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Forecasting time series using Vector Autoregressive Model

Lemya Taha Abdullah[a,*]

[a] *College of Arts - Informatin technology unit, University of Baghdad, Baghdad, Iraq.*

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Abstract

In this study, a vector Autoregressive model was used to analysis the relationship between two time series as well as forecasting. Two financial time series have been used, which are a series of global monthly oil price and global monthly gold price in dollars for a period from January 2015 to Jun 2019. It has 54 monthly values, where the data has been transferred to get the Stationarity, Diekey Fuller test for the Stationarity was conducted. The best three order for model was determined through a standard Akaike information AIC, it is VAR(7) , VAR(8) and VAR(10) respectively. The comparison was made between selected orders by AIC based on the accuracy measure and mean square error (MSE). It turns out that less MSE value of the VAR(10) model. Some tests were conducted like Lagrange-multiplier, Portmanteau, Jarque - Bera to residuals for the selected model, with forecasting for the VAR(10) model for the period from Jun 2019 to Jun 2021 , It is 24 monthly value. It turns out that less MSE for forcasting value for oil price series is to VAR(7) model and less MSE for forcasting value for gold price series is VAR(10) model. The results have been computed through the Stata program.

Keywords: Lagrange-multiplier test, Mean square error, Portmanteau test, Standard Akaike information model.
2010 MSC: Please write mathematics subject classification of your paper here.

1. Introduction

The Vector Autoregressive Models are important models in describing the dynamic behavior of economic variables, studying interactions and analyzing their relationship as well as in forecasting

*Corresponding author
Email address: lemyataha@yahoo.com (Lemya Taha Abdullah)

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such as forecasting foreign exchange rates, sales, profits and also in calculating the impact of various factors on consumer behavior and forecasting change in the future. Moreover, they are useful in analyzing meteorological variable. They are successful and flexible models in multivariate time series analysis.
Sims (1980) introduced Vector Autoregressive models and the basic principles for these models as it has been widely used in most economic research, and Lutkepohl (1991) considered as the main reference for the VAR models and their applications in the financial statements by Hamilton(1994) and Tsay(2001). Saputro et al. (2011) and Diani et al. (2013), Adenomon (2013) and Das (2013) used VAR model to analyze relationships between variables in the field of meteorology [2].
VAR model is a natural extension of the univariate autoregression model to multivariate time series, in which the variables are treated as Endogenous variables and each variable is an equation that includes the right side of which only lagged values for the same Variable and the lagged values for all variables in the model[6], The aim of research is to estimate the VAR model for two variable, that represents the first global oil price and second global gold price, and analyze their relationship and forecasting of these prices .

2. Materials and method [3, 5, 1]

The VAR(p) model of order p can be represented in the following formula:

$$Y_t = C + A_1 Y_{t=1} + A_2 Y_{t-2} + ... + A_p Y_{t-p} + \varepsilon_t \tag{2.1}$$

$y_t = (y_{1t}.....y_{kt})'$ denote an $(k\ x1)$ vector of time series variables
$A_i = (i = 1.2.....p)$ denote an $(k\ x\ k)$ matrices of parameters and ε_t denote an $(k\ x1)$ vector of randam error
$\varepsilon_t = (\varepsilon_{1t}...\varepsilon_{kt})'$ with mean zero and varaince covariance matrix $\sum = E(\varepsilon_t \varepsilon_t')$
And to be VAR model stable must be the Eigen values of the matrix A_i less than one and the randam error vector is normally Distributed with mean zero and variance covariance matrix $\sum$, the diagonal elements of the matrix A in the VAR model represents the autoregression parameters for the same variable over the time, and the off diagonal elements represents across autoregression parameters which determines the effect of each variable in time t on another variable in time $t-1$.
a bivariate VAR (2.1) model is as follows:

$$Y_t = C + A_1 Y_{t-1} + \varepsilon_t \tag{2.2}$$

$Y_t = \binom{y_{1t}}{y_{2t}},\ A_t = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$ and $\varepsilon_t = \binom{\varepsilon_{1t}}{\varepsilon_{2t}}, C = \binom{C_1}{C_2}$
$\binom{Y_{1t}}{Y_{2t}} = \binom{C_1}{C_2} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \binom{Y_{1t-1}}{Y_{2t-1}} + \binom{\varepsilon_{1t}}{\varepsilon_{2t}}$
Each equation can be written separately:
$Y_{1t} = C_1 + a_{11} Y_{1t-1} + a_{12} Y_{2t-1} + \varepsilon_{1t}$
$Y_{2t} = C_2 + a_{21} Y_{1t-1} + a_{22} Y_{2t-1} + \varepsilon_{2t}$
These Equation show that there are no current values of variable on the right side of the equation, the contemporary relations between variables are represented by the variance covariance matrix, each equation is estimated by the least-squares method, The least squares estimator for parameters is as follows:

$$\hat{A} = YZ'(ZZ')^{-1} \tag{2.3}$$

The vector $Z = (z_1.....z_k)$ represents the lagged values of Y_t, and the covariance matrix is as follows:
$\frac{1}{K-Q}(Y - \hat{A}Z)(Y - \hat{A}Z)'$
Q represents the number of estimated parameters.

2.1. Model order selection [8]

For the purpose of estimating the VAR model, it is requires determining the model order, since one of the most commonly used criteria in determining the VAR model order is the Akaike criteria,since the formula of the Akaike criteria is as follows

$$AIC(p) = -2LnL + \frac{2N}{T} \tag{2.4}$$

Where $\ln L$ is the log-likelihood of the model and N is the number of parameters estimated, T represent the sample size.

2.2. Residuals Autocorrelation tests [5]

After estimating the model, a number of tests must first be performed to diagnose the model before starting the forecasting process, there are anumber of important tests to test the autocorrelation of residuals in VAR models including two tests, Portmantau and Breusch Godfrey-LM, the statistics of the portmantau test are as follows:

$$Q_h = T\sum_{j=1}^{h} tr(\sum_{j}^{\hat{n'}}\sum_{0}^{\hat{-1}}\sum_{j}^{\hat{}}\sum_{0}^{\hat{-1}}) \tag{2.5}$$

Then null hypothesis $H_0 : E(\varepsilon_t\varepsilon'_{t-i} = 0.$ $(i = 1.2....)$ and the alternative hypothesis is that the autocovaraince of at least one is not equal to zero, to stationary and unrestricted VAR model , Then null hypothesis distributed as an approximate the distribution of $x^2(k^2(h-p))$ f or $h/T \to 0$, h is the lag number .The statistics for the Breusch Godfrey - LM test is as follows [4]:

$$BG - LM = TR_p^2 \sim x_p^2 \tag{2.6}$$

R^2 Represents the coefficient of determination, if the value of the test statistics is less than the tabular value, there is no autocorrelation in the residuals.

2.3. Jarque-Bera test [7]

This test was presented By Jarque-Bera (1987), this test used to see residuals are normally distributed or not , the test statistics is as follows:

$$JB = T\left(\frac{(\sqrt{b_1})^2}{6} + \frac{(b_2-3)^2}{24}\right) \tag{2.7}$$

b_1, b_2 represents the skewness and kurtosis respectively
$\sqrt{b_1 = \frac{m_3}{m_2^{\frac{3}{2}}}}.b_2 = \frac{m_4}{m_2^2}.m_i$ $i = (1.2.3.4)$
$m_i = \frac{\sum(x_i-\bar{x})^i}{n}$, m_i represents the central moments of observations.

Table 1: the Dickey Fuller test for original series

Series	Tset Statistic	1% Critical Value	5% Critical Value	10% Critical Value	Critical MacKinnon approximate p-value for Z(t)
Oil price Z(t)	−2.125	−3.576	−2.928	−2.599	0.2345
Gold price Z(t)	−1.652	−3.576	−2.928	−2.599	0.4560

3. Forecasting [10, 9]

VAR models considered natural tools for forecasting, as current variables are expressed in terms of variables in previous periods and are useful in forecasting as they contain information on the correlation of variable among them and then use this information to forecast the future change in these variables, the forecasting in VAR(p) model is the same as in AR(P) model, the forecasting for one step is as follows:

$$Y_{t+1/t} = C + A_1 y_t + ... + A_p y_{t-p+1} \tag{3.1}$$

Forecasting for h steps:
$Y_{t+h/t} = C + A_1 y_{t+h-1/t} + ... + A_p y_{t+h-p/t}$

4. Application

The research data represent two time series, the first represent the global monthly oil prices and the second represents the global monthly gold prices for the period from the first month of 2015 until the sixth month of 2019 and is thus 54 monthly value of the prices of oil and gold in dollars, obtained from websites

1. www.Kitco.com/script/histcharts/yearlygraphs.plx.goldprices
2. www.opec.org.oil prices

The results has been computed through the STATA. program. (STATA 13.0) Statistics/Data analysis.

4.1. View and discussion of the results

Due to the unstationary of these two series, a Dickey Fuller test [3] was prformed to as a certain the unstationary, table 1 shows that the absolute value of the test statistics of the two series is less than the tabular values for all the significant levels, this means accepting the null hypothesis of having a unit root and that the two series unstationary, Fig. 1, 2.

After taking the logarithm and the first difference of the two series to get the stationary, the Dickey fuller test performed again to test the stationary of the two series, table2, it was found that the absolute value of the test statistics of the two series is greater than the tabular value of all significant levels. this means rejecting the null hypothesisof having a unit root and that the two series become stationary Fig. 3, 4.

For the selection of order VAR model ,Akaike information criterionis calculated, table 3 shows that Akaike information criterion has the lowest value at the seventh order, followed by the eighth and the tenth.

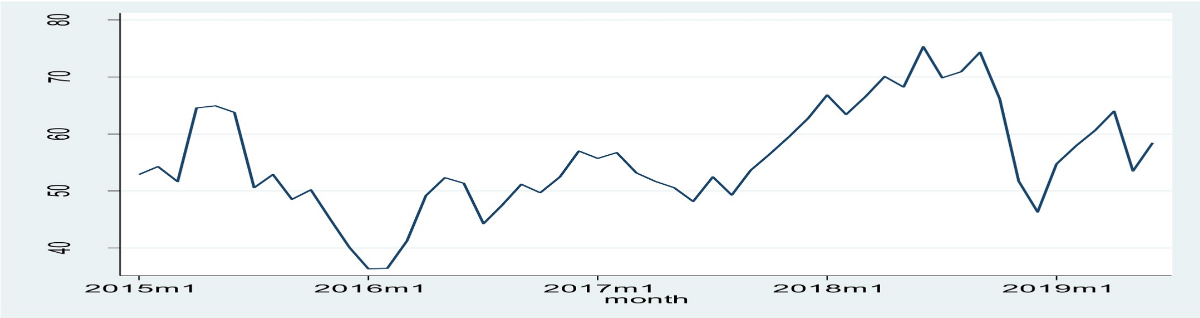

Figure 1: The original oil price series before conversion

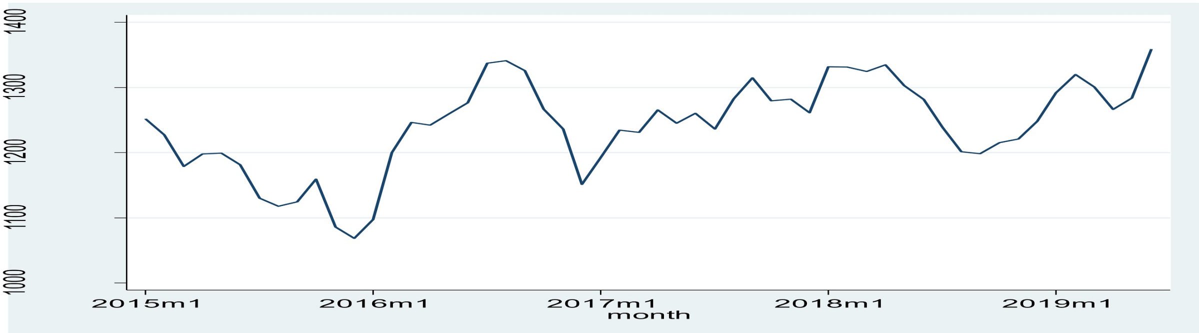

Figure 2: The original gold price series before conversion

Table 2: the Dickey Fuller test for series after taking the logarithm and the first difference

Series	Tset Statistic	1% Critical Value	5% Critical Value	10% Critical Value	Critical MacKinnon approximate p-value for Z(t)
Oil price Z(t)	-6.601	-3.577	-2.928	-2.599	0.0000
Gold price Z(t)	-5.532	-3.577	-2.928	-2.599	0.0000

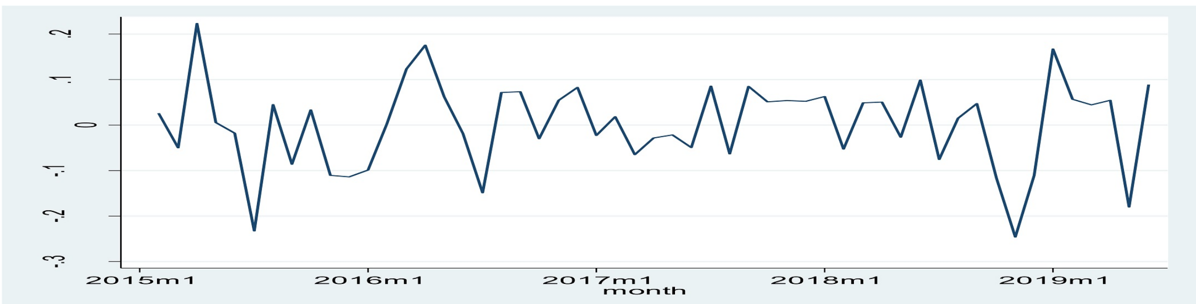

Figure 3: the stationary oil price series

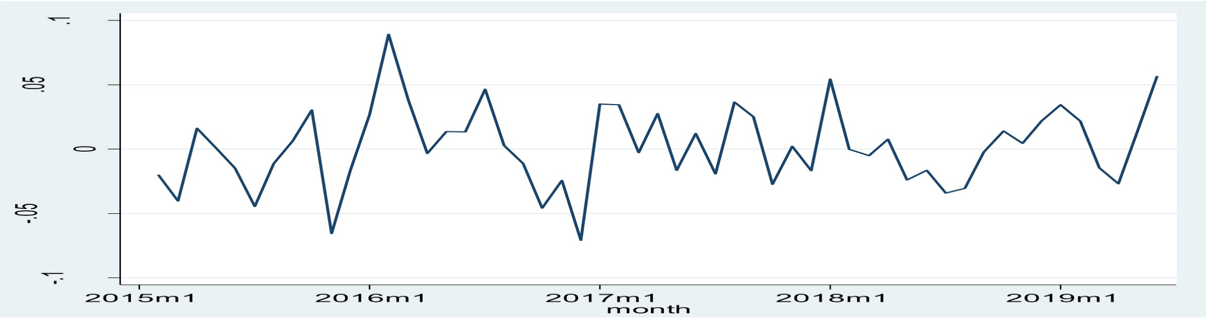

Figure 4: the stationary gold price series

Table 3: Akaike information criteria

VAR	AIC
Lag(1)	−5.877035
Lag(2)	−5.741628
Lag(3)	−5.86396
Lag(4)	−5.771343
Lag(5)	−5.628498
Lag(6)	−5.771343
Lag(7)	−6.091241
Lag(8)	−6.077813
Lag(9)	−5.84719
Lag(10)	−5.915636

After estimating VAR model and for the three orders, table 6 shows the values of the accurate measure MSE for VAR model and the three orders chosen on the basis of the Akaike criterion, since the lowest MSE value is for model VAR(10).

Table 5 shows estimation of VAR(10) parameters and notes that the price of oil influenced by its price for all lagged except for the first, fifth and eighth lagged, the price of oil affects the price of gold for all lagged, the price of gold is also affected by its price for all lagged.

VAR(10) model can be written in matrix form:

Table 4: MSE for the VAR model and for three order

Model	MSE
VAR(7)	.0057610903
VAR(8)	.0056654839
VAR(10)	.0047049522

Table 5: estimation result for VAR(10) model

Equation	Lag	Coef.	Std. Err	z	P>|z|	[95% Conf. Interval]	
Oil price Oil price	L1	-.0241769	1392085	-0.17	0.862	-.2970205	.2486668
	L2	-.3034834	.1475098	-2.06	0.040	-.5925972	-.0143696
	L3	-.1190402	.1491674	-0.80	0.425	-.4114029	.1733225
	L4	-.379405	.1505931	-2.52	0.012	-.674562	-.0842479
	L5	-.0009145	.1470354	-0.01	0.995	-.2890985	.2872695
	L6	0264014	.1476791	0.18	0.858	-.2630444	.3158472
	L7	-.1275907	.1492562	-0.85	0.393	-.4201273	.164946
	L8	-.0342173	.19271	-0.18	0.859	-.4119221	.3434874
	L9	.1602443	.2101231	0.76	0.446	-.2515894	.5720779
	L10	.4316072	.1987573	2.17	0.030	.04205	.8211643

Equation	Lag	Coef.	Std. Err	z	P>|z|	[95% Conf. Interval]	
Oil price Gold price	L1	.5153505	.5934465	0.87	0.385	-.6477833	1.678484
	L2	1.053561	.6128257	1.72	0.086	-.1475558	2.254677
	L3	1.481565	.5561642	2.66	0.008	.3915032	2.571627
	L4	.358201	.4623663	0.77	0.439	-.5480202	1.264422
	L5	.6879335	.4338566	1.59	0.113	-.1624098	1.538277
	L6	.6373622	.4421427	1.44	0.149	-.2292217	1.503946
	L7	1.069737	.485118	2.21	0.027	.1189232	2.020551
	L8	.3647393	.441435	0.83	0.409	-.5004574	1.229936
	L9	.601495	.440604	1.37	0.172	-.262073	1.465063
	L10	.5574078	.4188517	1.33	0.183	-.2635264	1.378342
	cons	-.007234	.0124627	-0.58	0.562	-.0316605	.0171925

Equation	Lag	Coef.	Std. Err	z	P>|z|	[95% Conf. Interval]	
Gold price	L1	-.0135037	.0339007	-0.40	0.690	-.0799479	.0529404
Oil price	L2	-.0203196	.0359223	-0.57	0.572	-.0907259	.0500867
	L3	-.0560397	.0363259	-1.54	0.123	-.1272372	.0151579
	L4	.0255508	.0366731	0.70	0.486	-.0463272	.0974288
	L5	.0147714	.0358067	0.41	0.680	-.0554085	.0849513
	L6	-.0390673	.0359635	-1.09	0.277	-.1095545	.0314199
	L7	-.167955	.0363475	-4.62	0.000	-.2391948	-.0967151
	L8	-.13236	.0469296	-2.82	0.005	-.2243404	-.0403796
	L9	-.0593787	.0511701	-1.16	0.246	-.1596703	.040913
	L10	-.0515088	.0484023	-1.06	0.287	-.1463756	.0433579

Equation	Lag	Coef.	Std. Err	z	P>|z|	[95% Conf. Interval]	
Gold price	L1	-.1771785	.1445188	-1.23	0.220	-.4604302	.1060732
Gold price	L2	-.1887575	.1492381	-1.26	0.206	-.4812589	.1037439
	L3	-.2819909	.1354397	-2.08	0.037	-.5474478	-.0165341
	L4	-.1569772	.1125976	-1.39	0.163	-.3776644	.06371
	L5	.0300013	.1056548	0.28	0.776	-.1770782	.2370808
	L6	-.3214134	.1076726	-2.99	0.003	-.5324479	-.1103789
	L7	-.1531023	.1181382	-1.30	0.195	-.3846489	.0784443
	L8	-.1970869	.1075003	-1.83	0.067	-.4077836	.0136098
	L9	-.0373176	.1072979	-0.35	0.728	-.2476177	.1729824
	L10	-.1150816	.1020007	-1.13	0.259	-.3149993	.084836
	cons	.008718	.003035	2.87	0.004	.0027695	.0146665

Table 6: Log likelihood for the Model and information criterian, AIC, HQIC, SBIC, FPE

Model	Log likelihood	AIC	HQIC	SBIC	FPE	Det(Sigma_ml)
VAR(10)	169.1862	-5.915636	-5.281264	-4.195394	.0000111	1.31e-06

Table 7: chi square test and the explanatory ability for each equation in three model

Model	Equation	Parms	RMSE	R-sq	chi2	P>chi2
VAR(7)	Oil price	15	.092459	0.2760	17.53548	0.2288
	Gold price	15	.023296	0.6258	76.92935	0.0000
VAR(8)	Oil price	17	.095421	0.2879	18.19709	0.3125
	Gold price	17	.022198	0.6931	101.6212	0.0000
VAR(10)	Oil price	21	.095896	0.4117	30.0952	0.0683
	Gold price	21	.023353	0.6951	98.05223	0.0000

$$
\begin{aligned}
\begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix} = \begin{pmatrix} -0.007234 \\ 0.008718 \end{pmatrix} &+ \begin{bmatrix} -0.0241769 & 0.5153505 \\ -0.0135037 & -0.1771785 \end{bmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} \\
&+ \begin{bmatrix} -0.3034834 & 1.053561 \\ -0.0203196 & -0.1887575 \end{bmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} \\
&+ \begin{bmatrix} -0.1190402 & 1.481565 \\ -0.0560397 & -0.2819909 \end{bmatrix} \begin{pmatrix} y_{1t-3} \\ y_{2t-3} \end{pmatrix} + \begin{bmatrix} -0.379405 & 0.358201 \\ 0.0255508 & -0.1569772 \end{bmatrix} \begin{pmatrix} y_{1t-4} \\ y_{2t-4} \end{pmatrix} \\
&+ \begin{bmatrix} -0.0009145 & 0.6879335 \\ 0.0147714 & 0.0300013 \end{bmatrix} \begin{pmatrix} y_{1t-5} \\ y_{2t-5} \end{pmatrix} + \begin{bmatrix} 0.0264014 & 0.6373622 \\ -0.0390673 & -0.3214134 \end{bmatrix} \begin{pmatrix} y_{1t-6} \\ y_{2t-6} \end{pmatrix} \\
&+ \begin{bmatrix} -0.1275907 & 1.069737 \\ -0.167955 & -.1531023 \end{bmatrix} \begin{pmatrix} y_{1t-7} \\ y_{2t-7} \end{pmatrix} + \begin{bmatrix} -0.0342173 & 0.3647393 \\ -0.13236 & -0.1970869 \end{bmatrix} \begin{pmatrix} y_{1t-8} \\ y_{2t-8} \end{pmatrix} \\
&+ \begin{bmatrix} 0.1602443 & 0.601495 \\ -0.0593787 & -0.0373176 \end{bmatrix} \begin{pmatrix} y_{1t-9} \\ y_{2t-9} \end{pmatrix} + \begin{bmatrix} 0.4316072 & 0.5574078 \\ -0.0515088 & -0.1150816 \end{bmatrix} \begin{pmatrix} y_{1t-10} \\ y_{2t-10} \end{pmatrix} \\
&+ \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}
\end{aligned}
$$

Table 7 shows the chi square test and the explanatory ability for each of the three models equations and notes the high value of the cofficient of determination for the gold price Equation for the three models and the oil price equation for VAR(10) model

Lagrange-multiplier test was performed on the residuals, table 8 shows the values of the test statistic in which it is not significant for all lagged, in this case, the null hypothesis, which states that there is no autocorrelation in the residuals, is accepted that is, the residuals are random, Fig.5. $H0$: There isn't Autocorrelation between residuals, $H1$: There is an Autocorrelation between residuals

Portmanteau test was performed on the residuals, table 9 shows the values of the test statistic in which it is not significant for all lagged, in this case, the null hypothesis, which states that there is no autocorrelation in the residuals, is accepted.

Jarque-Bera test was performed, table 10 shows the values of the test statistic in which it is not significant, this means accepting the null hypothesis and that the residuals are normally distributed. $H0 : normality \; H1 : nonnormality$

Table 8: LM test for VAR(10) model

lag	Chi2	df	Prob>chi2
1	1.7918	4	0.77399
2	4.7258	4	0.31661
3	1.1709	4	0.88286
4	6.4836	4	0.16583
5	0.8481	4	0.93188
6	2.6143	4	0.62429
7	2.6138	4	0.62438
8	0.6026	4	0.96278
9	1.9052	4	0.75320

Table 9: Portmanteau test for VAR (10) model

Portmanteau (Q) statistic	Lag order	Prob>chi2
0.0434	Lag(1)	0.8349
1.3359	Lag(2)	0.5128
1.6473	Lag(3)	0.6487
1.6479	Lag(4)	0.8002
1.6963	Lag(5)	0.8894
1.7234	Lag(6)	0.9433
1.7650	Lag(7)	0.9717
2.0539	Lag(8)	0.9793
2.0710	Lag(9)	0.9903

Table 10: Jarque-Bera test for VAR(10) model

Equation	Chi2	df	Prob>chi2
Oil price	4.264	2	0.11859
Gold price	1.063	2	0.58759
ALL	5.328	4	0.25530

Table 11: the Eigenvalue test for the parameter's matrix of the VAR (10) model

Eigenvalue	Modulus
.8869551 + .3420579i	.950628
.8869551 - .3420579i	.950628
.7174516 + .5920638i	.930202
.7174516 - .5920638i	.930202
-.8357042 + .3754943i	.916186
-.8357042 - .3754943i	.916186
-.6866495 + .5865535i	.903068
-.6866495 - .5865535i	.903068
-.3721356 + .8183349i	.898975
-.3721356 + .8183349i	.898975
.3015292 + .8363801i	.889073
.3015292 + .8363801i	.889073
.4453618 + .7635028i	.883903
.4453618 + .7635028i	.883903
.05315414 + .8430007i	.844675
.05315414 + .8430007i	.844675
-.8446004	.8446
-.3454234 + .5432055i	.643731
-.3454234 - .5432055i	.643731
.3141665	.314166

Table 11 the Eigen value test for the parameters matrix of the VAR (10) model, all the Eigen value are within the unit circle and the model fulfills the requirement of stability [3].

VAR(10) model is forecasting which has the lowest MSE value, Fig. 6, 7 shows the forecast of the gold and oil price series for 24 months, for the period from 6-2019 to 6-2021

The MSE value was calculated for the forecasting values of the two series and for VAR(7) and VAR(10), table 12 shows that the forecasting of the series of oil prices in the VAR(7) is better, while the forecasting of the series of gold prices is better in the VAR(10) according to the criterion of accuracy MSE.

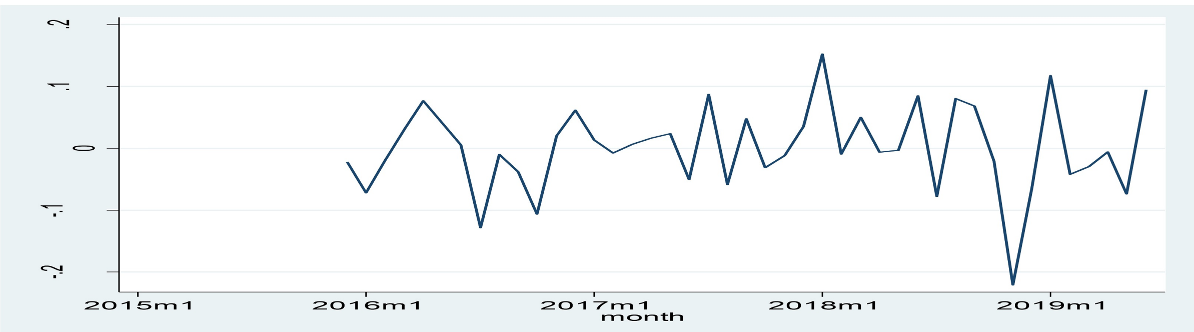

Figure 5: the residuals series of the VAR(10) model

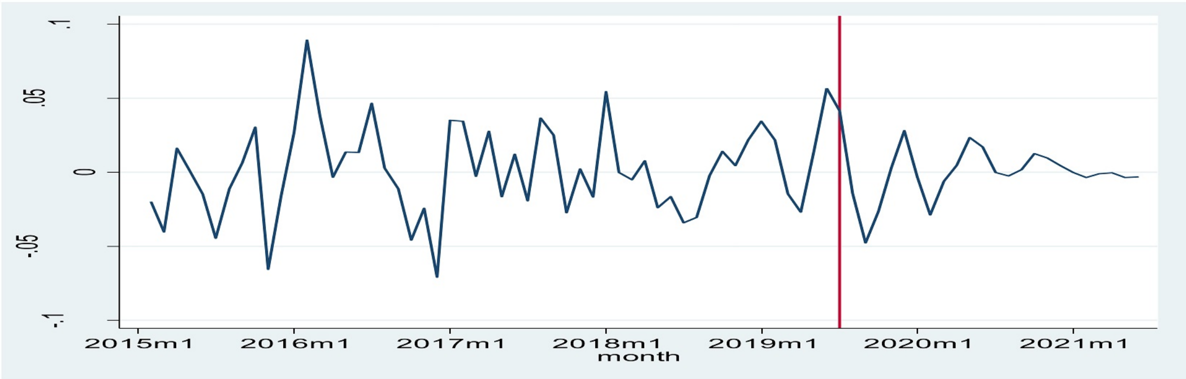

Figure 6: the forcasting for gold price series of the VAR(10) model

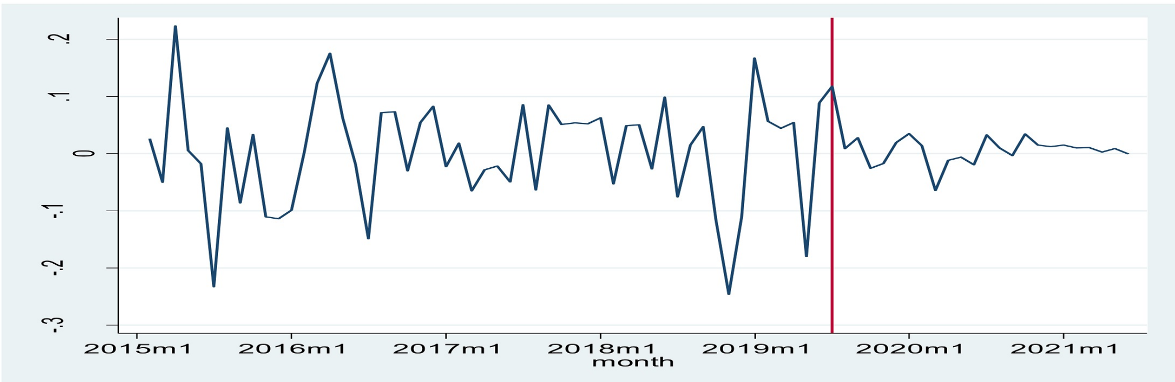

Figure 7: the forcasting for oil price series of the VAR(10) model

Table 12: MSE Value for the forcasting series of the models

Model order	Series	MSE
VAR(7)	Oil price	.0070777593
	Gold price	.0004834392
VAR(10)	Oil price	.0073288176
	Gold price	.0004436430

5. Conclusions

The best model according to the Akaike information is the VAR(7) model , and the best model according to the accurate measure MSE is the VAR(10) model. The series of Oil and gold prices are Volatility in nature, But The Volatility is decreasing in the series of Oil and gold prices forecasting for the larger forecasting period. The lowest value of the MSE criterion is for VAR(10) model, The forecasting of the oil price series is better in VAR(7) model, the forecating of the gold price series is better in VAR(10), and the price of oil affects the price of gold for all lagged, the price of gold is also affected by its price for all lagged, It is suggested to estimate, BayesianVAR, VAR with Exogenous Variables and VARMA Models with forecasting in subsequent studies

appendix

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Table 13: the global monthly oil and gold prices in dollars for the period from the first month of 2015 to the sixth month of 2019

Time-month	gold price	oil price
2015m1	1251.85	52.87
2015m2	1227.19	54.29
2015m3	1178.65	51.65
2015m4	1197.90	64.58
2015m5	1199.05	64.94
2015m6	1181.50	63.81
2015m7	1130.04	50.56
2015m8	1117.47	52.89
2015m9	1124.53	48.52
2015m10	1159.25	50.18
2015m11	1085.70	44.94
2015m12	1068.25	40.11
2016m1	1097.37	36.34
2016m2	1199.91	36.45
2016m3	1246.34	41.25
2016m4	1242.26	49.18
2016m5	1259.40	52.34
2016m6	1276.40	51.37
2016m7	1337.33	44.26
2016m8	1341.09	47.56
2016m9	1326.03	51.18
2016m10	1266.59	49.67
2016m11	1235.98	52.46
2016m12	1151.40	57.00
2017m1	1192.62	55.71
2017m2	1234.36	56.76
2017m3	1231.09	53.18
2017m4	1265.63	51.70
2017m5	1245.00	50.59
2017m6	1260.26	48.16
2017m7	1236.22	52.48
2017m8	1282.32	49.26
2017m9	1314.98	53.63
2017m10	1279.51	56.45
2017m11	1282.28	59.58
2017m12	1261.05	62.78
2018m1	1331.67	66.87
2018m2	1331.52	63.43
2018m3	1324.66	66.63
2018m4	1334.74	70.08
2018m5	1303.03	68.25
2018m6	1281.57	75.34
2018m7	1238.53	69.86
2018m8	1201.25	70.92
2018m9	1198.47	74.35
2018m10	1215.39	66.16
2018m11	1220.95	51.74
2018m12	1247.92	46.32
2019m1	1291.75	54.76
2019m2	1320.07	57.96
2019m3	1300.90	60.62
2019m4	1266.44	64.04
2019m5	1283.95	53.50
2019m6	1359.00	58.47