1 \varepsilon_{t-1} \quad . \tag{E12}$$

In the case of the ARFIMA model, the$(1 - B)^d$can be defined as the fractional differencing operator described in a natural way by using the binomial expansion for any real number$d$ with Gamma function as:

$$(1-B)^d = \sum_{k=0}^{\infty} \binom{d}{k} (-B)^k = \sum_{k=0}^{\infty} \frac{\Gamma(d+1)(-B)^k}{\Gamma(k+1)\Gamma(d+1-k)} \tag{E13}$$

where $\Gamma(\cdot)$ denotes the generalized factorial function. The parameter $d \in (-0.5, 0.5)$ and restricting d to integer values gives rise to the standard ARIMA model. Thus, the general form of the ARFIMA(p, d, q)process is defined as:

$$\Phi(B)(1-B)^d c_t = \Omega(B)\varepsilon_t. \tag{E14}$$

The essence is to test whether our preferred variant of the augmented Phillips curve model will outperform a typical time-series predictive models such as the HA, ARIMA, and ARFIMA to predict inflation in Nigeria.

Together, both the C-T and C-W statistics in Table 5 and Figures 3.1 to 3.4 below consistently show that the OP-APC-ASY:ER outperforms each of the time series models considered. We find the robustness of this evidence evident across both in-sample and out-of-sample forecasts.

6 Concluding Remarks and Policy Implications

Motivated by the distinctive paradoxical nature of the Nigerian economy as the only OPEC oil-exporting economy that yet depends heavily on the importation of gasoline, we were compelled to re-examine the accuracy of the oil-based augmented Philips curve model in the predictability of inflation. Essentially, we explored historical quarterly frequency data between 1970 and 2020 to examine whether extending the oil price-based augmented Phillips curve to include the channel through which changes in oil prices are transmitted into the economy matters for improving the accuracy of inflation forecasts in Nigeria.

Methodologically, we predicated the outcomes of our preliminary analysis on the Westerlund and Narayan (2015) procedure as the most appropriate to accommodate the presence of endogeneity, persistence, conditional heteroscedasticity, and other inherent statistical features exhibited by the series under consideration. Both the single method and pairwise approaches to evaluating forecast performance consistently gave preference to the extended variant of the oil price-based Phillips curve that includes the role of exchange rate pass-through as the most accurate for improving inflation forecasts in Nigeria.

Furthermore, when the exchange rate pass-through is captured in nonlinear form, we found improved inflation forecasts. This confirmed our hypothesis that asymmetries matter in the extent to which exchange rate pass-through enhances the forecasting power of oil prices in the Phillips curve predictability of inflation. We tested the robustness of our finding by comparing the forecast performance of the OP-APC-ASY:ER to that of time-series models (HA, ARIMA, and ARFIMA). The outcomes consistently favoured the OP-APC-ASY:ER predictive model as the most accurate for inflation forecasting in Nigeria.

On the whole, our results are robust to different measures of forecast performance and across both in-sample and out-of-sample forecasts. Thus, considering the exchange rate as the channel through which shocks to oil prices are transmitted into the economy seems essential for improving the predictability of inflation. More importantly, our findings can be used to provide to Nigeria's monetary policymakers a more accurate approach to inflation forecasting for the economy.

References

[1] Adelakun, O.J. and Ngalawa, H. (2020). The role of oil prices in Philips curve modelling and forecasting of inflation. Journal of Economic and Financial Sciences 13(1), pp. 1-11.

[2] Ahmad, A.H. and Hernandez, R.M. (2013). Asymmetric adjustment between oil prices and exchange rates: empirical evidence from major oil producers and consumers. Journal of International Finance, Market, Institution and Money, 27, pp. 306–317.

[3] Aloui, R., Aïssa, M.S.B. and Nguyen, D.K. (2013). Conditional dependence structure between oil prices and exchange rates: A copula-GARCH approach. Journal of International Money and Finance, 32, pp. 719-738.

[4] Alqaralleh, H. (2020). On the asymmetric response of the exchange rate to shocks in the crude oil market. International Journal of Energy Sector Management, 14(4), pp. 839-852.

[5] Amano, R. and Van Norden, S. (1998). Exchange rates and oil price. Review of International Economics, 6(4), pp. 683-694.

[6] Ang, A., Bekaert, G. and Wei, M. (2007). Do Macro variables, asset markets, or surveys forecast inflation better? Journal of Monetary Economics, 54, pp. 1163-1212.

[7] Ascari, G. and Marrocu, E. (2003). Forecasting inflation: A comparison of linear Phillips curve models and nonlinear time series models. Working Paper CRENoS 200307, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia.

[8] Atems, B., Kapper, D. and Lam, E. (2015). Do exchange rates respond asymmetrically to shocks in the crude oil market? Energy Economics, 49, pp. 227–238.

[9] Atkeson, A. and Ohanian, L. (2001). Are Phillips curves useful for forecasting in?ation? Federal Reserve Bank of Minneapolis Quarterly Review 25(1), pp. 2–11.

[10] Bal, D.P. and Rath, B.N. (2015). Nonlinear causality between crude oil price and exchange rate: A comparative study of China and India. Energy Economics, doi: 10.1016/j.eneco.2015.06.013.

[11] Banbura M. and Mirza H. (2013). Forecasting Euro Area Inflation with the Phillips curve. *mimeo*

[12] Bouoiyour, J., Selmi, R., Tiwari, A.K. and Shahbaz, M. (2015). The nexus between oil price and Russia's real exchange rate: Better paths via unconditional vs conditional analysis. Energy Economics (accepted manuscript), doi:10.1016/j.eneco.2015.06.001

[13] Brave, S. and Fisher, D.M. (2004). In search of a robust inflation forecast. Federal Reserve Bank of Chicago Economic Perspectives.

[14] Brown, F. and Cronin, D. (2010). Commodity prices, money and inflation. Journal of Economics and Business, 62, pp. 331–345.

[15] Campbell, J.Y. and Thompson, S.B. (2008). Predicting excess stock returns out of sample: can anything beat the historical average? Review of Financial Study, 21, pp. 1509–1531.

[16] Canova, F. (2007). G7 inflation forecasts: Random walk, Phillips curve, or what else? Macroeconomic Dynamics, 11, pp. 1-30.

[17] Cecchetti, S., Chu, R and Steindel, C. (2000). The unreliability of inflation indicators. Federal Reserve Bank of New York Current Issues in Economics and Finance, 6, pp.1-6.

[18] Çatik, A.N. and Önder, A.O. (2011). Inflationary effects of oil prices in Turkey: a regime-switching approach. Emerging Markets Finance and Trade, 47(5), pp. 125-140.

[19] Chen, Y., Turnovsky, J.S. and Zivot, E. (2014). Forecasting inflating using commodity price aggregates. Journal of Econometrics, 185, pp. 117-134.

[20] Chen, H., Liu, L., Wang, Y. and Zhu, Y. (2016). Oil price shocks and U.S. dollar exchange rates. Energy, 112, pp. 1036-1048.

[21] Chou, K. and Tseng, Y. (2015). Oil prices, exchange rate, and the price asymmetry in the Taiwanese retail gasoline market. Economic Modelling, 52, pp. 733–741.

[22] Ciner, C. (2011). Commodity prices and inflation: Testing in the frequency domain. Research in International Business and Finance, 25, pp. 229– 237

[23] Clark, T.E. and West K. D (2007). Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics, 138, pp. 291–311

[24] Devpura, N., Narayan, P.K. and Sharma, S.S. (2017). Is stock return predictability time-varying? Journal of International Financial Markets, Institutions & Money (2017), doi: http://dx.doi.org/10.1016/j.intfin.2017.06.001

[25] Diron, M. and Mojon, B. (2008). Are inflation targets good inflation forecasts? Economic Perspectives, Federal Reserve Bank of Chicago, pp. 33-45.

[26] Fernandez, V. (2014). Linear and non-linear causality between price indices and commodity prices. Resources Policy, 41, pp. 40–51.

[27] Fowowe, B. (2014). Modelling the oil price –exchange rate nexus for South Africa. International Economics, http://dx.doi.org/10.1016/j.inteco.2014.06.002

[28] Gelos, G. and Ustyugova, Y. (2016). Inflation responses to commodity price shocks – How and why do countries differ? Journal of International Money and Finance, 72, pp. 28-47.

[29] Golub, S.S. (1983). Oil prices and exchange rates. The Economic Journal, 93(371), pp. 576-593.

[30] Frankel, J.A. (2013). Effects of speculation and interest rates in a carry trade model of commodity prices. National Bureau of Economic Research, NBER Working Paper No. 19463

[31] Jiang, J. and Gu, R. (2016). Asymmetrical long-run dependence between oil price and US dollar exchange rate -Based on structural oil shocks. Physica A, 456, pp. 75-89.

[32] Kagraoka, Y. (2015). Common dynamic factors in driving commodity prices: Implications of a generalized dynamic factor model. Economic Modelling, 52, pp. 609-617

[33] Kapur, M. (2013). Revisiting the Phillips curve for India and inflation forecasting. Journal of Asian Economics, 25, pp. 17–27.

[34] Karlsson, N. and Karlsson, S. (2016). Forecasting of the Inflation Rates in Uganda: A Comparison of Arima, Sarima and Vecm Models.Örebro University School of Business.

[35] Isah, K.O. and Raheem, D.I (2019). The hidden predictive power of cryptocurrencies and QE: Evidence from the US stock market. Physica A: Statistical Mechanics and its Applications, pp. 536, 1-10.

[36] Krugman, P. (1983). Oil shocks and exchange rate dynamics, in Frankel, J.A. (Ed.) Exchange Rates and International Macroeconomics, University of Chicago Press, Chicago.

[37] Le and Chang. (2011). Dynamic relationships between the price of oil, gold and financial variables in Japan: A bounds testing approach, MPRA Paper No. 33030.

[38] Lewellen, J. (2004). Predicting returns with financial ratios. Journal of Financial Economics, 74, pp. 209–235.

[39] Marcellino, M. (2008). A benchmark model for growth and inflation. Journal of Forecasting, 27(4), pp. 305-340.

[40] Matheson, T. (2006). Phillips curve forecasting in a small open economy, Reserve Bank of New Zealand Discussion Papers, N0. 2006:01

[41] Moshiri, S. and Cameron, N. (2000). Neural network versus econometric models in forecasting inflation. Journal of Forecasting, 19, pp. 201-217.

[42] Narayan, P.K. and Bannigidadmath, D. (2015). Are Indian stock returns predictable? Journal of Banking and Finance 58, pp. 506–531.

[43] Narayan, P.K. and Gupta, R. (2015). Has oil price predicted stock returns for over a century? Energy Economics, 48, pp. 18–23.

[44] Park, J. and Ratti, R.A. (2008). Oil price shocks and stock markets in the U.S. and 13 European countries. Energy Economics, 30(5), pp. 2587-2609.

[45] Phillips, P.C.B. and Shi, Z. (2019). Boosting: Why you can use the HP filter. Cowles Foundation Discussion Paper No. 2212.

[46] Richards, T.J., Allender, W.J. and Hamilton, S.F. (2012). Commodity price inflation, retail pass-through and market power. International Journal of Industrial Organization, 30, pp. 50–57.

[47] Reboredo, J.C. (2012). Modelling oil price and exchange rate comovements. Journal of Policy Modeling, 34, pp. 419-440.

[48] Salisu, A.A. and Isah, K.O. (2018). Predicting US inflation: Evidence from a new approach. Economic Modelling, DOI: 10.1016/j.econmod.2017.12.008.

[49] Salisu, A.A., Ademuyiwa, A. and Isah, K.O. (2018). Revisiting the forecasting accuracy of Phillips curve: The role of oil price. Energy Economics, 70, pp. 334–356.

[50] Salisu, A.A., Isah, K.O, Oyewole, J.O. and Akanni, O.L. (2017). Modelling oil price-inflation nexus: The role of asymmetries. Energy 125, pp. 97-106.

[51] Stock, J.H., Watson, M.W. (2008). Phillips curve inflation forecast. NBER Working Paper 14322.

[52] Stock, J.H. and Watson, M.W. (2007). Why has U.S. inflation become harder to forecast? Journal of Money, Credit, and Banking 39, pp. 3-34.

[53] Stock, J.H. and Watson, M.W. (2003). Forecasting output and inflation: The role of asset prices. Journal of Economic Literature 41, pp. 788-829.

[54] Stock, J.H. and Watson. M.W. (2002). Forecasting using principal components from a large number of predictors. Journal of the American Statistical Association, 97, pp.1167-1179.

[55] Stock, J.H. and Watson, M.W. (2001). Forecasting Output and Inflation: The Role of Asset Prices, *mimeo*.

[56] Stock, J.H. and Watson, M.W. (1999). Forecasting inflation. Journal of Monetary Economics 44, 293–335.

[57] Turhan, M.I., Sensoy, A. and Hacihasanoglu, E. (2014). A comparative analysis of the dynamic relationship between oil prices and exchange rates. Journal of International Financial Markets, Institutions Money, 32, pp. 397–414.

[58] Tule, M., Salisu, A. and Chiemeke, C. (2020). Improving Nigeria's Inflation Forecast with Oil Price: The Role of Estimators. Journal of Quantitative Economics, Article in press.

[59] Westerlund, J. and Narayan, P.K. (2012). Does the choice of estimator matter when forecasting returns? Journal of Banking and Finance, 36, pp. 2632–2640.

[60] Westerlund, J. and Narayan, P.K. (2015). Testing for Predictability in Conditionally Hetoroscedasticity Stock Returns. Journal of Financial Econometrics, 13(2), pp. 342-375.

[61] Yang, L., Cai, X.J. and Hamori, S. (2017). Does the crude oil price influence the exchange rates of oil-importing and oil-exporting countries differently? A wavelet coherence analysis. International Review of Economics and Finance, http://dx.doi.org/10.1016/j.iref.2017.03.015

Table 1A: Descriptive Statistics and Unit Root Tests

Variable/Statistic	Mean	Std. Dev.	Skewness	Kurtosis	JB stat	ADF test Level	ADF test FD	I(D)
Inflation Rate (π)	49.1766	70.6241	1.6396	4.8682	119.2905***	-4.3608***	-	I(0)
Output Gap (YG)	-0.0039	0.0699	-0.3223	4.0777	13.2082***	-3.8226	-18.6290***	I(1)
Oil Prices (OP)	36.0043	27.6170	1.1509	3.4802	46.3084***	-2.4380	-11.8062***	I(1)
Exchange Rate (ER)	74.7341	91.5100	1.1440	3.4524	45.5603***	-0.2913	-12.4064***	I(1)

Table 1B: Serial Correlation and Conditional Heteroscedasticity Tests

	Ljung-Box test						ARCH LM test		
	$Q-Stat$			Q^2-Stat					
	$k=2$	$k=5$	$k=10$	$k=2$	$k=5$	$k=10$	$k=2$	$k=5$	$k=10$
Inflation Rate (π)	47.997***	105.40***	127.07***	37.976***	81.855***	98.124***	1265.257***	368.484***	104.073***
Output Gap (yg)	360.99***	832.74***	1484.8***	264.76***	501.46***	720.96***	1690.610***	544.228***	175.220***
Oil Prices (OP)	371.05***	838.96***	1428.1***	343.43***	710.88***	1051.7***	7574.691***	2920.631***	1389.579***
Exchange Rate (ER)	397.09***	968.64***	1852.2***	393.27***	940.63***	1716.5***	1265.257***	368.484***	104.073***

Table 1C: Testing for Persistence and Endogeneity

	Output Gap (yg)	Oil Prices (OP)	Exchange Rate (ER)
Persistence test results	0.96****(0.00)	0.97****(0.00)	0.98****(0.00)
Endogeneity test results	0.4743***(0.00)	0.4690***(0.00)	0.4690***(0.00)

Source: Authors' computation

Note: For the descriptive statistics, variables are expressed in levels but are log transformed for the unit root, serial correlation, conditional correlation, persistence, and endogeneity tests. The unit root test performed is the Augmented Dickey-Fuller (ADF) unit root test, while the expression *FD* implies first difference. For the serial correlation tests, we consider three different lag lengths (k) of 2, 5 and 10 periods for robustness purposes. The endogeneity test follows a three-step procedure: First, we run a predictive regression model with the OLS estimator: $\pi_t = \alpha + \lambda z_{t-1} + \varepsilon_{\pi,t}$, where π_t denotes the inflation rate and z_{t-1} is the lag of the predictor variable. In the second step, we follow Westerland & Narayan (2015) and model the predictor variable as follows: $z_t = \mu(1-\delta) + \delta z_{t-1} + \varepsilon_{z,t}$ and in the final step, the relationship between the predicting and predictor error terms ($\varepsilon_{\pi,t}$ and $\varepsilon_{z,t}$) is captured using the following regression: $\varepsilon_{\pi,t} = \rho \varepsilon_{z,t} + \eta_t$. If the coefficient ρ is statistically different from zero; then, the predictor variable is endogenous; otherwise, it is strictly exogenous. In each of the tests, the asyteric *** implies significance at the 1% level.

Table 2: Predictability Test Results using 50% of the Sample

Predictor	TPC	OP-APC	OP-APC-ER	OP-APC-ASY:ER
yg_{t-1}	0.0266*** (0.0026)	0.0431* (0.0242)	0.1370* (0.0745)	0.1015*** (0.0066)
op_{t-1}		0.0354* (0.0148)	0.1373** (0.0181)	0.1617** (0.0894)
er_{t-1}			-0.0340 (0.1174)	
$op*er_{t-1}$			0.3610*** (0.1897)	
er^{+}_{t-1}				0.2174** (0.0654)
er^{-}_{t-1}				-0.1279 (0.7298)
$op*er^{+}_{t-1}$				0.0717*** (0.0388)
$op*er^{-}_{t-1}$				1.9279 (1.6708)

Note: The terms TPC, OP-APC, OP-APC-ER, and OP-APC-ASY:ER are as described previously. The values in parenthesis are the standard errors while ***, ** & * implies 1%, 5% & 10% levels of significance, respectively.

Table 3: Single Method–based Forecast Performance Results using 50% of the Sample

	RMSE				MSE				MAE			
	In-sample	Out-of-sample			In-sample	Out-of-sample			In-sample	Out-of-sample		
Predictive model		*h*=2	*h*=4	*h*=6		*h*=2	*h*=4	*h*=6		*h*=2	*h*=4	*h*=6
TPC	0.0824	0.0847	0.0846	0.0846	0.0064	0.0066	0.0066	0.0065	0.0732	0.0751	0.0752	0.0754
OP-APC	0.0801	0.0814	0.0810	0.0807	0.0062	0.0061	0.0061	0.0060	0.0705	0.0719	0.0715	0.0713
	With Linear (Symmetric) Exchange Rate Pass-through											
OP-APC-ER	0.0790	0.0783	0.0778	0.0776	0.0062	0.0061	0.0061	0.0060	0.0681	0.0672	0.0669	0.0667
	With Nonlinear (Asymmetric) Exchange Rate Pass-through											
OP-APC-ASY:ER	0.0691	0.0690	0.0707	00729	0.0048	0.0048	0.0050	0.0053	0.0542	0.0540	0.0556	0.0575

Note: The table reports in-sample and out-of-sample forecast performance of the traditional Phillips curve predictive model vis-à-vis the oil price -based augmented Philips curve predictive model and across both linear and nonlinear exchange rate pass-through using RMSE, MSE and MAE forecast performance measures. The smaller the value of RMSE, MSE & MAE), the better the forecast accuracy of a predictor or model.

Table 4: Pairwise Method–based Forecast Performance Results using 50% of the Sample

	Campbell-Thompson (C-T) test				Clark & West (C-W) test			
		Out-of-sample				Out-of-sample		
Predictive model	**In-sample**	***h*=2**	***h*=4**	***h*=6**	**In-sample**	***h*=2**	***h*=4**	***h*=6**
OP-APC vs TPC	0.0283	0.0387	0.0430	0.0466	0.0008** (1.832)	0.0005** (2.189)	0.0004** (2.355)	0.0004** (2.525)
OP-APC-ER vs OP-APC	0.0130	0.0384	0.0387	0.0383	0.0013** (1.739)	0.0018** (2.223)	0.0021** (2.574)	0.0008** (2.890)
OP-APC-ASY:ER vs OP-APC-ER	0.1253	0.1194	0.0914	0.0603	0.0051** (3.897)	0.0013** (3.851)	0.0013** (3.640)	0.0013** (3.454)

Note: The C-T test results are based on the forecast performance comparison of the models. Hypothetically, a positive C-T value implies that OP-APC outperforms TPC. Similarly, a positive C-T value implies that OP-APC-ER outperforms OP-APC, and that OP-APC-ASY:ER (nonlinear/asymmetry) outperforms OP-APC-ER (linear/symmetry). In each of these cases, the reverse holds if the statistic is negative. In the case of C-W test, the t-statistics (values in parenthesis) are based on the critical values of 1.282 & 1.645 for (10%)* & (5%)** levels of significance, respectively.

Table 5: Pairwise method –based forecast performance results using 50% of the sample

Predictive model	Campbell-Thompson (C-T) test In-sample	Out-of-sample *h*=2	*h*=4	*h*=6	Clark & West (C-W) test In-sample	Out-of-sample *h*=2	*h*=4	*h*=6
HA vs OP-APC-ASY:ER	0.9778	0.9778	0.9772	0.9765	19.033**	19.058**	19.086**	19.117**
					(3.141)	(3.466)	(3.508)	(3.603)
ARIMA vs OP-APC-ASY:ER	0.8225	0.8242	0.8200	0.8148	0.280**	0.284**	0.288**	0.292**
					(4.688)	(3.708)	(3.064)	(2.120)
ARFIMA vs OP-APC-ASY:ER	0.9267	0.9271	0.9253	0.9230	1.732**	1.740**	1.740**	1.758**
					(7.067)	(7.255)	(7.424)	(7.661)

Note: The C-T test results are based on the forecast performance comparison of the preferred model (OP-APC-ASY:ER) with conventional time-series predictive models. Hypothetically, a positive C-T value implies that OP-APC-ASY:ER outperforms the time series models. For C-W test, the t-statistics which are the values in parenthesis are based on the critical values of 1.282 & 1.645 for (10%)* & (5%)** levels of significance, respectively.

Figure 1: Inflation predictability based on TPC and OP-APC Models

Figure 1.1: Output gap predictability of inflation using the traditional Phillips Curve model

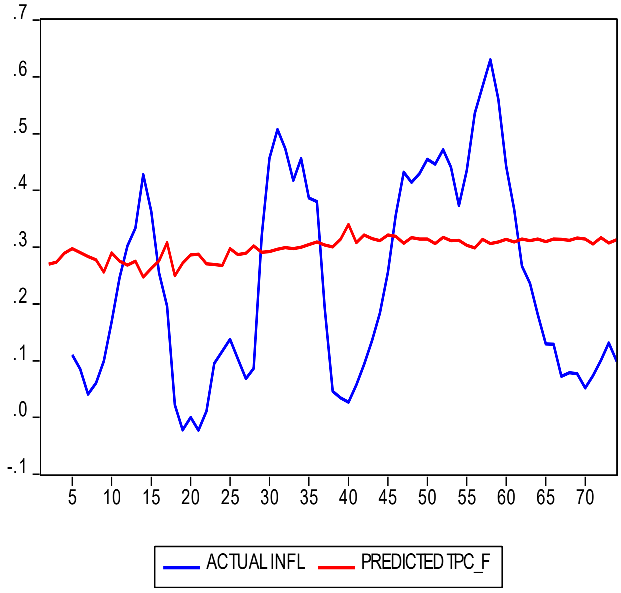

Figure 1.2: Oil price-based predictability of inflation using the Augmented Phillips Curve (APC) model

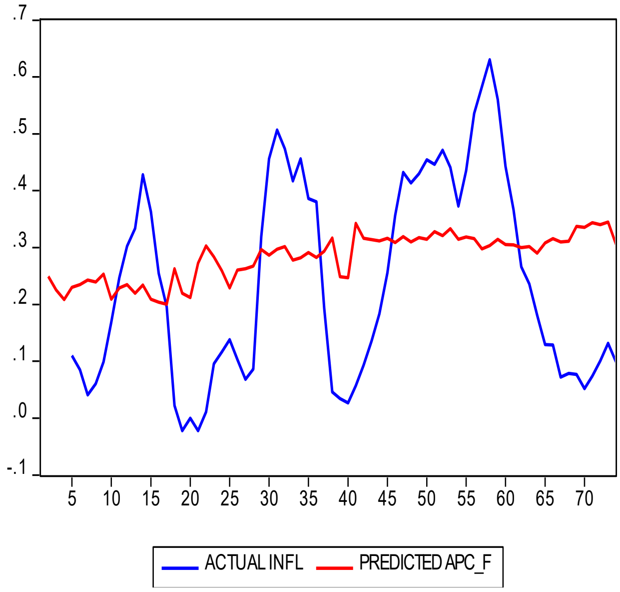

Figure 2: Inflation predictability based on OP-APC-ER Models

Figure 2.1: Oil price & exchange rate-based predictability of inflation

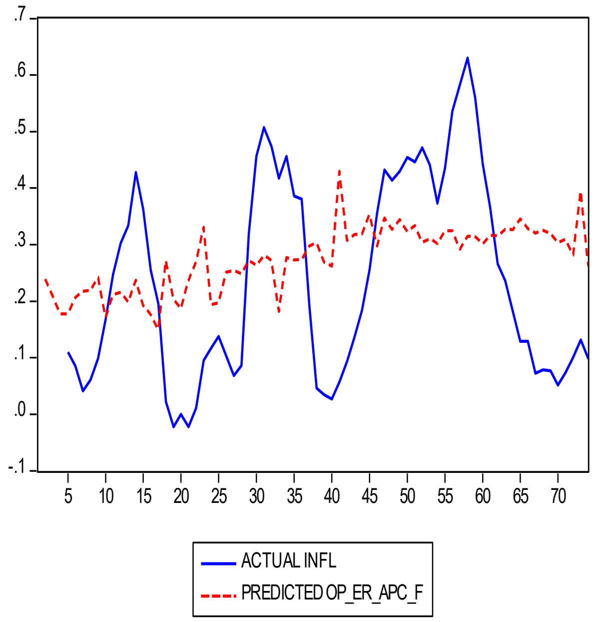

Figure 2.2: Oil price & asymmetry exchange rate predictability of inflation

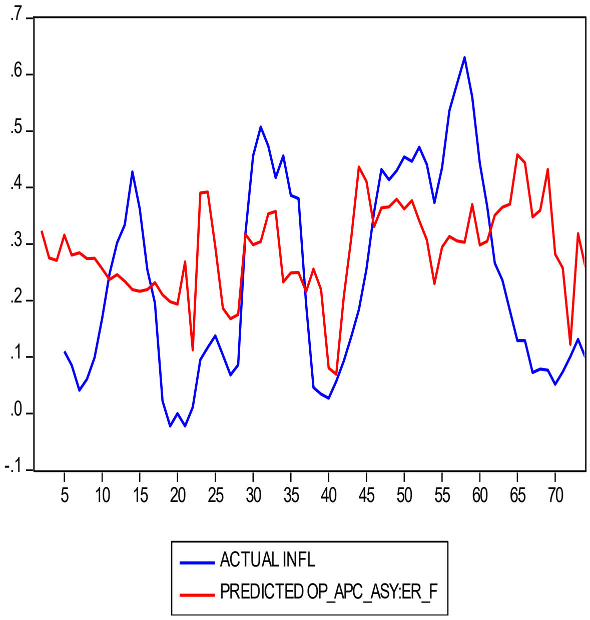

Figure 3: Inflation predictability based on time-series models and OP-APC-ASY:ER

Figure 3.1: Inflation predictability based on the historical average model(HA)

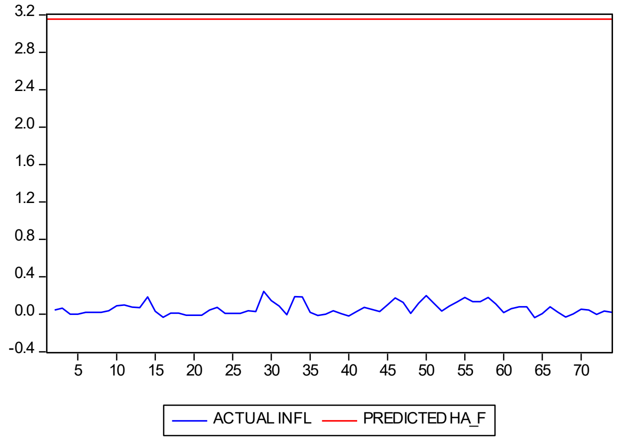

Figure 3.2: Inflation predictability using ARIMA

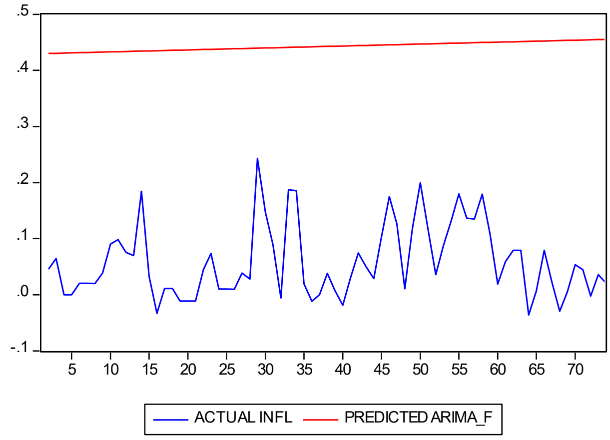

Figure 3.3: Inflation predictability using ARFIMA

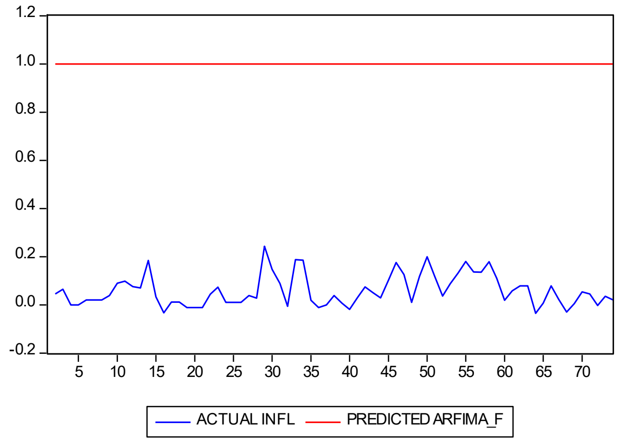

Figure 3.4: Oil price & asymmetry exchange rate based predictability of inflation