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COMPARING MULTIVARIATE MODELS' FORECASTS OF INFLATION FOR BRICS AND OPEC COUNTRIES

Olaoluwa Vincent AJAYI *

Department of Economics, Kingston University, London, Penrhyn Road, KT1 2EE, United Kingdom

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Abstract. *Purpose* – This study identifies the most appropriately selected multivariate model for forecasting inflation in different economic environments. In specifying the multivariate models, the study test for the orders of integration of variables and for those that are nonstationary. For nonstationary variables, this study examines whether they are cointegrated. Engle and Granger (1987) establish that a cointegrating equation can be represented as an error correction model that incorporates both changes and levels of variables such that all of the elements are stationary. However, VARs estimated with cointegrated data will be misspecified if all of the data are differenced because long-run information will be omitted, and will have omitted stationarity inducing constraints if all the data are used in levels. Further, including variables in both levels and differences should satisfy stationarity requirements. However, they will omit cointegrating restrictions that may improve the model. Of course, these constraints will be satisfied asymptotically; but efficiency gains and improved multi-step forecasts may be achieved by imposing the constraints (Engle and Granger 1987, p. 259). Therefore, this study test for order of integration and compare inflation forecasting performance of different multivariate models for BRICS and OPEC countries.

Research methodology – The following approaches were considered; the first approach is to construct a VAR model in differences (stationary form) to forecast inflation. The second approach is to construct a VECM without imposing cointegrating restrictions. The third approach is to construct a VEC that imposes cointegrating restrictions on the VECM. This will help to understand whether imposing cointegrating restrictions via a VEC improves long-run forecasts.

Research limitation – The proposed multivariate models focused on differencing and cointegrating restrictions to ensure the stationarity of the data, the available variables were combined and specified based on their level of integration to forecast inflation. For instance, a VAR model is estimated based on differenced variables I(0); the same holds true for VECM and VEC models, where differenced variables and linear combinations of I(I) covariates are stationary. In future, multivariate models guided by economic theory rather than the order of integration of variables are suggested.

Findings – The result shows that the forecast performance of inflation depends on the nature of the economy and whether the country experiencing higher inflation or low inflation. For instance, the model that includes long-run information in the form of a specified cointegrated equation generally improves the inflation forecasting performance for BRICS countries and one OPEC country (Saudi Arabia) that has a history of low inflation.

Practical implications – This research will improve the policy makers decision on how to select appropriate model to forecast inflation over different economic environment.

*Corresponding author. E-mails: *k1271217@kingston.ac.uk; vincent_ajayi@yahoo.com*

Originality/Value – These methods have not been used to forecast inflation for many emerging economies such as OPEC and BRICS countries despite the importance of many of these countries to the global economy. This study fills this gap by evaluating the forecasting performance of inflation using multivariate VAR and cointegrating models for OPEC and BRICS economies.

Keywords: inflation forecasting, cointegrating and stability tests.

JEL Classification: B22, C12, C22, C52, C53, E31.

Introduction

Previous studies clearly indicates that performance of inflation forecasting depends on the type of model in use, monetary policy regime, the sample period, the variables included in the model, transformations applied to the data for stationarity and structural breaks as well as the length of the forecasting horizon (Lee, 2012, Ozkan & Yazgan, 2015). Buelens (2012) and Stock and Watson (2008) stated that the accuracy of a forecasting model depends on the sample period in which they are estimated and evaluated. For example, the appropriate forecasting model to be used prior to the economic crisis may be different from that during the economic crisis. Fanchon and Wendel (1992) observed that the predictive performance of VAR and VEC models depends on the length of the forecasting horizon. For instance, the multivariate VEC model outperformed the VAR model 11 and 13 months ahead forecasting horizons. Also, Stock and Watson (1999) argued that the Phillips curve produced a better forecast when estimated with real economic variables (GDP) than when estimating the Phillips curve with the unemployment variable.

Multivariate specifications based on VARs and cointegration have been extensively used for modelling and forecasting macroeconomic variables in developed countries (especially, Europe and the United States) that have a history of low inflation (Hoffman, Anderson, & Rasche, 2002; Shoesmith, 1992, 1995a, 1995b; Timothy & Thoma, 1998). However, these methods have not been used to forecast inflation in many emerging economies such as OPEC and BRICS countries despite the importance of many of these countries to the global economy. This study fills this gap by evaluating the forecasting performance of inflation using multivariate VAR and cointegrating models for OPEC and BRICS countries.

BRICS countries comprise Brazil, Russia, India, China and South Africa. In recent times, they have emerged to form an international organisation body that will influence global financial trade and form a serious competitor to western economies. Accordingly, there are many common features between BRICS nations. For instance, they are fast developing nations with one of the largest economies in their regions. China has the largest economy in Asia and is second only to America in the world. Russia is a member of the G8 advanced leading countries in the world, and India has the third-largest economy in Asia. South Africa has the second-largest economy in Africa after Nigeria, while Brazil has the largest economy in South America (World Economic Outlook, 2019). Global Sherpa (2014) found BRICS countries ranked among countries in the world with largest and most influential economies in the 21st century. They account for 25% of world GDP, over a quarter of the world's land area and more than 40% of the global population. They control almost 43% of global foreign exchange reserves, and their share keeps rising (The Goldman Sachs Group, 2007; Agtmael, 2012).

The organisation of petroleum exporting countries (OPEC) comprise Iran, Iraq, Kuwait, Saudi Arabia, Venezuela, Qatar, Angola, Indonesia, Libya, United Arab Emirates, Algeria and Nigeria. OPEC has a rich diversity of cultures, languages, religions and united by their shared status as oil-producing developing countries. Many of these countries heavily depend on exportation of petroleum, which has contributed to the higher percentage of their export earnings. For example, Nigeria earned 70% of its total export revenue from crude oil, Kuwait derived almost 60% of its gross domestic product and 93% of export revenue from crude oil, Libya acquired almost 95% of its government revenues. In Qatar, oil and natural gas accounted for 60% of the country's gross domestic product and around 85% of export earnings. In Saudi Arabia, the oil and gas sector contributed to 50% of the gross domestic product and 90% of export earnings and in Venezuela, oil revenues accounted for about 95% of export earnings and 25% of gross domestic product (Organization of the Petroleum Exporting Countries, 2019). In total, the OPEC members produce almost 40% of the world's crude oil, which represents almost 60% of the total petroleum traded internationally, produces about a third of the world's daily consumption of 90 million barrels of crude oil, and controls 78% of the world's crude oil reserves (Energy Information Administration, 2013).

This paper forecast inflation using different multivariate specifications. In particular, it is aims to identify the most appropriately selected multivariate model for forecasting inflation in different economic environments. In specifying the multivariate models, this study faced different decisions, namely the variables to be included and how to deal with the non-stationarity variables. For non-stationary variables, this study test for the orders of integration and examine whether they are cointegrated. Modelling and forecasting any series that is not stationary may lead to spurious results. Engle and Granger (1987) establish that a cointegrating equation can be represented as an error correction model that incorporates both changes and levels of variables such that all of the elements are stationary. However, " VARs estimated with cointegrated data will be misspecified if all of the data are differenced because long-run information will be omitted, and will have omitted stationarity inducing constraints if all the data are used in levels. Further, including variables in both levels and differences should satisfy stationarity requirements. However, they will omit cointegrating restrictions that may improve the model. Of course, these constraints will be satisfied asymptotically; but efficiency gains and improved multi-step forecasts may be achieved by imposing the constraints " (Engle & Granger, 1987, p. 259).

This study considers different multivariate specifications using differencing and cointegrating restrictions to ensure stationarity and to produce forecasts. The following approaches were considered, two of which are discussed by Timothy and Thomas (1998). The first approach is to construct a VAR model in differences (stationary form) to forecast inflation. The second approach is to construct a VECM without imposing cointegrating restrictions. The third approach is to construct a VEC that imposes cointegrating restrictions on the VECM. This will help understand whether imposing cointegrating restrictions via a VEC improves long-run forecasts. The empirical analysis addresses the following issues: which of these models produces the best forecasting performance for each country? Is there a generally best performing specification across countries or for different forecasting horizons? Is it better to treat the oil price as endogenous or exogenous in multivariate models? Are models that use unemployment to capture the Phillips curve effect preferred to those that employ the output gap (when both variables are available)? Lastly, this study investigates whether each of the multivariate model (VAR, VECM and VEC) is structurally stable. If not, what is the implication of the instability for forecasting future inflation and what forecasting methods work well in the face of instability?

1. Literature review

There is a growing consensus that theoretical models are more accurate in forecasting when the economy is weak, especially during periods of economic crises, compared with ARIMA, Naïve and VAR models (Buelens, 2012; Dotsey, Fujita, & Stark, 2011; Onder, 2004). For example, Onder (2004) used quarterly data between 1987: q1 and 1999: q4 to forecast Turkish inflation with the Phillips curve, ARIMA, Vector Autoregression (VAR), VECM and naive models. The evidence revealed that the Phillips curve model outperformed other models for one-quarter ahead forecasts and the prediction of the 2001 financial crisis. This result is similar to the study of Pretorious and Rensburg (1996) who forecasted South African inflation and compared the forecasting abilities of different theoretical models (Phillips curve model, Traditional monetarist and money demand specifications) with the time series model (ARIMA) for the period 1991:q1- 1995:q3. The estimation period was divided into two different samples to reflect periods of stable and higher inflation. The study found that during the periods of higher inflation, the forecast produced by the money demand, Phillips curve and Traditional monetarist forecast models generated the lowest RMSE and MAE compared to the ARIMA model. However, the ARIMA models outperformed other multivariate models and theoretical model during periods of stable and low inflation.

A few studies also found Multivariate VAR model produce a better forecast than alternative models over the long horizon (Canova, 2007; Onder, 2004; Fritzer, Moser, & Scharler, 2002; Fanchon & Wendel, 1992). For example, Gupta, Eyden, and Waal (2015) examine whether the global vector autoregressive (GVAR) approach forecasts better than a vector error correction model (VECM) and a BVAR model for two key South African variables, GDP output and inflation between the period 1979q2-2009q4. Evidence revealed that the global multivariate VAR (GVAR) model outperforms VECM in forecasting inflation, especially at longer forecast horizons (more than four quarters ahead). However, the BVAR model was found to performs better than the best VECM when forecasting the output. Similarly, Fanchon and Wendel (1992) specified different multivariate VAR models (Vector error correction (VEC), VAR and Bayesian VAR models) to forecast cattle prices between the period of 1970-1989. The VEC model differenced the data to achieve stationarity and used an error-correction term to model the long-run information. The performance of all the estimated models was compared. The result shows that the VAR model generated the lowest mean square error for the 58- month horizon forecast. The VEC model outperformed the VAR model for 11 and 13-month horizons. The VAR and VEC models outperformed the Bayesian VAR models. They concluded that the performance of VAR and VEC models depend on the length of the forecast horizon.

Recent literature indicates the forecasting by a multivariate model (either by VAR or VECM) generally better than that of an alternative model (ARIMA and naive model). For example, Shan and Ghonasgi (2016) forecasted Indian inflation over a 24-period horizon and compared the predictive performance of the VAR with ARIMA models between 1994–2008. The VAR model has better forecasting performance than the ARIMA model. Also, Kelikume and Salami (2014) applied the ARIMA and VAR models to forecast inflation for Nigeria between January 2003 and December 2012 and found the VAR model outperformed the ARIMA specification.

The conclusion from this section is that the theoretical model, especially the Phillips curve, more accurately forecasts inflation when the economy is weak, especially during the economic crises, compared with the univariate ARIMA model. In contrast, the ARIMA models outperform other multivariate models and theoretical model (Phillips curve) during periods of stable and low inflation (Dotsey & Fujita, 2011; Lee, 2012; Mitra & Rashid, 1996; Nadal-De Simone, 2000; Pretorious & Rensburg, 1996). When comparing VAR models with VECM models, the former outperformed the latter over the longer horizon (more than four quarters ahead) (Fanchon & Wendel, 1992; Gupta et al., 2015).

This study compares the forecasting performance of multivariate VAR-based specifications and the naïve model for selected OPEC and BRICS countries. There have been very few such studies for these countries, especially for samples covering the recent period.

2. Empirical methods

This section describes the process of modelling with Vector autoregression (VAR) based specifications and the naïve model.

VAR is a stochastic process model that captures linear interdependencies among multiple time series and is estimated using differenced stationary data. The VECM model can be distinguished from the VAR model by including an error-correction term and is estimated with the nonstationary series that is known to be cointegrated. The VEC model imposes a cointegrating restriction on VECM. The unrestricted VAR approach models every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system and can be specified as:

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + Bx_t + e_t, \tag{1}$$

where y_t is a k vector of the endogenous variables, x_t is a d vector of exogenous variables, $A_1, \ldots, A_p$ and B are matrices of coefficients that need to be estimated, and e_t is a vector of innovations that may be contemporaneously correlated however they are uncorrelated with their own lagged values. The VECM representation of (1) is:

$$\Delta y_t = \delta + Bx_t + \Pi y_{t-1} + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{p-1} \Delta y_{t-p+1} + e_t, \tag{2}$$

where, Γ_i, $i = 1, \ldots, p-1$, (which are functions of A_i) reflect the short-run dynamic relationship. y_t are independent $I(1)$ variables, $\Delta = (1-L)$ while L is the lag operator, δ is the intercept, Π is the matrix containing long-run information and e_t is the residual. The Granger representation theorem indicates that if the matrix Π has reduced rank $r < k$ it can be decomposed as $\Pi = \alpha\beta'$. The dimension of α and β is r x k. The number of cointegrating equations is r, where β is the cointegrating vector and α is the speed of adjustment to the long-run equilibrium defined by the cointegrating relationships, which is determined primarily by the likelihood ratio (LR) trace test. Imposing r cointegrating equations on (2) gives the VEC representation. In this study, $r = 1$ for all our VEC specifications.

In VAR modelling, the first step is to estimate a VAR model with an appropriate lag length sufficient to capture the full dynamics of the system. The choice of appropriate lag order (p) is important because too short a lag length may not be able to remove the autocorrelation in the residuals and too long a lag length may reduce the precision (efficiency) of the estimates due to a reduction of degrees of freedom (Lack, 2006). This research chooses the maximum possible lag length (P*) as 10 for all countries except where only lower orders can be estimated. Different maximum lag lengths will be considered when the experimentation reveals a lag length below 10 cannot reject the hypothesis of no autocorrelation. Also, the Akaike information criterion (AIC) and Schwarz criterion (SC) will be employed to determine the initial lag length P^{**}. If there is no evidence of autocorrelation (of orders 1, 2, … 10), this initial lag length is selected. However, if there is evidence of autocorrelation, the VAR model is re-estimated using a lag length of P**+1. The process is repeated until the VAR model cannot reject the hypothesis of no- autocorrelation at the 5% level.

Further, Atkeson and Ohanian (2001) argued that an inflation forecasting model based on some hypothesised economic relationship cannot be considered a useful guide for policy if its forecasting performance is not better than a simple naïve model. This study estimates the naïve model as a benchmark model and compares its forecasting performance with the best selected multivariate models. The naïve model can be estimated by equating the observed value in the last quarter of the estimation period to forecast the present quarter, that is:

$$y_{T+h} = y_T , \tag{3}$$

where y_{T+h} is the h period ahead forecast and y_T is the observed data in the last period of the estimation sample.

3. Data and variable selection

Quarterly and annual data are collected from the World Bank, United Nation (UN DATA), Organisation for Economic Co-operation and Development (OECD) and International Financial Statistics (IFS) published by the International Monetary Fund (IMF). In selecting variables for the multivariate model, this study focuses on those commonly and mostly used to explain and forecast inflation in the literature as well as where the data is available (because there are some data constraints). An eclectic theoretical approach is considered in the sense of combining variables from different economic theories in the VAR specification.

The approach follows in this study includes the following steps: The VAR model is first specified based on variables available at quarterly frequency across the whole sample for any particular country. The variable may include money supply, interest rates and consumer prices (from which inflation can be generated). The ability of VAR model based on these variables are examined to forecast inflation. To avoid model misspecification (in particular omitted variable issues), additional information is incorporated, that is, added variables that are available only annually over the available sample and use frequency conversion tools to generate quarterly series. In this case, the VAR models, including all the available inflation determinants for each country are considered. In particular, the VARs are based on (a subset of) consumer prices, money supply, interest rates, real effective exchange rates, the output gap (or, alternatively the unemployment rate) as well as the world oil price. In addition, the index of industrial production or real output measured by real GDP is used to construct the output gap. When estimating output gap, this study follows Stock and Watson (1999) and use the Hodrick-Prescott (HP) filter. The general features of selected macroeconomic variables, shown in Table 1, were identified in each country by mainly focusing on seasonality and stationary characteristics to avoid the issue of seasonal integration. For each series, the autocorrelation functions of each series were plotted and if this indicated seasonality, the data was adjust seasonally using the Census X13 method. The seasonal indices obtained from the adjustment process were saved and used to reintroduce seasonality into the forecasts produced by this study. This study also employs the DF-GLS, augmented Dickey-Fuller (ADF), Phillips and Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests to identify the variables' orders of integration (Vogelsang & Perron, 1998; Perron, 1989). A summary of the data employed for each country and whether the data is seasonally adjusted or not as well as the orders of integration of these variables is given in Table 1, 2 and 3, respectively. All variables are transformed using natural logarithms except for the interest rate, unemployment and output gap.

Table 1. Summary of data availability for all the countries

Countries	Sample	Variables
Brazil	1999q4 2012q4	P, M, R, REE, UN, GAP and Oilp
Russia	2003Q2 2012q4	P, M, R, REE, UN, GAP and Oilp
India	1963q1 2012q4	P, M, R, GAP and Oilp
China	1992q1 2012q4	P, M, R, REE, GAP and Oilp
South Africa	1995q2-2012q4	P, M, R, REE, GAP and Oilp
Algeria	1999q2 2012q4	P, M, R, REE, GAP and Oilp
Angola	2002q4 2012q4	P, M, R, GAP and Oilp
Nigeria	1998q4 2012q4	P, M, R, REE, GAP and Oilp
Saudi Arabia	1983q1 2012q4	P, M, R, GAP and Oilp

P = consumer price, M = money supply, REE = real exchange rate, GAP = output gap, R = interest rate, UN = unemployment and Oilp = oil price.

Table 2. Summary of whether the data is seasonally adjusted or not

Countries / Variables	BRA	RUS	IND	CHI	SOU	NIG	ALG	ANG	SAU
P	UN	SA	SA	UN	UN	SA	SA	UN	UN
M	SA	UN	UN	UN	UN	UN	UN	SA	UN
R	UN	UN	UN	UN	UN	UN	UN	UN	
REE	UN	UN		UN	UN	UN	UN		UN
U	UN	SA							
OilP	UN	UN	UN	UN	UN	UN	UN	UN	UN
GAP	UN	SA	UN	UN	UN	UN	UN	UN	UN

SA indicates seasonally adjusted series and UN indicates unadjusted series. Blank indicates where the data is unavailable for the variable in that particular country. The country is represented by its first three letters.

Table 3. Orders of integration of the data

Variables/Countries	BRA	RUS	IND	CHI	SOU	NIG	ALG	ANG	SAU
P	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)**	I(1)
M	I(1)	I(1)	I(2)	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
R	I(1)	I(0)	I(0)	I(1)	I(1)*	I(1)	I(1)	I(1)*	
REE	I(1)	I(1)		I(1)	I(1)	I(1)	I(1)		I(1)
U	I(1)	I(1)							
OilP	I(1)	I(1)		I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
GAP	I(0)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

* Indicates a variable that may be stationary around a structural break while ** denotes a variable that may be I(1) around a structural break.

4. Model specifications

Based on the orders of integration of the data reported in Table 3, the following three multivariate models are estimated: first, an unrestricted VAR model that includes variables only in stationary form (typically through differencing); second, a VECM that includes all I(1) variables as endogenous. A test is conducted to determine whether a linear combination of the nonstationary variables is cointegrated, and if cointegrated the model is used to produce forecasts for inflation. Third, a VEC model is constructed that imposes a single cointegrating equation on the VECM to forecast inflation. Based on this analysis, the forecasting performance of all three multivariate specifications (VAR, VECM and VEC) are compared to the naïve model and to identify the best inflation forecasting model.

For the unrestricted VAR, four different variants for Brazil and Russia are estimated.[1] The first VAR model includes the output gap and excludes unemployment with all other available variables included. The second VAR includes unemployment and excludes the output gap with all other available variables included. The aim of these two VARs is to consider whether the VAR that includes the output gap provides superior forecasts to the VAR model that includes unemployment. The remaining two VARs are the same as the first two VARs, except the oil price is treated as exogenous because international oil prices are best regarded when determined outside the system for some countries – although, for oil producing countries or large oil-consuming countries, such as China, the assumption of endogeneity may be more appropriate. That is, these VARs considers oil price exogenous and all other available variables endogenous. The motivation behind the latter two VARs is to examine the impact of treating oil prices as exogenous on the inflation forecasts.

For the remaining countries (China, South Africa, Algeria, Angola, Nigeria and Saudi Arabia), two VARs were estimated. The first VAR model considers all variables as endogenous. The second VAR model treats the oil price as exogenous and all other available variables as endogenous. All VAR models consider the intercept to be exogenous. The model

[1] These two countries have two substitute variables for the economic activity measure (output gap and unemployment).

where oil prices are specified as exogenous, the oil price forecast produced between 2013q1a-nd 2014q4 based on an ARIMAX forecasting method is considered. A summary of the valid VAR, VECM and VEC models that are free from evident autocorrelation are available in Table 4 and 5 for stability test.

5. Stability tests for multivariate models

The stability of each multivariate model in Table 4 and 5 were determined to understand whether they have stable coefficients across the entire estimation sample. If not, the implications of the instability on forecasting inflation and type models that work well in the face of instability were examined. This study performs a CUSUM test for stability tests. The CUSUM test is based on the cumulative sum of the recursive residuals. If the line of the CUSUM test statistics fluctuates within the two 5% critical lines, the estimated models are said to be stable. In contrast, the models are unstable if the line of the CUSUM test goes outside the area between the 5% critical lines. The summarised results of the stability tests are available in Tables 4 and 5 for BRICS and OPEC countries, respectively.

Table 4. Summary of the stability tests for BRICS countries

Model	CUSUM test results
Brazil	
VAR(GAP)	Unstable
VAR(UN)	Unstable
VAR(GAP)_Exo	Stable
VAR (UN)_Exo	Stable
VECM(UN)	Stable
VECM(UN)_Exo	Stable
VEC(UN)	Unstable
VEC(UN)_Exo	Stable
Russia	
VAR(UN)	Stable
VAR(UN)_Exo	Unstable
VECM (UN)	Stable
VECM(GAP)	Stable
VECM(GAP)_Exo	Stable
VECM(UN)_Exo	Stable
VEC(UN)	Unstable
VEC(GAP)	Unstable
VEC(GAP)_Exo	Unstable
VEC(UN)_Exo	stable

Model	CUSUM test results
India	
VAR	Stable
VAR_Exo	Stable
VECM	Stable
VECM_Exo	Stable
VEC	Unstable
VEC_Exo	Unstable
China	
VAR	Unstable
VAR_Exo	Unstable
VECM	Stable
VECM_Exo	Stable
VEC	Unstable
VEC_Exo	Unstable
South Africa	
VAR	Unstable
VAR_Exo	Stable
VECM	Stable
VECM_Exo	Stable
VEC	Unstable
VEC_Exo	Unstable

Stable = result of the CUSUM test where the lines of CUSUM tests lie within the two critical lines. Unstable = result of the CUSUM test where the lines of CUSUM tests lie outside the two critical lines; VAR = VAR model that considers all variables endogenous; VECM = multivariate model estimated with all nonstationary variables that consider all variables endogenous; VEC = Multivariate model imposes cointegrating restrictions on the VECM and considers all variables endogenous.[2]

[2] VAR_Exo = VAR model that considers oil price exogenous and other variables endogenous; VECM_exo = VECM specification that considers oil price as exogenous and other variables as endogenous; VEC_Exo = VEC model that considers oil price as exogenous and other variables as endogenous. For Brazil and Russia, where the unemployment and output gap variables are available; VAR(UN) = VAR, where all variables are considered endogenous except output gap, which is excluded; VAR(GAP) = VAR where all variables are considered endogenous except the unemployment variable, which is excluded; VAR(UN)_Exo = VAR where oil price is specified as exogenous and all other variables as an endogenous variable, except for output gap; VAR (GAP)_Exo = VAR where oil price is specified as exogenous and all other variables as endogenous variables, except for the unemployment variable; VECM(UN) = VECM that considers all variables endogenous except for the output gap; VECM(UN)_Exo = VECM where oil price is specified as exogenous and all other variables as endogenous variables, except for the output gap, which is excluded; VECM(GAP) = VECM that considers all variables endogenous except for the unemployment variable; VECM(GAP)_EXO = VECM where oil price is specified as exogenous and all other variables as endogenous variables, except for the unemployment variable, which is excluded; VEC(UN) = VEC, where all variables are considered endogenous except for the output gap, which is excluded; VEC(GAP) = VEC, where all variables are considered endogenous except for the unemployment variable, which is excluded; VEC(UN)_Exo = VEC, where oil price is specified as exogenous and all other variables as endogenous except for output gap; VEC(GAP)_Exo = VEC, where oil price is specified as exogenous and all other variables are endogenous variables except the unemployment variable.

Table 5. Summary of the stability tests for OPEC countries

Model	CUSUM test results
Algeria	
VAR	Stable
VAR_Exo	Stable
VECM	Stable
VECM_Exo	Stable
VEC	Unstable
VEC_Exo	Unstable
Angola	
VAR	Unstable
VAR_Exo	Unstable
VECM	Unstable
VECM_Exo	Stable
VEC	Unstable
VEC_Exo	Unstable
Nigeria	
VAR	Unstable
VAR_Exo	Stable
VEC	Unstable
VEC_Exo	Unstable
Saudi Arabia	
VAR	Stable
VAR_Exo	Stable
VECM	Stable
VECM_Exo	Stable
VEC	Unstable
VEC_Exo	Unstable

Note: see Table 4.

For the BRICS countries (Table 4), the CUSUM test suggests evidence of instability for all models except the following: all VECM models for all selected countries, all VARs specification for India, South Africa and Brazil (except for the VAR where all variables included as endogenous except the unemployment variable, which is excluded, the VAR where all variables are considered endogenous except output gap, which is excluded for Brazil and the VAR model that considers all variables endogenous for South Africa). The following models are also structurally stable: the VEC model where the oil price is specified as exogenous and all other variables included as endogenous variable except output gap for Brazil and Russia.

For OPEC countries (Table 5), all models show evidence of structural instability except the VAR and VECM specifications, which consider all variables endogenous for Saudi Arabia, the VECM model that specifies oil price as exogenous for Angola, as well as the VAR and VECM specifications for Algeria.

In general, the CUSUM test indicates evidence of instability in the coefficients for the VAR, VECM and VEC for both BRICS and OPEC countries (except VECM for BRICS). This study produces forecasts for all models presented in Table 4 and 5 despite the evidence of structural instability for many of these specifications because the literature suggests that models being subject to structural instability may or may not affect their forecasting performance (Clark & Mccacken, 2006; Stock & Watson, 1999). Hence, it will be interesting to see whether models with evident instabilities have poor forecasting performance in either absolute or relative terms.

6. Forecast performance and evaluation

The m-step ahead forecasts are made for the valid VAR, VEC and VECM models reported in Table 4 and 5. Following Sarantis and Stewart (1995), Alles and Horton (2002); Ogunc et al. (2013) and Garcia, Medeiros, and Vasconcelos (2017); the forecasting performance were compared using rolling regressions. First, a series of rolling regressions were conducted and out-of-sample forecasts calculated for all the multivariate models free from autocorrelation. Each model is estimated over the sample period available for each country with the period ending in 2012q4 (the start of the estimation period varies across models and countries). These models are used to produce forecasts over the ex-post forecasting period 2013q1–2014q4. These produce 1-step ahead forecasts for 2013q1, 2-step ahead forecasts for 2013q2 and so on up to 8-step ahead forecasts for 2014q4. The identified models were then re-estimated by adding one observation to the end of the sample, hence the models are estimated over a period ending in 2013q1. These estimated models are used to produce 1-step ahead forecasts for 2013q2, 2-step ahead forecasts for 2013q3 and so on up to 7-step ahead forecasts for 2014q4. This process is then repeated with one observation being added to the estimation period (with the last rolling regression's sample period ending in 2014q3), and m-step ahead forecasts produced up to the end of the forecast period. These rolling regressions produce eight 1-step ahead forecasts, seven 2-step ahead forecasts, six 3-step ahead forecasts, five 4-step ahead forecasts and so on up to one 8-step ahead forecast for each estimated model. Second, the forecasting performance of each model over the different step ahead forecasting horizons using the Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE) and Theil's inequality coefficient (U) are calculated. The best forecasting model over any horizon will have the lowest value of these forecasting performance measures. To avoid space, only the forecast produced by the naïve model with the best forecasting multivariate models for each country were recorded, shown in the Tables 6 and 7 (the details of the forecast produced by the VAR, VECM and VEC are available on request).

Table 6. Summary of the best forecasting multivariate models for OPEC countries

			1-step	2-step	3-step	4-step	5-step	6-step	7-step	8-step
Algeria	Naïve model	RMSE	0.012	0.017	0.019	0.029	0.020	0.016	0.016	0.017
		MAPE	76.740	111.200	108.200	136.000	147.200	55.960	30.380	38.770
		U	0.173	0.267	0.265	0.243	0.266	0.195	0.1670	0.168
	VAR_ Exo	RMSE	0.007*	0.012*	0.017*	0.027	0.027	0.025	0.016*	0.0003*
		MAPE	44.074*	101.566*	102.855*	257.60	207.500	94.940	29.649*	30.555*
		U	0.098*	0.180*	0.255*	0.338	0.313	0.263	0.157*	0.003*
	VEC (GAP)_ Exo	RMSE	0.012	0.016	0.019	0.021*	0.016*	0.014*	0.016	0.029
		MAPE	66.931	114.508	111..534	132.570*	112.274*	38.803*	30.550	48.950
		U	0.157	0.240	0.274	0.207*	0.232*	0.185*	0.204	0.324
Angola	Naïve model	RMSE	0.007	0.013	0.017	0.022	0.022	0.015	0.013	0.013
		MAPE	18.100	20.050	20.730	21.680	29.990	30.640	27.600	16.970
		U	0.094	0.116	0.117	0.194	0.147	0.148	0.130	0.088
	VAR	RMSE	0.007*	0.008*	0.007*	0.006*	0.009*	0.009*	0.008*	0.005*
		MAPE	7.203*	12.626*	19.545*	20.047*	27.366*	18.621*	17.984*	16.308*
		U	0.047*	0.085*	0.111*	0.136*	0.138*	0.097*	0.091*	0.079*
Saudi Arabia	Naïve model	RMSE	0.004	0.007	0.011	0.014	0.017	0.020	0.025	0.026
		MAPE	10.980	21.810	36.910	50.880	62.060	72.960	87.830	92.610
		U	0.070	0.128	0.238	0.342	0.450	0.574	0.771	0.862
	VECM	RMSE	0.002*	0.003*	0.003*	0.003*	0.003*	0.002*	0.001*	0.001*
		MAPE	7.828*	10.060*	10.930*	10.270*	12.710*	9.188*	2.891*	2.427*
		U	0.046*	0.061*	0.064*	0.058*	0.063*	0.046*	0.015*	0.012*
Nigeria	Naïve model	RMSE	0.025	0.044	0.066	0.078	0.086	0.090	0.099	0.123
		MAPE	21.830	48.040	72.650	92.760	101.500	107.800	116.500	153.000
		U	0.139	0.218	0.296	0.330	0.350	0.359	0.377	0.433
	VAR	RMSE	0.021	0.036	0.048*	0.050*	0.037*	0.027*	0.024*	0.013*
		MAPE	19.121	38.90	54.872*	59.583*	37.772*	29.997*	28.762*	17.152*
		U	0.111	0.182	0.220*	0.242*	0.193*	0.147*	0.112*	0.079*
	VAR_ Exo	RMSE	0.019*	0.033*	0.051	0.053	0.041	0.031	0.025	0.044
		MAPE	18.075*	37.632*	56.531	63.63	47.18	36.42	29.73	49.690
		U	0.105*	0.169*	0.238	0.248	0.204	0.159	0.133	0.199

See Table 6 for definition of each model. The best multivariate forecasting model is identified by measure (RMSE, MAPE and U) and asterisk* for each forecasting horizon (1, 2, …, 8 steps ahead).

Table 7. Summary of the best forecasting multivariate models for BRICS countries

			1-step	2-step	3-step	4-step	5-step	6-step	7-step	8-step
Brazil	Naïve model	RMSE	0.005	0.006	0.006	0.004	0.004	0.027	0.028	0.002
		MAPE	6.699	9.612	8.738	4.885	5.417	9.859	12.310	13.014
		U	0.040	0.052	0.049	0.029	0.025	0.053	0.066	0.015
	VAR(UN)	RMSE	0.006	0.012	0.013	0.011	0.015	0.020	0.014*	0.001*
		MAPE	8.533	17.66	18.470	17.650	23.510	28.970	12.090*	12.440*
		U	0.046	0.090	0.097	0.085	0.110	0.143	0.002*	0.011*
	VEC(UN)	RMSE	0.004	0.007	0.006	0.004	0.009	0.019	0.017	0.011
		MAPE	5.181	10.100	6.880*	4.906	9.919	24.460	24.110	18.080
		U	0.029	0.056	0.045*	0.029	0.066	0.137	0.133	0.083
	VEC (UN)_Exo	RMSE	0.004*	0.006*	0.005*	0.003*	0.003*	0.013*	0.019	0.017
		MAPE	5.084*	7.054*	7.304	4.479*	3.542*	9.830*	29.040	28.860
		U	0.021*	0.044*	0.052	0.025*	0.022*	0.012*	0.134	0.126
Russia	Naïve model	RMSE	27.111	49.350	48.790	54.980	73.400	51.870	47.930	85.540
		MAPE	23.760	45.730	44.610	49.940	65.090	52.180	55.600	112.600
		U	0.116	0.196	0.194	0.218	0.285	0.218	0.212	0.360
	VAR(GAP)	RMSE	0.008	0.015*	0.0185	0.013	0.017	0.031	0.042	0.053
		MAPE	8.867	14.690*	19.313	16.138	19.918	37.316	49.234	56.152
		U	0.058	0.100*	0.124	0.085	0.122	0.227	0.320	0.394
	VAR(UN)	RMSE	0.009	0.019	0.015*	0.012*	0.051	0.022	0.027*	0.031*
		MAPE	8.208	15.218	15.205*	14.408*	23.698	24.699	28.006*	33.366*
		U	0.063	0.130	0.106*	0.086*	0.104	0.155	0.187*	0.200*
	VAR(UN)_ Exo	RMSE	0.009	0.022	0.022	0.019	0.013*	0.019*	0.034	0.059
		MAPE	9.095	20.789	21.252	20.689	0.150*	22.815*	40.623	62.371
		U	0.064	0.153	0.148	0.124	0.088*	0.131*	0.251	0.453
	VEC(GAP)	RMSE	0.007*	0.015	0.022	0.021	0.025	0.037	0.045	0.056
		MAPE	7.940*	18.103	23.916	25.771	27.892	43.893	51.781	58.632
		U	0.049*	0.105	0.150	0.147	0.186	0.285	0.349	0.414
	VEC (GAP)_Exo	RMSE	0.009	0.021	0.0273	0.027	0.0279	0.039	0.056	0.077
		MAPE	11.667	26.099	33.324	32.166	28.511	47.853	65.972	80.493
		U	0.057	0.100	0.192	0.197	0.209	0.312	0.479	0.674
India	Naive model	RMSE	10.701	17.570	22.240	17.730	19.090	19.770	29.290	37.020
		MAPE	15.215	24.670	18.810	29.760	28.570	29.400	33.610	48.740
		U	0.152	0.133	0.132	0.182	0.188	0.193	0.141	0.196
	VEC	RMSE	0.012*	0.018*	0.018*	0.021*	0.017*	0.017*	0.016*	0.014*
		MAPE	14.620*	20.910*	17.490*	28.760*	26.560*	26.660*	23.870*	28.890*
		U	0.066*	0.104*	0.110*	0.132*	0.117*	0.124*	0.122*	0.126*

			1-step	2-step	3-step	4-step	5-step	6-step	7-step	8-step
China	Naïve model	RMSE	1.541	2.360	2.806	3.720	5.423	7.522	10.660	11.250
		MAPE	7.191	13.788	15.915	19.417	23.848	27.91	39.005	61.91
		U	0.086	0.770	0.132	0.129	0.122	0.173	0.344	0.363
	VAR	RMSE	0.006	0.011	0.010	0.013	0.016	0.017*	0.023*	0.030*
		MAPE	10.281	16.464	14.271	18.873	22.643	25.104*	38.205*	51.647*
		U	0.057	0.091	0.093	0.121	0.154	0.168*	0.240*	0.348*
	VEC	RMSE	0.004*	0.007*	0.010*	0.012*	0.016*	0.022	0.026	0.033
		MAPE	5.001*	11.636*	12.310*	18.109*	22.292*	30.721	42.81	55.378
		U	0.034*	0.067*	0.089*	0.113*	0.114*	0.214	0.282	0.382
South Africa	Naïve model	RMSE	4.512	10.640	12.950	11.040	4.355	4.579	2.757	10.560
		MAPE	10.041	13.900	14.43	9.856	8.077	12.816	18.175	12.350
		U	0.118	0.112	0.091	0.043	0.047	0.059	0.061	0.078
	VEC	RMSE	0.006	0.009	0.011*	0.006*	0.005*	0.007*	0.007*	0.003*
		MAPE	9.001	12.676	13.350*	8.706*	6.174*	10.260*	10.085*	5.751*
		U	0.057	0.060	0.061*	0.040*	0.045*	0.040*	0.058*	0.029*
	VEC_Exo	RMSE	0.006*	0.009*	0.011	0.007	0.007	0.011	0.011	0.006
		MAPE	8.716*	12.199*	15.098	12.280	12.280	16.500	15.631	10.681
		U	0.057*	0.078*	0.093	0.066	0.076	0.093	0.088	0.056

See Table 6 for definition of each model. The best multivariate forecasting model is identified by measure (RMSE, MAPE and U) and asterisk* for each forecasting horizon (1, 2, …, 8 steps ahead).

7. Empirical results

Table 6 summarises the best forecasting multivariate models for OPEC countries in each forecasting horizon while Table 7 summarises the best forecasting models for the BRICS nations in each forecasting horizon. A general impression from the tables is that there is no single model that dominates across all countries. It was generally found that while both unemployment and the output gap are available as indicators of the Phillips curve (for Brazil and Russia), models including unemployment outperform those that use output gap. This view is contrary to the studies of Bjornland, Jore, Smith, and Thorsrud (2008) and Stock and Watson (1999), who argue that models including output gap contain the most valuable information in inflation forecasting rather than models based on alternative indicators (unemployment).

The VAR model often produces the best forecasting performance for OPEC countries except in Saudi Arabia, which has a history of relatively low inflation. VAR models have superior forecasting performance over all forecasting horizons for Algeria (except over the 4 to 6 step-ahead horizons), Angola and Nigeria. In contrast, the VAR model rarely produced the best forecasts for BRICS countries. VAR models were only favoured over the 7 to 8 step ahead horizons for Brazil, 6 to 8 step-ahead horizons for China and the 2 to 8 step ahead horizons for Russia. VECM was only favoured for 1 out of the 4 selected OPEC countries

(Saudi Arabia over all forecasting horizons) and was never favoured for BRICS countries. The VEC models have better forecasts over all forecasting horizons for all BRICS countries with the following exceptions: China over the 6 to 8 step ahead horizons, Brazil over the 7 to 8 step ahead horizons and Russia over the 2 to 8 step ahead horizons. However, the VEC model is rarely favoured for the selected OPEC countries (VEC is only favoured over the 4 to 6 step ahead horizon for Algeria). The naïve model was never favoured.

In general, the results of this study indicate that VAR models have the best forecasting performance for OPEC countries while the VEC model produces better forecasts for BRICS countries. The forecasting performance of the VEC model for BRICS countries and possibly the VECM for Saudi Arabia may be because inflation in many of these countries is relatively moderate and kept in check by good monetary policy, especially when compared with OPEC countries. As noted earlier, forecasts are most likely to improve by applying error-correction techniques if the data strongly supports the cointegration hypothesis (Engle & Yoo, 1987). The VEC specification can also minimise the effect of model misspecification and thus avoid the long-run information lost due to non-differentiating a stationary variable (see Christoffersen & Diebold, 1998; Sa-ngasoongsong, Bukkapatnam, Kim, Iyer, & Suresh, 2012). Also, the evidence of good forecast performance of the unrestricted VAR models for OPEC countries may not be surprising because these VAR models have been estimated using the stationary series. The model estimated using first differencing (stationary data) has the ability to capture different characteristics of instability in high inflation economy such as OEPC countries. Indeed, the results of this study generally support the view that the inclusion of cointegrating equations improve the inflation forecasting performance for BRICS countries and Saudi Arabia (both have a history of low inflation). Notably, the naïve benchmark models were never favoured over the best forecasting multivariate models for each country. This result contrasts with that of Atkeson and Ohanian (2001) who found that the naïve model produces superior forecasts than the multivariate VAR-based models.

Whether the inclusion of oil prices as exogenous or endogenous improves forecasting performance differs substantially according to the form of model employed and the country under consideration. For both BRICS and OPEC countries, the model that considers the oil price endogenous generally secures better forecasting performance than the model that considers the oil price exogenous. Exception include Algeria over all forecasting horizons, Brazil over the 1 to 6 step ahead horizons, Russia over the 5 to 6 step ahead horizons and over the 1 to 2 step ahead horizons for both South Africa and Nigeria. This is interesting because both BRICS and OPEC countries dependent heavily on oil import for domestic consumption and/or oil export for revenue (Organization of the Petroleum Exporting Countries, 2019). Therefore, increases or decreases in the global oil price will directly affect the government revenue and expenditure in many of these countries. However, the impact of oil shock on inflation in few economies especially Algeria, Brazil, South Africa, Russia and Nigeria, over a few steps may not be a surprise because many of these countries have recently implemented good monetary policies to manage their inflationary pressures. Therefore, it is possible good monetary policy can help to minimise the impact of changes in the global oil price for this country.[3] This view is supported by the findings of Hooker (2002), Taylor (2000), Cologni and Manera (2008), Chen (2009), LeBlance and Chinn (2004), Mandal, Bhattcharya, and Bhoi (2012) and Dedeoglu and Kaya (2014) who indicate that the effect of the oil price on inflation is weaker when adequate monetary policies are implemented.

The range of the MAPE values for all favoured models for BRICS and OPEC countries is above 20 percentage points except for South Africa (5% to 14%), Brazil (5% to 13%) and Saudi Arabia (2%–13%) that have a history of the lower inflation. This suggests that countries with higher inflation will likely have higher MAPE values.

The stability test indicates that the stability of a model can enhance inflation forecasting performance for a few countries. For example, structurally stable models produce the best forecasts for 3 out of 4 selected OPEC countries. In particular, the favoured VAR specification is stable and produces the best forecasting performance for Algeria and Nigeria (at least 2 steps ahead). The favoured VECM specification that is structurally stable produces the best forecast over all horizons for Saudi Arabia. In contrast, all the best forecasting multivariate models for BRICS countries are structurally unstable. The good forecasting performance of the structurally unstable models for BRICS countries is consistent with the observations of Stock and Watson (2003), Rossi (2012) and Gabrielyan (2016) in the sense that structural instability does not necessarily imply poor forecasting performance, especially in out-of-sample. Rossi (2012) documents that out-of-sample forecast comparisons are robust to model instabilities because their procedures can minimise the effect of structural breaks on the forecasting model.

Conclusions and summary

This research utilised explanatory variables commonly employed to model and forecast inflation subject to data availability. The order of integration and seasonally adjusting the data were carried out to avoid issues involving seasonal unit roots. The motivation for considering a range of VAR-based dynamic models is as follows: models involving non-stationary series may lead to problems of spurious regression that can adversely affect forecasting accuracy. Therefore, this study conducted differencing and cointegration restrictions to transform non-stationary series into stationary variables. VARs estimated with cointegrated data will be mis-specified if all of the data were found to be different because the long-run information will be omitted and will have omitted stationarity inducing constraints if all of the data are used in levels. Therefore, the order of integration of all the considered variables were tested for cointegration. Based upon this analysis, the forecasting performance of the following three

[3] For example, Brazil launched a growth acceleration program in 2007 to provide tax incentive and reduce energy costs, strengthen its investment through foreign participation and restructure its oil royalty payment to increase revenue and provide more capital to the private sector. Similarly, Algeria government has recently imposed a policy that reduces licensing of importation of luxury furniture's. Also, Government has approved the quantitative easing of printing almost 570 billion dinars (about 5 billion dollars) to help the Central Bank lend money to Public Treasury. In addition, government has also approved the plan to diversify its economy by boosting domestic engineering, petrochemical and pharmaceutical and food industries to make them more globally competitive (The reuter, 2016).

multivariate specifications with the benchmark model (Naive Model) was compared – first, the VAR model with only (difference) stationary variables; second, VECM without imposing cointegrating restrictions; and third, the VEC that imposes a single cointegrating equation on the VECM.

The main results in this paper confirm no single model can dominate across all the countries. The forecast performance of inflation depends on the nature of the economy and whether the country experiencing higher inflation or low inflation. For instance, the model that includes long-run information in the form of a specified cointegrated equation generally improves the inflation forecasting performance for BRICS countries and one OPEC country (Saudi Arabia) that has a history of low inflation. An explanation for this result is that country with moderate inflation tend to have low instability and may not require further differencing of macroeconomic variables. This is consistent with previous findings that stated that forecasts are most likely to be improved by applying error-correction techniques if the data strongly supports the cointegration hypothesis (see, Timothy & Thomas, 1998; Christoffersen & Diebold, 1998).

This study also showed that the unrestricted VAR model has a superior inflation forecast than cointegrating models and naïve model for OPEC countries that have a history of higher inflation. As noted earlier, that first differencing (stationary data) can capture different characteristics of instability in high inflation economy such as OPEC countries.

Further, areas where both unemployment and the output gap are available as indicators of the Phillips curve, models including unemployment outperform those that use the output gap because unemployment indicator contains the most valuable information in inflation forecasting rather than models based on alternative indicators (output) for the selected countries.

The evidence also revealed that the model that considers oil price endogenous appears to secure better forecasting performance than the model that considers the oil price as exogenous for both BRICS and OPEC countries. This is not surprising because OPEC countries export oil while the BRICS countries (except Russia) import oil. Therefore, increases or decreases in the global oil price will directly affect government revenue and expenditure in many of these countries. Lastly, the application of structural stability tests provides evidence that using stable models enhances inflation forecasting performance for some OPEC countries. In contrast, all the favoured forecasting models for BRICS countries are structurally unstable. The performance of the favoured unstable forecasting models is consistent with the study of (Stock & Watson, 2003; Rossi, 2012) who argued that an unstable theoretical model could mislead the favoured out-of-sample forecasting.

Finally, some limitations of this study are worth mentioning. First, the proposed multivariate models focused on differencing and cointegrating restrictions to ensure the stationarity of the data, where available variables were combined and specified based on their level of integration to forecast inflation. For instance, a VAR model is estimated based on differenced variables I(0); the same holds true for VECM and VEC models, where differenced variables and linear combinations of I(I) covariates are stationary. In future, multivariate models guided by economic theory rather than the order of integration of variables are suggested. Also, this study only compares the forecasting performance of different multivariate models (VAR, VECM and VEC) with a naive model. Therefore, more non-linear models and dynamic models (such as switching Markov, Dynamic stochastic general equilibrium modelling and neural network) need to be considered for forecasting in both OPEC and BRICS countries in the future to develop the work further.

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