MANAS Sosyal Araştırmalar Dergisi | 2020 | Cilt: 9 | Sayı: 2
MANAS Journal of Social Studies | 2020 | Volume: 9 | No: 2
ISSN: 1694-7215
Research Paper / Araştırma Makalesi

The Modelling of Exchange Rate Volatility Using Arch-Garch Models: The Case of Turkey

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Abstract
This study investigates the most appropriate method for modelling the volatility for nominal exchange rate by using the ARCH type models. The research covers the period of 2002-2017 of nominal exchange rate using daily data. It is observed that the volatility of nominal exchange rate has the ARCH effect and the most appropriate model for forecasting the volatility of nominal exchange rate is GARCH(1,2) because it has the lowest Akaike Information Criterion. Furthermore, during the crises and uncertain periods, the volatility of nominal exchange rate series increases and volatility clustering is observed, meaning high volatility tends to follow high volatility and it is true for vice versa.

Key Words: ARCH, GARCH, Akaike information criterion, Volatility, Clustering

Arch-Garch Modelleri Kullanılarak Döviz Kurundaki Dalgalanmanın Modellenmesi: Türkiye Örneği

Öz
Bu çalışma, ARCH tipi modelleri kullanarak nominal döviz kurundaki oynaklığı modelleyen en uygun metodu bulmaya çalışmaktadır. Araştırma verisi 2002-2017 yılları için günlük verileri kapsamaktadır. Döviz kurundaki dalgalanmanın ARCH etkisine sahip olduğu ve nominal döviz kurunu tahminde en uygun modelin en düşük Akaike bilgi kriterine sahip olmasından dolayı GARCH(1,2) olduğu bulunmuştur. Ayrıca, kriz ve belirsizlik dönemlerinde nominal döviz kuru serisinde artışlar olduğu ve yüksek dalgalanmayı yüksek dalgalanmanın takip ettiği kümelenmenin görüldüğü gözlemlenmiştir.

Anahtar Kelimeler: ARCH, GARCH, Akaike Bilgi Kriteri, Dalgalanma, Kümelenme

Atıf İçin / Please Cite As:

Sekmen, F. & Ravanoğlu, G. A. (2020). The modelling of exchange rate volatility using Arch-Garch models: The case of Turkey. *Manas Sosyal Araştırmalar Dergisi, 9*(2), 834-843.

Geliş Tarihi / Received Date: 18.03.2019 **Kabul Tarihi / Accepted Date:** 04.10.2019

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Introduction

Volatility can be defined as instantaneous movements in prices. Volatility typically refers to the standard deviation of the asset return. Last 50 years, many researchers have investigated volatility in financial markets; for example, Mandelbrot (1963) and Fama (1965) found that one of the most important features of the volatility is *volatility clustering*, meaning large changes tend to follow large changes in periods, and vice versa. Another characteristic of the volatility is the unconditional distribution of returns. From 1960's, volatility has attracted attention. Because increasing volatility means increasing risk; for example, rising volatility in stock prices implies that stock holders bear risk. If investors expect high profitability, but they may tolerate loss or low profits, it can be mentioned an existence of a risk.

The aim of this paper is to examine the exchange rate volatility and try to find out the best ARCH type models for the exchange rate data of Turkish economy. The acceptance of the flexible exchange rate system in 1973 produced a significant volatility and uncertainty in exchange rates. Many economists allege that exchange rate volatility is a risk and this hinders or restricts trade volume. However, Oskooee and Hegerty (2007) claim that the increase in exchange rate volatility since 1973 has an indeterminate effects on international export and import flows. When exchange rate volatility is accepted as a risk among relative parties, such as exporters and importers, it is necessary to mitigate negative effects of this risk and to predict future courses of the volatility. This study focuses on ARCH-GARCH models since Engle (1982, 1993) and Crag (1982) proved that variances of the error terms are not equal, meaning error terms may reasonably be expected to be larger for some points or ranges of the macroeconomic time series. Additionally, as stated by Bollerslev (1986), economic theory is deficient in explaining changes related to time in conditional variances. Therefore, this study uses ARCH-GARCH models to predict the nominal exchange rate volatility for Turkish economy. Previous studies have concentrated on volatility in stock prices and tried to predict these uncertainties.

This article is organized as follows: the following section presents literature review; the third section includes statistical model and ARCH-GARCH analysis; the fourth section covers discussion and results.

Literature Review

In the world finance literature, from the beginning of 1980, the numbers of the studies related to modelling uncertainties of stock prices have increased. Mandelbrot (1963) stated that large price changes tend to be followed by large changes-of either sign-and small price changes tend to be followed by small changes. These properties of financial variables indicate that there is a dynamic structure, not static one.

With regard to conceive the behavior of dynamic structure of financial markets, a lot of studies have been done. Akgiray (1989) claimed that time series of daily stock returns exhibit significant levels of dependence. He presented some evidence that daily return series cannot be modeled as linear white-noise process, but GARCH (1,1) processes fit to data very satisfactorily. Baillie and De Gennaro (1990) used GARCH in mean models to examine the relationship between mean returns on a stock portfolio and its conditional variance or standard deviation. Cao and Tsay (1992) presented empirical evidence that the volatilities of monthly stock returns are nonlinear. They compared TAR models with GARCH and EGARCH models.

Talke (2003) compared ARCH and GARCH models for modelling of the South African Rand against three foreign currencies (the US Dollar, the Swiss Franc, and the UK Pound) all on a daily, weekly, and monthly basis. In general, the author found that the GARCH models are superior to the ARCH models for all sampling frequencies with an exception of the weekly UK Pound against South African Rand, and monthly Swiss Franc against South African Rand data.

Huang, Wang, and Yao (2008) stressed that the class of generalized autoregressive conditional heteroscedastic (GARCH) models has proved particularly valuable in modelling time series with time varying model. They meant financial data, which can be particularly heavy tailed.

Alberg et al. (2008) used GARCH, EGARCH, and GJR-GARCH models to analyze the performance of the volatility forecasting for standard Poor's 100 stock index series with three different types of distributions, which are normal, student-t, skewed generalized error distribution. They concluded that skewed generalized error distribution and student-t distributions performed slightly better than a normal distribution, but GJR-GARCH model was the most suitable one to achieve the most accurate volatility forecasts.

Karmakar (2008) analyzed the volatility of daily returns in the Indian stock market over the period 1961 to 2005. Volatility was investigated using the combined data set of the Economic Time Index and the S&P CNX Nifty together. The GARCH (1,1) model was estimated and the result revealed evidence of time varying volatility. The author also used the TARCH (1,1) model to test the asymmetric volatility effect and the result suggested that there was an asymmetry in volatility. This conclusion is consistent with previous studies.

Dralle (2011) used ARCH and GARCH models to model the volatility of financial time series data. The result of his study revealed that the stochastic volatility models were less commonly used to compare to the Univariate GARCH models and the stochastic volatility was restricted to the form of AR(1) owing to its complication of fitting higher order modes.

Statistical Model and ARCH-GARCH Analysis

Statistical Model

Like for in most time series analysis, it is obvious that constant variance assumption is not true for financial series. Initially, Engle (1982) pointed out that constant variance assumption is not provided in time series and introduced autoregressive conditional heteroscedasticity (ARCH) models.

Engle (1982) initially presented the first-order auto regression model.

$$y_t = \gamma y_{t-1} + \varepsilon_t \tag{1}$$

where ε_t is a white noise $V(\varepsilon_t) = \sigma_\varepsilon^2$. In the model, the conditional mean of y_t is γy_{t-1}. When necessary improvements are made, the conditional variance of y_t is σ^2 while unconditional variance is $\sigma^2 / 1-\gamma^2$. A salient characteristic of this result is that conditional variance is smaller than unconditional variance. Then, conditional predictions which suggested by Engle is desirable since it includes additional information from the past and has the smallest prediction error variance. Adding to assumption of normality, ARCH regression model can be expressed as followed.

$$y_t \left| \Psi_{t-i} \right. \sim N(x_t \beta, h_t) \tag{2}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 \tag{3}$$

$$\varepsilon_t = y_t - x_t \beta \tag{4}$$

where (2) represents mean model and (3) shows variation model. h_t is conditional variance in ARCH model, p is the order of the ARCH process, and α is a vector of unknown parameters. The ARCH process presented in (3), there are some restrictions on parameters; for example, conditional variance (h_t) must be positive for all accrued values of e_t. Thus; there are these restrictions such as $\alpha_0 > 0$, $i = 1, 2, \ldots, p$, and $\alpha_i \geq 0$. Since the values of $\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \varepsilon_{t-3}^2, \ldots, \varepsilon_{t-p}^2$ in the ARCH process, which is in equation (3), cannot retrieve negative values, conditional variance equation cannot be negative for all e_t values. The second restrictions for the ARCH process is that the value of α_i must be smaller than 1 and $\sum_{i=1}^{p} \alpha_i < 1$. Otherwise, meaning that if $\sum_{i=1}^{p} \alpha_i > 1$, the process will have infinite variance. The process of the ARCH (p), for p = 1, it will be the ARCH (1) and this process can be demonstrated as followed:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{5}$$

It is necessary that the value of the conditional variance in the ARCH (1) process is not negative, thus α_0 has to be positive and $\alpha_1 \geq 0$.

Engle's ARCH model has some critics. The first criticism is that the ARCH model needs many parameters to capture the volatility and second one is that the ARCH model needs relatively long lags with constant lag structure. Bollerslev presented the GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model in 1986 in order to eliminate these restrictions and to prevent negative variance parameter estimates. Bollerslev approach lets past volatilities which affect the present volatility. The GARCH model provides both autoregressive and the terms of moving average in modelling in the conditional variance. The GARH (p,q) can be written as followed.

$$y_t | \Psi_{t-i} \sim N(0, h_t) \qquad (6)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} = \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t \qquad (7)$$

$$\varepsilon_t = y_t - x_t b \qquad (8)$$

where the series of y_t, depending upon Ψ_{t-i} information set, has zero (0) conditional average and with h_t conditional variance it has normal distribution. The GARCH(p,q) model has to provide these conditions:

$$p > 0,\ q \geq 0 \qquad 9)$$

$$\alpha_0 > 0,\ \alpha_i \geq 0, \quad i = 0,1,2,\ldots p$$

$$\beta_j \geq 0, \quad j = 0,1,2,\ldots q$$

For, $p = q = 0$, ε_t is simply white noise. GARCH(p,q) model can be considered as ARMA model which has single variable. In the ARCH(q) process the conditional variance is specified as a linear function of past sample variances only, whereas the GARCH(p,q) process allows lagged conditional variances to enter as well (Bollerslev, 1990, p. 309).

Statistical Analysis and Findings

This study has employed a daily nominal exchange rate which begins form 2002 until 2017 and used 3989 observation. The data set was obtained from Central Bank of Turkey official website. To conduct statistical test, Eviews 9 software package was used.

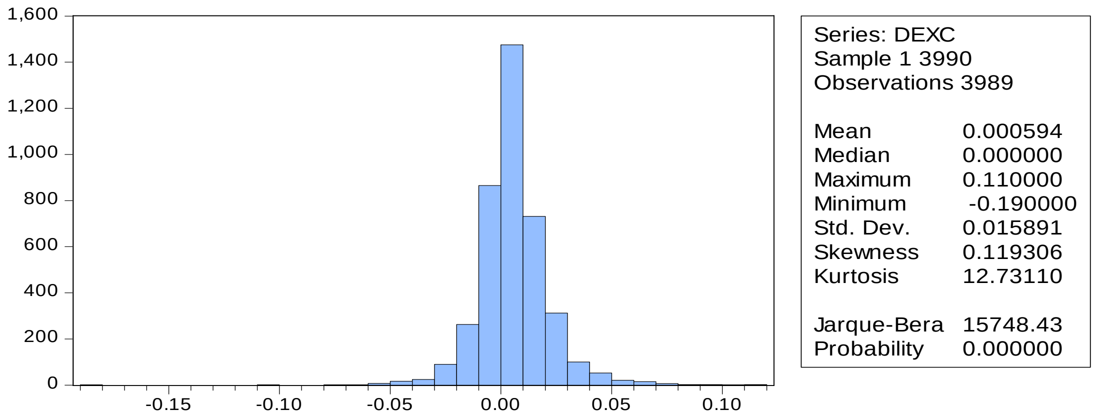

Figure 1. *Descriptive Statistics and Test (Histogram and Statistics)*

Source: Own elaboration

Figure 1 shows that the data of exchange rate exhibits leptokurtic because the kurtosis value is higher than 3. Thus, according to the Jarque-Bera statistic, the null hypothesis is set up as "series are normally distributed", but the result of the Jarque-Bera statistic indicates that the null hypothesis is rejected since the probability is lower than 5 percent level. On the other hand, it can be easily understood from Jarque-Bera statistic, standardized residuals are not normally distributed at 1% significance level.

Since the data set used in this study is time series, the stationarity of the data is must be checked. Without checking the stationarity of series, the result of the estimated model will be spurious.

Stationarity Test

A time series is called as nonstationary if either its mean or variance changes over time. The major consequence of working with nonstationary time series is to have a spurious correlation that inflates R-square and t-scores of nonstationary independent variables, which means incorrect model specification. In time series analysis, *stationarity* is very important since if a time series are not stationary, it exhibits different behavior in different data sets. Thus, in order to prevent spurious correlation, all series must be stationary in time series analysis.

In order to check the stationarity property of the exchange rate, three types of tests are used in this study. Zivot-Andrews (ZA) (1992) test, which permits for structural breaks in the series along with Augmented Dickey Fuller (ADF) (1979) test and Phillips-Perron (PP) (1988) is implemented.

Table 1. *Test of Unit Root for Exchange Rate*

Variable:	ADF Level	First Difference	PP Level	First Difference	ZA Level	Remark	First Difference
Exchange rate	2.098	-61.98***	2.03	-61.99***	-1.31	I(1)	-63.18***

(a) *The critical values are those of MacKinnon (1991)*

(b) ****, **, and * represent the rejection of null hypothesis at 1%, 5%, and 10% level of significance respectively.*

Table 1 show that exchange rate series are not stationary at the level, but after taking first differences it becomes stationary.

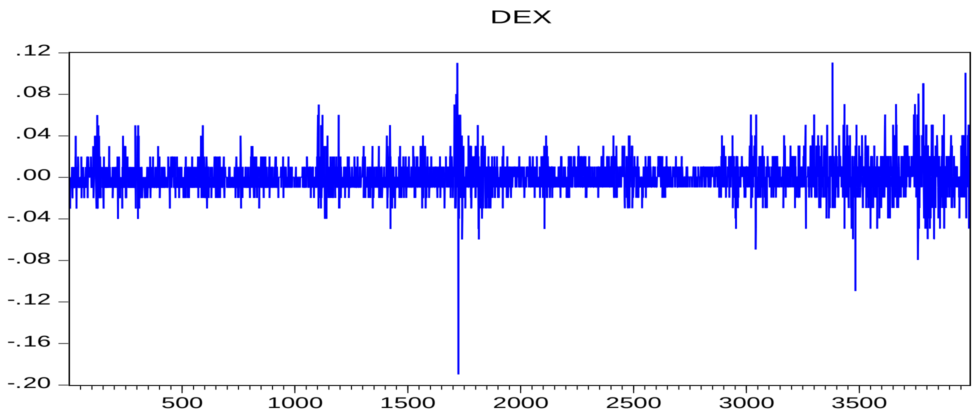

Figure 2. *First Differences of the Nominal Exchange Rate Series*

From figure 2 it can be seen that the volatility clustering which is considered as the period where there is a wide swing in nominal exchange rate for an extended time period followed by a relatively calm period. This means that the variance of financial time series varies over time. Thus, one of the conditions is satisfied since figure 2 shows that there is a *volatility clustering* for nominal exchange rate data.

The condition of the stationarity is fulfilled after taking first difference of the data. The ARCH-LM test is used in order to find out if the variable used in this study has ARCH effect or not. Then, among the alternative models, ARMA(2,2) model is determined as the best one for the structure of the series. According to the Table 2, selected ARMA model is (2, 2) since the model (2, 2) has the lowest AIC and significant coefficients.

Table 2. *Model Selection Criteria*

Dependent Variable: DLOG(EXC)
Sample:1 3990
Included observation: 3989

Model	LogL	AIC*	BIC	HQ
(2,2)	13314.804105	-6.671080	-6.661619	-6.667726
(3,3)	13316.279859	-6.670817	-6.658202	-6.666345
(4,4)	13318.075696	-6.670715	-6.654946	-6.665124
(4,2)	13316.065721	-6.670710	-6.658095	-6.666238
(2,4)	13316.058903	-6.670706	-6.658092	-6.666234
(3,2)	13314.942482	-6.670648	-6.659610	-6.666735
(2,3)	13314.933920	-6.670644	-6.659606	-6.666730
(4,3)	13316.081964	-6.670217	-6.656025	-6.665185
(3,4)	13316.058603	-6.670205	-6.656013	-6.665174
(0,0)	13308.742310	-6.670046	-6.666893	-6.668928
(4,1)	13312.843485	-6.669596	-6.658558	-6.665683
(0,1)	13308.769418	-6.669559	-6.664828	-6.667882
(1,0)	13308.769215	-6.669559	-6.664828	-6.667881
(1,4)	13312.765782	-6.669557	-6.658519	-6.665644
(2,0)	13308.798620	-6.669072	-6.662765	-6.666836

Source: Own elaboration

For the residuals of forecasted ARMA(2,2), according to the result of the ARCH-LM test, the null hypothesis of the residuals do not have ARCH effect is rejected since the probability value is lower than 5 % level. This means that nominal exchange rate series do have ARCH effect. This result is shown in the Table 3. Thus, for the nominal exchange rate series, alternative models of conditional heteroskedastic should be estimated.

Table 3. *ARCH-LM Test Results*

Heteroskedasticity Test ARCH			
F-Statistic:	120.9701	Prob. F(1, 3986)	0.0000
Obs*R-squared	117.4659	Prob. Chi.Square (1)	0.0000

Source: Own elaboration

In all alternative models, as a result of evaluation criteria, the GARCH(1,2) model has been found as the most suitable model. In this model, the ARCH effect which was existed among the residuals is eliminated, meaning that there is no ARCH effect anymore.

In the Table 5, the null hypothesis of there is no ARCH effect cannot be rejected since the probability value is higher than 5 percent. Thus, it can be concluded that there is no ARCH effect.

Table 4. *Alternative ARCH-GARCH Prediction Results for Exchange Rate Series*

	ARCH (1)	ARCH (2)	ARCH (3)	ARCH (4)	ARCH (5)	GARCH (1,1)	GARCH (1,2)
C	0.000161	0.000120	9.69E-05	8.13E-05	6.91E-05	2.87E-06	9.30E-12
α_1	0.425052	0.338361	0.305987	0.234679	0.204166	0.006549	0.165462
α_2		0.273675	0.201101	0.140461	0.120714		
α_3			0.205436	0.151070	0.147483		
α_4				0.214134	0.123271		
α_5					0.184546		
β_1						0.005992	0.157655
β_2							0.670193
β_3							
R-Squared	-0.014449	-0.023106	-0.022088	-0.002284	-0.000555	-0.000292	0.99
Adjusted R-squared	-0.015467	-0.024133	-0.023114	-0.003852	-0.001559	-0.001296	0.99
S.E. of Regression	0.016014	0.016082	0.016074	0.015922	0.015904	0.015902	2.44E-05
Sum squared resid	1.021643	1.030362	1.029337	1.009957	1.007651	1.007386	2.37E-06
Log likelihood	11088.13	11182.28	11250.99	11368.99	11425.70	11519.85	37381.14
Mean dependent var.	0.000594	0.000594	0.000594	0.000594	0.000594	0.000594	0.000594
S.D.dependent var	0.015891	0.015891	0.015891	0.015891	0.015891	0.015891	0.015891
Akaike info criterion	-5.555846	-5.602546	-5.636494	-5.695157	-5.723087	-5.771799	-18.7376
Schwarz criterion	-5.544806	-5.589929	-5.622300	-5.679386	-5.705739	-5.759182	-18.72340
Hannan-Quinn criter	-5.551932	-5.598073	-5.631462	-5.689566	-5.716937	-5.767326	-18.73257
Durbin-Watson stat	2.018001	1.918361	1.954231	1.924858	1.965810	1.926105	1.899707

	GARCH (1,3)	GARCH (2,1)	GARCH (2,2)	GARCH (2,3)	GARCH (3,1)	GARCH (3,2)	GARCH (3,3)
C	7.17E-09	2.39E-06	1.20E-11	-1.08E-12	1.95E-11	1.45E-11	5.22E-08
α_1	0.197548	0.152498	0.119990*	0.206037	0.194664	0.15263*	0.166640
α_2		-0.057297	0.039993*	-0.20540	0.060393	-0.07456*	-0.116895
α_3					-0.182282	-0.00045*	-0.045449
α_4							
α_5							
β_1	0.327411	0.900274	0.455694*	1.145041	0.924574	1.06528*	1.019886
β_2	0.473142		0.020501*	0.483760		-0.14655*	0.647398
β_3	-0.03216			-0.629368			-0.671609
R-Squared	0.999248	-0.00048	1.000000	0.999409	0.999988	0.999992	-0.000399
Adjusted R-squared	0.999248	-0.00149	1.000000	0.999408	0.999988	0.999992	-0.001404
S.E.of regression	0.000436	0.015903	1.30E-07	0.000387	5.46E-05	4.37E-05	0.01592
Sum squared resid	0.000757	1.007578	6.76E-11	0.000595	1.19E-05	7.61E-06	1.007494
Log likelihood	25875.02	11523.27	45193.34	26359.40	34196.77	35046.54	11542.68
Mean dependent var.	0.000594	0.000594	0.000594	0.000594	0.000594	0.000594	0.000594
S.D.dependent var	0.015891	0.015891	0.015891	0.015891	0.015891	0.015891	0.015891
Akaike info criterion	-12.96817	-5.773011	-22.65397	-13.21053	-17.14052	-17.56608	-5.781239
Schwarz criterion	-12.95240	-5.758817	-22.63820	-13.19318	-17.12475	-17.54873	-5.762313
Hannan-Quinn criter	-12.96258	-5.767979	-22.64838	-13.20438	-17.13493	-17.55993	-5.774529
Durbin-Watson stat	1.971391	1.921444	1.973498	1.912963	2.215444	1.922353	1.942971

*Source: Own elaboration *shows %1, %5 and % 10 insignificancy*

Table 5. *ARCH-LM Test for the GARCH (1,2 Model)*

Heteroskedasticity Test: ARCH			
F-statistic	0.082857	Prob. F(1, 3986)	0.7735
Obs*R-squared	0.082897	Prob. Chi-square(1)	0.7734

Source: Own elaboration

Conclusions

In this study, exchange rate volatility has been modelled by using the ARCH and GARCH models. Especially, the ARCH and GARCH models are preferable since they are successful in modelling with high-frequency financial data. In this paper, it has been found that the GARCH (1, 2) model is the best among the models since it has the lowest Akaike Information Criterion. In the ARCH and GARCH models, it is assumed that the effect of the variance is symmetric. In other words, the effect of negative and positive shocks is the same. Yet, in the nominal exchange rate data, there is a volatility clustering. Thus, it is conceivable that the GARCH models produce better results. Indeed, aftershocks and uncertainties can be seen in the GARCH(1,2) model high volatility tends to follow high volatility and it is true for vice versa. This result is conformed to the period of crises and uncertainties because in these periods there is a volatility clustering.

Central Bank of the Republic of Turkey (CBRT) is responsible for implementing monetary policy and exchange rate policies. Last 15 years, the primary objective of the CBRT is to achieve and maintain price and financial stability. The CBRT has adopted free floating exchange rate regime, but in this regime, exchange rates are highly volatile, which in turn affects interest rates and economic well-being. Thus, it is very important to know how the exchange rate will be in the future since volatility will force firms to add risk premium to prices of their products. This study presents some perspective about trend and how the exchange rate varies over time.

Ethical Declaration

In the writing process of the study titled "The Modelling of Exchange Rate Volatility Using Arch-Garch Models: The Case of Turkey", there were followed the scientific, ethical and the citation rules; was not made any falsification on the collected data and this study was not sent to any other academic media for evaluation.

References

Akgiray, V. (1989). Conditional heteroscedasticity in time series of stock returns: evidence and forecasts. *The Journal of Business, 62*, 55-80.

Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating stock market volatilityusing asymmetric GARCH models. *Applied Financial Economics, 18*(15), 1201-1208.

Baillie, R. T., & De Gennaro, R. P. (1990). Stock returns and volatility. *Journal of Financial and Quantitative Analysis, 25*(2), 203-214.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics, 31,* 307-327.

Cao, C. Q., & Tsay, R. S. (1992). Nonlinear time-series analysis of stock volatilities. *Journal of Applied Econometrics, 7,* 165-185.

Dralle, B. (2011). *Modelling volatility in financial time series* (Master's Thesis). Mathematics, Statistics and Computer Science, University of KwaZulu-Natal, Pietermaritzburg.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom Inflation. *Econometrica, 50,* 987-1007.

Engle, R. F. (1982). Statistical models for financial volatility. *Financial Analysts Journal, 49,* 72-78.

Fama, E. F. (1965). The behavior of stock market prices. *Journal of Business, 38*(1), 34-105.

Huang, D., Wang, H., & Yao, Q. (2008). Estimating GARCH models: When to use what? *The Econometrics Journal, 11,* 27-38.

Karmakar, M. (2006). Stock market volatility in the long run, 1961-2005. *Economic and Political Weekly, 41*(18), 1796-1802.

Mandelbrot, B. (1963). The variation of certain speculative prices. *Journal of Business, 26,* 394-419.

Oskooee, M. B., & Hegerty, S. W. (2007). Exchange rate volatility and trade flows: a review article. *Journal of Economic Studies, 34*, 211-255

Talke, I. S. (2003). *Modelling volatility in financial time series data* (Master's Thesis). Mathematics, Statistics, and Information Technology, University of Kwazulu-Natal, Pietermaritzburg.

TÜRKÇE GENİŞ ÖZET

Bu çalışma, ARCH tipi modelleri kullanarak nominal döviz kurundaki oynaklığı modelleyen en uygun metodu bulmaya çalışmaktadır. Araştırma verisi 2002-2017 yılları için günlük verileri kapsamaktadır. Çalışmada 3989 veri kullanılmıştır. Veri seti Türkiye Cumhuriyet Merkez Bankası sitesinden alınmıştır. Çalışmada 2018 yılı verilerinin kullanılmayış sebebi, çalışmada elde edilen sonuçların Ağustos 2018'den itibaren döviz kurunda meydana gelen artışları ve dalgalanmayı doğru tahmin edip etmediğini analiz etmektir. Çalışmada yapılan tüm istatistiki testlerde Eviews 9 paket programı kullanılmıştır.

Çalışma Türkiye için döviz kuru dalgalanma yön ve trendini belirlemede ilk olarak Engle (1982) tarafından ortaya konan, zaman serilerinde sabit varyans varsayımının sağlanmadığını vurgulayan ve otoregressive koşullu heteroscedasticity (ARCH) olarak ifade edilen modeli kullanmaktadır. Ancak, Engle'in ARCH modelinde bazı eleştirilen yönler vardır. Bu eleştiriler şu şekilde ifade edilebilir: ARCH modelinin dalgalanmayı yakalamak için birçok parametreye ihtiyaç duyması ve ARCH modelinin sabit gecikmeli yapıya sahip nispeten uzun gecikmelere ihtiyaç duymasıdır. Bollerslev, 1986 yılında bu kısıtlamaları ortadan kaldırmak ve negatif değişkenlik saptaması tahminlerini önlemek için GARCH (Genelleştirilmiş Otoregressif Koşullu Heterosidasyon) modelini sundu. Bollerslev yaklaşımı, mevcut oynaklığı etkileyen geçmiş oynaklıklara izin verir. GARCH modeli, koşullu varyanstaki modellemede hem otoregresif hem de hareketli ortalama terimlerini sağlar. Böylece ARCH-GARCH modellerinden hangisinin daha uygun olduğuna karar vermektedir.

Çalışmada kullanılan nominal döviz kuru serisi için betimleyici istatistik ve testler yapılmıştır. Kurtosis değeri 3'ten daha yüksek olduğu için döviz kuru verilerinin leptokurtik gösterdiği sonucu elde edilmiştir. Böylece, Jarque-Bera istatistiğine göre, boş hipotez "seri normal dağılmış" olarak ayarlanmıştır, ancak Jarque-Bera istatistiği, olasılık yüzde 5'in altında olduğundan "serinin normal dağıldığı" boş hipotez ret edilmiştir.

İlk olarak, çalışmada kullanılan veri bir zaman serisi olduğu için durağanlık analizi yapılmıştır. Bir serinin zaman içerisinde ortalaması veya varyansı değişiyor ise bu zaman serisinin durağan olmadığı ifade edilir. Durağan olmayan zaman serileriyle çalışmanın ana sonucu, modelin R-kare ve t-puanlarını şişiren sahte bir korelasyona sahip olmaktır. Böylece, zaman serilerinin durağan olup olmadığı yapılan analiz için önem arz etmektedir. Çalışmada üç farklı durağanlık testi kullanılmıştır. Bunlar: Zaman serilerinde yapısal kırılmaları dikkate alan Zivot-Andrewa (ZA) (1992) testi, Augmented Dickey Fuller (ADF) testi ve Phillis-Perron (PP) tarafından 1988 yılında gerçekleştirilen testidir. Çalışmada kullanılan döviz kuru serisinin seviyede durağan olmadığı, ancak verinin birinci farkı alındıktan sonra durağan hale geldiği görülmüştür.

Çalışmada kullanılan serinin birinci farkı alındıktan sonra, uzun bir süre boyunca nominal kurda geniş bir dalgalanma olduğu ve ardından nispeten sakin bir dönem izleyen dalgalanma kümelenmesinin görüldüğü grafik yardımıyla tespit edilmiştir. Bu durum, finansal zaman serilerinin varyansının zaman içinde değiştiği anlamına gelir. Bu nedenle, ARCH etkisinin varlığını kabul etmek için gerekli olan koşullardan biri olan nominal döviz kuru verileri için bir oynaklık kümelenmesinin olması gerektiği açıklamasıyla örtüşmektedir.

Kullanılan serilerin durağanlığı verilerin birinci farkının alınmasıyla sağlanmıştır. Bu çalışmada kullanılan değişkenin ARCH etkisinin olup olmadığını anlamak için ARCH-LM testi kullanılmıştır. Ardından, alternatif modeller arasında ARMA (2,2) modeli, serinin yapısı için en iyi model olarak belirlenir. Alternatiflerin sunulduğu Tablo 2' de, seçilen ARMA modeli (2, 2) olarak bulunmuştur, çünkü model (2, 2) en düşük AIC ve önemli katsayılara sahiptir.

Çalışmada, nominal döviz kurunun ARCH etkisine sahip olduğu ve en düşük Akaike Bilgi Kriterine (AIC) sahip olduğu için nominal döviz kurundaki dalgalanmayı tahmin etmede en uygun modelin GARCH(1,2) olduğu tespit edilmiştir. Bu modelde hata kalıntıları arasında var olan ARCH etkisinin giderildiği, yani ARCH etkisinin artık olmadığı sonucu elde edilmiştir. Ayrıca, kriz gibi belirsizlik dönemlerinde nominal döviz kuru serisindeki dalgalanmaların arttığı ve dalgalanma kümesinin olduğu, yani yüksek dalgalanmayı yüksek dalgalanmaların takip ettiği sonucu bulunmuştur.

Türkiye gibi sanayisinin aşırı derecede ithalata bağımlı hale geldiği, ihracat yapabilmek için ithalatın zorunlu olduğu ülkelerde döviz kurunda meydana gelen dalgalanmalar son derece önemlidir. Zira döviz kurundaki artış yurtiçi üretimi, fiyatları ve istihdamı etkilemektedir. Ülkemizde para ve döviz kuru politikalarını uygulamakla sorumlu Türkiye Cumhuriyet Merkez bankasının amaçları arasında düşük ve istikrarlı bir fiyat seviyesini gerçekleştirmek ve finansal piyasalarda istikrar sağlamak vardır. Türkiye'de serbest piyasa ekonomisine uygun olarak döviz kurları serbest piyasa tarafından belirlenmektedir. Ancak zaman zaman Merkez Bankasının piyasaya müdahale ettiğini görmekteyiz. Bu müdahalelerin ardında, önceleri sadece düşük fiyat (enflasyon) gerçekleştirme amacı olan Merkez Bankasının döviz kurundaki dalgalanmaları da içine alacak şekilde finansal piyasalarda istikrar sağlama amacının olduğunu söyleyebiliriz.

Böylece, döviz kurundaki dalgalanmanın üreticilere ve tüketicilere bir risk yüklediğinden dolayı döviz kurunun gelecekte ne olacağı oldukça önemlidir. Bu çalışma döviz kurunun nasıl değişeceği ve alacağı trendi göstermesi açısından önem arz etmektedir. Çalışmanın sonuçlarından biri olan " kriz gibi belirsizlik dönemlerinde nominal döviz kuru serisindeki dalgalanmaların arttığı ve dalgalanma kümesinin olduğu, yani yüksek dalgalanmayı yüksek dalgalanmaların takip ettiği" sonucu geçen yıldan itibaren döviz kurunda yaşanan gelişmeleri açıklamaktadır.