Forecasting Inflation Rate of Bangladesh : ARIMA and VAR Model Comparison

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[Abstract : Policymakers need to monitor inflation closely since it is considered as one of the major social problems. Although forecasting inflation is not so easy, it needs to perform a successful monetary policy for a country. Economists use different types of approaches to forecast a time series variable. Here, Autoregressive Integrated Moving Average (ARIMA) model and Vector Autoregressive (VAR) model are used to forecast the inflation rate of Bangladesh. In this paper, within-sample forecasting is performed using ARIMA and VAR model; where the comparison based on the different evaluation criteria suggests that VAR model approach is better than ARIMA model.]

Keywords : Inflation, forecasting, ARIMA, VAR, model comparison

1. Introduction

The phenomenon of inflation is characterized by a rising price level. From an elementary demand-supply model, we know that price rises in response to excess demand. Therefore, inflation is related to excess demand. An excess demand situation arises due to both from the changes in supply or demand. Policymakers need to monitor inflation closely since it is considered as one of the major social problems. Although forecasting inflation is not so easy, it is important to perform a successful monetary policy for a country. Economic growth with a stable price level is an important policy goal of a developing country. Since there is a trade-off between inflation and unemployment in the short run of an economy, sometimes the government becomes unable to maintain a stable rate of inflation, which reduces the purchasing power of money and living standards. High inflation can lead to uncertainty making domestic and foreign investments reluctant to invest in the economy. Because the real return falls with a persistent rise in the price level, sensible spending and saving decisions by economic agents are hindered by it and also discourages saving. Thus, inflation worsens the country's terms of trade by making domestic goods and services costly relative to foreign goods and services.

According to the theory of adaptive expectations, people form their expectations of inflation based on past and recently observed inflation rates. Expectation of the future rates of inflation affects the decision of economic agents. It is claimed by Milton Friedman (1970) that "Inflation is always and everywhere a monetary

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phenomenon in the sense that it is and can be produced only by a more rapid increase in the quantity of money than in output" (p. 24).On the other hand, conforming to neo-Keynesians, through the inflationary gap, prices are expected to change due to the changes in real income (aggregate demand).Traditionally, the wage/price (Phillips curve) approach was used to explain inflation, and also it has been claimed to explain both demand-pull and cost-push inflation.

This paper attempts to evaluate some of the inflation forecasting models used in time series econometrics. There are several factors that affect the rate of inflation of a country. Changes in the money supply play a very important role in changing the inflation rate. If the money supply grows faster than the rate of real output in the economy then it causes creating inflation. This is the case where aggregate demand increases while aggregate supply remains static. The most obvious asset is a currency, sum of outstanding paper money, and coins. The second type of asset used for the transaction is demand deposits, traveller's check, money market deposits, and other checkable deposits. The combination of all these is referred to as broad money (M2). Where, M2 is a wider categorization than M1, because it includes highly liquid assets, not only cash. The relationship between inflation and money supply can be explained by the Quantity Theory of Money proposed by Irving Fisher (1911), postulates that the quantity of money paid for goods and services must be equal to the value of money. That is, changes in the quantity of money affect inflation rate by changing the overall price level in the economy. This relationship can also be shown by the following equation of exchange :

$$MV = PT$$

Where, M = money supply, V = velocity of money, P = price level, and T= number of transactions. However, the value of transactions (PT) is proportional to the value of output (PY) since higher level of production implies larger number of transactions in the economy.

An increase in the price of factors of production can influence an economy by a supply shock. Changes in oil price affect the cost of production of the goods made with petroleum products. Therefore, the rate of inflation and oil prices are assumed to change in the same direction. Bangladesh is highly dependent on oil imports from the rest of the world. Since oil is used from the production level to the transportation of goods, it affects the final cost of a good or service which accelerates the rate of inflation. Using two sample periods of 1962-1980 and 1981-2000, Hooker (2002) tried to figure out the relationship between inflation and oil price. It was shown that the impact of oil price on inflation was significant for the first sample and insignificant for the second sample period. For selected emerging Asian countries, Chou and Tseng (2011) examined the effect of oil prices on the rate of inflation. After the short run and long run breakdown of the pass-through effect of oil price on inflation, the result found that this effect was significant for the long run, while insignificant in the short-run. The study of Sek & Wong (2015) postulated that oil price has a direct impact on the low oil

dependency group and an indirect impact on the high oil dependency group in determining domestic inflation.

The inflation-exchange rate relationship has significant importance for emerging countries. There is an indirect effect of exchange rate on the rate of inflation by changing the import cost of goods and services. An appreciation of domestic currency makes foreign goods cheaper relative to domestic goods. Hence, the price of imports will fall which decelerate the inflationary pressure. However, the depreciation of domestic currency causes to increase the prices of imported goods. On the other hand, domestically produced goods may also become more expensive as the domestic producers face weaker competition from abroad. Woo (1984) explained four channels through which the exchange rate influences domestic inflation. First, the domestic inflation rate is directly affected by the price of imported goods. Second, the price of imported goods immediately affects the cost of domestic goods. Third, fluctuations in the exchange rate have an immediate effect on the current account which affects the total demand in the economy. Fourth, the price of foreign commodities will increase.

Inflation and interest rates are inversely related. A lower interest rate stimulates investment and consumer spending, causing the economy to grow and higher inflation. That is, a lower interest rate means a lower price for holding money or loaning money, which in turn increases the demand for loans by the individuals and businesses. With a higher demand for loans, banks increase their money supply, leading to higher rate of inflation. The opposite holds true for a higher rate of interest. The opportunity cost of holding money and the cost of borrowing money rises with an increase in interest rate. It also reduces the aggregate demand and causes lower output and inflation in the economy. Besides, higher interest rate attracts foreign investors to invest more in domestic economy, leading to an appreciation of domestic currency and lower rate of inflation thereby. Another definition arises from Fisher. Fisher effect shows that higher inflation means a higher nominal interest rate and vice versa. Booth and Ciner (2001) performed a co-integration analysis to test the relationship between interest rate and inflation rate for 9 European countries and the USA. The result shows a long-run relationship between these two variables. A similar finding was mentioned in the study of Brazoza and Brzezina (2001); and Fave and Auray (2002).

2. Literature review

The objective of this study is to forecast inflation by using a univariate and vector autoregressive model (VAR). Therefore, the literature review mainly focuses on the influential papers concerning inflation forecasting.

Taslim (1982) found that an increase in the money supply contributes significantly to increase the rate of inflation. The wage variable seems to function essentially as a transmitter of inflationary impulse rather than being the cause of

it. The domestic currency can devaluate in any amount due to an equal proportionate increase in the inflation rate. Robinson, W.(1998) forecast the inflation rate of Jamaica using the VAR model, augmented by an error correction term. Where the VAR model revealed some interesting that is an expansionary monetary policy has an unambiguous effect on prices and has at least two months lag effect. Exchange rate stabilization was considered as the most effective way of short term stabilization. Faisal F. (2012) conducted a study to forecast Bangladesh's inflation rate where the Box-Jenkins ARIMA time series model was applied. The validity of the model was tested using standard statistical techniques, and the best model was proposed on the basis of various diagnostic and several evaluation criteria. But the main disadvantage of the ARIMA model is that it ignores many explanatory variables that extremely affect the inflation rate. Suliman & Mc Cann (1991) showed that the existence of feedback causality between money and real income (aggregate demand) indicates that changes in aggregate demand affect prices through their impact on the money supply. It was also found that any increase in producer prices through higher wages is passed immediately to consumer prices. Mehra (1991) argued that the long-run movements in the rate of growth in prices and labour costs are correlated over time. But the presence of this correlation appears due to Granger-causality running from inflation to wage growth, not from wage growth to the rate of inflation. Hoa (2017) used univariate and VAR (vector autoregressive) models to forecast the inflation rate in Vietnam. Where univariate model only uses the inflation rate series to forecast it, and the multivariate model requires other variables to perform inflation forecast, such as quarterly series of real GDP, exchange rate, commercial banks' lending rate, oil price, etc.Zardi(2017)used univariate models as Random Walk, SARIMA, a Time-Varying Parameter model, and a suite of multivariate autoregressive models as Bayesian VAR and Dynamic Factor models to forecast the inflation rate of Tunisia. The results reveal that the forecast combination leads to a reduction in forecast error compared to individual models.

To forecast the inflation rate of Albania, Sinaj (2014) used ARIMA and VAR models and obtained data of 17 years period about CPI, M2, and interest rate. Results gained by this analysis indicate a significant relation between CPI, M2, interest rates, and a statistically significant autoregressive relation to the CPI with time delay. Alnaa and Ahiakpor (2011) used monthly inflation data of Ghana from 2000 : 6 to 2010 : 12 to forecast the inflation rate of Ghana. They used the ARIMA model, and ARIMA (6,1,6) was the best-fitted model in this study. This paper completely ignores the importance of many variables that are influencing to cause inflation. Okafor, C., & Shaibu, I. (2013) also applied the ARIMA model to forecast the inflation rate of Nigeria. Bokhari, S. M., & Feridun, M. (2006) forecast the inflation rate of Pakistan using ARIMA and VAR models. Results indicate that the VAR model does not perform better than the ARIMA (2, 1, 2) model.

A comparative model analysis to forecast the rate of inflation is totally absent in Bangladesh. This paper will contribute to forecast rate of inflation by considering univariate and multivariate model.

3. Data and Methodology

A long time series data is required for univariate time series forecasting. It is usually recommended to have at least 50 observations. This study researches on monthly inflation data based on consumer price index (CPI), which have been collected from 2002M1 to 2020M6 for Bangladesh. The VAR model includes money supply, exchange rate, oil prices, financial interest or lending rate. Data on money supply, exchange rate, and interest rate or lending rate are collected from "International Financial Statistics (IFS)", a data section of IMF. While the data on crude oil prices are collected from "U.S. Energy Information Administration (eia)".

3.1 ARIMA model

The Box-Jenkins methodology (Anderson, 1976) indicates a set of procedures that are used for identifying, fitting, and checking autoregressive integrated moving average (ARIMA) models with time series data. ARIMA methodology is not attached within any fundamental theory of economics or structural relationship. The forecasts from the fitted models are based purely on the memory of past behaviour and previous error terms of the series of interest (Hanke & Winchern, 2008). In making forecast, the Box-Jenkins (ARIMA) model technique completely ignores independent variables. ARIMA models have three model parameters, a parameter for AR(p) process, one for I(d) or integrated process, and another one for MA(q) process; all these combining and interacting among each other are rearranged into the ARIMA (p,d,q) model.
ARIMA (p,d,q) can be written as;

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + u_t + \alpha_1 u_{t-1} + \cdots + \alpha_q u_{t-q}$$

Where, Y_t= rate of inflation; β_0,β_i, and $\alpha_i$are the parameters to be estimated; $u_t =$ error term. Before applying this equation to a time series, however, the assumption is that the series is non-stationary. So, some steps must be taken to convert the series into a stationary one. Using univariate models to perform forecasting is to use only one variable's historical data to predict its future. The first advantage of this approach is that it needs only one variable to forecast it. It does not require a large dataset, with many different variables, which is very difficult to obtain and is not usually available in developing or emerging economies. Despite having no direct economic interpretation, many pieces of literature show the use of ARIMA or ARMA models to forecast a series. If the series is stationary in the level form, then no transformation is needed, and our model turns into an ARMA model.

3.1.1 ADF test for stationarity

In econometrics, the Augmented Dickey-Fuller (ADF) test checks the null hypothesis to find whether a unit root is present in our series or not. The ADF testing procedure is similar to the Dickey-Fuller test, but it is applied to the model.

$$\Delta y_t = (\rho_1 - 1) y_{t-1} + \sum_{j=2}^{p} p_j \left(\Delta y_{t-j+1}\right) + \varepsilon_t$$
$$\Delta y_t = \gamma y_{t-1} + \sum_{j=2}^{p} p_j \left(\Delta y_{t-j+1}\right) + \varepsilon_t$$

This is called the Augmented Dickey-Fuller (ADF) test and is implemented in many statistical and econometric software packages. Where $\rho_1 = (\beta_1 + \beta_2 + \cdots + \beta p$, $\gamma = (\rho 1 - 1)$ and $\Delta yt = yt - yt - 1$.

The test statistics value is computed as follows :

$$\text{DF} = \frac{\hat{\gamma}}{SE(\hat{\gamma})}$$

Where $\hat{\gamma}$ is the estimated coefficient and SE($\hat{\gamma}$) is the standard error of the estimated coefficient. The hypothesis test for the ADF test :

$$H_0 : \gamma = 0 \quad \text{vs} \quad H_1 : \gamma < 0$$

The computed value of the test statistic is compared with the relevant critical value for the Dickey–Fuller Test. If the test statistic is less than the critical value, then reject the null hypothesis, and no unit root is present.

3.1.2 Model Selection and Forecasting

The correlograms examine the time series data by plotting the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) in order to get the functional form of the data. ACF represents the degree of persistence over respective lags of variables while PACF measures the amount of correlation between two variables, which is not explained by their mutual correlation with a specified set of other variables. Besides, the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn criterion are used to select a best model.

Forecasting performance of various types of ARIMA models will be compared by computing statistics like AIC, BIC, Root Mean Square Percentage Error (RSMPE), Mean Absolute Error (MAE), etc. The smaller is the statistics, the better will be the model. In addition, by plotting the residuals of the estimated model, the autocorrelation among errors is checked. If there is no autocorrelation, then the estimated model can be used for forecasting purposes.

3.2 VAR Model

The vector autoregressive (VAR) model was proposed by Christopher A. Sims in 1980. For the analysis of multivariate time series, VAR is considered as one of the foremost successful, flexible, and practical models. The univariate time series model cannot ensure any economic reason for inflation. But the VAR model uses multiple variables that highly affect the inflation rate of an economy. All variables in a VAR model enter in the same way : each variable has an equation, and its evaluation is based on its own lagged values, the lagged values of other model variables, and an error term.

Let, $Y_t = (y_{1t}, y_{2t}, \dots, y_{nt})$,denote an (nx1) vector of time series variable; such as (inflation,money supply, oil price, exchange rate, and interest rate). A VAR model can be expressed as :

$$Y_t = C + \gamma_1 Y_{t-1} + \gamma_2 Y_{t-2} + \cdots + \gamma_p Y_{t-p} + \varepsilon_t$$

Where γ_i is an (nxn) coefficient matrix, $\varepsilon_t$is an (nx1) error matrix which are pure white noise and C is an (nx1) vector of constants (intercept).

It is problematic to use non-stationary time series in VAR modelling concerning statistical inference because the standard statistical test used for inference is based on the condition that all of the series used must be stationary. If the series are non-stationary, then we need to make the series stationary by first or higher-order differencing. In the VAR model, endogenous variables are expressed as a function of its own lags and lags of other variables. So, it is very important to select the lag length properly; otherwise, the VAR model cannot perfectly explain our model and will lose the degrees of freedom by adding unnecessary lags. In most cases, systematic lags are used to estimate the VAR models; that is, in all equations of the model, the same lag length is used for all variables. Frequently, the lag length is selected using an explicit statistical criterion such as the AIC, SIC, HQ, etc.

4. Results

This chapter displays the empirical results from the modelling of inflation using ARIMA and VAR models, respectively.

4.1 ARIMA Model

The following inflation series of Bangladesh displays a mean diverting process, which indicates the non-stationarity of our data. Since our data are not stationary in the level form, first-order differencing is necessary. That is why our model turns into an ARIMA model, where the integrating order I(d) is one.

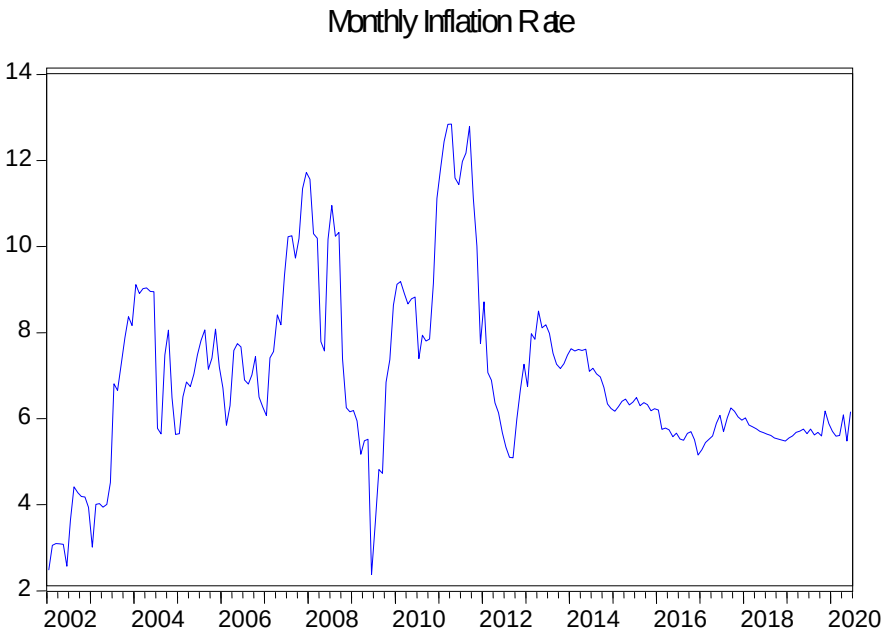


Figure 1 : Monthly Inflation Rate in Bangladesh (January, 2002 to June, 2020)

Augmented Dickey-Fuller (ADF) Test					
In level			**In First Difference**		
None	Constant	Constant and linear trend	None	Constant	Constant and linear trend
-0.579 (0.466)	-3.163 (0.024)**	-3.473 (0.045)**	-13.308 (0.000)***	-13.282 (0.000)***	-13.279 (0.000)***

Table 1 : Unit Root test of Inflation Rate

***, **, and * imply statistically significant at 1%, 5%, and 10% level, respectively. Probability values in the parentheses.

In level form, the inflation rate series is non-stationary with no constant and trend. But the series is stationary at 5% level of significance with constant, and constant and linear trend. To make our model more precise and correct, first difference is taken to stationarise the series. The correlogram result also gives us a similar result of being the series inflation rate non-stationary, which is ACF falling gradually and PACF is not significant after the first lag (see appendix-Figure : 5).

4.1.1 ACF-PACF Plots and Model Selection

To get a best fitted ARIMA model, we need to determine AR and MA process of a time series, after the series has been stationarised by taking the appropriate difference. We can identify the possible numbers of AR and/or MA terms that are needed, by looking at the autocorrelation function (ACF) and partial autocorrelation (PACF) plots of the differenced series. ACF plot is just a bar chart of the coefficients of correlation between a time series, and its lags, while the PACF plot is a plot of the partial correlation coefficients between the series, and its lags. The ACF and PACF suggest the significance of the 12th lag of AR and MA series (see appendix-Figure : 6). So our model turns to ARIMA (12,1,12) model, which minimizes all the information criteria. In-sample forecasting is necessary to compare the different models to forecast out of sample. It is generally accepted that a model which performs better within sample will better forecast out of sample.

Type of Model	Information Criteria		
	Akaike Info Criterion	Schwarz Criterion	Hannan-Quinn Criterion
ARIMA (12, 1, 12)	1.9699***	2.0019***	1.9828***
ARIMA (12, 1, 13)	2.1257	2.1577	2.1386
ARIMA (1, 1,1)	2.2493	2.2801	2.2617
ARIMA (12,1,1)	2.1407	2.1726	2.1536
ARIMA (1,1, 12)	2.0289	2.0598	2.0414

Table : Model selection based on Information Criteria
*** indicates lowest information criteria among the models.

4.1.2 Diagnostic checking

Various diagnostic checking of estimated regression is necessary to measure the accuracy of a model. Residual normality test and autocorrelation test are widely used in time series data. The following normality test indicates that our model is correctly specified.

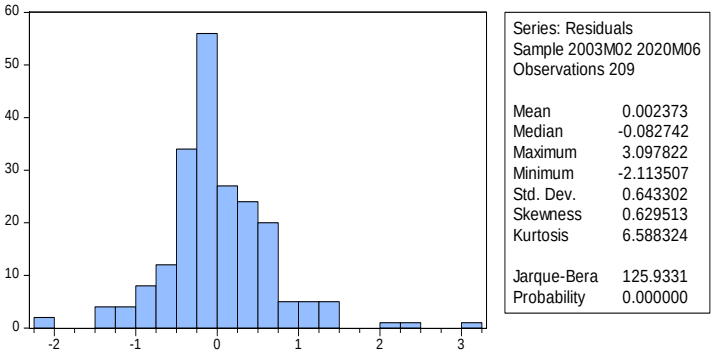


Figure 2 : Residual Normality Test

4.2 VAR Model Estimation and lag length selection

In the VAR model, we take the inflation series as dependent variable. The VAR contains five variables, money supply, interest rate, oil price, and exchange rate. The following figure at level form shows that all the variables are non-stationary. So, log transformation and then first difference is taken to make data stationary. In the following graph, all of the variables show a mean-reverting variable. Since log of money supply needs to take second-order differences to make the series stationary, we will use the first difference of log of money supply in our VAR model. The first difference of the log of money supply implies the growth rate of money supply. After estimating the VAR model, the VAR lag length criteria suggest two models based on the information criteria. Schwarz information criterion and Hannan-Quinn information criterion minimizes information at first lag, whereas Akaike information criterion suggests the 12^{th} lag for our model (see appendix-Table : 5).For the parsimony of our model, we have estimated the VAR model using first lag considering the minimization of information criteria based on Schwarz information and Hannan-Quinn information criteria. This implies that any change in the variables affect inflation immediately after the first lag. This matches with the normal economic theories. The post estimation test for accuracy of the model suggests that the model is free of heteroscedasticity and autocorrelation problem, which makes our model eligible for the forecasting purpose.

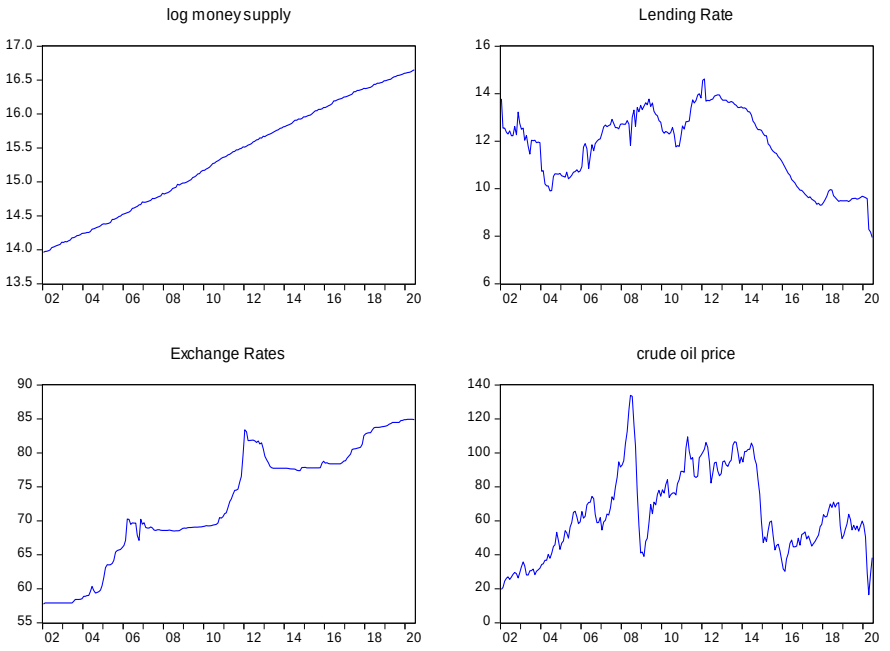


Figure 3 : Monthly Money Supply, Lending Rate, Exchange Rate and Crude Oil Price series

Variables	Augmented Dickey-Fuller (ADF) Test					
	In level			In First Difference		
	None	Constant	Constant and trend	None	Constant	Constant and trend
Growth rate of money supply	-0.639 (0.439)	-1.627 (0.466)	-2.003 (0.596)	-15.967 (0.000)***	-15.936 (0.000)***	-15.938 (0.000)***
Exchange rate	2.187 (0.993)	-1.042 (0.738)	-2.180 (0.499)	-10.517 (0.000)***	-10.875 (0.000)***	-10.862 (0.000)***
Interest or lending rate	-1.427 (0.143)	-0.606 (0.865)	-0.959 (0.946)	-16.959 (0.000)***	-17.026 (0.000)***	-17.099 (0.000)***
Crude oil Price	-0.872 (0.334)	-2.954 (0.041)**	-2.840 (0.185)	-9.753 (0.000)***	-9.732 (0.000)***	-9.760 (0.000)***

Table 3 : ADF test of the series in level form and after first differences
***, **, and * imply statistically significant at 1%, 5% and 10% level respectively. Probability values in the parentheses.

4.3 Model comparison

Finally, we compare the ARIMA and VAR models' prediction accuracy. The model with smallest error is a better model to forecast inflation. In-sample forecasting suggests that the VAR predication minimizes all the error criteria (see appendix-Figure : 7). Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and The inequality coefficient are lowest for VAR model. The estimated criteria table is shown in the following. In-sample forecasting comparison graph also suggests that the deviation from the actual inflation rate is lowest for the VAR model (see appendix-Figure : 7& Figure : 8).

Criteria	ARIMA model	VAR model
RMSE (root mean square error)	0.484	0.242
MAE (mean absolute error)	0.430	0.205
MAPE (mean absolute percentage error)	7.724	3.587
Thei inequality coefficient	0.041	0.021

Table 4 : Model selection based on Criteria

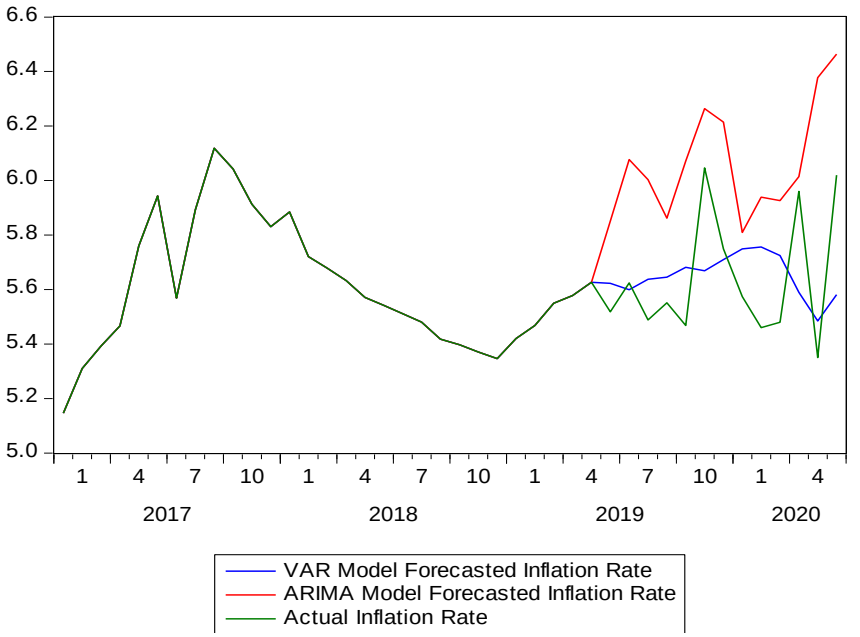


Figure 4 : In-sample forecasting comparison graph

5. Limitations

There are some limitations which may be noted for this study. Since the monthly data of the supply of money is not available for the period before 2001 M12, the data set used in this study is for a short period of time. However, the analysis of this paper is based on the monthly inflation data, meaning that the points of data seem enough to conduct the study. In the VAR model, there are many other factors that influence the inflation rate, such as- unemployment rate, gross domestic product (GDP), remittance, etc. The effect of these factors are not considered in the analysis of this study because of the unavailability of monthly data of those factors.

6. Conclusion

This study analyses a comparative evaluation of forecasting the monthly rate of inflation in Bangladesh using ARIMA and VAR models, where the forecasting power of historical inflation data are investigated. In the ARIMA model, we use the inflation rate from 2002M1 to 2020M6, where the best ARIMA (12,1,12) model is used for forecasting the inflation rate. The study shows that despite the exclusion of explanatory variables, there is evidence of substantial inflation inertia according to the definition of Solow(1969). This model is selected according to information

criteria; that is, the prediction power will be higher for lower information. VAR model takes into account the factors that affect the rate of inflation. By comparing ARIMA and VAR models using the post forecast comparison criteria, this study suggest that the VAR model performs better within-sample forecast and reduces all the forecasting error. That means, if a model performs better within the sample then it will also perform better out of the sample. Therefore, within the available monthly data of the macro indicators, forecasting the rate of inflation using VAR model is suggested by the analysis of this study.

References

C. A. Sims (1980). 'Macro economics and reality'. *Econometrica : journal of the Econometric Society*, 1–48.

C. Okafor & I. Shaibu (2013). 'Application of ARIMA models to Nigerian inflation dynamics'. *Research Journal of Finance and Accounting*, *4*(3), 138–150.

F. Faisal (2012). 'Forecasting Bangladesh's inflation using time series ARIMA models'. *World Review of Business Research*, *2*(3), 100–117.

G. G. Booth & C. Ciner (2001). 'The relationship between nominal interest rates and inflation : international evidence'. *Journal of Multinational Financial Management*, *11*(3), 269–280.

I. Fisher (1911). *The purchasing power of money : its' determination and relation to credit interest and crises*. Cosimo, Inc.

J. Hanke& D.Wichern (2008). *Business Forcasting, 9th edition; USA*, Person International Edition, ninth edition.

K. W. Chou & Y. H. Tseng (2011). "Oil price pass-through into CPI inflation in Asian emerging countries : the discussion of dramatic oil price shocks and high oil price periods." *British Journal of Economics* 1 (2011) : 1–13.

M. A. Hooker (2002). 'Are oil shocks inflationary? Asymmetric and nonlinear specifications versus changes in regime'. *Journal of money, credit and banking*, 540–561.

M. A. Taslim (1982). 'Inflation in Bangladesh : A reexamination of the structuralist–Monetarist controversy'. *The Bangladesh development studies*.

M. Brazoza Brzezina (2001). 'The Relationship between Real Interest Rate and Inflation'. *Research Department, WP*, *23*.

M. Friedman (1970). 'Counter-Revolution in Monetary Theory'. Wincott Memorial Lecture, Institute of Economic Affairs, Occasional paper 33.

M. O.Suliman& K. McCann (1991). 'Inflation : Some Empirical Evidence'. *The American Economist*, *35*(2), 49–59.

O. D. Anderson (1976). *Time series analysis and forecasting : the Box-Jenkins approach* (Vol. 19). London : Butterworths.

P. Fave & S. Auray (2002). 'Interest rate and inflation in monetary models with ingenious money growth rate'. *Economic Bulletin*, *5*(1), 1–10.

R. Solow (1969). *Price Expectations and the Behavior of the Price Level*. University of Manchester Press.

S. C. Zardi (2017). *Forecasting inflation in a macroeconomic framework : An application to Tunisia* (No. 07–2017). Graduate Institute of International and Development Studies Working Paper.

S. E. Alnaa & F. Ahiakpor (2011). ARIMA (autoregressive integrated moving average) approach to predicting inflation in Ghana. *Journal of economics and international finance*, *3*(5), 328–336.

S. K. Sek, X. Q. Teo & Y. N. Wong (2015). 'A comparative study on the effects of oil price changes on inflation. *Procedia Economics and Finance*, *26*, 630–636.

S. M. Bokharı & M. Feridun (2006). Forecasting inflation through econometric models : an empirical study on Pakistani data.

T. T. Hoa (2017). *Forecasting inflation in Vietnam with univariate and vector autoregressive models* (No. BOOK). The Graduate Institute of International and Development Studies, International Economics Department.

V. Sinaj (2014). Models to forecast inflation in Albania. *International Journal of Scientific Research*, *5*(1), 2229-5518.

W. Robinson (1998). Forecasting inflation using VAR analysis. *Bank of Jamaica*.

W. T.Woo&P. Hooper (1984). Exchange rates and the prices of nonfood, nonfuel products. *Brookings Papers on Economic Activity*, *1984*(2).

Y. P. Mehra (1991). 'Wage growth and the inflation process : An empirical note'. *The American Economic Review*, *81*(4).

Appendix

Sample: 2002M01 2020M06
Included observations: 222

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.924	0.924	192.10	0.000
		2	0.836	-0.118	350.25	0.000
		3	0.753	-0.013	479.06	0.000
		4	0.675	-0.019	582.88	0.000
		5	0.596	-0.048	664.42	0.000
		6	0.514	-0.075	725.33	0.000
		7	0.436	-0.025	769.23	0.000
		8	0.360	-0.037	799.39	0.000
		9	0.280	-0.090	817.74	0.000
		10	0.212	0.025	828.26	0.000
		11	0.152	-0.007	833.71	0.000
		12	0.102	0.006	836.16	0.000
		13	0.091	0.223	838.11	0.000
		14	0.071	-0.121	839.31	0.000
		15	0.039	-0.096	839.68	0.000
		16	0.002	-0.063	839.68	0.000
		17	-0.030	-0.009	839.91	0.000
		18	-0.057	-0.033	840.70	0.000
		19	-0.058	0.172	841.51	0.000
		20	-0.065	-0.096	842.56	0.000

Figure 5 : ACF and PACF in level form after first difference

Sample: 2002M01 2020M06
Included observations: 221

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.105	0.105	2.4496	0.118
		2	-0.027	-0.039	2.6178	0.270
		3	-0.041	-0.034	2.9924	0.393
		4	-0.003	0.004	2.9951	0.559
		5	0.012	0.010	3.0297	0.695
		6	0.013	0.010	3.0708	0.800
		7	0.005	0.003	3.0767	0.878
		8	0.025	0.026	3.2236	0.920
		9	-0.090	-0.096	5.1057	0.825
		10	-0.069	-0.048	6.2017	0.798
		11	-0.081	-0.075	7.7594	0.735
		12	-0.335	-0.340	34.149	0.001
		13	0.101	0.176	36.580	0.000
		14	0.091	0.037	38.543	0.000
		15	0.045	0.014	39.023	0.001
		16	-0.042	-0.025	39.449	0.001
		17	-0.024	0.003	39.594	0.001
		18	-0.114	-0.138	42.760	0.001
		19	0.048	0.074	43.316	0.001
		20	-0.038	-0.069	43.666	0.002

Figure 6 : ACF and PACF

VAR Lag Order Selection Criteria

ndogenous variables : D(INFLATION RATE) D(DLNMS) D(EXCH_RATE) D(LEND_RATE) D(OIL_P)

Exogenous variables : C

Sample : 2002M01 2020M06

Included observations : 200

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-500.6078	NA	0.000108	5.056078	5.138536	5.089447
1	-416.4295	163.3059	5.98e-05	4.464295	4.959042*	4.664512*
2	-378.8722	70.98331	5.27e-05	4.338722	5.245759	4.705786
3	-358.5829	37.33222	5.53e-05	4.385829	5.705156	4.919741
4	-342.7928	28.26438	6.08e-05	4.477928	6.209544	5.178686
5	-290.4482	91.07947	4.64e-05	4.204482	6.348389	5.072088
6	-262.3964	47.40762	4.53e-05	4.173964	6.730160	5.208417
7	-241.3583	34.50242	4.74e-05	4.213583	7.182069	5.414884
8	-217.3973	38.09807	4.84e-05	4.223973	7.604748	5.592121
9	-202.8060	22.47050	5.44e-05	4.328060	8.121125	5.863056
10	-177.8651	37.16204	5.53e-05	4.328651	8.534005	6.030494
11	-94.85823	119.5299	3.15e-05	3.748582	8.366227	5.617272
12	-53.16546	57.95294*	2.73e-05*	3.581655*	8.611589	5.617192
13	-32.21575	28.07262	2.93e-05	3.622157	9.064381	5.824542
14	-15.76009	21.22780	3.30e-05	3.707601	9.562114	6.076833
15	-1.214960	18.03596	3.80e-05	3.812150	10.07895	6.348229
16	13.22335	17.18159	4.43e-05	3.917767	10.59686	6.620693
17	32.05143	21.46401	4.96e-05	3.979486	11.07087	6.849260
18	55.68119	25.75644	5.35e-05	3.993188	11.49686	7.029809
19	86.40372	31.95143	5.42e-05	3.935963	11.85192	7.139431
20	113.5153	26.84042	5.75e-05	3.914847	12.24310	7.285163

Table 5 : VAR Lag Order Selection Criteria
* indicates lag order selected by the criterion

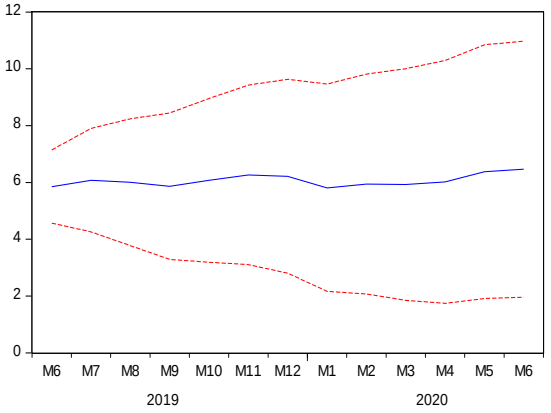
LR : sequential modified LR test statistic (each test at 5% level)

FPE : Final prediction error

AIC : Akaike information criterion

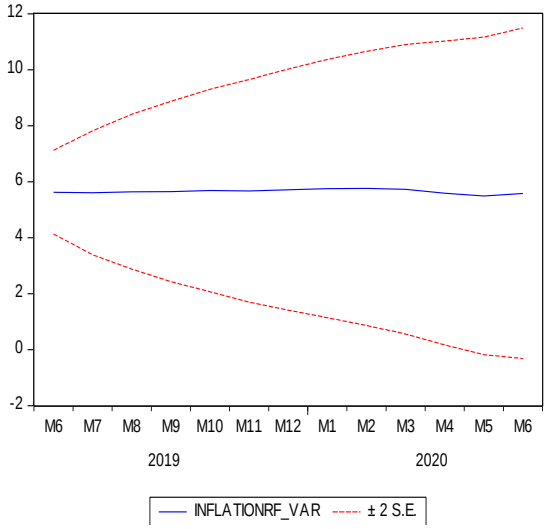
SC : Schwarz information criterion

HQ : Hannan-Quinn information criterion



Forecast: INFLATIONRF_ARIMA	
Actual: INFLATIONRATE	
Forecast sample: 2019M06 2020M06	
Included observations: 13	
Root Mean Squared Error	0.484043
Mean Absolute Error	0.429528
Mean Abs. Percent Error	7.724473
Theil Inequality Coefficient	0.041327
Bias Proportion	0.787436
Variance Proportion	0.002496
Covariance Proportion	0.210068

Figure 7 : ARIMA Model in Sample Forecasting



Forecast: INFLATIONRF_VAR	
Actual: INFLATIONRATE	
Forecast sample: 2019M06 2020M06	
Included observations: 13	
Root Mean Squared Error	0.241601
Mean Absolute Error	0.204842
Mean Abs. Percent Error	3.587270
Theil Inequality Coefficient	0.021395
Bias Proportion	0.002634
Variance Proportion	0.380878
Covariance Proportion	0.616488

Figure 8 : VAR Model in Sample forecasting