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FORECASTING REAL EFFECTIVE EXCHANGE RATES FOR JAPAN USING FOR THE YEARS 2008-2019 USING ARIMA MODELS

VESEL USAJ*

TATJANA SPASESKA**

*PhD student at "St. Clement Ohridski" University in Finance department

**Professor Assistant at "St. Clement Ohridski" University

ABSTRACT

Real effective exchange rate is the nominal effective exchange rate (a measure of the value of a currency against a weighted average of several foreign currencies) divided by a price deflator or index of costs. Forecasting of (macro)economics variables is an important part of economics analysis. ARIMA models provide forecasts of these variables by taking information from the past values to predict their future behavior. The time series models are based on the assumption that the time series involved are (weakly) stationary, the mean and variance for a weakly stationary time series are constant and its covariance is time-invariant.

The aim of this paper is to make a forecast of REER for Japan yen, taking for base the historical data of the 2008.01-2019.03. Following the steps of identification, estimation, diagnostics we successfully have forecasted the REER for Japan yen. In the first step the ARIMA(1,1,1) was identified as the best model for forecast, but after diagnostics results suggested that the AR(1)MA(1)MA(2) fits better for the forecast. The REER increases and decreases within the months and the chosen model is a good model that has predicted very close these movements.

***Keywords**: REER, ARIMA, forecast*

1. Introduction

In a world where there are many national and regional currencies, exchange rates define the rate or ratio of which one of these currencies can be exchanged for any other at any given point in time (Ewans 2014). It is possible to talk about two kinds of exchange rates, real exchange rates and nominal exchange rates. The real exchange rate (RER) is defined as the relative national price levels between two economies with the corresponding nominal exchange rate being an auxiliary to convert the unit of account such that two price levels are measured in a single currency.

Nominal exchange rate is defined as the price of a currencyin terms of another currency. In parallel, real currency exchange rate should be defined as the price of the currency in real terms (Yang and Zeng 2014). The history of Japanese exchange rates, though short by British or American standards, is exceedingly rich, both from the standpoint of variation in the data and in the institutions governing exchange rate arrangements and Japanese monetary conditions (Lothian 1991).

This study tries to make a forecast of exchange rates of japanese yem currency to US dollars using ARMA models for the period 2018 m03 to 2019 m03, by making use of historical monthly data from 2008-2018.

2. Literature Review

Real exchange rate is a useful summary indicator of essential economic information. It has occupied a major place in theoretical discussion between economists of different countries. However, among all those works there is no clear agreement on how real exchange rate should be measured. This fact has led to the existence of many alternative models, theories and indices that could be used for the construction of real effective exchange rate (Betliy 2002). Economists and policymakers often refer to the exchange rate as a key macroeconomic variable. As a relative price, the exchange rate plays a crucial role in theoretical models and open economy and transactions between countries. However, the link between the theoretical concept of the exchange rate and the empirical application is not a straightforward one (Chinn 2002).

Academic treatments of the real exchange rate typically abstract from how to measure real exchange rates when countries engage in transactions with a number of partners. By far the most common means of calculating an “effective” real exchange rate is to weight the currencies by trade weights (Chinn 2002). A country’s international transactions tend to be denominated in a range of different currencies where it faces many exchange rates and a weighted average measure of individual bilateral exchange rates against the country’s currency is necessary to summarize the country’s exchange rate position. These summary measures are often referred to as an effective exchange rate or a trade weighted exchange rate index (TWI) (Kite 2006).

The methodology of determining the nominal and effective exchange rate applied by the ECB for the case of the EU is based on a weighted geometric average of the bilateral exchange rates of the euro relative to three sets of commercial partners of the Euro zone. The first set takes into account twelve countries, namely: Australia, Canada, Denmark, Hong Kong, Japan, Norway, Singapore, South Korea, Sweden, Switzerland, United Kingdom and US. The second set adds the ten new EU member states and China, while in the third set there are included altogether 42 countries: those in the second set to which four other candidates and the following countries are added: Algeria, Argentina, Brazil, India, Indonesia, Israel, Malaysia, Mexico, Morocco, New Zealand, Philippines, Russia, South Africa, Taiwan and Thailand (Pelinescu and Caraiani 2006).

The real effective exchange rate is calculated as a weighted average of real exchange rates of the national currency to the currencies of its main trading partners. For example, if the exchange rate of one country appreciates relative to the currency of the neighboring country with the higher inflation rate and depreciates at the same time relative to the currency of another country-partner with the lower inflation rate, the real effective exchange rate will reflect the exchange rate of the national currency of the country as a weighted average of these changes. Weights of countries in total foreign trade of the country under consideration are defined in order to calculate effective exchange rate indices. The weights reflect a relative importance of this or that currency for the other particular country. The effective exchange rate indices are calculated on the basis of the weights of bilateral trade (weights of export and import could be also used or their total average index). The formula for calculation the weights is the following (NBRK 2002):

$$W = \frac{M_i + X_i}{\sum_{i=1}^{n} X_i + \sum_{i=1}^{n} M_i}$$

Where,

W_i – weight of country i in the overall trade volume of the country, $\sum_{i=1}^{n} W_i = 1$

M_i – Import of the domestic country from country i

X_i – Export of the domestic country to country i

$\sum_{i=1}^{n} X_i$ – Exports of the domestic country to main trading partners

$\sum_{i=1}^{n} M_i$ – Imports of the domestic country from main trading partners

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A strong Yen has repeatedly cause distress among Japanese policymakers and manufacturers. Since the demise of the Bretton Woods system in 1971, the Yen has seen several episodes of strong appreciation, including in the late 1970s, after the 1985 Plaza Agreement, the early and late 1990s and after 2008. These appreciations have not only been associated with "expensive Yen recessions" resulting from negative effects on exports; since the late 1980s, the strong Yen has also raised concern about a de-industrialisation of the Japanese economy. Between 1980 and 2017, the standard deviation of Japan's annual real effective exchange rate was 17.0, compared to 12.3 for the U.S., 10.4 for the United Kingdom, and 5.3 for Germany (Belke and Volz 2018).

Kiyotaka, et al. 2012 examine the industry-specific REER of the yen from the beginning of 2005 to the 2012 to reveal the industry-level difference in the impact of the nominal yen appreciation vis-à-vis the US dollar and found that the level of REER is the lowest in the electric machinery industry, which suggests that the electric machinery industry still has export price competitiveness compared to the other industries.

3. Data and Methodology

The aim of this paper is to make a forecast of real effective exchange rate for Japan using ARIMA models. Popularly known as the Box–Jenkins (BJ) methodology, but technically known as the ARIMA methodology, the emphasis of these methods is on analyzing the probabilistic, or stochastic, properties of economic time series on their own under the philosophy let the data speak for themselves. The BJ-type time series models allow Y_t to be explained by past, or lagged, values of Y itself and stochastic error terms. For this reason, ARIMA models are sometimes called atheoretic models because they are not derived from any economic theory and economic theories are often the basis of simultaneous-equation models (Gujarati and Porter 2009).

ARIMA(p, d, q), model it is an autoregressive integrated moving average time series, where p denotes the number of autoregressive terms, d the number of times the series has to be differenced before it becomes stationary, and q the number of moving average terms (Gujarati and Porter 2009).

For this purpose, a time series data of real effective exchange rate (REER) for Japan has been taken for the 2008-2019 time period. These data are monthly and are generated from BIS. Established in 1930, the Bank for International Settlements (BIS) is the oldest international financial institution.

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From its inception to the present day, the BIS has played a number of key roles in the global economy, from settling reparation payments imposed on Germany following the First World War, to serving central banks in their pursuit of monetary and financial stability. BIS is owned by 60 central banks, representing countries from around the world that together account for about 95% of world GDP. Its head office is in Basel, Switzerland and it has two representative offices: in Hong Kong SAR and in Mexico City (BIS n.d.).

A trade weighted index is used to measure the effective value of an exchange rate against a basket of currencies. The importance of other currencies depends on the percentage of trade done with that country. For example in calculating the trade weighted index of the Pound Sterling, the most important exchange rate would be with the Euro. If the UK exports 60% of total exports to the EU, the value of £ to Euro would account for 60% of the trade weighted index. A trade weighted index is useful for measuring the overall performance of a currency. For example, if the Pound appreciates against the dollar, that might be due to the dollar's weakness. But, if the trade weighted Sterling index increases, this shows the Pound is getting stronger against its main trading partners (EconomicsHelp n.d.).

From the AR(p) and MA(q) models, we can observe a pattern wherein *reer* is explained by its own past values and the current past values of the error term, hence called the ARMA (p, q) model is constructed as:

$$\mathrm{ARMA}(p,q)\text{: } \mathrm{reer}_t = a_0 + \sum_{i=1}^{p} b_1 \mathrm{reer}_{t-i} + d_0 u_t + \sum_{j=1}^{q} d_j u_{t-j}$$

where model contains p lags of dependent variable and q lags of the error term.

To continue further, we have analyzed data using EViews 10 software. The following analyses are performed using the logarithm of the data.

3.1 Identification

We proceed with unit root test of the variables to be employed in our model. The results of our times series unit root test are displayed in Table 1. After taking the first difference, according to the table 1, probability of Augmented Dickey-Fuller test statistic is less than 5%, and the real effective change rate variable is significant (p=0,000<0.05). Hence, by rejecting the null hypothesis, we accept that time series is stationary at the first difference.

Table 1: Results of unit root tests (ADF test statistics and probabilities)

Null Hypothesis: D(LEXCHANGE_RATE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.999973	0.0000
Test critical values:	1% level	-3.480038	
	5% level	-2.883239	
	10% level	-2.578420	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEXCHANGE_RATE,2)
Method: Least Squares
Date: 05/18/19 Time: 15:45
Sample (adjusted): 2008M03 2019M03
Included observations: 133 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LEXCHANGE_RATE(-1))	-0.656128	0.082016	-7.999973	0.0000
C	-0.000569	0.002030	-0.280437	0.7796

R-squared	0.328204	Mean dependent var	1.65E-05
Adjusted R-squared	0.323075	S.D. dependent var	0.028439
S.E. of regression	0.023399	Akaike info criterion	-4.657362
Sum squared resid	0.071721	Schwarz criterion	-4.613898
Log likelihood	311.7146	Hannan-Quinn criter.	-4.639700
F-statistic	63.99958	Durbin-Watson stat	2.013353
Prob(F-statistic)	0.000000		

We have drawn the graph at the actual level to check visually the (non)stationarity of the data and according to the graph data are not stationary.

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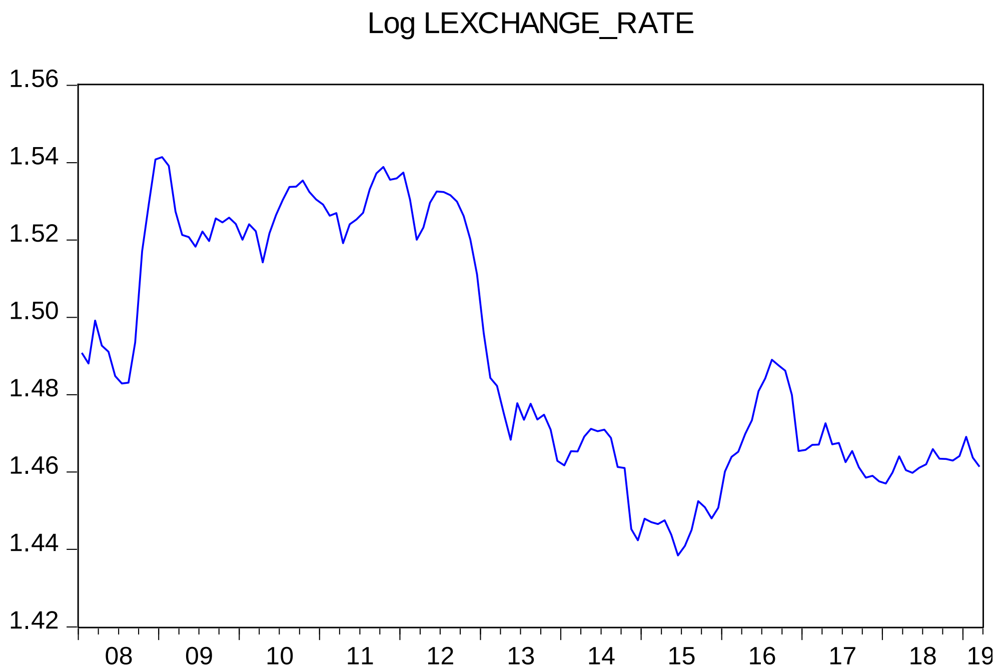

Fig. 1: Graph of REER series data

To be sure that the series is not stationary, it is plotted the correlogram as following. To plot the correlogram automatically determined 36 lags were used. “A rule of thumb is to compute ACF up to one-third to one-quarter the length of the time series. Since for our economic data we have 135 monthly observations, by this rule lags of 33 to 45 will do” (Gujarati & Porter, 2009). The broken lines on the graph represent the standard error bounds. The graph shows some significant autocorrelations that are out the standard error bounds and the autocorrelation declines very slowly to zero. From lag 1 to lag 32, the lags are very significant and the decline is very gradually to zero. This series is indicative of non-stationary series. To make stationary the data, the first deference has been used.

Now, it can be seen that there is big difference from the first correlogram. The autocorrelation of lag 1, lag 2 and lag 6, and 15 is significant. After that, the autocorrelation declines and keeps declining to zero for other lags too. As per PACF, only the lag 1 is significant. From this observation, we can see that this an ARIMA model, because both ACF and PACF have exponential decay from lag 1, that is, rapid decline from lag 1.

Table 2: Correlogram for exchange rates data for Japan

Date: 05/18/19 Time: 15:46
Sample: 2008M01 2019M03
Included observations: 135

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.982	0.982	132.97	0.000
		2	0.953	-0.285	259.24	0.000
		3	0.919	-0.095	377.56	0.000
		4	0.883	-0.012	487.66	0.000
		5	0.851	0.125	590.74	0.000
		6	0.824	0.071	688.16	0.000
		7	0.804	0.090	781.50	0.000
		8	0.784	-0.088	871.08	0.000
		9	0.764	-0.055	956.78	0.000
		10	0.741	-0.059	1038.1	0.000
		11	0.715	-0.048	1114.3	0.000
		12	0.683	-0.078	1184.5	0.000
		13	0.651	0.011	1248.7	0.000
		14	0.618	-0.015	1307.0	0.000
		15	0.586	-0.009	1359.8	0.000
		16	0.560	0.116	1408.6	0.000
		17	0.538	-0.013	1453.9	0.000
		18	0.520	0.032	1496.6	0.000
		19	0.503	-0.029	1536.9	0.000
		20	0.486	-0.016	1574.8	0.000
		21	0.466	-0.037	1610.1	0.000
		22	0.445	0.019	1642.6	0.000
		23	0.419	-0.147	1671.5	0.000
		24	0.390	-0.010	1696.9	0.000
		25	0.357	-0.115	1718.3	0.000
		26	0.324	-0.026	1736.1	0.000
		27	0.290	-0.053	1750.5	0.000
		28	0.257	-0.051	1761.9	0.000
		29	0.230	0.150	1771.1	0.000
		30	0.207	0.011	1778.6	0.000
		31	0.187	0.025	1784.9	0.000
		32	0.169	-0.024	1790.0	0.000
		33	0.148	-0.047	1794.0	0.000
		34	0.126	-0.009	1796.9	0.000
		35	0.099	-0.073	1798.7	0.000
		36	0.071	-0.006	1799.7	0.000

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Table 3: First difference correlogram for exchange rates data for Japan

Date: 05/18/19 Time: 15:47
Sample: 2008M01 2019M03
Included observations: 134

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.344	0.344	16.170	0.000
		2	0.209	0.104	22.225	0.000
		3	0.027	-0.084	22.325	0.000
		4	-0.140	-0.169	25.061	0.000
		5	-0.159	-0.067	28.631	0.000
		6	-0.207	-0.102	34.757	0.000
		7	-0.020	0.125	34.812	0.000
		8	-0.004	-0.002	34.814	0.000
		9	0.073	0.031	35.589	0.000
		10	0.112	0.031	37.442	0.000
		11	0.147	0.089	40.648	0.000
		12	0.073	-0.032	41.436	0.000
		13	-0.028	-0.056	41.552	0.000
		14	-0.056	-0.026	42.024	0.000
		15	-0.197	-0.135	47.953	0.000
		16	-0.113	0.034	49.922	0.000
		17	-0.141	-0.058	53.003	0.000
		18	-0.030	0.024	53.142	0.000
		19	0.042	0.015	53.419	0.000
		20	0.042	-0.018	53.703	0.000
		21	0.094	0.001	55.132	0.000
		22	0.170	0.166	59.816	0.000
		23	0.112	0.002	61.881	0.000
		24	0.072	0.033	62.730	0.000
		25	0.037	0.027	62.961	0.000
		26	-0.021	0.011	63.038	0.000
		27	0.008	0.069	63.050	0.000
		28	-0.130	-0.126	65.947	0.000
		29	-0.087	-0.049	67.264	0.000
		30	-0.096	-0.079	68.893	0.000
		31	-0.040	0.035	69.183	0.000
		32	0.028	-0.002	69.327	0.000
		33	0.033	-0.007	69.529	0.000
		34	0.099	0.019	71.308	0.000
		35	0.029	-0.018	71.464	0.000
		36	0.066	0.069	72.271	0.000

The following graph represents the differenced logarithm real effective exchange rate time series and as it can be seen now the data are stationary with slightly deviations.

Thus, according to correlogram, the possible models would be as ARIMA(1,1,1); ARIMA(2,1,1); ARIMA(6,1,1), ARIMA (15,1,1). The next step is to estimate these models and define the best model.

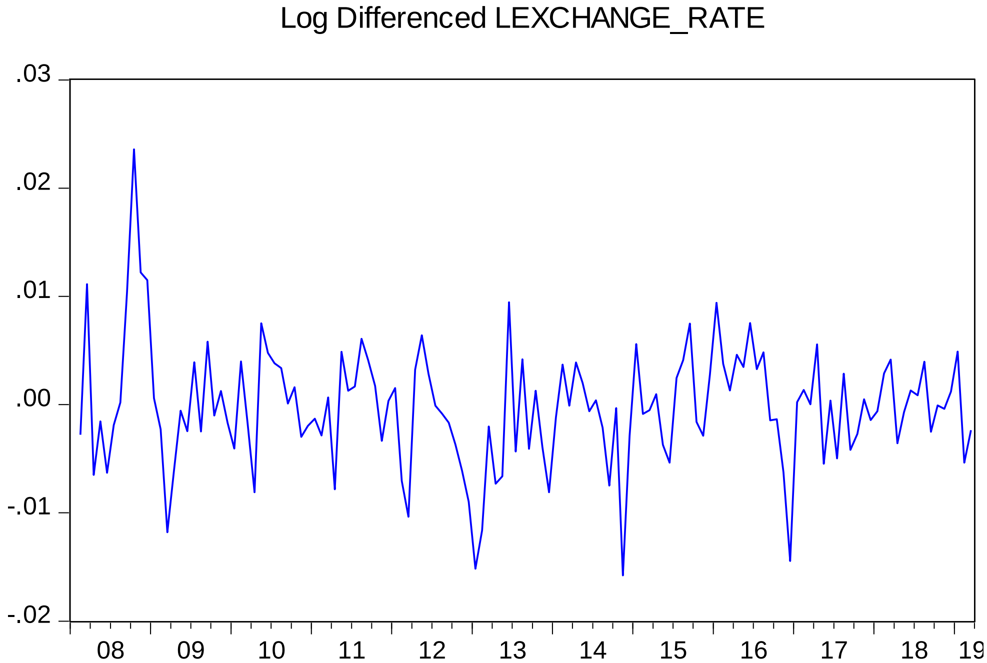

Fig 2: Differenced exchange rates for Japan

3.2 Estimation

After identifying the tentative models, in the next section the estimation of each model is done. Results of each model are given in the Appendix. Deciding for the best model is more an act of art than science. The criteria for choosing the most appropriate model is simple. We need to choose the model that has the most significant coefficients, the lowest volatility (represented by SIGMASQ), the lowest Akaike information criterion, the lowest Schwarz criterion, and the highest adjusted R-squared.

Table 4: A summarizing of criteria for choosing the most appropriate model

Differenced REER	Significant coefficients	Sigma^2 (volatility)	Adj. R^2	AIC	SBIC
ARIMA(1,1,1)	**3**	**0.000544**	**0.971615**	**–4.592564**	**–4.506482**
ARIMA(2,1,1)	2	0.000594	0.969042	–4.501657	–4.415574
ARIMA(6,1,1)	3	0.001976	0.896971	–3.278608	–3.192526
ARIMA(15,1,1)	3	0.003831	0.800245	–2.610096	–2.524013

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To find the most appropriate model, we have summarized the above-mentioned information in the above table. As it can be seen from the table, the ARIMA(1,1,1) looks the most appropriate model, as it has significant coefficients, the lowest volatility (0,000544), the highest adjusted R-square (0,971615) the lowest AIC and SBIC (–4,592564 and –4,506482).

3.3 Diagnostics

To identify the ARIMA(1,1,1) as the most appropriate model, we should perform diagnostics to be sure that there's no information left uncaptured. An ideal correlogram should be flat. However, in our example the residuals correlogram given in next page shows that the lag 3 is significant and therefore is not flat. This indicates that lag 2 has some information that must be captured; thus, we need to re-estimate the model. Re-estimation is done by adding AR(2) and MA(2).

After running the re-estimation, the general information is summarized in the Table 6 as shown in following page. Tables of estimated models are presented in the Appendix. The information from the table suggests that the AR(1) MA(1) MA(2) model fits better than the two ones, because it has the lowest volatility and with very slight differences in other criteria better than two other models.

Table 5: Correlogram of residuals

Date: 05/18/19 Time: 16:12
Sample: 2008M01 2019M03
Included observations: 135
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.058	0.058	0.4668	
		2	0.218	0.215	7.0559	
		3	0.022	-0.001	7.1232	0.008
		4	-0.105	-0.161	8.6812	0.013
		5	-0.062	-0.059	9.2290	0.026
		6	-0.182	-0.126	13.997	0.007
		7	0.054	0.109	14.426	0.013
		8	-0.013	0.045	14.449	0.025
		9	0.085	0.045	15.501	0.030
		10	0.083	0.028	16.525	0.035
		11	0.134	0.105	19.209	0.023
		12	0.067	0.019	19.893	0.030
		13	-0.030	-0.056	20.024	0.045
		14	0.015	0.009	20.059	0.066
		15	-0.178	-0.131	24.942	0.023
		16	-0.017	0.023	24.989	0.035
		17	-0.120	-0.036	27.241	0.027
		18	0.007	0.014	27.249	0.039
		19	0.049	0.032	27.628	0.049
		20	0.031	0.011	27.786	0.065
		21	0.063	-0.036	28.432	0.075
		22	0.150	0.164	32.127	0.042
		23	0.073	0.046	33.002	0.046
		24	0.053	0.027	33.479	0.055
		25	0.047	0.045	33.854	0.067
		26	-0.038	-0.006	34.101	0.083
		27	0.061	0.094	34.747	0.093
		28	-0.128	-0.089	37.573	0.066
		29	-0.026	-0.058	37.694	0.083
		30	-0.076	-0.093	38.720	0.086
		31	-0.025	0.010	38.834	0.105
		32	0.040	0.013	39.123	0.123
		33	0.001	-0.014	39.123	0.150
		34	0.109	0.029	41.294	0.126
		35	-0.020	-0.033	41.364	0.151
		36	0.101	0.079	43.279	0.132

Fig 6: Residuals correlogram for exchange rates data for Russia

Table 6: A summarizing of criteria for choosing the most appropriate model after residual correlogram

Differenced Exchange Rates	ARIMA(1,1,1)	AR(1) AR(2) MA(1)	**AR(1) MA(1) MA(2)**
Significant coefficients	3	3	**4**
Sigma^2 (volatility)	0.000544	0.000521	**0.000519**
Adj. R^2	0,971615	0.972624	**0.972742**
AIC	–4,592564	–4.620419	**–4.624686**
SBIC	–4,506482	–4.512816	**–4.580959**

We can construct our model as following:

$$\mathrm{reer_t} = \mathrm{a_0} + b_1 reer_{t-1} + d_0 u_t + d_1 u_{t-1} + d_2 u_{t-2}$$

After selecting AR(1)MA(1)MA(2) as the best model for this data, we have run again the residual correlogram as shown in next page in Table 7. The correlogram of the residuals is flat, showing that all lags are under the broken lines which indicates that all the information has been captured, so the forecast will be based on this model. Before doing the forecast, we have run the Ljung-Box test to test for the absence of serial autocorrelation, up to a specified lag k . "The Box–Pierce and Ljung–Box Q-statistics serve as a check to see if the residuals from an estimated ARMA(p,q) model behave as a white-noise process" (Enders 2015). The results for autocorrelation in Table 8 show that the probability from the lag 1 to lag 36 is higher than 5%. This indicates that there is no autocorrelation in this model, so our model is good.

After the Ljung-Box test we have performed the normality-test histogram in Figure 3. In the right side of the figure descriptive statics are given. The histogram shows visually that the data are pretty close to the normal distribution. Finally, we have ran the Heteroskedasticity Test and we can see that this test is significant. This test was given place in the Appendix.

3.4 Forecasting the Model

We have done the forecast of REER for Japan for the year interval of 2018.03 to 2019.03. So, the essence of fitting the ARIMA model is to forecast the future values of the series using past

Table 7: Residuals correlogram after diagnostics

Date: 05/18/19 Time: 16:18
Sample: 2008M01 2019M03
Included observations: 135
Q-statistic probabilities adjusted for 3 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.034	0.034	0.1551	
		2	0.027	0.026	0.2570	
		3	0.089	0.088	1.3762	
		4	-0.077	-0.085	2.2228	0.136
		5	-0.079	-0.079	3.1000	0.212
		6	-0.150	-0.152	6.3406	0.096
		7	0.072	0.103	7.0821	0.132
		8	0.015	0.027	7.1128	0.212
		9	0.042	0.058	7.3744	0.288
		10	0.080	0.029	8.3315	0.304
		11	0.137	0.124	11.119	0.195
		12	0.049	0.023	11.479	0.244
		13	-0.017	-0.000	11.522	0.318
		14	0.015	-0.001	11.558	0.398
		15	-0.143	-0.120	14.710	0.258
		16	-0.010	0.031	14.725	0.325
		17	-0.097	-0.071	16.188	0.302
		18	0.009	0.030	16.201	0.369
		19	0.079	0.044	17.187	0.374
		20	-0.004	-0.013	17.189	0.442
		21	0.044	-0.029	17.499	0.489
		22	0.152	0.153	21.278	0.322
		23	0.060	0.039	21.880	0.347
		24	0.034	0.068	22.071	0.395
		25	0.027	0.018	22.191	0.449
		26	-0.018	0.010	22.247	0.505
		27	0.063	0.103	22.933	0.524
		28	-0.102	-0.060	24.720	0.478
		29	-0.029	-0.038	24.863	0.527
		30	-0.054	-0.121	25.378	0.553
		31	-0.020	0.003	25.451	0.603
		32	0.033	-0.012	25.644	0.644
		33	0.012	0.008	25.669	0.692
		34	0.072	0.002	26.627	0.691
		35	-0.010	-0.034	26.644	0.734
		36	0.107	0.108	28.797	0.677

values of the series itself. After plotting the forecast on EViews, we have extracted the graph shown on Figure 4. This graph does not make a much sense in the solution. To know how close is the forecast to actual values, we need to plot the forecast graph against the actual graph. To do so we cut the data set only for the period 2018.03 to 2019.03.

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Table 8: Ljung-Box test for testing the autocorrelations of residuals

Date: 05/18/19 Time: 16:18
Sample: 2008M01 2019M03
Included observations: 135

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.137	0.137	2.5885	0.108
		2	0.000	-0.019	2.5885	0.274
		3	-0.086	-0.085	3.6284	0.304
		4	-0.096	-0.074	4.9241	0.295
		5	0.057	0.082	5.3931	0.370
		6	0.070	0.046	6.0938	0.413
		7	0.075	0.047	6.9062	0.439
		8	-0.073	-0.090	7.6777	0.466
		9	-0.041	0.000	7.9254	0.542
		10	-0.058	-0.039	8.4318	0.587
		11	0.094	0.105	9.7440	0.554
		12	-0.008	-0.067	9.7545	0.637
		13	-0.067	-0.069	10.435	0.658
		14	-0.012	0.018	10.457	0.728
		15	-0.038	-0.004	10.683	0.775
		16	0.014	-0.006	10.713	0.827
		17	0.028	0.012	10.832	0.865
		18	0.000	-0.020	10.832	0.901
		19	0.136	0.173	13.780	0.796
		20	-0.007	-0.043	13.789	0.841
		21	-0.029	-0.027	13.928	0.873
		22	0.042	0.053	14.220	0.893
		23	-0.018	-0.009	14.274	0.919
		24	-0.035	-0.047	14.480	0.935
		25	0.079	0.085	15.526	0.928
		26	-0.016	-0.061	15.571	0.946
		27	-0.098	-0.080	17.218	0.926
		28	-0.100	-0.084	18.947	0.900
		29	-0.064	-0.008	19.665	0.903
		30	0.030	-0.003	19.823	0.921
		31	0.063	0.050	20.532	0.924
		32	0.036	0.025	20.770	0.937
		33	-0.036	-0.036	21.000	0.948
		34	-0.013	0.035	21.032	0.960
		35	-0.041	-0.006	21.337	0.966
		36	-0.021	-0.074	21.418	0.974

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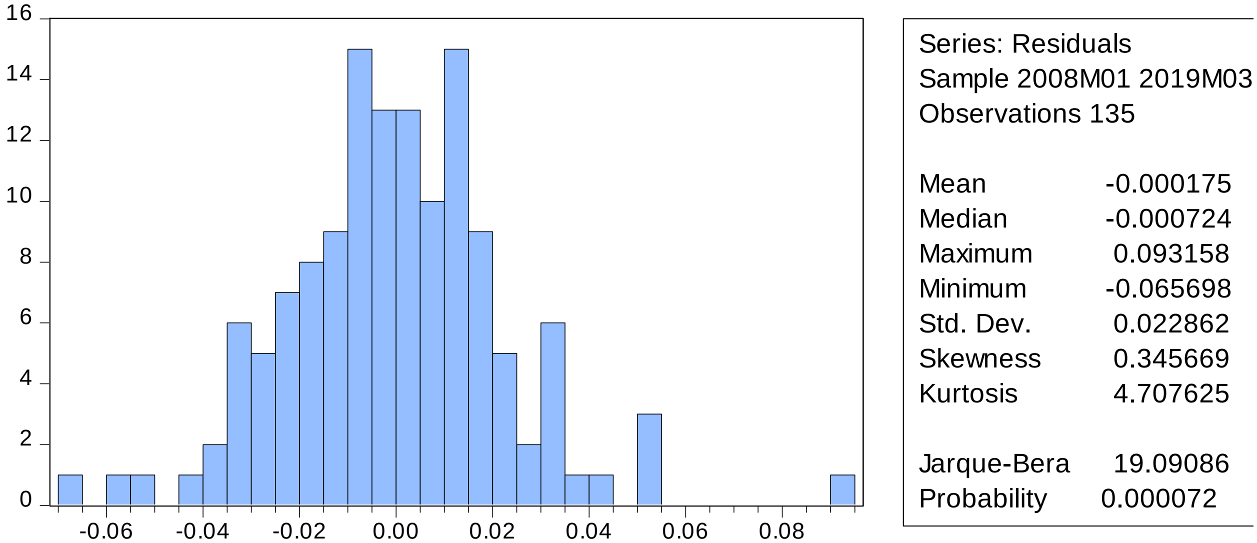

Fig 3: Normality test

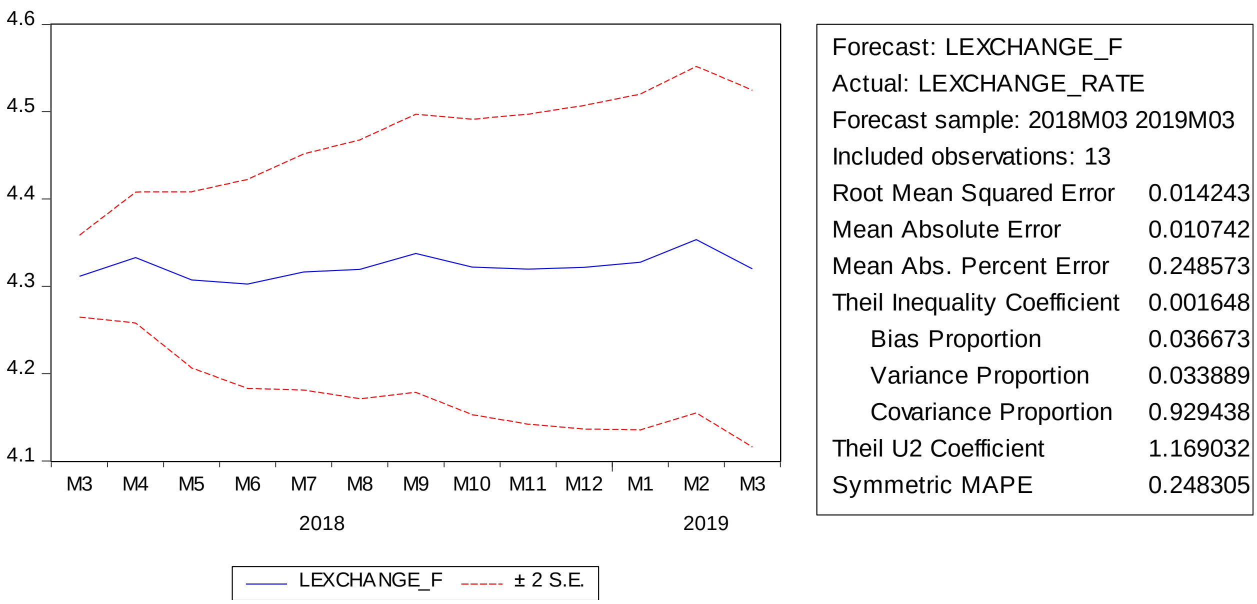

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Fig 4: The graph of the forecast of REER for Japan

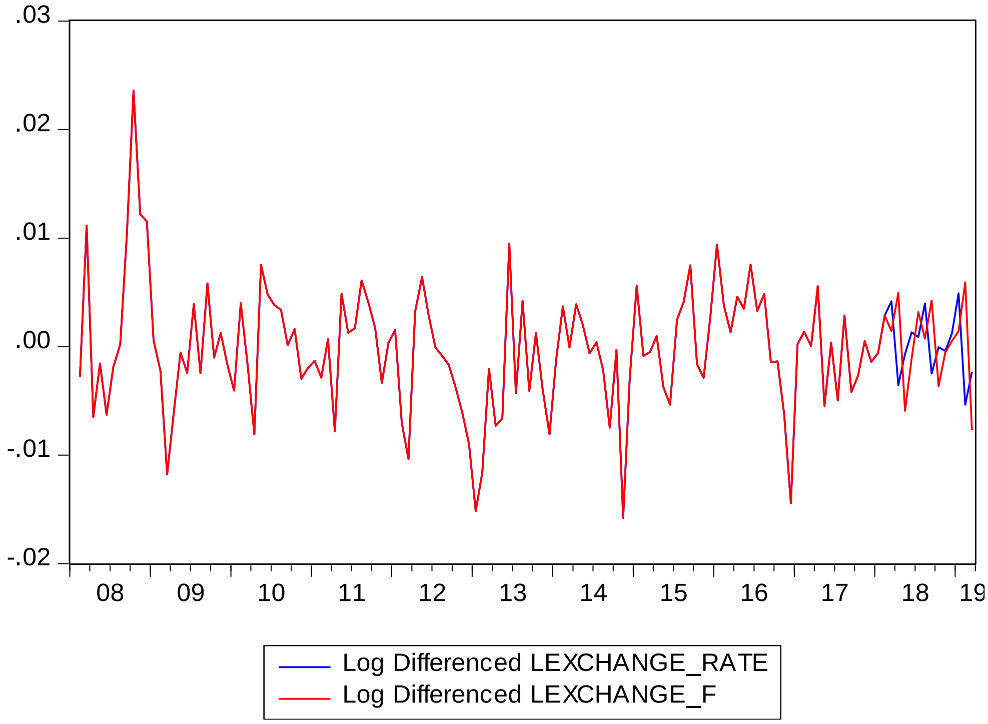

Fig 5: Forecast of REER from actual values

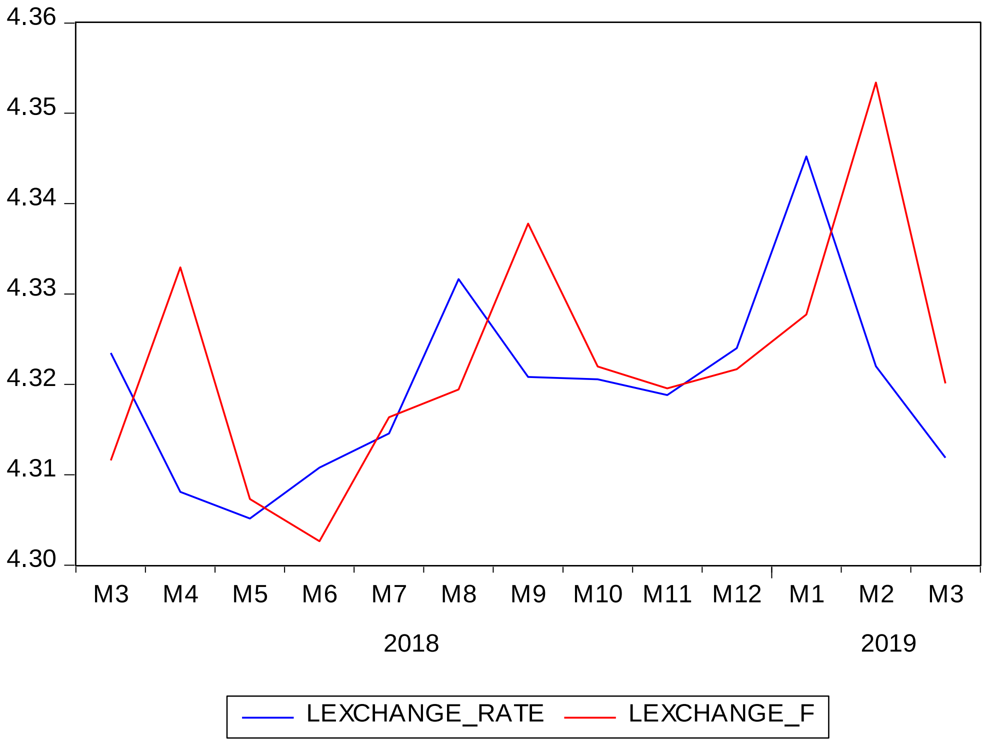

Fig 6: Forecast of the model of REER for Japan

Figure 5 and 6 give a clearer view of the forecast of REER for Japan. In Figure 6, forecasting is done by plotting the forecast graph against the actual graph. The blue line represents the actual REER, while the red color represents the forecasted REER. We can see that the forecast for month 3 of 2018 is enough close. From month 4 to month 5 there's a slight deviation, but from month 6 to month 8, the forecast is close. Slight deviations from month 9 to ten, and good forecast from month 10 of 2018 to month 1 of 2019. Slight deviation from month 2, but coming very close for the month 3 of 2019. We can conclude that our forecast is very close and the chosen model fits very good.

4. CONCLUSION

Forecasting is an important part of econometric analysis. This study tried to make a forecast of real effective exchange rate of Japanese yen to US dollars, using ARMA models. The time series models are based on the assumption that the time series involved are (weakly) stationary, the mean and variance for a weakly stationary time series are constant and its covariance is time-invariant. But we know that many economic time series are nonstationary, that is, they are integrated. If a time series is integrated of order 1 (i.e., it is I[1]), its first differences are I(0), that is, stationary. Therefore, if we have to difference a time series d times to make it stationary and then apply the ARMA(p, q) model to it, we say that the original time series is ARIMA(p, d, q) (Gujarati and Porter 2009).

With a data set generated from BIS, we identified four models as possible models for our forecasting and we resulted with the ARIMA(1,1,1) as the best model to continue with. However, after diagnostics analyses, there were found that lag 2 is significant, that is, it has some information to be captured. We included the lag 2 in the model and we found that the AR(1)MA(1)MA(2) is the best model for our forecasting. We checked again for the residuals correlogram and there were no other information to be captured. The correlogram was flat and all lags were under the broken lines. Furthermore, after we performed the autocorrelation test, we found that all lags have been greater than 5%, so there is no autocorrelation problem in our problem. Finally, we plotted the forecast and the graph in general showed a very good estimation of the real effective exchange rate for Japan.

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APPENDIX A:

In this section we have given place to some useful tables from the identification and estimation steps.

Null Hypothesis: LEXCHANGE_RATE has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.299810	0.6285
Test critical values:	1% level	-3.480038	
	5% level	-2.883239	
	10% level	-2.578420	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LEXCHANGE_RATE)
Method: Least Squares
Date: 05/18/19 Time: 15:45
Sample (adjusted): 2008M03 2019M03
Included observations: 133 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LEXCHANGE_RATE(-1)	-0.018797	0.014462	-1.299810	0.1960
D(LEXCHANGE_RATE(-1))	0.354904	0.082240	4.315445	0.0000
C	0.082910	0.064256	1.290304	0.1992

R-squared	0.129626	Mean dependent var	-0.000876
Adjusted R-squared	0.116235	S.D. dependent var	0.024825
S.E. of regression	0.023337	Akaike info criterion	-4.655237
Sum squared resid	0.070801	Schwarz criterion	-4.590041
Log likelihood	312.5733	Hannan-Quinn criter.	-4.628744
F-statistic	9.680504	Durbin-Watson stat	2.026580
Prob(F-statistic)	0.000120		

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Tentative Models:

Dependent Variable: LEXCHANGE_RATE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/18/19 Time: 16:09
Sample: 2008M01 2019M03
Included observations: 135
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.418302	0.100832	43.81855	0.0000
AR(1)	0.973805	0.020531	47.43082	0.0000
MA(1)	0.277975	0.076708	3.623822	0.0004
SIGMASQ	0.000544	5.33E-05	10.22064	0.0000

R-squared	0.972251	Mean dependent var	4.439542
Adjusted R-squared	0.971615	S.D. dependent var	0.140591
S.E. of regression	0.023686	Akaike info criterion	-4.592564
Sum squared resid	0.073497	Schwarz criterion	-4.506482
Log likelihood	313.9981	Hannan-Quinn criter.	-4.557582
F-statistic	1529.947	Durbin-Watson stat	1.882965
Prob(F-statistic)	0.000000		

Inverted AR Roots	.97	
Inverted MA Roots	-.28	

Dependent Variable: LEXCHANGE_RATE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/18/19 Time: 16:09
Sample: 2008M01 2019M03
Included observations: 135
Failure to improve objective (non-zero gradients) after 16 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.413900	0.101724	43.39110	0.0000
AR(2)	0.957581	0.032036	29.89124	0.0000
MA(1)	1.000000	87.93497	0.011372	0.9909
SIGMASQ	0.000594	0.001189	0.499347	0.6184

R-squared	0.969735	Mean dependent var	4.439542
Adjusted R-squared	0.969042	S.D. dependent var	0.140591
S.E. of regression	0.024737	Akaike info criterion	-4.501657
Sum squared resid	0.080160	Schwarz criterion	-4.415574
Log likelihood	307.8618	Hannan-Quinn criter.	-4.466675
F-statistic	1399.141	Durbin-Watson stat	1.306057
Prob(F-statistic)	0.000000		

Inverted AR Roots	.98	-.98
Inverted MA Roots	-1.00	

Dependent Variable: LEXCHANGE_RATE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/18/19 Time: 16:10
Sample: 2008M01 2019M03
Included observations: 135
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.425975	0.040969	108.0323	0.0000
AR(6)	0.805221	0.068859	11.69370	0.0000
MA(1)	0.968906	0.032342	29.95773	0.0000
SIGMASQ	0.001976	0.000198	9.960486	0.0000

R-squared	0.899278	Mean dependent var	4.439542
Adjusted R-squared	0.896971	S.D. dependent var	0.140591
S.E. of regression	0.045127	Akaike info criterion	-3.278608
Sum squared resid	0.266773	Schwarz criterion	-3.192526
Log likelihood	225.3060	Hannan-Quinn criter.	-3.243627
F-statistic	389.8701	Durbin-Watson stat	0.920553
Prob(F-statistic)	0.000000		

Inverted AR Roots	.96	.48-.84i	.48+.84i	-.48+.84i
	-.48-.84i	-.96		
Inverted MA Roots	-.97			

Dependent Variable: LEXCHANGE_RATE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/18/19 Time: 16:10
Sample: 2008M01 2019M03
Included observations: 135
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.433601	0.023967	184.9889	0.0000
AR(15)	0.579558	0.089394	6.483187	0.0000
MA(1)	0.874657	0.049964	17.50560	0.0000
SIGMASQ	0.003831	0.000623	6.146537	0.0000

R-squared	0.804717	Mean dependent var	4.439542
Adjusted R-squared	0.800245	S.D. dependent var	0.140591
S.E. of regression	0.062836	Akaike info criterion	-2.610096
Sum squared resid	0.517228	Schwarz criterion	-2.524013
Log likelihood	180.1814	Hannan-Quinn criter.	-2.575114
F-statistic	179.9403	Durbin-Watson stat	0.519314
Prob(F-statistic)	0.000000		

Inverted AR Roots	.96	.88+.39i	.88-.39i	.65-.72i
	.65+.72i	.30-.92i	.30+.92i	-.10+.96i
	-.10-.96i	-.48+.84i	-.48-.84i	-.78-.57i
	-.78+.57i	-.94-.20i	-.94+.20i	
Inverted MA Roots	-.87			

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Dependent Variable: LEXCHANGE_RATE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/18/19 Time: 16:17
Sample: 2008M01 2019M03
Included observations: 135
Convergence achieved after 37 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.422675	0.087372	50.61869	0.0000
AR(1)	1.501957	0.215915	6.956252	0.0000
AR(2)	-0.521870	0.214310	-2.435116	0.0162
MA(1)	-0.196058	0.247383	-0.792529	0.4295
SIGMASQ	0.000521	5.14E-05	10.14562	0.0000

R-squared	0.973442	Mean dependent var	4.439542
Adjusted R-squared	0.972624	S.D. dependent var	0.140591
S.E. of regression	0.023261	Akaike info criterion	-4.620419
Sum squared resid	0.070343	Schwarz criterion	-4.512816
Log likelihood	316.8783	Hannan-Quinn criter.	-4.576692
F-statistic	1191.221	Durbin-Watson stat	2.011224
Prob(F-statistic)	0.000000		

Inverted AR Roots	.96	.55
Inverted MA Roots	.20	

Dependent Variable: LEXCHANGE_RATE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/18/19 Time: 16:17
Sample: 2008M01 2019M03
Included observations: 135
Convergence achieved after 32 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.418896	0.094016	47.00154	0.0000
AR(1)	0.966112	0.024928	38.75660	0.0000
MA(1)	0.293956	0.071050	4.137333	0.0001
MA(2)	0.231045	0.095292	2.424601	0.0167
SIGMASQ	0.000519	4.99E-05	10.40190	0.0000

R-squared	0.973556	Mean dependent var	4.439542
Adjusted R-squared	0.972742	S.D. dependent var	0.140591
S.E. of regression	0.023212	Akaike info criterion	-4.624686
Sum squared resid	0.070041	Schwarz criterion	-4.517083
Log likelihood	317.1663	Hannan-Quinn criter.	-4.580959
F-statistic	1196.492	Durbin-Watson stat	1.931690
Prob(F-statistic)	0.000000		

Inverted AR Roots	.97	
Inverted MA Roots	-.15+.46i	-.15-.46i

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Heteroskedasticity Test:

Heteroskedasticity Test: White

F-statistic	3.59E+23	Prob. F(20,114)	0.0000
Obs*R-squared	135.0000	Prob. Chi-Square(20)	0.0000
Scaled explained SS	231.3932	Prob. Chi-Square(20)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/18/19 Time: 16:19
Sample: 2008M01 2019M03
Included observations: 135

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000519	5.17E-15	1.00E+11	0.0000
GRADF_01^2	2.92E-15	5.75E-15	0.506941	0.6132
GRADF_01*GRADF_02	-4.15E-16	1.40E-16	-2.962745	0.0037
GRADF_01*GRADF_03	-1.77E-16	4.21E-16	-0.420531	0.6749
GRADF_01*GRADF_04	-1.00E-15	5.13E-16	-1.947733	0.0539
GRADF_01*GRADF_05	5.81E-19	2.90E-19	2.004368	0.0474
GRADF_01	2.48E-16	5.91E-16	0.420367	0.6750
GRADF_02^2	5.16E-17	3.13E-17	1.650089	0.1017
GRADF_02*GRADF_03	4.04E-16	1.02E-16	3.979799	0.0001
GRADF_02*GRADF_04	-8.12E-17	1.32E-16	-0.614959	0.5398
GRADF_02*GRADF_05	-3.39E-19	9.06E-20	-3.744838	0.0003
GRADF_02	-4.46E-17	1.54E-16	-0.289803	0.7725
GRADF_03^2	-2.00E-16	2.13E-16	-0.939865	0.3493
GRADF_03*GRADF_04	-8.06E-16	3.37E-16	-2.394676	0.0183
GRADF_03*GRADF_05	-3.18E-19	2.01E-19	-1.586199	0.1155
GRADF_03	7.68E-14	5.28E-16	145.2582	0.0000
GRADF_04^2	-3.27E-16	2.73E-16	-1.195024	0.2346
GRADF_04*GRADF_05	5.14E-19	4.24E-19	1.210087	0.2287
GRADF_04	2.21E-14	6.19E-16	35.80080	0.0000
GRADF_05^2	7.28E-23	1.69E-22	0.431707	0.6668
GRADF_05	5.38E-07	5.42E-18	9.94E+10	0.0000

R-squared	1.000000	Mean dependent var	0.000519
Adjusted R-squared	1.000000	S.D. dependent var	0.001001
S.E. of regression	4.33E-15	Sum squared resid	2.13E-27
F-statistic	3.59E+23	Durbin-Watson stat	1.933799
Prob(F-statistic)	0.000000		