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AN EVALUATION OF REAL EFFECTIVE EXCHANGE RATE FORECASTING WITH ARCH AND GARCH MODELS: THE CASE OF TURKEY

ARCH VE GARCH MODELLERİ İLE REEL EFEKTİF DÖVİZ KURU TAHMİNİ ÜZERİNE BİR DEĞERLENDİRME: TÜRKİYE ÖRNEĞİ

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Öz

İkinci Dünya Savaşı sonrasında ortaya çıkan küreselleşme, mikroekonomik aktörlerin uluslararası ticaret ve finans sistemine entegrasyonunu artırmıştır. Dolayısıyla döviz kurları ekonomik karar alma sürecinde önem kazanmıştır. Buna ek olarak, döviz kurları ticari dengeyi etkilemektedir. 1973 yılında Bretton Woods anlaşmasının sona ermesini takiben esnek döviz kuru uygulanmaya başlanmıştır. Bu nedenle, yapısal sorunları ve yeterince gelişmemiş finansal sisteme sahip gelişmekte olan ülkeler için güvenilir döviz kuru tahmini önem arz etmektedir. Ayrıca, Covid-19 salgını sırasında güvenilir döviz kuru tahmini daha zor hale gelmiştir. Bu iktisadi koşullarda reel döviz kuru, finansal yatırımcıların ülkenin rekabet gücünü analiz etmeleri için önemli bir göstergedir. Bu çalışma, ARCH ve GARCH modellerinin tahmin gücünü karşılaştırarak Covid-19 pandemisinde (2019M12-2021M08) reel efektif döviz tahminini araştırmayı amaçlamaktadır. Analiz bulguları, ARIMA(1,1,3)-GARCH(1,1) modelinin tahmin doğruluğu için en iyi model olduğunu göstermektedir. Elde edilen bulgulara göre politika yapıcılar ve iktisadi ajanlar Covid-19 pandemi sürecinde reel efektif döviz kuru tahmininde ARIMA(1,1,3)-GARCH(1,1) modeline göre karar vermelidir.

Anahtar Kelime: Reel Efektif Döviz Kuru Tahmini, ARCH Modellemesi, GARCH Modellemesi, Covid-19 Pandemisi.

Abstract

The globalization emerging in the post-World War II increases the integration of microeconomic players into the international trade and financial system. Hence, exchange rates gain importance for economic decision-making. Moreover, exchange rates affect the trade balance. Following the dismissal of the Bretton Woods agreement in 1973, governments began to implement the flexible exchange rate regime. Thus, reliable exchange rate forecasting has importance for developing countries having structural problems and underdeveloped financial systems. Moreover, reliable exchange rate forecasting is more complicated during the Covid-19 pandemic. In this ecoonomic conditions, the real exchange rate is an important indicator for financial investors to analyze the competitiveness of the country. This study aims at investigating the real effective exchange forecasting in the Covid-19 pandemic (2019M12-2021M08) by comparing the forecast power of ARCH and GARCH models. The analysis findings demonstrate that ARIMA(1,1,3)-GARCH(1,1) model is the best model for forecasting accuracy. According to the findings, the policy-makers and economic agents must decide on the ARIMA(1,1,3)-GARCH(1,1) model for real effective exchange rate forecasting during the Covid-19 pandemic.

Keywords: Real Exchange Rate Forecasting, ARCH Modelling, GARCH Modelling, Covid-19 Pandemic.

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Genişletilmiş Özet

Küreselleşme süreci ile birlikte artan ekonomiler arasındaki etkileşim, ülkeler arasındaki dış ticaret hacmini ve sermaye hareketlerini artırmaya başlamış ve böylece ülke ekonomilerinde dış ticareti etkileyen faktörlerin önemi artmıştır. Şüphesiz, dış ticareti etkileyen en önemli faktörlerden birisi olan döviz kuru da onlardan birisidir. Döviz kurunun ülke ekonomilerini dış ticaret ve sermaye hareketleri baz alınarak incelendiğinde, ülke ekonomileri üzerinde çeşitli etkileri bulunmaktadır. Birincisi, şirketlerin karar alma süreçlerininin etkilenmesidir. İkinci olarak, döviz kurları diğer mikro ekonomik ajanların karar verme süreçlerinde temel unsurlardan birisidir. Mikroekonomik ajanlar, portföylerini seçerken döviz kurlarını dikkate almaktadır. Son olarak, döviz kurları ekonomilerde dış ticaret dengesini etkilemektedir. Bretton Woods anlaşması, 1973 yılında sona ermiş ve güvenilir döviz kuru tahmini elde etmek zorlaşmıştır. Böylece, döviz kuru tahmini, firmaların ve diğer mikro ekonomik oyuncuların karar verme süreçlerinde daha önemli hale gelmiştir. Bahsedilen sebeplerden ötürü, döviz kurlarının gelecek değerlerinin tahmin edilmesi ülke ekonomilerinde uygulanacak politikalarının belirlenmesi ve gelecekteki olası ekonomik problemlerin öngörülebilmesi için önem arz etmektedir. Türkiye gibi gelişmekte olan ülkeler yapısal ekonomik sorunlara, yetersiz derinleşen finansal piyasalara sahiptir. Bu nedenle, gelişmekte olan ülkelerdeki ekonomik aktörlerin etkin kararlar alabilmeleri için döviz kurlarının düşük sapma düzeyinde tahmin edilmesi önem arz etmektedir.

Mevcut literatürde döviz kuru tahmini, nominal döviz kuru tahminlerine odaklanmaktadır. Buna rağmen, çok az sayıda çalışma reel döviz kuru tahminini analiz etmiştir. Finansal yatırımcıların ülkenin rekabet gücünü ölçmede reel döviz kuru belirleyicidir. Bu nedenle reel döviz kuru tahmini, firmaların ve portföy yatırımcılarının etkin karar almasında ve etkin makroekonomik sonuçlar için çok önemlidir. 2019 yılının sonunda Çin'de ortaya çıkan Covid-19 pandemisi, ekonomileri olumsuz etkilemiştir. Dolayısıyla Covid-19 krizi sırasında döviz kuru oynaklığı artmıştır. Öngörülemeyen ve benzeri görülmemiş Covid-19 pandemisinin, döviz kurları üzerindeki etkisini anlamak çok önemlidir. Bu çalışma, Covid-19 pandemisi sürecinde Türkiye'deki TÜFE bazlı reel efektif döviz kuru tahmininde ARCH ve GARCH modellerinin tahmin gücünü karşılaştırmayı amaçlamaktadır. Bu çalışmanın mevcut literatüre iki şekilde katkı sağlaması beklenmektedir. İlk olarak, önceki çalışmalar Türkiye'de nominal döviz kuru tahminine odaklanmaktadır. Türkiye'de TÜFE bazlı reel efektif döviz kurlarını öngören sınırlı sayıda çalışma bulunmaktadır. Bu çalışma, TÜFE bazlı reel efektif döviz kurunu tahmin ederek literatürde var olan bu boşluğu doldurmaya çalışacaktır. İkinci olarak, Covid-19 pandemisi sırasında Türkiye'de döviz kuru tahminlerinin güvenilirliğini araştıran az sayıda çalışma bulunmaktadır. Bu çalışma, Covid-19 pandemi dönemini (2019M12-2021M08) öngörerek literatürdeki bu boşluğu doldurmayı amaçlamaktadır. Bu çalışmada, 1994M01 ile 2021M08 arasındaki TÜFE bazlı reel efektif döviz kuru (aylık) veri seti, Türkiye Cumhuriyet Merkez Bankası Elektronik Veri Dağıtım Sistemi'nden alınmıştır. Tahmin sürecinde örneklem dışı zaman aralığı ise 2019M12-2021M08 dönemlerini kapsamaktadır. Ayrıca, statik tahmin yöntemi ise tahmin yöntemi olarak tercih edilmiştir. Yapılan analizler sonucunda ARCH-LM Testi ile değişen varyansın varlığı doğrulanmıştır. Buna ek olarak en uygun süreç kombinasyonları AR (1), ARIMA (1,1,1), ARIMA (2,1,1), ARIMA (1,1,3), ARIMA (1,1,5), ARIMA (2, 1,3), ARIMA (2,1,5), MA (3), MA (5) modelleri olarak belirlenmiştir. Ayrıca, tahmin gücünü artırmak için tüm ARIMA modellerine AR (12) süreci eklenmiştir. Tahmin sonuçları ARIMA (1,1,3)-GARCH (1,1) modelinin, en düşük Theil eşitsizlik katsayısına, ortalama karesel hata köküne ve ortalama mutlak hata değerlerine sahip olduğunu göstermektedir. Böylece bu üç kriter, ARIMA (1,1,3)-GARCH (1,1) modelinin en yüksek tahmin gücüne sahip olduğunu doğrulamaktadır. ARIMA (2,1,1) modeli de dahil diğer modeller 0,2'den büyük sapma oranına sahiptir. Başka bir deyişle, bu modeller sistematik hataya sahiptirler. Ayrıca en düşük varyans oranı değerine sahip ARIMA (1,1,3)-GARCH (2,1) gerçek seriye göre en düşük varyasyona sahiptir. Öte yandan, ARIMA (1,1,3)-GARCH (1,1) ve sonraki ARIMA (2,1,1) modellerinde sistematik tahmin hatası en yüksek kovaryans oran değerini aldıklarından dolayı en düşük seviyededir. Buna rağmen ARIMA (2,1,1) modeli sistematik hataya sahiptir. Analiz bulguları, ARIMA (1,1,3)-GARCH (1,1) modelinin doğru değerlere en yakın tahmin çıktısına sahip olduğunu göstermektedir. Buna ek olarak diğer modellere göre daha iyi tahmin gücüne sahiptir. Sonuç olarak, ARMA-GARCH modeli daha doğru tahmin sonuçlarına sahiptir. Bu çalışma, politika yapıcıların ve ekonomik birimlerin, Covid-19 pandemisi sırasında reel döviz kuru tahminleri için ARIMA (1,1,3)-GARCH (1,1) modelini dikkate almalarını önermektedir.

INTRODUCTION

Firms have a more international scale since they integrate the international trade and finance system in post-World War II (Gerlow & Irvin, 1991: 133). In this period, they begin to use foreign currency due to increasing international financial and trade transactions. Thus, exchange rates become one of the determinants for macroeconomic performance. Exchange rates affect the economy through three channels. Firstly, exchange rates affect the decision-making processes in companies operating in different countries, planning long and short-term borrowings from international financial markets, and only entering the domestic market (Newaz, 2008: 55). Secondly, exchange rates are one of the determinants in the decision-making processes of other microeconomic players. Microeconomic players such as portfolio investors and consumers consider exchange rates while determining their portfolios (Akgül & Sayyan, 2008: 464). Finally, exchange rates affect trade balance in economies (Mankiw, 2016). Thus, they are determinants of the macroeconomic equilibrium in countries. The Bretton Woods agreement expired in 1973. Thus, the governments prefer a flexible exchange rate regime, and this regime complicates obtaining reliable exchange rate forecasting. So, exchange rate forecasting has become more substantial in the decision-making processes of firms and other microeconomic players.

Developing countries face more structural problems, insufficient deepening of financial markets, and government intervention in exchange rates than developed countries. Similar to other developing countries, Turkey has these problems. Accordingly, forecasting the exchange rates in low deviation has importance for the economic actors in developing countries to make efficient decisions. In the existing literature, exchange rate forecasting concentrates on nominal exchange rate estimations. However, few studies study to forecast the real exchange rate. The real exchange rate is determinative for financial investors to measure the competitiveness of the country (Ca'Zorzi, Kocięcki & Rubaszek, 2015: 53). Hence, real exchange rate forecasting is crucial for the efficient decisions of firms and, portfolio investors and macroeconomic outcomes. The Covid-19 pandemic, which emerged in China at the end of 2019, negatively affects the economies. Thus, the exchange rate volatility increases during the Covid-19 crisis. In the unpredictable and unprecedented Covid-19 pandemic, it is crucial to understand its impact on exchange rates (Aloui, 2021). This study aims at comparing the ARCH and GARCH models in the CPI-based real effective exchange rate forecasting in Turkey during the Covid-19 pandemic. This study is expected to contribute to the existing literature in two ways. Firstly, previous studies focus on nominal exchange rate forecasting in Turkey. A limited number of studies forecast CPI-based real effective exchange rates in Turkey. This study will try to fill this existing gap in the literature by forecasting the CPI-based real effective exchange rate. Secondly, few studies investigate the reliability of exchange rate forecasting in Turkey during the Covid-19 pandemic. This study intends to fill this gap in the literature by forecasting the Covid-19 pandemic period (2019M12-2021M08).

The study aims to compare the CPI-based real effective exchange forecasting of ARCH and GARCH models in the Covid-19 pandemic. Moreover, the most reliable model for the Covid-19 pandemic is investigated in this study. In Chapter 2, previous studies are mentioned. In Chapter 3, the methodology and dataset are provided. In Chapter 4, empirical results are shown and interpreted. Finally, the results are discussed in Chapter 5.

1. LITERATURE REVIEW

Several studies investigate the forecasting value of the exchange rate. Ca'Zorzi, Kocięcki, and Rubaszek (2015) investigate real exchange rates forecasting (European Union (EUR), the United Kingdom (GBP), Switzerland (CHF), Japan (JPY), and the United States (USD)) by comparing to the accuracy Bayesian VAR with a Dornbusch prior methodology and standard VAR models. The analysis results confirm that the Bayesian VAR with a Dornbusch prior methodology is better. Akgül and Sayyan (2008) compare long memory, stable and integrated GARCH models in exchange rate volatility in Turkey. The results show that the stable GARCH model has better predictive performance. Esenyel (2017) tests the forecasting accuracy of ELM, ARMA, and ARMA-GARCH models in exchange rate returns in Turkey. Analysis findings indicate that ELM had higher predictive power in forecasting exchange rate returns. Sağlam and Başar (2016) study to forecast exchange rate (USD, EUR, and GBP) volatility in Turkey with ARCH, GARCH, EGARCH, TARCH models. They find that asymmetric models for EUR and USD have better forecasting performance and that symmetric models are the most appropriate model for GBP.

In the previous studies, limited studies investigate the real effective exchange rate forecasting in Turkey. Uysal and Özşahin (2012) analyze the real effective exchange rate forecasting in Turkey using ARCH and GARCH models. The analysis results confirm that the GARCH(1,1) is the most appropriate model for the real effective exchange rate forecasting. Aydın and Güneri (2011) forecast the real effective exchange rate values (based on PPI and CPI) employing three non-parametric regression methods. They find that spline correction regression provides better predictive results. Çuhadar, Demirbaş, and Dayan (2019) analyze forecasting output of the CPI-based real effective exchange rate compared to an artificial neural network, exponential smoothing, and Box-Jenkins methods. The findings display that the ARIMA(0,1,1)(1,0,0) model makes a more accurate forecast .

As a result, a limited number of studies predict the real effective exchange rate in Turkey. Furthermore, few studies have tested the reliability of real effective exchange rate forecasts during the Covid-19 pandemic in Turkey. This study intends to fill these gaps in the literature by forecasting real effective exchange rates (based on CPI) in the Covid-19 pandemic period (2019M12-2021M08).

2. DATA AND METHODOLOGY

In this study, ARMA-ARCH and ARMA-GARCH modeling approaches are employed to forecast the CPI-based real effective exchange rates. The CPI-based real effective exchange rate (Monthly) dataset between 1994M01 and 2021M08 is obtained from the Turkish Central Bank Electronic Data Delivery System.

2.1. ARIMA Modelling

The ARIMA (The Autoregressive Integrated Moving Average Method) is often used in times series forecasting analysis (Ediger, Akar, & Uğurlu., 2006: 3838). An equation of ARMA(p, q) model that has a stationary time series is as follows (Taneja, Ahmad, Ahmad, & Attri, 2016: 587):

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \ldots + \varphi_p Y_{t-p} + \mathcal{E}_t + \mathcal{E}_t - \theta_1 \mathcal{E}_{t-1} - \theta_2 \mathcal{E}_{t-2} - \ldots - \theta_q \mathcal{E}_{t-p} \quad (1)$$

ARIMA is of the form ARIMA(p, d, q) where (Aasim, & Mohapatra 2019: 760):

- p presents the order of the autoregression (AR) model, which is the number of lags.
- d is called differencing order (I) and ensure the model stationarity.
- q is named the order of the moving average (MA) model and is the number of lags of the estimation errors.

The (AR) term indicates the current time series (Y_t) as a its function of past values Y_{t-1}, Y_{t-2},…, Y_{t-p} themselves. The terms φ_1, φ_2,…, φ_p is autoregressive coefficients. The moving average term refers to $\mathcal{E}_{t-1}$, $\mathcal{E}_{t-2}$,…, $\mathcal{E}_{t-p}$ that are the past random shocks.

2.2. ARMA-ARCH and ARMA-GARCH Models

Engle (1982) developed a methodology including mean and variance simultaneously in the model. In this methodology, if the conditional mean of y_{t+1} is forecasted by assuming the stationary ARMA model ($y_t = a_0 + a_1 y_{t-1} + \varepsilon_t$), equations are obtained as follows

$$E_t|Y_{t+1}| = a_0 + a_1 y_t \quad (2)$$

Thus, forecast error variances are as follows

$$E_t[(y_{t+1} - a_0 - a_1 y_t)^2] = E_t|\varepsilon_{t+1}^2| = \sigma^2 \quad (3)$$

The mean are found as $a_0/(1\text{-}a_1)$ using unconditional forecasting. In this case, the unconditional error variance is as follows

$$E\{[y_{t+1} - a_0/(1 - a_1)]^2\} = E[(\varepsilon_{t+1} + a_1\varepsilon_t + a_1^2\ \varepsilon_{t-1} + a_1^3\varepsilon_{t-2} + \cdot\cdot\cdot)^2] = \sigma^2/(1 - a_1^2) \quad (4)$$

Because $1/(1- a_1^2) > 1$, the conditional forecast has less variance than the unconditional forecast. Hence, conditional forecast is more favorable. The conditional variance of y_{t+1} is as follows

$$Var(y_{t+1}|y_t) = E_t[(y_{t+1} - a_0 - a_1y_t)^2] = E_t(\varepsilon_{t+1})^2 = \sigma^2 \quad (5)$$

Equation 5 shows that $Var(y_{t+1}|y_t)$ is equal to the constant value! σ^2. Assumed changing conditional variance, the estimation process of autoregressive conditional heteroskedastic (ARCH) model is performed (Enders, 2015: 124). It includes the square of the estimated residuals

$$\hat{\varepsilon}\,_t^2 = \alpha_0 + \alpha_1\,\hat{\varepsilon}\,_{t-1}^2 + \alpha_2\,\hat{\varepsilon}\,_{t-2}^2 + \cdots + \alpha_q\,\hat{\varepsilon}\,_{t-q}^2 + v_t \quad (6)$$

and a white-noise process (v_t) in the model. Thus, ARMA(p,q)-ARCH(m) model is as follows

$$Y_t = d + \varphi_a \Sigma_{a=1}^{p} Y_{t-a} + \theta_c \Sigma_{c=1}^{q} \varepsilon_{t-c} + \varepsilon_t\ , \varepsilon_t \sim i.i.d.\ N(0, \sigma_t^2) \quad (7)$$

$$\sigma_t^2 = \alpha_0 + \alpha_i\ \Sigma_{i=1}^{m} \varepsilon_{t-i}^2 \quad (8)$$

where m is the order of the ARCH term.

Eq.(8) shows the mean equation including constant and ARCH part (ε_{t-i}^2). The stationarity conditions in ARCH process are $\alpha_i > 0$ and $\alpha_i < 1$. ARCH model is a model that makes analysis considering the volatility of the variable in financial time series. Although traditional econometric models assume the assumption of constant variance in the analysis, the ARCH model is based on heteroskedasticity assumptions over time. The ARCH model increases the number of estimated parameters and causes other problems (such as multicollinearity problems) since it frequently involves a larger order (Lin, 2018: 964). Due to problems in the ARCH model, Bollerslev developed the GARCH model (Lin, 2018: 964). The ARMA(p,q)-GARCH (m, n) is as follows

$$\sigma_t^2 = \alpha_0 + \alpha_i\ \Sigma_{i=1}^{m} \varepsilon_{t-i}^2 + \beta_j \Sigma_{j=1}^{n} \sigma_{t-j}^2 \quad (9)$$

where n is the order of the GARCH term.

Eq. 9 provides the mean equation and errors in the ARMA-GARCH model. Eq. 9 consists of constant, ARCH part (ε_{t-i}^2) and GARCH part (σ_{t-j}^2). For the GARCH process to be stationary, the conditions $\alpha_i > 0$, $\beta_1 > 0$ and $\alpha_i + \beta_j < 1$ are required. GARCH modeling has mainly four-stage for estimation as follows (Enders, 2015: 129)

1. Checking Stationary: The first step is checking whether series are stationary or not. For checking stationary, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are applied. If the series is not stationary, they could be made stationary by taking the difference.
2. Heteroskedasticity Detection: The ARCH heteroskedasticity test is performed to detect changing variance.
3. Determination of Mean Equation: The suitable ARMA model is determined as the mean equation using the Correlogram of Residuals Squared.
4. Checking Stationarity Process of ARCH and GARCH Models: Variance equation coefficients are used for checking ARCH and GARCH models stationarity.

2.3. Augmented Dickey-Fuller (ADF) Unit Root Test

Dickey and Fuller (1979) assume an autoregressive model in the unit root test they developed:

$$Y_t = \omega_1 Y_{t-1} + e_t\ ,\ \ t = 1, 2, \ldots.., \quad (10)$$

In this model, the time series is stationary when $|\omega_1| < 1$. If $|\omega_1| \geq 1$, the time series is not stationary. Subtracting Y_{t-1} from both sides of Equation 11, the equation $\Delta Y_t = \gamma Y_{t-1} + \varepsilon_t$ where $\gamma = \omega_1 - 1$ is derived. The ADF test tests whether a unit root exists in the time series by three different models (Enders, 2015: 206):

$$\Delta Y_t = \gamma Y_{t-1} + \sum_{i=2}^{a} \beta_i \Delta Y_{t-i+1} + \varepsilon_t \quad (11)$$

$$\Delta Y_t = \omega_0 + \gamma Y_{t-1} + \sum_{i=2}^{a} \beta_i \Delta Y_{t-i+1} + \varepsilon_t \quad (12)$$

$$\Delta Y_t = \omega_0 + \gamma Y_{t-1} + \omega_2 t + \sum_{i=2}^{a} \beta_i \Delta Y_{t-i+1} \quad \varepsilon_{t!!} \quad (13)$$

They define intercept model as equation 13 and intercept and linear time trend model as equation 14. If $\gamma = 0$ in Equation 9, $\omega_0 = \gamma = 0$ in Equation 13, $\omega_0 = \gamma = \omega_2 = 0$ in Equation 14, Y_t series contains unit root.

2.4. Phillips Perron (PP) Unit Root Test

Phillips and Perron (1988) developed a unit root test considering the distorting effects of serial correlation. They use the Dickey–Fuller test equation as follows

$$Y_t = \omega_0 + \omega_1 Y_{t-1} + e_t \quad (14)$$

Next, they modified the t-ratio of the μ_1 coefficient in equation 15 to eliminate its distorting effect of serial correlation on the asymptotic distribution. The PP test statistic is as follows

$$\tau_{\hat{\omega}_1} = (\hat{\omega}_1 - \omega_1) / (se(\hat{\omega}_1)^2 c_3)^{1/2} \quad (15)$$

The test is performed by comparing McKinnon critical values.

In Equation 15, $\hat{\omega}_1$, se($\hat{\omega}_1$) and c_3 present the ω_1 estimator, the standard error of $\hat{\omega}_1$ and the third diagonal matrix element $((X^I X)^{-1})$ respectively (Phillips, & Perron, 1988: 338). Similar to the ADF, when the model is $|\omega_1| < 1$, the time series is stationary. If $|\omega_1| \geq 1$, the time series is not stationary.

2.5. ARCH-LM Heteroskedasticity Test

The ARCH test is based on a Lagrange multiplier (LM) test in the residuals (Engle 1982). It is an easy way to test the ARCH effects and, its null hypothesis is no ARCH type heteroskedasticity of order m. The null hypothesis of no existing ARCH(m) is run by following regression.

$$\sigma_t^2 = \alpha_0 + \alpha_i \sum_{i=1}^{m} \varepsilon_{t-i}^2 + v_t \quad (16)$$

The two test statistics are employed for analysing ARCH effects. Firstly, F-statistics is performed for omitted variable testing in all lagged squared residuals. Secondly, the Obs. R-squared statistic, which uses Engle's LM test statistic, tests ARCH effects by estimating observations times the R^2.

3. EMPIRICAL RESULTS

In the forecasting process, out-of-sample covers 2019M12-2021M08 periods. Table 1 shows descriptive statistics of Real Effective Exchange Rate (CPI based) (Monthly) in level and first difference. It verifies that the mean is close to zero (-0.072026) in the first difference while it is high in level (98.91). Thus, it is possible to interpret the series is stationary at the first difference. Jarque-Bera values indicate that it does not have normal distribution for level and first differenced series. Since the ratio of the standard error in the first difference to the mean (approximately 4642%) is extremely high, a high level of volatility might exist in the series. It also shows the ARCH heteroskedasticity test results for order of 1,2 and 3. The null hypotheses (H_0= no ARCH type heteroskedasticity of order 1,2 and 3) are rejected at a 1% significance level. Thus, they confirm the existence of ARCH type heteroskedasticity.

Table 1: Descriptive Statistics

	Real Effective Exchange Rate (CPI based)	D(Real Effective Exchange Rate (CPI based))
Mean	98.91360	-0.072026
Median	101.0846	0.338748
Maximum	127.5151	10.41365
Minimum	63.54491	-15.59381

Std. Dev.	14.60728	3.344023
Skewness	-0.180836	-1.279341
Kurtosis	2.060461	7.504074
Jarque-Bera	13.13379	346.5999
Probability	0.001406	0.000000
ARCH-LM Test (Order of 1) (Prob.)	0.0000	0.0000
ARCH-LM Test (Order of 2) (Prob.)	0.0000 !	0.0000
ARCH-LM Test (Order of 3) (Prob.)	0.0000 !	0.0000
Sum	30762.13	-22.32816
Sum Sq. Dev.	66145.47	3455.389
Observations	311	310

Figure 1 and 2 display the real effective exchange rate (CPI-based) graphs in level and first differences. After the 1994 crisis in Turkey, the real effective exchange rate increases excessively. However, in the 2000 and 2001 crises, it has extreme declines. Furthermore, there is a linear trend in the series. In the first difference, there is no linear trend in the series. However, there might be a heteroskedasticity.

Figure 1: Real Effective Exchange Rate (CPI based) in Level

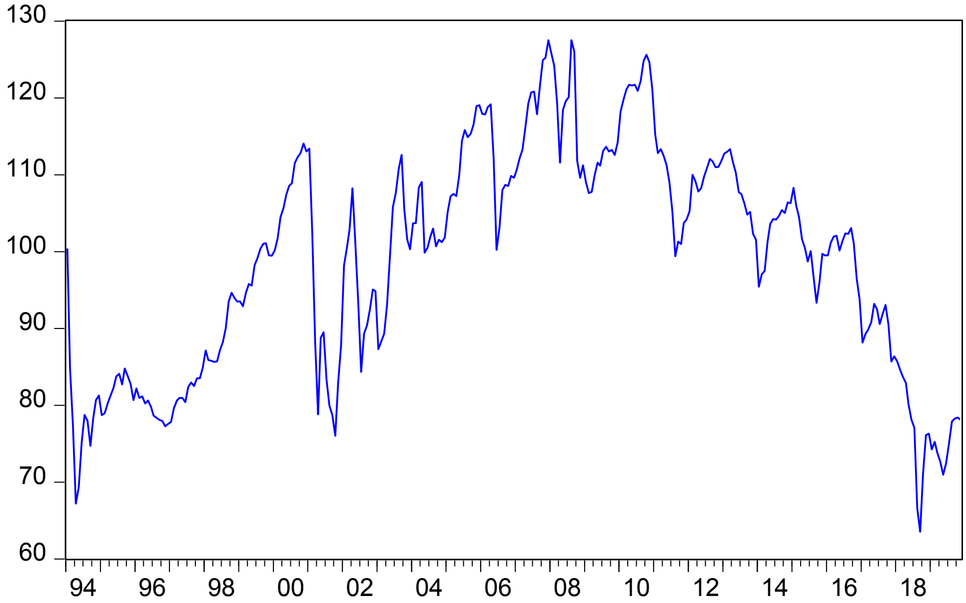

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Figure 2: Real Effective Exchange Rate (CPI based) in First Difference!

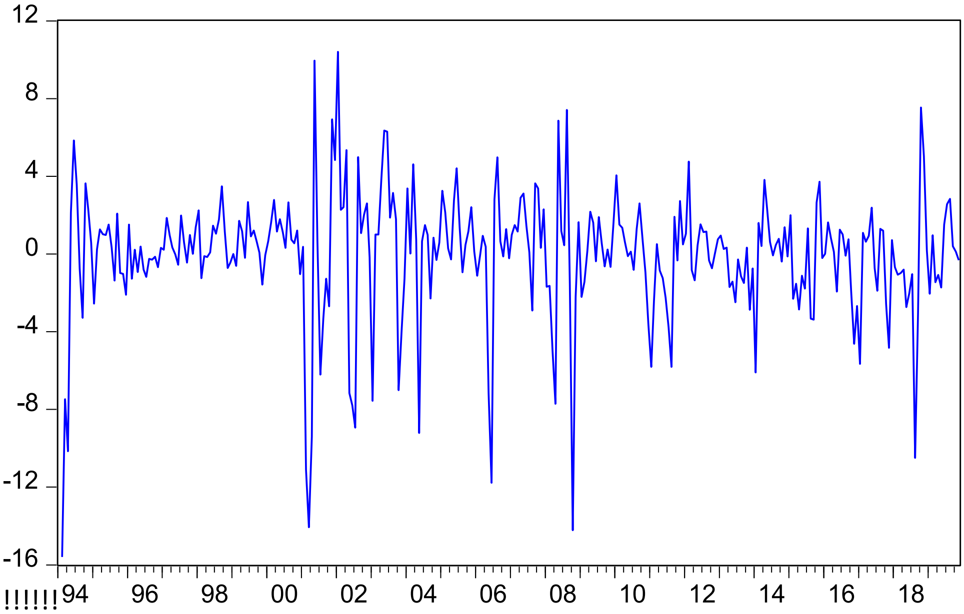

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Table 2: ADF and PP Unit Root Test Results

Augmented Dickey-Fuller (ADF) Unit Root Test

Variable	***Level Intercept***	***Trend and Intercept***	***Variable***	***First Difference Intercept***	***Trend and Intercept***
rex	-2.274402	-2.065126	*rex*	-12.58431***	-12.63044***

Phillips-Perron (PP) Unit Root Test

Variable	***Level Intercept***	***Trend and Intercept***	***Variable***	***First Difference Intercept***	***Trend and Intercept***
rex	-2.020967	-1.941763	*rex*	-13.43837***	-14.39554***

The symbols *, **, *** show that the statistical values are significant at 1%, 5% and 10% respectively.

Table 2 provides the ADF and PP unit root test results. ADF and PP unit root test results show that the *rex* (real effective exchange rate (CPI-based)) is not stationary in level. Nevertheless, it is stationary in the first difference at the 1% significance level. To sum up, ADF and PP unit root tests confirm that the series is integrated of order one.

Figure 3: Correlogram of Real Effective Exchange Rate (CPI based) in First Difference

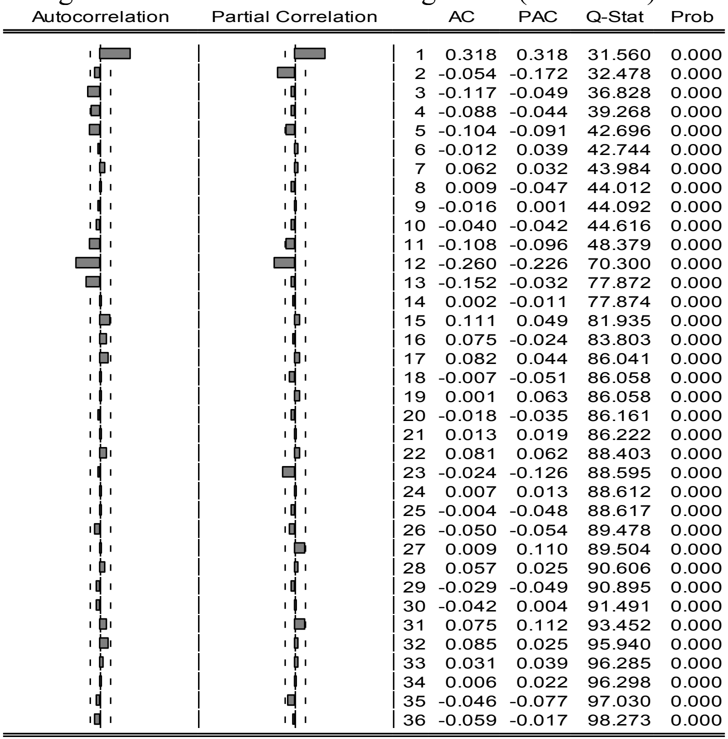

Table 3: ARMA–ARCH Estimation Results

		ARMA-ARCH(1) Estimation Results			
	AR(1)	ARIMA(1,1,1)	ARIMA(2,1,1)	ARIMA(1,1,3)	ARIMA(1,1,5)
Akaike Criteria	4.868518	4.856540	4.851173	4.872299	4.865682
Schwarz Criteria	4.930550	4.930979	4.925611	4.946737	4.940121
Coefficients (Variance Equation)					
ε_{t-1}^2	0.415525***	0.400335***	0.383076***	0.429360***	0.413628***
	ARIMA(2,1,3)	ARIMA(2,1,5)	MA(3)	MA(5)	
Akaike Criteria	4.907725	4.898571	4.913601	4.905162	
Schwarz Criteria	4.982163	4.973009	4.975632	4.967193	
Coefficients (Variance Equation)					
ε_{t-1}^2	0.405406***	0.475926***	0.390595***	0.438691***	
		ARMA-ARCH(2) Estimation Results			
	AR(1)	ARIMA(1,1,1)	ARIMA(2,1,1)	ARIMA(1,1,3)	ARIMA(1,1,5)
Akaike Criteria	4.732920	4.710810	4.695025	4.738365	4.732550
Schwarz Criteria	4.807358	4.797655	4.781870	4.825209	4.819395
Coefficients (Variance Equation)					
ε_{t-1}^2	0.240705***	0.259411***	0.232551***	0.256758***	0.236671***
ε_{t-2}^2	0.597095***	0.700159***	0.776495***	0.621769***	0.660201***
	ARIMA(2,1,3)	ARIMA(2,1,5)	MA(3)	MA(5)	
Akaike Criteria	4.808673	4.803578	4.805395	4.799084	
Schwarz Criteria	4.895517	4.890422	4.879833	4.873522	
Coefficients (Variance Equation)					
ε_{t-1}^2	0.306340***	0.293345***	0.309013***	0.295560***	
ε_{t-2}^2	0.600696***	0.650203***	0.480040***	0.530686***	

The symbols *, **, *** show that the statistical values are significant at 1%, 5% and 10% respectively.

Figure 3 displays the correlogram of *rex* in the first difference. It verifies that the ACF values are close to 1 and that *rex* is I(1). The next stage is to select suitable models. According to Figure 3, the most suitable process combinations are AR(1), ARIMA(1,1,1), ARIMA(2,1,1), ARIMA(1,1,3), ARIMA(1,1,5), ARIMA(2,1,3), ARIMA(2,1,5), MA(3), MA(5). Moreover, AR(12) process is added to all ARIMA models for increasing forecast power.

Table 4: ARMA – GARCH Estimation Results

	ARMA-GARCH(1,1) Estimation Results				
	AR(1)	ARIMA(1,1,1)	ARIMA(2,1,1)	ARIMA(1,1,3)	ARIMA(1,1,5)
Akaike Criteria	4.744775	4.743671	4.745008	4.746671	4.746611
Schwarz Criteria	4.819213	4.830516	4.831852	4.833515	4.833456
Coefficients (Variance Equation)					
ε_{t-1}^2	0.284655***	0.287247***	0.287208***	0.291457***	0.291772***
σ_{t-1}^2	0.582234***	0.573422***	0.570503***	0.577822***	0.574833***
	ARIMA(2,1,3)	ARIMA(2,1,5)	MA(3)	MA(5)	
Akaike Criteria	4.819056	4.819908	4.813076	4.815612	
Schwarz Criteria	4.905900	4.906752	4.887514	4.890051	
Coefficients (Variance Equation)					
ε_{t-1}^2	0.381651***	0.385739***	0.377867***	0.370818***	
σ_{t-1}^2	0.474697***	0.474768***	0.479250***	0.490293***	
	ARMA -GARCH(2,1) Estimation Results				
	AR(1)	ARIMA(1,1,1)	ARIMA(2,1,1)	ARIMA(1,1,3)	ARIMA(1,1,5)
Akaike Criteria	4.720082	4.715330	4.701677	4.723765	4.722188
Schwarz Criteria	4.806927	4.814581	4.800928	4.823016	4.821439
Coefficients (Variance Equation)					
ε_{t-1}^2	0.252157***	0.257396***	0.233146***	0.266610***	0.244605***
ε_{t-2}^2	0.602554***	0.626454***	0.770604***	0.565477***	0.655789***
σ_{t-1}^2	0.105427	0.053529	0.004025	0.118915*	0.093351
	ARIMA(2,1,3)	ARIMA(2,1,5)	MA(3)	MA(5)	
Akaike Criteria	4.808423	4.802843	4.801716	4.796329	
Schwarz Criteria	4.907674	4.902094	4.888560	4.883174	
Coefficients (Variance Equation)					
ε_{t-1}^2	0.320257***	0.310325***	0.320112***	0.307466***	
ε_{t-2}^2	0.408713***	0.498968***	0.410517***	0.521220***	
σ_{t-1}^2	0.128954	0.093916	0.127802	0.085605	
	ARMA-GARCH(2,2) Estimation Results				
	AR(1)	ARIMA(1,1,1)	ARIMA(2,1,1)	ARIMA(1,1,3)	ARIMA(1,1,5)
Akaike Criteria	4.716881	4.715505	4.690292	4.722751	4.716643
Schwarz Criteria	4.816132	4.827162	4.801949	4.834408	4.828300
Coefficients (Variance Equation)					
ε_{t-1}^2	0.220303***	0.219775***	0.253546***	0.223218***	0.224217***

ε^2_{t-2}	0.692420***	0.691530***	0.838900***	0.673934***	0.729551***
σ^2_{t-1}	0.001345	-0.009236	0.010437	0.009371	-0.007176
σ^2_{t-2}	0.093887**	0.076584*	-0.041136	0.090982**	0.090090**
	ARIMA(2,1,3)	ARIMA(2,1,5)	MA(3)	MA(5)	
Akaike Criteria	4.810841	4.808096	4.804347	4.801388	
Schwarz Criteria	4.922498	4.919753	4.903598	4.900639	
Coefficients (Variance Equation)					
ε^2_{t-1}	0.297137***	0.295078***	0.299366***	0.295482***	
ε^2_{t-2}	0.502805***	0.551301***	0.488517***	0.548429***	
σ^2_{t-1}	-0.028101	0.006879	-0.021780	0.008822	
σ^2_{t-2}	0.102999	0.057532	0.101845	0.056646	

The symbols *, **, *** show that the statistical values are significant at 1%, 5% and 10% respectively.

Tables 4 and 5 indicate estimation ARMA-ARCH and ARMA-GARCH results. The coefficient/sum of the coefficients in the variance equation is less than one in all models. Thus, Akaike and Schwarz Criteria autocorrelation, and heteroskedasticity problems are considered in model selection. The ARCH(1) models have mostly autocorrelation problems. Therefore, it is not chosen as the appropriate model. In ARCH(2) models, the AR (1) process is selected as the appropriate model due to taking the lowest Akaike and Schwarz Criteria values and having no autocorrelation problem. Since GARCH(1,1) models have mostly autocorrelation problems, the appropriate ARMA process is chosen as ARIMA(1,1,3). In GARCH(2,1) models, the ARIMA(1,1,3) process is determined as the forecasting model by Akaike and Schwarz criteria and having no autocorrelation problem. GARCH(1,2) models are excluded from the analysis because they have negative coefficients in the variance equation. The GARCH(2,2) models is not selected as the appropriate model owing to not having a negative coefficient and insignificant coefficient in the variance equation. According to the lowest Akaike and Schwarz Criteria's values, the ARIMA(1,1,3)-GARCH(2,1) and AR(1)-ARCH(2) models are the most appropriate process among the estimated models.

3.1. Forecasting Results

In this subchapter, the forecasting results between 2019M12 and 2021M08 discuss by analysing statistical indicators. Moreover, the static forecast is performed as a forecasting method. Error term statistics are employed to determine the forecasting power in different models. Thus, the forecasting power in the models is compared by analyzing the error term statistics. The error term statistics are root mean squared error, mean absolute error, theil inequality coefficient, bias proportion, variance proportion, and covariance proportion. If the theil inequality coefficient is zero, the model has the highest forecasting power. A smaller values of theil inequality coefficient increase the forecasting power of the model. Moreover, bias, variance and covariance proportions derived from Theil inequality coefficient are determinant criteria for the forecasting power.

Table 5: Forecasting Success Criteria in the ARMA-ARCH and ARMA-GARCH Models

	ARIMA(2,1,1)	AR(1)-ARCH(2)	ARIMA(1,1,3)-GARCH(2,1)	ARIMA(1,1,3)-GARCH(1,1)
Root Mean Squared Error	1.721042	1.754671	1.770238	1.685682
Mean Absolute Error	1.384026	1.405006	1.436188	1.370600
Theil Inequality Coeffcient	0.012900	0.013144	0.013258	0.012644
Bias Proportion	0.203446	0.239217	0.248930	0.160341
Variance Proportion	0.085155	0.082584	0.080424	0.090462
Covariance Proportion	0.711399	0.678200	0.670646	0.749197

Table 6 displays the forecasting success criteria of ARIMA, ARMA-ARCH and ARMA-GARCH models. The ARIMA(1,1,3)-GARCH(1,1) model gets the lowest the Theil inequality coefficient, root mean squared error, and mean absolute error values. Thus, these three criteria confirm that the ARIMA(1,1,3)-GARCH(1,1) model has the highest forecasting power. The other models including ARIMA(2,1,1) have proportion values bigger than 0.2. In other words, They have systematic error. Furthermore, the ARIMA(1,1,3)-GARCH(2,1), which has the lowest variance proportion value, has the lowest variation compared to the actual series. On the other hand, the systematic forecasting error is at the lowest in the ARIMA(1,1,3)-GARCH(1,1) and later ARIMA(2,1,1) models because they take the highest covariance proportion value and have a value closest to 1.!To sum up, the ARIMA(1,1,3)-GARCH(1,1) model has higher forecasting power, and ARIMA (2,1,1) has a systematic error and the most second predictive power.

Figure 4: The Real Effective Exchange Rate (CPI based) and Its Forecasted Values

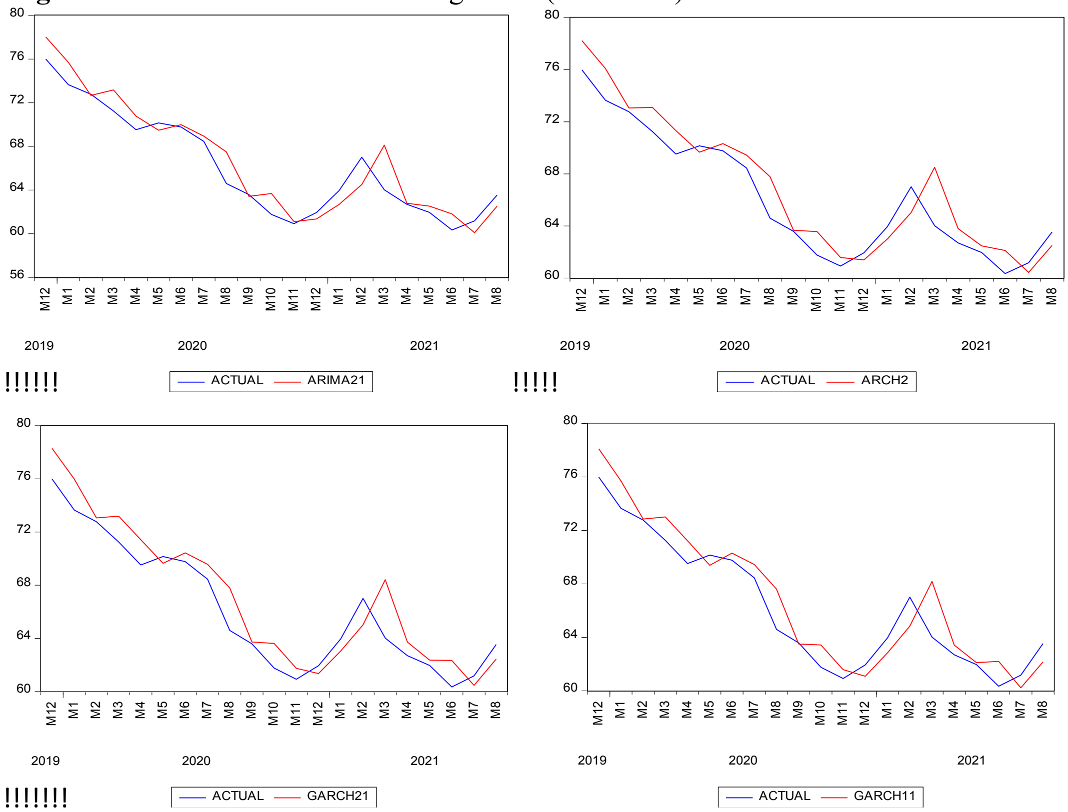

Figure 4 provides the actual and forecasting values of the real effective exchange rate. It supports the forecast success criteria. According to it, ARIMA(1,1,3)-GARCH(1,1) and ARIMA(2,1,1) models are the closest forecasting values to the actual value. However, the ARIMA(1,1,3)-GARCH(1,1) model performs better than the ARIMA(2,1,1) model which has systematic forecasting error.

CONCLUSIONS

The globalization emerging in the post-World War II increases the integration of microeconomic economic players into the international trade and financial system. Thus, they started to use foreign currencies in their transactions. Exchange rates affect economic performance in three ways. Firstly, exchange rates are a crucial determinant in firm decision-making (such as entering the domestic market, short, and long-term borrowings and operating in different countries). Secondly, other economic agents (such as portfolio investors and consumers) adapt their portfolio selection preferences to changes in exchange rates. Hence, exchange rates are associated with economic growth through the real and financial sectors. Thirdly, the import and export balance in economies are affected by exchange rates. The dismissal of the Bretton Woods agreement in 1973 caused many governments to implement the flexible exchange rate regime. The flexible exchange rate regime has complicated the exchange rate forecasting process. Therefore, reliable exchange rate forecasting has importance for the economic performance in developing countries since developing countries have the problems of structural and financial system deepening. The real effective exchange rate forecasting is a determinant indicator for measuring the country's competitiveness, and it contributes to decision-making processes by providing more effective predictions.

The deteriorated macroeconomic effects of the Covid-19 pandemic rise the volatility of the exchange rate. Thus, reliable exchange rate forecasting becomes even more complex during the Covid-19 pandemic. This study aims at analyzing the real effective exchange forecasting during the Covid-19 pandemic (2019M12-2021M08) by comparing ARIMA, ARCH and GARCH models. The analysis findings demonstrate that ARIMA(1,1,3)-GARCH(1,1) model has the closest forecasting output to the accurate values. In addition to this, it has better predictive power than other models. Concluding remarks, the ARMA-GARCH model has more accurate forecasting results. This study offers that the policy-makers and economic agents consider the ARIMA(1,1,3)-GARCH(1,1) model for real exchange rates forecasting during the Covid-19 pandemic.

Etik Beyan: *Bu çalışmada "Etik Kurul" izini alınmasını gerektiren bir yöntem kullanılmamıştır.*

Yazar Katkı Beyanı: *1.Yazarın katkı oranı %100'dür.*

Ethics Statement: *In this study, no method requiring the permission of the "Ethics Committee" was used.*

Author Contributions Statement: *1st author's contribution rate 100%*

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