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Exchange rate volatility: A forecasting approach of using the ARCH family along with ARIMA SARIMA and Semi-Structural-SVAR in Turkey

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ABSTRACT The ability to predict the volatility of exchange rate is an enormous challenge when it comes to economic and financial considerations. In this context, it is important to be able to predict the exchange rate volatility in financial markets and the world economy. This paper proposes a heightened approach to modelling and forecasting of exchange rate volatility in Turkey. For past recent years, Turkey experienced political turbulence that the possibility of effecting exchange rate, thus create uncertainty volatility of exchange rate. The daily exchange rate data have been taken from 2005-2017 and applied autoregressive conditional heteroscedasticity ARCH and GARCH families (EGARCH, IGARCH, and PARCH) to forecast exchange rate volatility. The proposed methodology able to calculate the breakpoint by including dummy variables. The result is more confined after including dummy that EGARCH (1,1) is best performing to forecast exchange rate volatility and successfully overcome the leverage effect on the exchange rate. Moreover, this paper also investigates the monthly data forecasting by applying ARIMA SARIMA along with SVAR technique for next few months. The Exchange rate pass-through also encounter it, which indicates the pass-through is more pronounced in PPI than CPI. The forecast result of SARIMA and SVAR distribute the same direction of fluctuation in exchange rate that is declining of current exchange rate in the future. However, ARIMA's forecast tends to increase and different with two models.

KEYWORDS: Exchange rate; Forecast; SVAR; Volatility; Turkey

INTRODUCTION

The Forecasting of the volatility in the exchange rate are key factors that influence the global financial market. As the global financial market is most liquid markets in the world. Fluctuation in the exchange rate affects the profitability of financial institution. Forecasting the exchange rate is crucial as it has significant impact on the macroeconomic fundamental such as oil price, interest rate, wage, unemployment and the level of economic growth.(Ramzan, S 2011); (Broll and Hansen-Averlant, 2010). In practice, most countries are administered by a floating exchange rate system. The interventions taken from the central bank need to be prevent unwanted or disparaging movements in the stock market. (Akincilar, 2011).

The Exchange rate has taken a long part of history of Turkish economy since 19's. At the beginning of 2000, the central bank of the Republic Turkey (CBRT) implemented the inflation targeting regime towards exchange rate. Arat (2003) argued that the inflation targeting regime itself has a purpose to determine increases of exchange rate. However, since the crisis hits Turkish financial and banking sector in 2001, the Turkish exchange rate regime has changed to be free and floating in the market. Therefore, the CBRT only have to intervene and prevent reserve accumulation and excessive volatility. In other word, there might be risk of high volatility in Turkish lira in recent decades (Tuncay, 2010).

The election result chooses Erdogan party to mandate the government office in 2002 and has impacted the Turkish lira to lifting up. However, the Erdogan regime's achievements are still worse and far from over. In 2006, before the subprime mortgage crisis contracted world economies, several speculations on emerging economies came up, include Turkey. The Turkish lira and other emerging economy's currencies depreciate deeply together with other developing economies due to the outflowing amount of capital (WEF, 2015).

Despite the subprime mortgage crisis began in developed countries, it quickly spreads to the world and drags some developing countries include Turkey. Thus, the pressure on the Turkish lira has responded by CBRT to proceed actions on the economy with some policies in monetary. This includes stabilizing inflation and exchange rate. CBRT targets its self are met

Forex market demand of the private sector and lessen the volatility in exchange rate (Cömert and Çolak, 2014).
In World Bank Economic (2012) view, raise concerns about capacity of Turkey to maintain the progress had begun after the 2008 crisis influencing hardly the economy. Several major events in its region has been impacting the economy and challenged Turkey's macroeconomic achievements in the future. Slowed growth in the European Union and deteriorating geopolitical in Turkey's neighborhood impacting negatively on export, investment, and growth of the economy.
The election in June and November also created challenges for Turkish economy in the future. Some speculation about Erdogan's party or AKP unfairly win the election has provided Turkish lira to boost it's depreciate in three month high against US Dollar. Turkish lira as most vulnerable emerging market currency dragging deeply until the lowest level on record (WEF, 2015). Moreover, the global oil prices are falling until 48 US Dollar, the lowest since the price in 2009. The falling of oil price possibly effecting world's economy due to shortening revenue of oil exporter countries.
Turbulence of politics in Turkey and its neighborhoods also could make consequents to the deteriorating Turkish economy. Cabinet reshuffle, an attempted coup in July, have affected market trust on Turkish economy and momentum to reform the government. This also fostered by Turkish referendum in April, 2017 that allowed the current government to be authoritative. Tourism sector also declining and hitting the Turkish economy in recent years.
To the same degree IMF comment about turkey, economy in February 2017 that after failed coup attempt increased the political uncertainty, Along with rising global interest rate, political uncertainty cause of loss in investor confidence and to be exposed Turkey to liquidity shocks. IMF future remark on the turkey, economy that Turkey's net international investment position (NIIP) will continue to depreciate by 10% until the current account deficit reduced. REER was slightly above average in October 2016, and an average of 5-15 percent REER continue to lose over-year in 2016. In response, the IMF gives some policy suggestion to come out this volatility by decreasing the Current account deficit net international reserves should continue to increase by CBRT. Limits currency sales for extreme volatility time period. [1]
One of the highlighted comment on IMF regarding forecasting of turkey economy growth Turkish economy will grow only 2.5% in the end of 2017, well below the average 4.5%.In the report IMF predicts that consumer inflation will remain in double digits and close at 10.1% a year before it declines to 9.1% in 2018.[2]
Deputy Prime Minister of Turkey Mehmet Simsek responses to the IMF forecasting by saying Turkey economy will again disapprove the IMF projected forecast.(Mehmet Simsek tweeted April 18) He is optimistic on the turkey economic growth. In line with CBRT monetary policy committee meeting.

LITERATURE REVIEW

Financial analysts have begun to model and explain the model of exchange rate returns and volatility using time series econometric models because of unexpected events, unstable fluctuations in financial markets, and uncertainties in prices and returns. Güloğlu, B et al (2007) examined the volatility in the nominal exchange rate (TL / $) in Turkey between in March 2001 and March 2007 week was estimated by using ARCH, GARCH and SWARCH models. The period covered corresponds to the period when the exchange rate is floating. First, exchange rate volatility is estimated by using ARCH and GARCH models and the deficiencies of these models are revealed. The estimation results show that various economic and political events in Turkey and in the world affect exchange rate volatility and that these periods of volatility are permanent. As Bala, A, D et al(2013) studied the monthly exchange rate return series volatility with GARCH models and the results show the presence of volatility in three currencies, and most of the asymmetric models deny the existence of volatility. Volatility persistence and log likelihood statistics showed that volatility model with breakdowns were improved the results by predicting volatility models with breaks compared to GARCH models without volatility breaks and reduced majority persistence of the model.

Exchange rate interventions are used to control the volatility of irregular movements in the exchange market. Ramzan, S et al (2012) studied the Forecasting exchange rate by using an ARCH family of model in Pakistan. The monthly exchange rate data of Pakistan for the period of July 1981-May 2010 obtained. The GARCH model performed the best model to remove volatility and EGARCH performed better by an encounter leverage effect on exchange rate return and provide a legitimately forecasting. We can also see that Barunik, J et al(2016) analysis the An improved approach to modelling and predicting volatility using high frequency data. By realizing GARCH framework, explore how the decomposed integrated volatility and jumps influence the upcoming volatility. The results show that jump variation from the integrated variation is essential to predict performance. We have found that most of the information on future fluctuations comes from the high frequency portion of the spectrum that represents the very short investment horizon. Correspondingly Pilbeam, K et al (2014) examined the exchange rate forecasting by using GARCH MODEL and versus implied volatility forecast. In paper used to daily closing prices for four currency pairs the euro, pound, Swiss franc and yen against the dollar. The data covers the period from 1/1-

[1] 03-02-2017 IMF Executive Board Concludes 2017 Article IV Consultation with Turkey
[2] The International Monetary Fund's (IMF) April 2017 World Economic Outlook report

2002 to 30/12-201. The result indicates that GARCH models are not useful to predict foreign exchange rate volatility in period of both low and high volatility.

For Turkey economy exchange rate volatility encounter by Güvenek, Betal (2009). The real exchange rate index has been testified by using ARCH, GARCH. After volatility expending the equation and taking TGARCH. They concluded that suitable model is the Two-Sided TARCH (1,1) model as a result of the analysis for the purpose of smoothing the self-centeredness. In terms of Turkey's economy. It is necessary to create an investment climate where policies can easily shape the investments of middle and long term foreign investors. Moreover Öztürkö, K (2010) worked on the exchange rate volatility in Turkey. In this study, the explanatory power of the Student-t distribution is compared with the normal distribution by adapting the standard GARCH and GARCH models to the dollar / lira exchange rate (USD / TRY). The results obtained, unlike the previous findings, show that the leptokurtic property of the t distribution is not better than the normal distribution in the description. However, when the Akaike and Schwartz information criteria are taken into consideration, it is observed that t-distribution is better than normal distribution and TGARCH models are better than GARCH models.

ARIMA estimation had been used in the econometric and financial purpose to forecast exchange rate volatility. Gadwala and Mathur (2014) used ARIMA model as one of their analysis to forecast the fluctuation of exchange rates in India. ARIMA model together with OLS can explain exchange rate volatility way better than VAR model. The analytical framework of comparing performance of time series models to forecast exchange rate by news (2008) resulted that the ARIMA model provides better than another time series models such as exponential smoothing and Naive models. The forecasting of the exchange rate in the case of Turkey also conducted by Akincilar, themes, and Sahin (2011) which used ARIMA model to forecast the volatility of exchange rate, along with Holt's method and Winer's method.

Since there is possibility of seasonal peak of exchange rate volatility in some periods of observation, some scholars also using Seasonal ARIMA model to forecast exchange rate volatility. Etuk (2013) suggests that SARIMA model might be better to use as the model to forecast Naira-Euro daily exchange rate. In addition, Kadilar, Simsek, and Aladag (2009) also build time series forecasting models like SARIMA to result the forecasting of the exchange rate in Turkey, together with ARCH model and alternative model of neural network.

The semi-structural method allows their use by restricting the set of structural models (Stock, H, Watson, W 2001) (Beraj et al 2015). For this Bouakez, H et al (2010) examined the U.S. monetary policy and uncovered interest rate parity shocks on the bilateral exchange rate between the U.S. and each of the G7 countries by using structural vector auto regression (SVAR). Their end result is that the nominal exchange rate has been delayed in the monetary expansion response and declined about ten months after it began to be appreciated. The shock is caused by large and persistent decoupling from the uncovered interest rate parity. The variance decomposition results show that monetary policy shocks constitute a negligible proportion to exchange rate fluctuations. Of particular significance of volatility Brunet, A et al (2015) working on the impact of monetary policy shocks on the price level, output, and exchange Applied SVAR with the recursive model, variance decomposition analysis in SVAR and flip flop analysis. The result indicates that in maturing financial markets, financial signals may gradually be transmitted to the real sector. In this sense, the mechanism of monetary transmission perhaps may be fragile and delayed. Variance decomposition shows When we started using money, we found that it added valuable information, explaining significantly more exchange rate fluctuations compared to the non-monetary model. Flip flop explained that during 2001-2008 monetary policy is most influenced factor to explain exchange rate fluctuations monitored by inflation fluctuations. Furthermore Mwase, N (2006) studied the effect of exchange rate on consumer price in Tanzania. The data have been collected from the year 1990-2005 and used vector autoregression (VAR) and structural vector autoregression (SVAR), VEC, Granger Causality test. The findings showed that 10% depreciation leads to 0.05 percent increase in inflation after a two-quarter lag. It is also stated that there is a negative relationship between exchange rate depreciation and inflation in the long run.

Masha, I et al (2012) examined the Exchange Rate Pass Through to Prices in Maldives during 1994–2010.ERPT using nonparametric: recursive vector autoregression approach on CPI and PPI. The assessment shows that ERPT is quite high to ICP and about 79 percent of the exchange rate pass through to the consumer price. On the basis of variance decomposition, international commodity price shocks are a major source of change in the two price index in addition to exchange rate changes. The findings also deliver valuable information that most of the shocks of prices Most of the shocks in prices continue for the first year, and show that any response to changes in the price level due to external shocks or intentional policies must take account of a long horizon. Same analysis Leigh,D et al (2002) studied the exchange rate pass-through in Turkey. This paper used data from 1994-2002 and using the recursive VAR model to measure the ERPT effect of nominal exchange rate of CPI and WPI. The exchange rate pass-through to prices in turkey approximately one year, but mostly in the first quarter of the year. ERPT more visible in WPI than CPI. McCarthy, J. (2007) scrutinizes the effects of exchange rates and import prices on local PPI and CPI in selected industrialized economies using post-1982. The empirical model VAR that contains the price distribution chain used. Impulse responses show that import prices have a strong influence, while foreign exchange rates have a slight influence on the local price. The transition is bigger in countries with a larger share of imports and more permanent exchange rates and import prices. During 1996-98, most of these external factors had a great deal of disinflation in the country, but not in the US.

METHODOLOGY

3.1. ARCH- (Autoregressive conditional hetroskedasticity) Family Model

In economics and financial econometric we also required the model who not only deal with expected return, but also encounter the uncertainty, risk. Such models are ARCH-Family models that are capable of dealing with the volatility (variance) of the series.
In any econometric analysis always assumed that there is no problem of Hetroskedastic means the variance of the disturbance term as constant over the time. However, many financial as well as econometric time series reveals periods of volatility so in such a case the assumption of homoskedasticity (constant variance) is very limited. In order to corporate the behaviour of conditional variance or more appropriately of conditional hetroskedastic we used ARCH-family model.

$$Y_t = x_t{}'\Upsilon + \mu_t \qquad (1)$$

$$\sigma_t^2 = \omega + \alpha\mu_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (2)$$

The first one equation is mean equation is written as a function of exogenous variables with an error term. σ_t^2 is the conditional variance equation as it is a pre-period estimation variance based on previous period information. The second equation has three terms: the mean (ω), the ARCH term(μ_{t-1}^2)it indicates that when a big shock happen in the period t-1 , it is more likely that the value of μ_t(in absolute term because of mean square) will be bigger as well. That is, when μ_{t-1}^2large/small, the variance of the next innovation μ_t is also large/small. The estimated coefficient α must be positive for the positive variance. The GARCH termσ_{t-1}^2. As one of the drawbacks of ARCH specification, according to ENGLE (1995) was it is looking more like a moving average than an interrogation. So by Tim Bollerslev, published an article and start a new GARCH family. So in GARCH family included lagged conditional variance terms as autoregressive term.
So this terms is interpreted in a perspective that if a currency trader want to predicts the current period's variance by giving a weighted average of a long term average, i.e. the constant, the forecasted variance from the last period (the GARCH term), and information about the volatility observed in the past period (the ARCH term)
The variance equation can be expanded to allow the inclusion of exogenous repressors or dummy variables with breaks.

$$\sigma_t^2 = \omega + \alpha\mu_{t-1}^2 + \beta\sigma_{t-1}^2 + \xi dum_{it} \qquad (3)$$

Where dum= $dummy_{1t}$….$dummy_{nt}$ variables Corresponds to the periods of important policy changes in the foreign exchange market. A high order GARCH model with dummy is written as

$$\sigma_t^2 = \omega + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 + \sum_{i=1}^{p}\alpha_i\mu_{t-i}^2 + \sum_{k=1}^{k}\xi_k dum_{t-k} \qquad (4)$$

As above mentioned, p is the order of the ARCH term, q is the order of the GARCH term, and k is corresponds to the dummy variable.
In 1991 the exponential GARCH (EGARCH) model suggested by Nelson, that deals with the asymmetric effect between positive and negative effect. The specification of the conditional variance written as

$$log\sigma_t^2 = \omega + \sum_{j=1}^{q}\beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p}\alpha_i \left|\frac{\mu_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r}\gamma_k \frac{\mu_{t-i}}{\sigma_{t-k}} \qquad (5)$$

In the above equation, note that when μ_{t-i} is positive ('good new') the total effect of μ_{t-i} is $(1+\gamma_i)|\mu_{t-i}|$: while when μ_{t-i} is negative ('bad news') the total effect of μ_{t-i} is $(1-\gamma_i)|\mu_{t-i}|$.The EGARCH is covariance stationary provided$\sum_{j=1}^{q}\beta_j$.(Zivot, 2009).
If the parameters of the GARCH models are restricted to the one from the total and the constant term is left we will get *integrated* GARCH (IGARCH) model, which is given by

$$\sigma_t^2 = \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 + \sum_{i=1}^{p}\alpha_i\mu_{t-i}^2 \qquad (6)$$

3.1.2. Types of forecasting

Since the collapse of the 1970 Bretton Woods fixed exchange rate system, countries have been very important in predicting exchange rate or currency value. For this reason, he developed various methods and techniques to estimate exchange rates. For example, the following are types of forecasting;

Non-Structural System

In the non-structural system that does not require the existence of predefined associations between variables. The non-structural model is explained as a vector autoregressive model and allows variables to interact freely without constraints. The non-structural system as a whole produces superior estimates in the series and lead to poorest forecast. (Kimberly, 2014) The below forecasting approach came under the non-structural forecast

- ARMA, ARIMA, ARFIMA, SARIMA
- VAR, BVAR, VEC, BVECM

Semı-Structural System

The semi-structural method allows their use by restricting the set of structural models (Stock, H, Watson, W 2001) (Beraj et al 2015). Semi-structural equations formulate, articulate macroeconomic forecasts, accomplish scenario analysis, and inform the monetary policy formulation process

- SVAR
- SBVECM

Structural System

The structural equations show that error correction terms add value to the predictions (Kimberly, 2014). Structural models are established as regression models where the explanatory variables are the functions of the time and the coefficient factors are allowed to change over time. (Proietti, T1991)

- DSGE(Dynamic Stochastic General Equilibrium)
- SEM(Simultaneous Equation Model)

3.2. ARMA- Autoregressive Moving Average

The general form of the ARMA is an ARMA (p,q) models of the form :

$$Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + \mu_t + \sum_{j=1}^{q} \theta_j \mu_{t-j} \qquad (7)$$

The implication behind the time series behaviour of Y_t is largely determined by its own value in the previous year. So, what will happen in t time (present time will depend on the t-1 (previous time period) It is called an AR (p^{th}) process. And the other term μt is an MA (q^{th}) process means moving average. The insinuation behind of MA method is that Y_t depend on the value of the immediate past error, which is known at t time period.[3] The stationary property of the model is dealt with AR (p^{th}) part of the specification. Similarly, the property of inevitability for the ARMA (p,q) model will have to do with an MA(qth) part of the model.

3.2.1. ARIMA- Autoregressive Integrated Moving Average

ARMA process can deal only that model who satisfied the stationary properties, that is mean, variance and the covariance is constant over the time. However, most of economic and financial series has time trend, so mean of Y_t one period is different from mean of another time. So this reject the property of stationary that mean is not constant over the time. So in order to avoid the problem, The ARIMA process induced stationarity by detrend the data through taking the difference. It can be writing as

$$\Delta Y_t = Y_t - Y_{t-1} \qquad (8)$$

In general, if we take difference of a series d time in order to induce stationarity, and invertible ARMA process, so undiffernced series is following an ARIMA (p,d,q) notation.

3.2.2. SARIMA- Seasonal Autoregressive Integrated Moving Average

The above model is deal with the non-seasonal time series analysis. Thus with the intention of adjusting seasonality in the time series, we applied SARIMA model. Therefore, if there is a seasonally autoregressive parameter P (SAR) or if there is at least a seasonal moving average parameter Q (SMA) or both parameters (P, Q). A seasonally SARIMA model is embodied as SARIMA(P,D,Q), where P is the number of autoregressive lag, D is the differencing lag , and Q is the moving average lag and can be written as

$$Y_t = \sum_{i=1}^{P} \phi_{iS} Y_{t-i} + \mu_t + \sum_{j=1}^{Q} \theta_{jS} \mu_{t-j} \quad (9)$$

3.3. SVAR (Structural Variance Auto Regressive)
SVAR dynamic structural model is interpreted by vector form. The system of equation can be written as follow:

$$B_0\, y_t = k + B_1\, y_{t-1} + B_2\, y_{t-2} + \ldots B_p\, y_{t-p} + u_t \quad (10)$$

Where y_t is an n x 1 vector, k is an n x 1 vector of constants, u_t is n x 1 structural error vector, and p is the number of lags. B_0 matrix is defined as

$$B_0 = \begin{bmatrix} 1 & -B_{12}^{(0)} & \cdots & -B_{1n}^{(0)} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ -B_{n1}^{(0)} & -B_{n2}^{(0)} & \cdots & 1 \end{bmatrix} \quad (11)$$

B_t is an nxn matrix which has *i* row and *j* column. Thus
$B_{ij}^{(s)}$ = 1,2,...,p we assumed each side of (3,1) is pre multiplied by B_0^{-1}, thus the result is

$$y_t = c + \varphi_t y_{t-1} + \varphi_t y_{t-2} + \ldots + \varphi_t y_{t-p} + \varepsilon_t \,, \quad (12)$$

Where $c = B_0^{-1}$ (13)

$$\varphi_s = B_0^{-1} B_s \quad (14)$$

$$\varepsilon_t = B_0^{-1} u_t \quad (15)$$

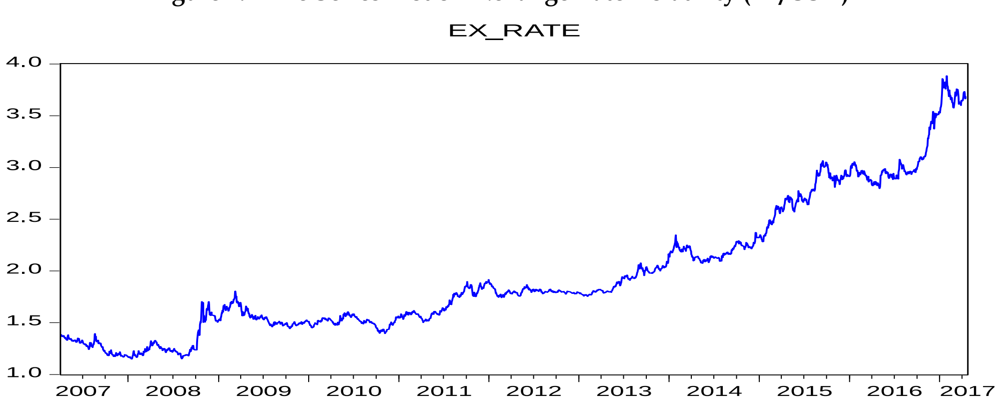
The VAR equation (3,3) is a reduced form of the dynamic structural model of VAR equation (3,1). However, the structural error u_t has a relation with reduced form of residuals as

$$u_t = B_0^{-1} \varepsilon_t \quad (16)$$

ESTIMATION

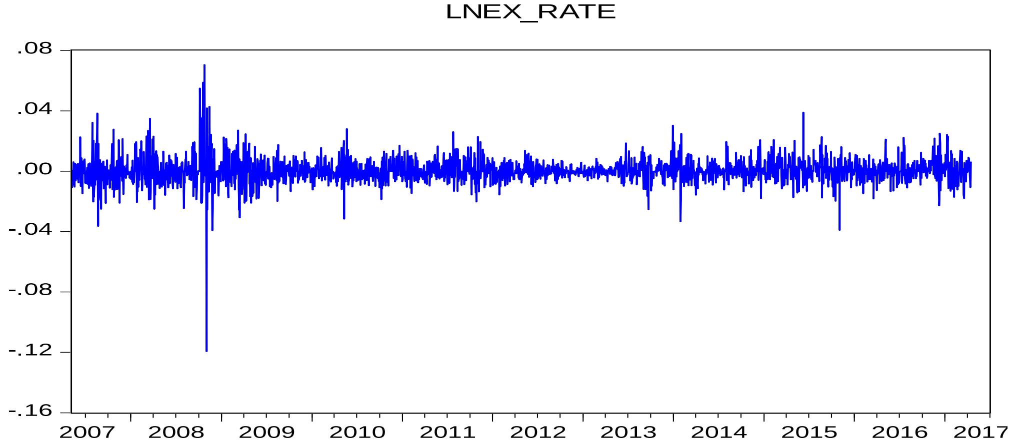
4.1. ARCH and GARCH Families Model
This study uses daily data to estimate the ARCH models. We also have estimated the ARCH model with monthly data on Real Exchange Rate. However, there is no present of ARCH effect in the model. Thus, we decide to use daily data in our model to control the autocorrelation pattern and Leverage effect on the models to predict the presence of asymmetric response in the volatility of exchange rate. Estimation of sample period is started from January 1st, 2005 through April 21st, 2017 (See figure 1, 2).

Figure 1. Time Series Plot of Exchange Rate Volatility (TL/USD)



Source: The Central Bank of the Republic of Turkey

Figure 2. Time Series Plot of Exchange Rate Return (TL/USD)



Source: The Central Bank of the Republic of Turkey

The first step, we need to estimate ARMA model with the AIC test approach. The AIC test result suggests ARMA (2, 2) model is our best model among the other ARMA models (see Table-1).

Table 1. The Akaike Info Criterion result of ARMA model

AR / MA	0	1	2	3	4	5
0	-6.753566	-6.753943	-6.753334	-6.752709	-6.753587	-6.753350
1	-6.753639	-6.753226	-6.752691	-6.752076	-6.752815	-6.753391
2	-6.753567	-6.753022	-6.760606	-6.760506	-6.760116	-6.759512
3	-6.752695	-6.752152	-6.755162	-6.759903	-6.759309	-6.759562
4	-6.753087	-6.752650	-6.759572	-6.759012	-6.758423	-6.759668
5	-6.752816	-6.752962	-6.758653	-6.758158	-6.758877	-6.759347

Author estimation

Thus, the second step is evaluating heteroscedasticity effect by ARCH LM test. According to ARCH LM test results in table 2, there is a presence of ARCH effect in ARMA (2,2) model since the probability is less than 5% (p-value=0.00).

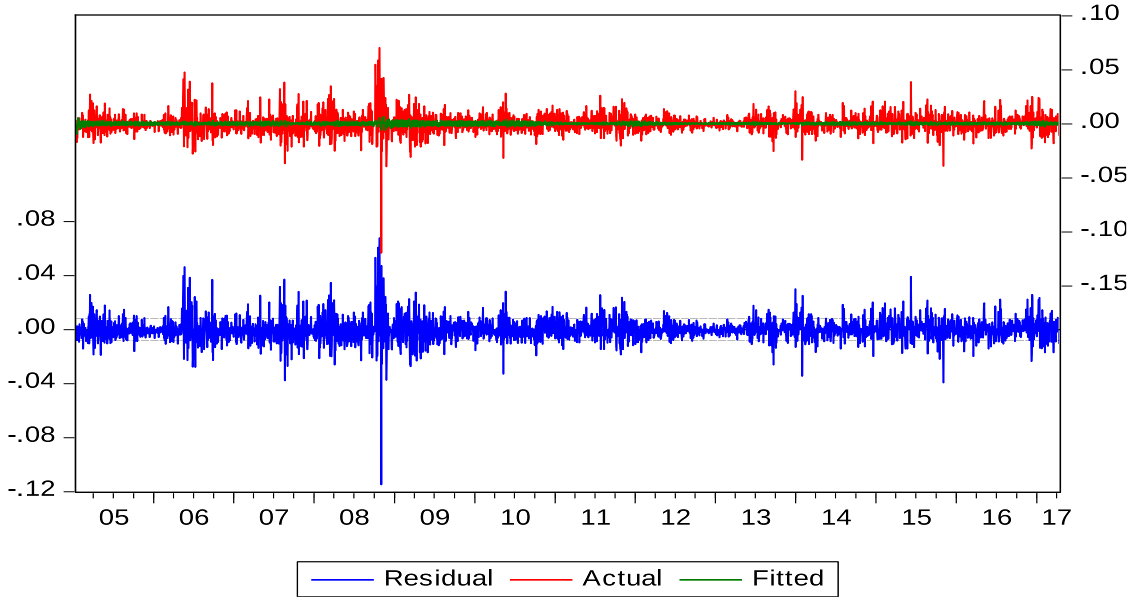
Table 2. ARCH LM test on ARMA (2,2) model

Heteroskedasticity Test: ARCH			
F-statistic	90.01529	Prob. F(1,3200)	0.0000
R-squared	87.60718	Prob. Chi-Square(1)	0.0000

Author estimation

In addition, ARMA (2, 2) also has persistence of residual (see Figure 3), therefore we can decide to focus on ARCH families to be further analysed.

Figure 3. Persistence of Residual, Actual, and Fitted.



Author estimation

Since the conditional heteroscedsticity of ARMA (2, 2) came out as our best model, thus we need to focus to the other specification of ARCH families modes such as ARCH, GARCH, IGARCH, and EGARCH (see table 3).

Table 3. Parameter for ARCH and GARCH models (TL/US) without volatility breaks

Parameter	$ARCH$	$GARCH$	$EGARCH$	$IGARCH$
C	8.58E-05	0.0001	0.000324	0.000170
	0.000139	0.00011	0.000106	8.58E-05
$AR(1)$	-1.106401	-0.5911	-1.901292	0.930267
	0.075977	0.18421	0.012527	0.293919
$AR(2)$	-0.687104	-0.6694	-0.960703	-0.424835
	0.061956	0.15772	0.012246	0.273715
$MA(1)$	1.165001	0.6317	1.916336	-0.891929
	0.066958	0.17939	0.009668	0.297271
$MA(2)$	0.739991	0.6916	0.975990	0.399356
	0.054827	0.15174	0.009481	0.276230
ω	5.07E-05	7.51E-07	-0.348111	-
	4.27E-07	1.16E-07	0.024089	-
α	0.268048	0.1081	0.073508	0.072745
	0.017120	0.0067	0.007268	0.002857
β	-	0.8873	0.977086	0.927255
	-	0.0056	0.002245	0.002857
Leverage effect- γ	-	-	0.162686	-
	-	-	0.009640	-
$\alpha + \beta$				
AIC	-6.836997	-7.083153	**-7.086881**	-7.062677
SW	-6.823727	-7.067987	-7.069820	-7.051303
obs	3203	3203	3203	3203

Author estimation

The variance equation parameters of ARCH, GARCH, IGARCH, and EGARCH models results, alpha and beta, have positive effects and significant with probability less than 1%. In case of GARCH, if the variance of exchange rate returns increase 1 unit, it might be affect the expected variance exchange rate return about 0.887. However, EGARCH and IGARCH models have more effect to the variance of exchange rate returns. The variance of exchange rate returns shock before or its residual also might be influencing the exchange rate returns variance increases. However, the result of AIC and SW test criteria suggest that ARMA (2,2)-EGARCH (1,1,1) model is suitable to be cited.

4.1.1. Leverage Effect

EGARCH model generally is used to define the asymmetric of variance exchange rate return of forecast models. Therefore, it can capture the possibility of leverage effect in our model. Since our GARCH model also has significant parameter, thus there might be a persistence of GARCH effect in our EGARCH model. The parameter of EGARCH has a positive significant effect, means that in the Turkish case, it has more positive information than negative information influencing the exchange rate return. Therefore, we can conclude that the exchange rate value appreciate for some periods. This finding is consistent with Ağcaer (2003), Ünal (2008) and Central Bank of The Republic of Turkey (2010) research findings result.

There might be also a possibility of exchange rate persistence in our sample of observation. Thus, we decided to analyze the effect of ARCH families models by dummy variable. The dummy variables are important to remove the effect of the conditional mean and variance equation. According to Quandt-Andrews Breakpoint test, there are some major extreme effect in the year of 2008, 2010 and 2015.

After the dummy variable implied in our model, the result of ARCH family's models is better than the result of ARCH family's models without dummy variable. The explanation of EGARCH model has also become better than our EGARCH model without dummy variable (see table 4).

Table 4. Parameter for ARCH and GARCH models (TL/US) with volatility breaks

Parameter	$ARCH$	$GARCH$	$EGARCH$	$IGARCH$
C	7.69E-05 0.000135	0.00012 0.00011	0.00111 0.00159	0.000171 8.51E-05
$AR(1)$	-0.529206 0.035310	0.88772 0.28293	0.20433 0.23029	0.91602 0.28871
$AR(2)$	-0.898904 0.033683	-0.38271 0.26484	0.79484 0.23041	-0.40408 0.26065
$MA(1)$	0.558197 0.036505	-0.83841 0.28648	-0.19034 0.22186	-0.87337 0.29181
$MA(2)$	0.893146 0.034383	0.35335 0.26833	-0.80907 0.22259	0.37726 0.26326
ω	5.07E-05 4.59E-07	1.02E-06 1.29E-07	-0.43012 0.02306	- -
α	0.232420 0.016206	0.11637 0.00713	0.07783 0.00779	0.07853 0.00299
β	- -	0.87249 0.00545	0.96959 0.00239	0.92147 0.00299
Leverage effect- γ	- -	- -	0.17186 0.00963	- -
$\xi - dummy$	0.001543 0.002203	0.00014 3.49E-05	1.36715 0.15988	8.28E-05 1.75E-05
$\alpha + \beta$				
AIC	-6.836997	-7.090736	**-7.094039**	-7.068484
SW	-6.823727	-7.073675	-7.075083	-7.055214
obs	3203	3203	3203	3203

Author estimation

4.2. ARIMA and SARIMA

To estimate ARIMA model, we used monthly data with sample of observation started from January 2010 through March 2017 to avoid the financial crisis effect on our estimation. We also calculated the exchange rate return to be used as our estimation.

Table 5. Akaike Info Criterion result of ARMA model

AR / MA	*0*	*1*	*2*	*3*	*4*	*5*
0	*-4.391280*	*-4.434739*	*-4.411707*	*-4.398007*	*-4.399670*	*-4.377147*
1	*-4.436085*	*-4.411739*	*-4.452364*	*-4.444490*	*-4.415550*	*-4.404784*
2	*-4.414273*	*-4.450604*	*-4.415644*	*-4.402680*	*-4.405677*	*-4.374042*
3	*-4.404955*	*-4.430461*	*-4.408421*	*-4.372111*	*-4.488663*	*NA*
4	*-4.386050*	*-4.409660*	*-4.383116*	*-4.395075*	*-4.453468*	*-4.497673*
5	*-4.363957*	*-4.354195*	*-4.364610*	*-4.353784*	*-4.444576*	*-4.338059*

Author estimation

The correlogram analysis resulted that autocorrelation and partial correlation are gradually decline. Therefore, it can be concluded that the ARIMA model is fit enough to be intrepeted. Thus, we continued to check the best ARIMA models for further analysis. Formerly, according to AIC, it suggested that ARIMA (4,1,5) came out as the best ARIMA model among the others (see table 5).

AR (4) can be explained as follows. AR (1), Exchange rate in previous month have a positive effect. It means 1 percent increasing in exchange rate return giving an increase in exchange rate return for the next month with value 0.56. After that, the exchange rate affecting its own value for 4 months. MA (5) means that the exchange rate gives a shock by its own within 5 lag (see table 6).

After finding the best model of ARIMA, thus we need to recheck the residual correlogram. Finally, the residual correlogram resulted that there is no autocorrelation in our ARIMA model. It is important also to check normality assumption in our ARIMA model. The Jarque-Bera test resulted that the probability is bigger than p-value 5% (with value 0.676). It means that the distribution of data in our ARIMA model suitable with normality assumption. By LM test, we can evaluate if there is serial correlation or not. With value of probability 0.9469 (which bigger than 5%), it can be concluded that there is no serial correlation in our ARIMA model. Heterocedasticity test also resulted that there is no ARCH effect with probability 0.44. Therefore, our model is good enough to be intrepeted.

Table 6. Time Series Result of ARMA model

Dependent Variable: EX_R
Method: Least Squares
Sample: 2010M09 2017M03
Included observations: 79

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.011185	0.003719	3.007146	0.0037
AR(1)	0.568905	0.117000	4.862451	0.0000
AR(2)	-0.500742	0.119260	-4.198753	0.0001
AR(3)	0.383623	0.104273	3.679014	0.0005
AR(4)	-0.674057	0.080373	-8.386562	0.0000
MA(1)	-0.363491	0.158974	-2.286485	0.0253
MA(2)	0.465044	0.121603	3.824283	0.0003
MA(3)	-0.430294	0.119578	-3.598442	0.0006
MA(4)	0.638932	0.109384	5.841186	0.0000
MA(5)	0.360845	0.140077	2.576045	0.0121
R-squared	0.284119			

4.2.1. Forecast of ARIMA

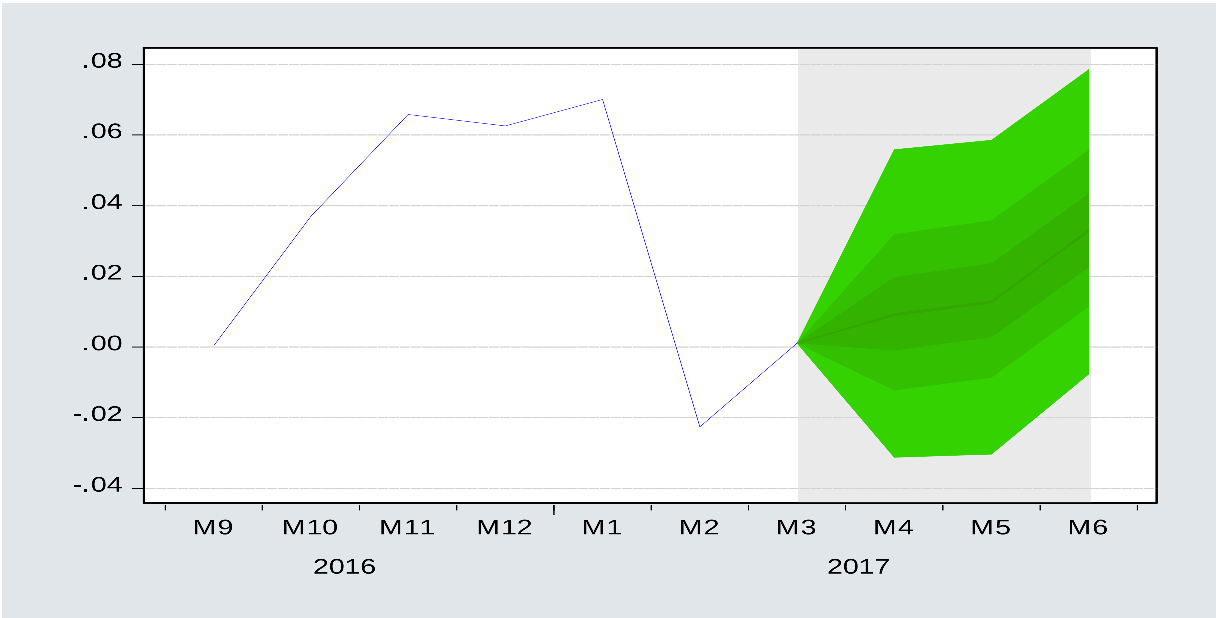
To forecast the exchange rate, we applied 3 month forecast of ARIMA (4,1,5) model. The last value of the exchange rate in March, 2017 is 3.67 in Turkish Lira. Our ARIMA model expecting that the exchange rate will increase in the next three months until 3.88 TL (see figure 4-5).

The green colour of chart showed how the exchange rate volatility forecasted. Upper bound and lower bound mean highest volatility and lowest volatility. If the exchange rate volatility goes from the darkest green area to the light green area, it means forecast less of probability. In the next three months (until June) with 60% probability level, the exchange rate will be increase with confidence of interval 3.6-4.1. Therefore, it can be concluded that Turkish Lira will depreciate in next three months.

However, the forecast of next 6 months predicted that the exchange rate still continues to increase until 3.98 TL. For six months forecasting (until September) with 60% probability level, Turkish lira will be rising with confidence of interval 3.5-4.5.

In addition, we also estimated Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to evaluate the accuration of forecasting. RMSE and MAE give value 0.030807 and 0.026144 in respectively (we put the value in table 4.11).

Figure 4 Months Ahead ARIMA (4,1,5) model Forecast of Turkish Lira Using Fan Chart.



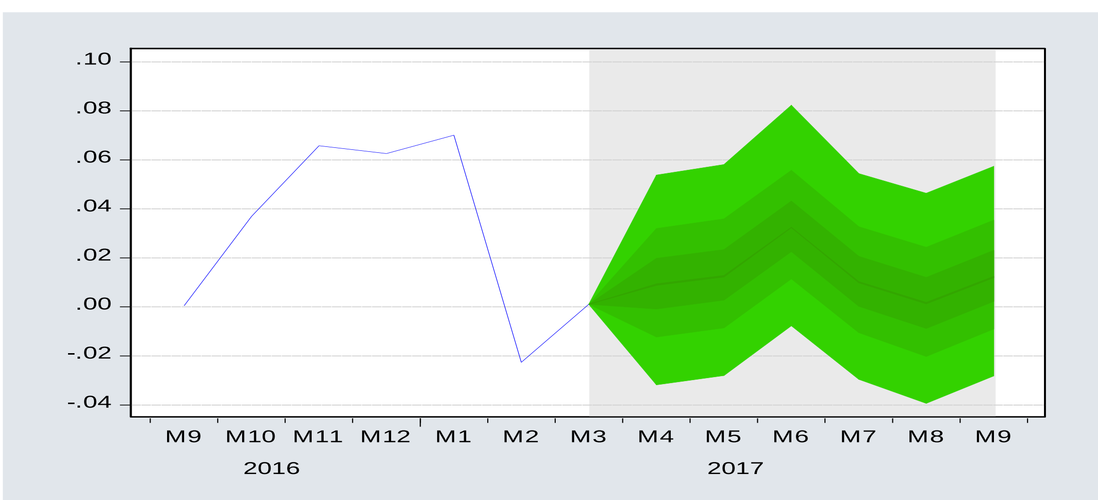
Author estimation

4.2.1. SARIMA

SARIMA model used monthly data started from January, 2005 through March, 2017. Since the volatility of our monthly data is high, it is important to evaluate in which periods our data have high volatility (some crisis or other events might create high peak of volatilities in the period of the sample). According to Quandt-Andrews Breakpoint Test, it can determine in which periods our data has high peak of volatilities. The Quandt-Andrews Breakpoint test resulted that in the period of April, 2010 through March, 2017, it has no higher peak of volatilities than other periods.

Thus, we also need to check the possibilty of seasonality in our data. However, by Census X-13 analysis, we found that our data has seasonality effect since the level value is 0.07. Therefore, we can continue to analyzed with SARIMA model. By 577 times estimations of SARIMA analysis, SARIMA (4,1,4) came out as the best model of our SARIMA analysis.

Figure 5. Months Ahead ARIMA (4,1,5) model Forecast of Turkish Lira Using Fan Chart.



It is also important to check residual diagnostic of our SARIMA model. As we estimated above; ccorrelogram of residuals squared resulted that there is no correlation. LM test has probability 0.4373 bigger than 10% means that there is no serial correlation in our data. By ARCH test, probability of heteroscedasticity gives value 0.5032 and bigger than 10%. It can be concluded that there is no ARCH effect in SARIMA model. According to Jarque-Bera test, the probability of normality is 0.223, thus our data is normally distributed. Therefore, oour SARIMA model has meet the assumptions criterias, thus we can continue to forecast the exchange rate by SARIMA model (see table 7).

Table 7. Time Series Result of SARIMA model

Dependent Variable: EX_R
Method: Least Squares
Date: 04/19/17 Time: 14:18
Sample: 2010M04 2017M03
Included observations: 84

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.021531	0.004127	5.217058	0.0000
AR(1)	1.290727	0.087617	14.73141	0.0000
AR(2)	-0.556737	0.123780	-4.497799	0.0000
AR(3)	0.640247	0.161594	3.962074	0.0002
AR(4)	-0.492293	0.088397	-5.569116	0.0000
SAR(6)	0.890419	0.037715	23.60937	0.0000
MA(1)	-1.192052	0.009412	-126.6568	0.0000
MA(2)	0.407824	0.015854	25.72356	0.0000
MA(3)	-1.153639	0.011998	-96.15446	0.0000
MA(4)	0.942843	0.008076	116.7421	0.0000
SMA(6)	-0.911305	0.012540	-72.67424	0.0000

R-squared	0.499443	Mean dependent var	0.010437
Adjusted R-squared	0.430873	S.D. dependent var	0.026932
S.E. of regression	0.020318	Akaike info criterion	-4.833090
Sum squared resid	0.030135	Schwarz criterion	-4.514769
Log likelihood	213.9898	Hannan-Quinn criter.	-4.705127
F-statistic	7.283752	Durbin-Watson stat	2.015396
Prob(F-statistic)	0.000000		

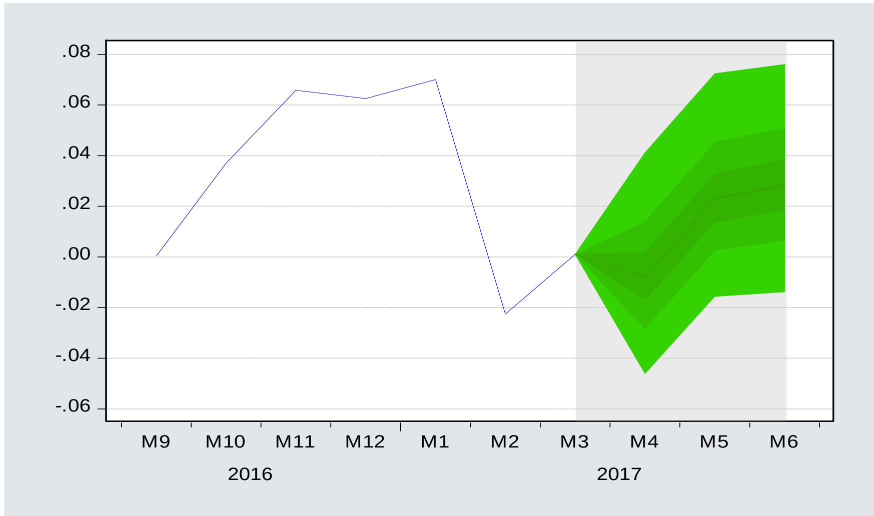
Author estimation

4.2.2. Forecast of SARIMA

The last value of the exchange rate in March, 2017 is 3.67 TL. Our forecast of 3 month exchange rate resulted that the exchange rate tends to increase until June, 2017. However, the value of exchange rate in April is decline, and then the exchange rate remains to increase until 3.85 TL.

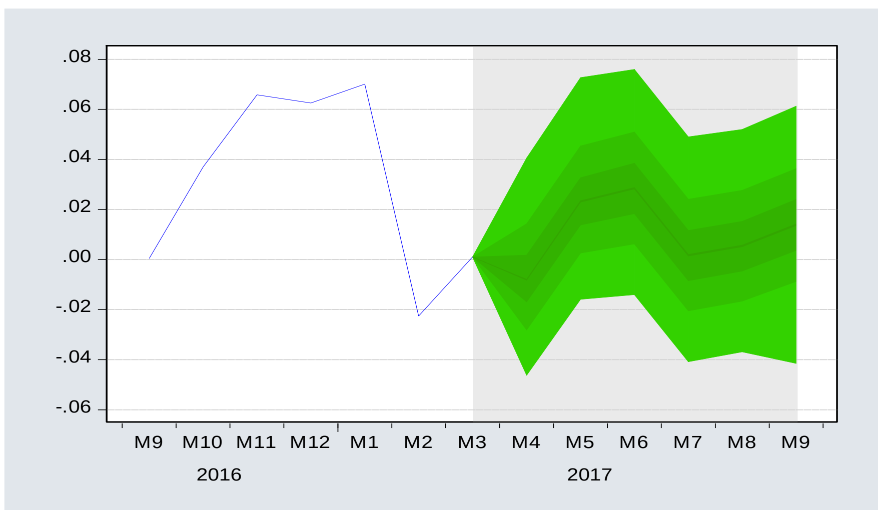
The green colour of chart show how the exchange rate volatility forecasting. Upper bound and lower bound mean highest volatility and lowest volatility. If the exchange rate volatility goes from the darkest green area to the light green area means forecast less of probability. In the next three months (until June) with 60% probability level, Turkish lira will be increase with confidence interval 3.6-4.0 (see figure 6-7)).

Figure 6. Months Ahead SARIMA (4,1,4) model Forecast Of Turkish Lira Using Fan Chart.



Author estimation

Figure 7. Months Ahead SARIMA (4,1,4) model Forecast of Turkish Lira Using Fan Chart.



Author estimation

For six months forecasting (until September) with 60% probability level, Turkish lira will be increase with confidence interval 3.4-4.5. The next 6 month forecast also shows that the exchange rate slowly increases until 3.93 TL. Moreover, to checked the accuration of this forecast we need to estimated Root Mean Square Error (RMSE) and Mean Square Error (MSE). Root Mean Square Error (RMSE) and Mean Square Error (MSE) giving value 0.026 and 0.0229 respectively (see table 4.11).

4.3. SVAR

4.3.1. Identification

SVAR model is identified by five models of the structural shock, using Cholesky variance decomposition and the variance-covariance matrix. The first model is supply shock which identified by oil price. The demand shock will be identified by output gap with proxy industrial production index and it has oil price shock and its own shock respectively. The exchange rate itself is identified in the third variable. The fourth and fifth variable will be identified by different series of prices, production price index and consumer price index.

$\pi^{oil} = E_{t-1}\,[\pi^{oil}] + \varepsilon_t^{oil}$ (17)

$\Delta y_t = E_{t-1}\,[\Delta y_t] + \alpha_1 \varepsilon_t^{oil} + \varepsilon_t^{\Delta y}$ (18)

$\Delta e_t = E_{t-1}\,[\Delta e_t] + \beta_1 \varepsilon_t^{oil} + \beta_2 \varepsilon_t^{\Delta y} + \varepsilon_t^{\Delta e}$ (19)

$\pi_t^{PPI} = E_{t-1}\,[\pi_t^{PPI}] + \gamma_1 \varepsilon_t^{oil} + \gamma_2 \varepsilon_t^{\Delta y} + \gamma_3 \varepsilon_t^{\Delta e} + \varepsilon_t^{PPI}$ (20)

$\pi_t^{CPI} = E_{t-1}\,[\pi_t^{CPI}] + \gamma_1 \varepsilon_t^{oil} + \gamma_2 \varepsilon_t^{\Delta y} + \gamma_3 \varepsilon_t^{\Delta e} + \gamma_3 \varepsilon_t^{\Delta PPI} + \varepsilon_t^{CPI}$ (21)

We applied monthly data with sample of observation started from March, 2007 through February, 2017 as our analysis. In spirit of Mc Carthy (1999) VAR analytical framework which explained pass through of exchange rate and import prices to domestic inflation, some variables will be implied in our Structural VAR framework. We describe variables like oil price, output gap, exchange rate, consumer price index, and producer price index in table 8.

The result of SVAR analysis will be divided in 3 parts. The first part is interpretation of responses of two variables of prices on exchange rate with impulse response graphics. After resulted the value of cumulative impulse responses, we applied the analytical framework of Exchange Rate Pass Through (ERPT) to identify the effect of change in exchange rate towards two of our index prices (Masha and Park, 2012). The coefficient changes of pass through:

$PT_{t,t+s} = \frac{CP_{t,t+s}}{EP_{t,t+s}}$ (22)

Where $PT_{t,t+s}$ the pass through coefficient at horizon s and period t is, $CP_{t,t+s}$ are the cumulative impulse responses of consumer price index at horizon *s* and period *t*, and $EP_{t,t+s}$ is the cumulative impulse responses of exchange rate at horizon *s* and period *t*. The last parts in our SVAR model is calculating the amount of the variable shock by variance decomposition tables. In the end of SVAR analysis, we compile our forecast of exchange rate.

Table 8. Descriptions of variables

Data	Descriptions	Source
Oil price	Crude oil price in USD (petroleum), simple average of three spot prices; Dated Brent; West Texas intermediate; and the Dubai Fateh	IMF Primary Comodity Index
Output gap	Industrial Production Index-Total	Turkish Statistical Institute
Exchange rate	Nominal exchange rate	Central Bank of the Republic of Turkey
Producer Price Index	PPI is a measure of the change in the prices of goods and services sold as output by domestic producers in a given reference period (2003=100).	Turkish Statistical Institute
Consumer Price Index	CPI is a measure the changes of the current retail prices of goods and services purchased by consumers over a given time period (2003=100).	Turkish Statistical Institute

The above measurement of variable is explained as annual growth since it is important to normalized data series and transferred all variable in the same unit of measurement. Hence we took annual growth rate of all variables to avoid the problem of level of integration (see table 9).

Table 9. Unit Root Test Reult by ADF test

		The equation type		Level	
Variables	Lag order	none (b=a=0)	intercept(a≠0, b=0)	ADF Test H0: p=0 there has unit root (P-value)	level of integration
Oil price-Π^{oil}	0		+	0.01***	I(1)
Output gap-y	0	+		0.01***	I(1)
exchange rate-e	0	+		0.05**	I(1)
Producer price index- PPI	0		+	0.01***	I(1)
Consumer price index- CPI	0		+	0.02***	I(1)

Level of significance 1%***, 5%**, 10%*, *Author estimation*

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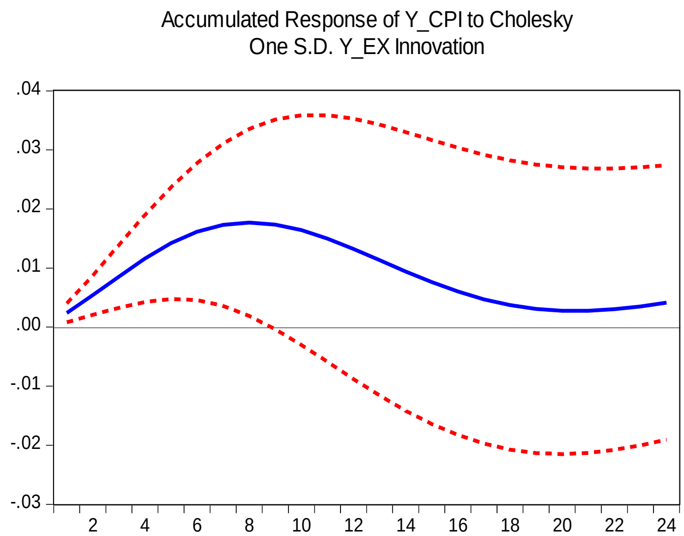
4.3.2. Impulse Response

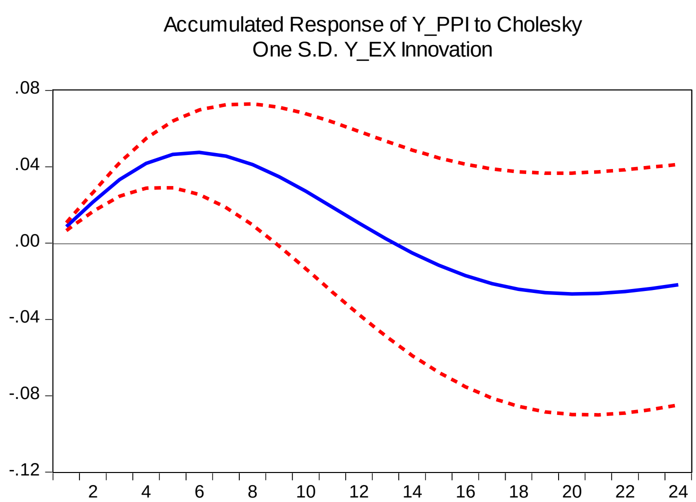
The exchange rate annual growth affecting inflation strongly 0 Lag order from 1-9 month significantly with 5% probability. In early five months the exchange rate shock is increasing inflation rates until 5 months. However, after seventh month, the influences are gradually slowed. Then after ninth months later the exchange rate shocks are not significantly affecting the inflations. According to Leigh and Rossi (2002), exchange rate pass through to consumer price and wholesale price index are only has effets on first fourth months, then the effect is fall down. However, since the exchange rate recently has strong influence to prices in Turkey, thus the exchange rate shock effecting CPI and PPI more than Leigh and Rossi (2002) findings (see figure 8).

Figure 8. Impulse Repsonse of CPI annual growth.



Author estimation

Figure 4.8. Impulse Response of PPI annual growth.

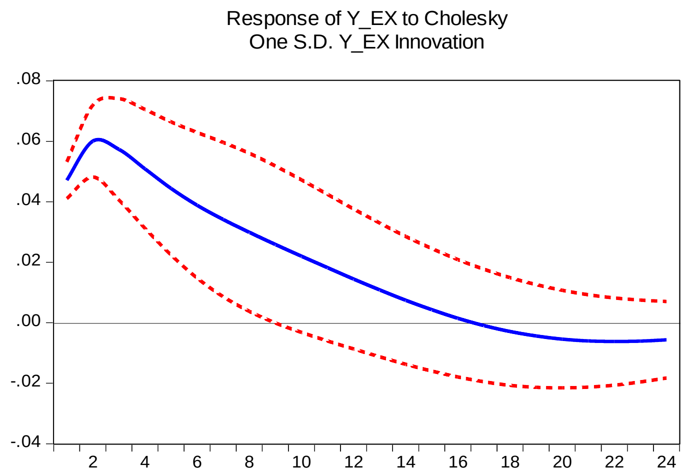


Author estimation

Several changes in Turkish economy recently might be possible to create this strong inffluences. First, the exchange rate volatility in Turkey is high for decades due to major market events that affecting Turkish economy. Second, After 2002, Turkish trade policy has chaged rapidly and more open to create trade with other partner countries. Exchange rate shock to CPI is more pronounced compared to PPI.

First two months, exchange rate responses by its own shock, give a strong effect to increase. Then, after two months the exchange rate response gradually slowly, and after six month its own response back to return (see figure 9).

Figure 9. Impulse Response of Exchange Rate Annual Growth.

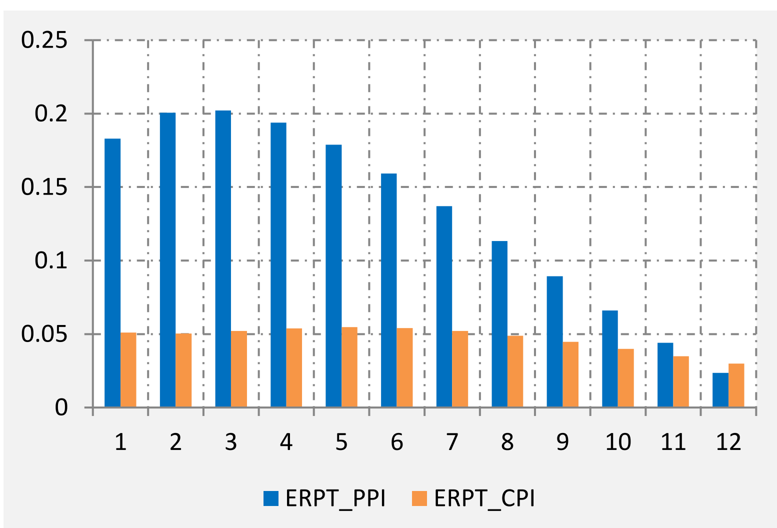


Author estimation

4.3.3. Exchange rate pass through -ERPT

We also used ERPT coefficient to measure how responsive inflation rate to changes in exchange rate. In the early 5 month, exchange rate pass through on PPI is 20 percent and 5% on CPI. One percent increases/decrease in the exchange rate will remain increase/decrease in annual inflation 0.05. After effect of Exchange rate shocks on inflation decrease, inflation changed about 55% (see figure 10).

Figure 10. Impulse Response of Exchange Rate Annual Growth.



Author estimation

4.3.4. Variance Decomposition

Impulse response fictions are useful to tell the direction and magnitude of shocks. Meanwhile variance decomposition tells us the amount of the shock. The exchange rate shocks appear to be important in explaining the composition of PPI inflation than CPI inflation. PPI is explained predominantly by its own innovative shock accounting 33% in the first two months and then it declines. As we saw in the impulse response fiction, it is significant until the 9 months, thus the exchange rate shocks explain about 50% in the first two month and until 9 months the inffluence is decrease about 36% (see table 10).

Table 10. Variance decomposition of PPI annual growth

	Variance Decomposition of Y_PPI:				
Period	Y_OIL	Y_OUTGAP	Y_EX	Y_PPI	Y_CPI
2	14.01	0.72	51.41	33.85	0.00
8	31.72	4.13	36.38	17.88	9.89
12	26.76	4.23	41.05	13.75	14.20
24	25.40	3.69	45.04	11.96	13.92

Author estimation

CPI is explained its own innovative shock accounting 76.63% in first two months and after that it declines. Exchange rate shock explains CPI variance about 17% in first 8 months. CPI in general explains its own inertia and mostly explains exchange rate fluctuation (see table 11).

Table 11. Variance decomposition of CPI annual growth

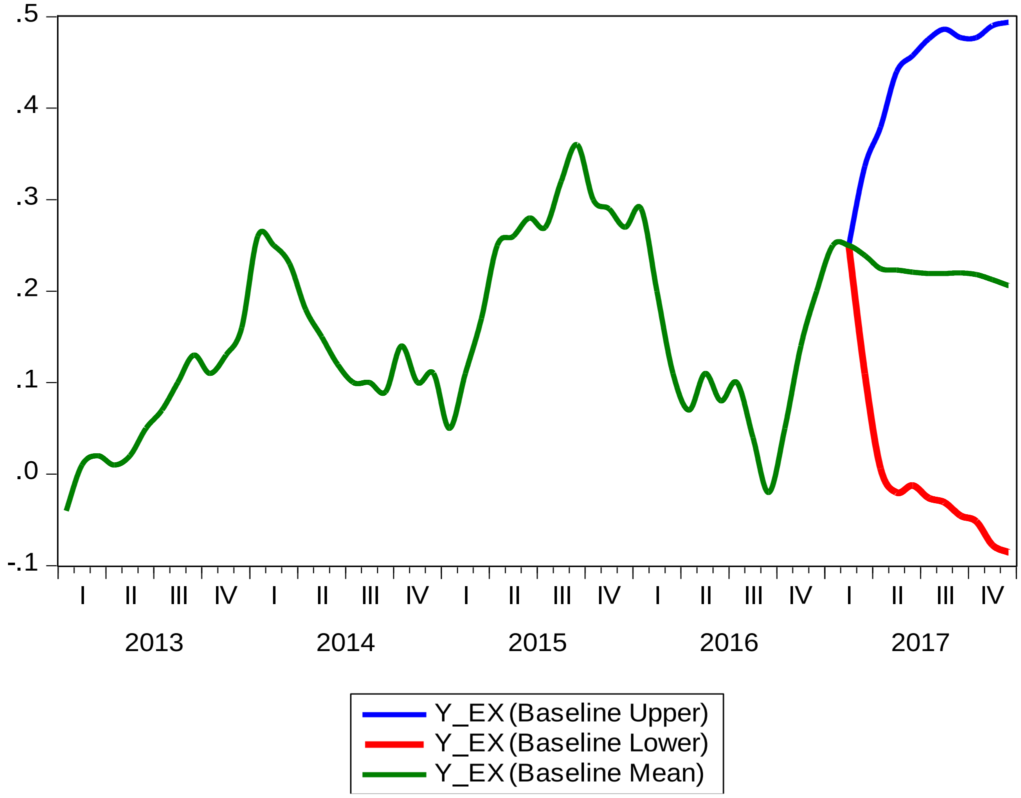
	Variance Decomposition of Y_CPI:				
Period	Y_OIL	Y_OUTGAP	Y_EX	Y_PPI	Y_CPI
2	4.05	3.65	10.17	5.50	76.63
8	17.93	2.14	16.46	5.17	58.30
12	25.16	2.02	16.34	4.57	51.91
24	24.50	2.08	19.71	4.56	49.16

Author estimation

4.3.4. Forecast of SVAR

After explaining SVAR analysis results, the forecast of exchange rate can be described on the figure 4.11. The last calculating of exchange rate is on March 17, 2017 with value 3.67 TL. Then the exchange rate from April to June is expected to decline until 3.56 TL. However, until in the end of the year, the exchange rate slowly increases to 4.22 TL (see figure 11).

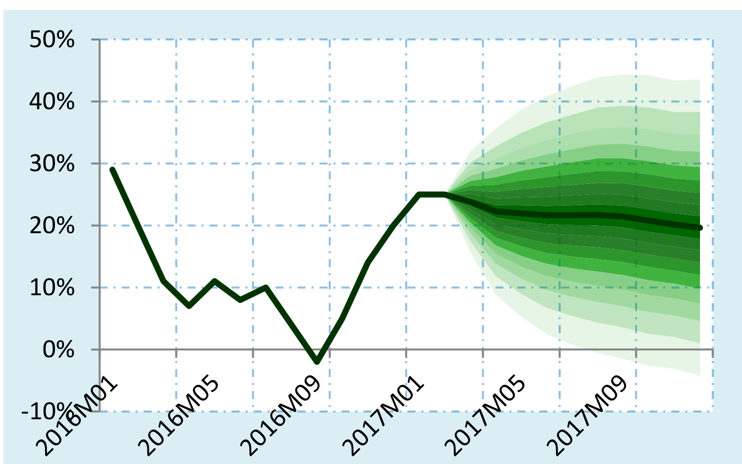
Figure 11. Forecast of Exchange Rate Annual Growth.



Author estimation

By the estimation result of Root Mean Square (RMSE) and Mean Absolute Error (MAE), it is posible to choose which model of the exchange rate would be the best in explaining of the exchange rate forecast. SVAR analysis of CPI variable's RMSE and MAE give result with value 0.1306 and 0.1061 respectively (see figure 12).

Figure 12. Months Ahead SVAR model Forecast of Turkish Lira Using Fan Chart.



Author estimation

4.4. Comparison of Forecasts

After analysing several techniques to forecasts the exchange rate , we compare which models would give the most accurate on forecasting the exchange rate. The figure 4.13. Shown the comparison of exchange rate forecast results. We had analyzed forecasting of exchange rate in 5 months, start from April, and 2017 through September, 2017.

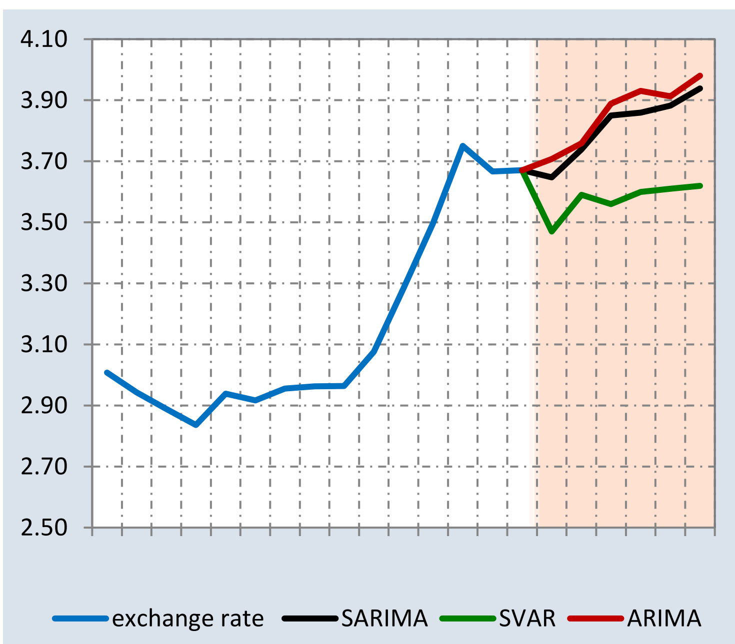
In the first month of forecasting or in April, all the models are expecting that exchange rate will continue to decrease as like the months before. SVAR give value the exchange rate forecasting about 3.47. However, SARIMA and ARIMA give values 3.65 and 3.71 in respectively. Moreover, the forecast of SARIMA has a value exchange rate nearly same with the actual value of the exchange rate (3.65) in April, 2017.

In April, 2017, SARIMA and SVAR also give the same trend of fluctuation in exchange rate due to the declining of current exchange rate. However ARIMA's forecast tends to increase and different with two models.

All the models expected to the rise in the exchange rate after April, 2017 and until September, 2017. ARIMA and SARIMA give a value of exchange rate 3.98 and 3.93 respectively. However, SVAR give more less value about 3.62 (see figure 13).

The forecast result by our 3 models expecting that Turkish Lira is continuing to rise untill the end of 2017. Since the developing countries includes Turkey has experienced slow on its economic growth, it might lead to increase more capital ouflow from developing countries in future. Problem of refugees also create such political instability in Turkey and it will effect Turkish economy reform in the future. Political insatbility was one of the reaason to decline tourism in the country as tourism sector is the sources of the huge foreign reserve in the Turkey. Because of week tourism season, failed coup attempt, and the contraction of Russian trade caused more deficit in the Current Account. Moreoever, net international investment possition will continue to deteriorate until there will be reduction in the current account deficit .

Figure 13. Comparison of Forecast Models



Author estimation

With the aim of checking which model are more appropriate for checking the volatility because applying one technique is not appropriate as advised by Bollerslev et al. (1994), Diebold and Lopez (1996) and Lopez (2001) we applied Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) analysis, we can conclude that SARIMA become more accurate to forecast the exchange rate since it has RMSE and MAE value low and close to zero. However, in case of SVAR model, the CPI variable's RMSE and MAE has a lower value than SARIMA's RMSE and MAE.

$$MAE_1 = n^{-1}\sum_{t=1}^{n}|actual - Forecast|$$

So generalized form is

$$MAE_1 = n^{-1}\sum_{t=1}^{n}|\sigma_t - h_t|$$

$$RMSE = \sqrt{n^{-1}\sum_{t=1}^{n}(\sigma_t - h_t)\,^\wedge 2}$$

Table 12. Error Statistic for ARIMA, SARIMA, and SVAR

	ARIMA	SARIMA	SVAR
Root Mean Square Error	0.030807	0.026	0.1306
Mean Absolute Error	0.026144	0.0229	0.1061

Author estimation

CONCLUSION

This study has evaluated a large number of volatility model in terms of their ability to forecast the daily and monthly volatility of Turkish Lira against US Dollar. The forecasting of the volatility of the TL/USD has been measured by using ARMA, ARIMA, SARIMA, and SVAR model. We also applied ARCH, GARCH, EGARCH model to check the autocorrelation pattern and volatility shocks is positive or negative. Forecasting exchange rate for next 3 months by using ARIMA (4,1,5) model expecting that the exchange rate will increase in the next three month until TL 3.88. With SARIMA forecasting, exchange rate will rise with interval confidence 3.5-4.5 in the next 3 months and with interval confidence 3.4-4.5 in the next 6 months. The result of SVAR model divided into 3 parts. CPI and PPI responses on exchange rate shocks increase until 5 months but the responses are lost its effect in ninth month. However, exchange rate shock is more pronounced to PPI as compare to CPI. Exchange rate pass through (ERPT) on PPI is 20% and on 5% on CPI. Variance decomposition ensued that PPI and CPI explained predominantly by its own shocks accounting 33% and 76.6% respectively. Forecasting the exchange rate through SVAR, exchange rate expected to decrease until 3.56 in the months of April-June and in the end of the year exchange rate slowly rise until 4.22.

Thus in the end of our analysed, we evaluated 3 models of forecasting, ARIMA, SARIMA, and SVAR. The result from SVAR and SARIMA suggested that From March 2017 to April 2017 the exchange rate will depreciate but after that on May, 2017 to September, 2017 appreciation in exchange rate and more devaluation in the Turkish lira. The forecast comparison by RMSE and MAE also predict that SARIMA model forecast more accurate than other models.

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