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Analyzing Exchange Rate Volatility: A Comparative Study of ARCH and GARCH Methods

Döviz Kuru Oynaklığının ARCH ve GARCH Yöntemleriyle Karşılaştırmalı Olarak Analizi

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MAKALEBİLGİSİ

Anahtar Kelimeler
Döviz Kuru,
Zaman Serisi,
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ÖZET

Döviz kurlarındaki dalgalanmalar hükümetleri, şirketleri ve yatırımcıları ilgilendirmekte ve dalgalanmalar hakkında bilgi sahibi olmalarını gerektirmektedir. Çünkü döviz kurları sadece uluslararası ticareti değil aynı zamanda ekonomik aktörlerin yatırım kararlarını da etkilemektedir. Bu nedenle döviz kurlarındaki dalgalanmalar günümüzde önemini artırmaktadır. Bu çalışmada dünyada en çok işlem gören iki uluslararası para birimi olan ABD doları ile Avrupa Birliği para birimi Euro arasındaki haftalık döviz satış fiyatlarındaki oynaklığın Türkiye üzerindeki etkileri 1999-2022 yılları arasındaki 1232 gözlem verisi kullanılarak incelenmiştir. Araştırmanın analiz kısmında zaman serisi analizlerinde sıklıkla kullanılan otoregresif koşullu varyans (ARCH) ve genelleştirilmiş otoregresif koşullu varyans (GARCH) yöntemleri kullanılmıştır. Bu yöntemlerin modelleri her iki döviz kuru için ayrı ayrı tahmin edilmektedir. Model tahminleri sonucunda GARCH (1,1) modelinin her iki döviz kurundaki oynaklığı açıklamada başarılı olduğu tespit edilmiştir. Sonuç olarak, Türkiye'de 1999-2022 yılları arasında (döviz kurlarının tarihsel fiyatlarına göre) dolar ve euro döviz kurlarındaki oynaklığın GARCH modeli kullanılarak tahmin edilebileceği ve GARCH etkisine sahip olduğu sonucuna varılmıştır.

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ABSTRACT

Governments, companies, and investors must be informed about fluctuations in exchange rates since they affect not only international trade but also economic actors' investment decisions. Hence, fluctuating exchange rates are of increasing importance. This study examines the impact of weekly volatility on the Turkish lira exchange rate with the US dollar and the Euro, the two most heavily traded international currencies. 1232 observations from 1999 to 2022 are used for the analysis. This study employed two commonly used time series analysis methods, namely Autoregressive Conditional Variance (ARCH) and Generalized Autoregressive Conditional Variance (GARCH). It was determined that the GARCH (1,1) model was successful in explaining the volatility in both exchange rates based on the model's predictions. Therefore, we concluded that the volatility in the dollar and euro exchange rates in Türkiye between 1999 and 2022 (based on the date prices of exchange rates) can be predicted by the GARCH model and is characterized by a GARCH effect.

Exchange rate is of great importance in the country's economy as one of the four monetary transmission mechanisms in the macro economy. It has the power to directly affect macroeconomic indicators such as foreign trade balance, total

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supply and total demand, especially in countries that adopt a free exchange rate regime (Dornbusch et al., 2007). Therefore, governments, entrepreneurs (exporters or importers) and investors (individuals or corporates) need to carefully monitor the fluctuations in exchange rates and be informed.

In the study, fluctuations in the US dollar and Euro currencies between 1999 and 2022 were examined using ARCH and GARCH models. Therefore, it is useful to explain the ARCH and GARCH models. In econometrics, the change of variance in cross-sectional data analysis and the autocorrelation problem in time series analysis are seen as the main problems. In their studies, Engle (1982) and Engle (1983) explained that the volatility and variance observed in time series analyses, especially in financial time series, are not constant with the autoregressive conditional variance (ARCH) model. Later, Bollerslev (1986) improved the ARCH model and developed the generalized autoregressive conditional variance (GARCH) model. These models for variance estimation in financial time series follow models developed for different purposes such as M-ARCH, EGARCH and TGARCH (Gujarati and Porter, 2012). Since Türkiye is a country with a fragile economy, it is affected by international financial and foreign exchange movements. Compared to countries with a fragile structure (e.g. India), a small volatility in the exchange rate affects Türkiye more. This is because the Turkish economy is more affected by exchange rate fluctuations than the countries with fragile structure (India, South Africa, Brazil, etc.) because it is a country dependent on imported inputs. This leads to negative consequences on macroeconomic variables, especially the balance of payments. Volatility of the United States (US) Dollar and the EU common currency Euro was investigated in Türkiye in the period until 2022, based on 1999, when the European Union (EU) switched to the common currency Euro. Volatility of exchange rate is defined as the deviations in the returns of financial assets or the ups and downs in the prices of financial assets (Kılıç & Ayrıçay, 2020). Therefore, this article will positively affect the economic behavior of economic decision-making units and contribute to the literature.

In the research, firstly the historical changes of both currencies in the data years have been examined, and then theoretical explanations have been made about the classical ARCH and GARCH models, which are the methods to be used in the implementation of the analysis. Second, classic ARCH and GARCH models were estimated for both exchange rates, and they were accepted when the assumptions and diagnostic tests were met. Finally, according to the analysis findings, it has been concluded that Türkiye, which is both an exporter and an importer in foreign trade, increased the volatility in its exchange rate as a result of the economic crises experienced both at home and abroad.

1. OVERVIEW OF EXCHANGE MOVEMENTS IN TÜRKİYE (1999-2022 PERIOD)

Under this title, the course of Türkiye's foreign exchange movements will be evaluated under three subtitles. These will be discussed in the form of the 2001 economic crisis in the country and the developments after it, the Mortgage Crisis experienced abroad and the developments after it, and finally the change in the foreign exchange movements in the process until today.

1.1. 2001 Domestic Economic Crisis and Afterwards

The crisis experienced in 2001 was a crisis that directly affected the banking and finance sectors and left deep scars. In this crisis, high level of budget deficits occurred in banks in the private and public sectors, high capital outflows occurred as a result of the increase in overnight interest rates, and in this context, foreign exchange reserves rapidly decreased. In the face of these developments, the Turkish lira lost more than 50% of its value, production decreased and unemployment and poverty rates increased in Türkiye. As a result, Türkiye's GDP decreased by 6% (Pamuk, 2020).

Türkiye's recovery from the 2001 crisis was rapid and its GDP grew again a year later. In order to prepare a new program and to provide international support to this program, Kemal Derviş, who worked as a senior manager at the World Bank, was invited to the country as the minister responsible for the economy. The new program, prepared with the support of Kemal Derviş and the IMF, includes economic stability and structural reforms. In the elections held at the end of 2002, the Justice and Development Party (AKP) won the election and implemented the program prepared with the support of the IMF. To summarize this program; tight fiscal policy and low budget deficit, tight monetary policy and the fight against inflation were implemented, and finally, the flexible exchange rate regime with intervention was switched to the floating exchange rate regime (Eğilmez, 2019a; Pamuk, 2020). Macroeconomic data for this period are shown in Table 1. shows that GDP and per capita income decreased and unemployment increased from 1999 to 2002. After the 2001 crisis, with the programme prepared with the support of IMF, GDP, per capita income and growth data increased while inflation and unemployment decreased. However, the balance of payments deficit gradually deepened.

Table 1: The macroeconomic situation of Türkiye in the period 1999-2007

Years	GDP (billion USD)	Per Capita Income USD	Growth (%)	Inflation (%)	Unemployment (%)	Current Balance (%)
1999	256.4	4.057	-3.3	64.9	7.5	-0.4
2000	274.29	4.278	6.9	54.9	6.3	-3.6
2001	201.75	3.100	-5.8	54.4	8.4	1.9
2002	240.25	3.640	6.4	45	10.3	--0.3
2003	314.6	4.704	5.8	21.6	10.6	-2.4
2004	408.87	6.031	9.8	8.4	10.8	--3.5
2005	506.31	7.369	9.0	8.2	10.6	--4.1
2006	557.08	8.003	6.9	9.6	8.7	--5.6
2007	681.32	9.711	5.0	8.8	8.9	-5.4

Source: The World Bank Data (2024).

Between 1999 and 2007, Türkiye continued to pursue the IMF program, the primary goal of which was to reduce inflation, without taking the growing imbalances in its own economy seriously. Thanks to the program, the rate of inflation decreased, budget deficits were limited, and banks were strengthened by the BDDK (Banking Regulation and Supervision Agency). Along with, there was a constant inflow of funds into Türkiye, which resulted in the appreciation of the Turkish Lira. As a result of this situation, the current account deficits continued to increase (Kazgan, 2017).

1.2. 2008 Mortgage Crisis Abroad and After

The crisis, which started with the bankruptcy of the investment bank "Lehman Brothers" in the fall of 2008, was expressed as a "crisis that will happen once in a century" by the then Chairman of the FED, Alan Greenspan. The crisis reached a global dimension and spread to Europe, and the economists of the period began to compare it with the Great Depression of 1929 and emphasized that the mistakes of that time should be avoided (Kazgan, 2017).

The crisis experienced in the USA and caused by the bursting of the bubble in the real estate sector was perceived differently by politicians, laborers and capital circles in Türkiye. Politicians have stated that the crisis will not affect Türkiye much in order not to demoralize the society or because they cannot understand the depth of the crisis. However, in the fourth quarter of 2008, Türkiye became the second country that contracted the most after Taiwan. While the unemployment rate in Türkiye was 11% in 2008; In January 2009, it increased to 16.1%. As this crisis deeply shook Europe, which is Türkiye's exporter, export revenues in May 2009 decreased by 39.9% compared to the previous year in Türkiye. In addition, although the banking sector was strengthened after the 2001 crisis, the 2008 crisis also affected the banking sector, and the number of non-performing loans increased and the ratio of bad loans to total loans exceeded 4.5% in 2009 (Tiryaki & Ekinci, 2015).

1.3. Current Situation of Foreign Exchange Movements in the Last Ten Years

Eğilmez (2019b); In an analysis he made in 2011, he stated that there are three stages of the global crisis. According to Eğilmez (2019b), the first stage of the 2008 Mortgage Crisis will affect the USA, the second stage will affect the EU, and the third stage will affect developing economies. As a result of this predictable view, while the Turkish economy shrank by 3% in the last quarter of 2018, it shrank by 2.6% in the first quarter of 2019. At the same time, unemployment and inflation in the economy lead the Turkish economy to slumpflation.

Table 2. Macroeconomic indicators of Türkiye in the period 2017-2022.

Indicators	Unit	2017	2018	2019	2020	2021	2022	Explanation	Situation
Per capita income	USD	10.695	9.568	9.215	8.638	9.743	10.674	End of the year	-
Growth	%	7.5	3	0.8	1.9	11.4	5.5	End of the year	-
Unemployment	%	10.8	10.9	13.7	13.1	12	10.4	End of the year	-
Inflation	%	11.1	16.3	15.2	12.3	19.6	72.3	End of the year	-
Total Government debt /GDP	%	29.7	29.2	33.9	41.8	42.6	35.2	End of the year	-
Current balance /GDP	%	-4.7	-2.6	1.4	-4.4	-0.9	-5.4	End of the year	+

Economic confidence index	104.5	89.8	99.9	95.1	99.4	98.2	End of the year (December)	-
Consumer cofidence index	88.2	80.1	80.7	80.1	68.9	75.6	End of the year (December)	-

Source: The World Bank Data (2024); TÜİK (2024)

The duty of the Central Bank of the Republic of Turkiye is to ensure financial stability. However, starting from September 2021, the Monetary Policy Committee has regularly reduced the policy rate. This situation not only increased the current account deficit in the economy, but also caused inflation and budget deficits by decreasing the value of the Turkish Lira against the exchange rate. Meanwhile, central government elections were held in Turkiye in 2023 and there were huge public expenditures before these elections were held. These public expenditures also caused the budget deficit to increase (Aktaş 2024 and Özatay, 2024). It is possible to see this situation in Table 2 in the 2022 data.

A second development that has affected the world economically, healthwise, and socially in the last decade is the Covid-19 epidemic. The US has taken some measures to protect public health. Closing entrances and exits to the country, quarantine practices, and closing cafes, restaurants, and shopping malls are all examples of these measures. As a result of these practices, supply and demand shocks occurred and production came to a halt. Additionally, the world economy in general has shrunk. Along with these developments, there were also changes in the exchange rate. After the first Covid-19 case was seen in Türkiye, which has a trading volume in global markets, the BIST100 index, one of the most important indicators of the capital markets, lost approximately 11 percent of its value in a 25-day period. In addition to stock market indices, exchange rates and gold prices are also important indicators. During this period, the dollar and euro, which were among the strongest currencies, gained value against TL. Due to the fluctuations in the stock market during the said period, investors turned to gold, which they saw as a safe haven in the domestic market. At the same time, it has been observed that as gold gains value in global markets, gold prices also increase, similar to exchange rates (Kayral and Tandoğan, 2020).

2. LITERATURE REVIEW

In this section, in addition to the international literature, since the study is specific to Turkey, studies that examine Turkey's volatility indicator using ARCH and GARCH models are included.

Afuecheta, Okorie, Nadarajah and Nzeribe (2024) investigated the volatility of African currencies (8 units) with financial markets using a time-dependent DCC-GARCH model. The study found weak correlations between variables. This shows that the African economy is governed by certain economic factors.

Bhat, Shakika, Prakash and Thonse (2024) examined the volatility of the Indian stock market with the GARCH model. Crude oil prices and daily closing prices of the INR/USD exchange rate were used in the analysis. In the research, a strong correlation relationship was found between exchange rate and crude oil price.

Tondapu (2024) investigated the fluctuation of the Great British Pound (GBP) against the US Dollar and Euro with the help of daily data range from 15.06.2018 to 15.06.2023. Exponential weighted moving average (EWMA) and Generalized autoregressive conditional heteroscedasticity (GARCH) models were used in the analysis. As a result, the existence of EUR/GBP asymmetric returns was found, but the existence of US Dollar/GBP asymmetric returns was not found.

Baydaş (2023); In his study, he investigated the volatility between the fear index (VIX) and BIST 100 and BIST 30 indices with the help of the CCC-GARCH model. Baydaş (2023) created the research model based on the period of 02.01.2015-17.01.2023. According to the results of the research, it has been found that there is no volatile interaction from the BIST 100 index to the VIX, but there is a volatile interaction from the VIX to the BIST 100 index. No volatile transfer was found between VIX and BIST 30.

Bekar (2023) drew attention to the exchange rate risk by constructing the model as Two-Component Beta-Warp-t-EGARCH+ Leverage based on the 2005-2021 period over the US dollar/Turkish Lira exchange rate.

Köse (2023) investigated the volatility of cryptocurrencies (BTC and ETH) with ARCH, GARCH, ARCH-M, GARCH-M, IGARCH, EGARCH, TGARCH, APARCH and ACGARHC models. As a result of the research, while negative shocks in BTC return series provide positive shocks on volatile; Positive shocks in ETH return series cause negative shocks on volatile.

Şeker (2023) examined the deviations from the efficient markets hypothesis and investigated the anomalies in the US dollar returns based on the period 02.01.2020-31.12.2020. In the study, no day of the week anomaly was detected in the ARCH equation, and it was concluded that ARCH-M and GARCH-M models, which explain the risk and return relationship on volatile, are not a valid model that explains the day of the week anomaly.

Kılıç and Ayrıçay (2020) determined the indices of the sub-sectors in BIST and the volatility of the monthly return series between 1997:01-1999:7 with ARCH-GARCH models. The study revealed that each index had a different volatility.

Demirgil and Kesekler (2019) modelled volatile interaction in the return series of the currencies (US Dollar, Euro, Russian Ruble, British Pound and Japanese Yen) of the five countries that are effective in Türkiye's foreign trade on the basis of the period 2005:01-2019:03. M-GARCH was used as a model in the study and it was determined that there was a volatile interaction for five variables.

Gün (2019) modelled US Dollar/Turkish Lira exchange rate volatility for the period from July 2001 to February 2020 was modeled using the MSGARCH method. The MSGARCH model, which was chosen as the most appropriate model compared to other models, confirms that high and low risks in the exchange rate bring the exchange rate back into balance.

Yaman and Koy (2019) modelled the periods 01.06.2001-01.06.2018 and 01.06.2001-30.04.2019 separately and comparatively analyzed due to Türkiye's transition to a floating exchange rate in 2001 and the Turkish Lira's great depreciation against the US Dollar. In the study, GARCH, TARCH, and EGARCH models were employed, and it was determined that all of these models exhibited statistical significance.

Uysal and Özşahin (2012) examined the volatile interaction in the monthly TL/dollar exchange rate index values of the period from March 2001 to May 2010 with the GARCH (1,1) model and it was determined that this model was the most appropriate model and to eliminate the volatility of the real effective exchange rate.

Akar (2007) modelled the volatility effect using the weekly closing data of the Istanbul Stock Exchange (IMKB100) index. ARCH, GARCH and SWARCH models were used in the research and the prediction performance of the SWARCH model was found to be more appropriate.

When the literature is examined in general, it is concluded that risks increase volatility in the stock market, but volatility comes to balance again with ARCH and GARCH models and different models derived from these models.

3. DATA SET

Two separate time series have been generated for the two distinct variables under consideration: USD (US Dollar in Turkish Lira) and Euro (European Union common currency in Turkish Lira). The research sample comprises a total of 1,243 observations, utilizing weekly data spanning September 1, 1999, to August 19, 2022. This dataset was obtained via the Electronic Data Distribution System based on the weekly foreign exchange selling rates reported by the Central Bank of the Republic of Turkey (TCMB, 2022).

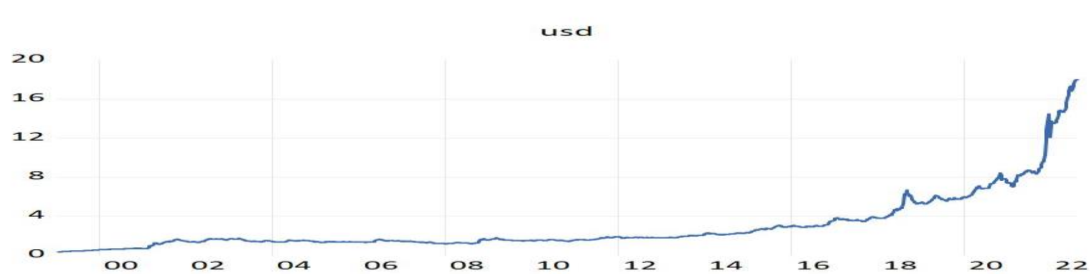


Figure 1. Graph of Raw Data of the variable usd

Source: It was created by us using the raw data obtained from the TCMB (2022).

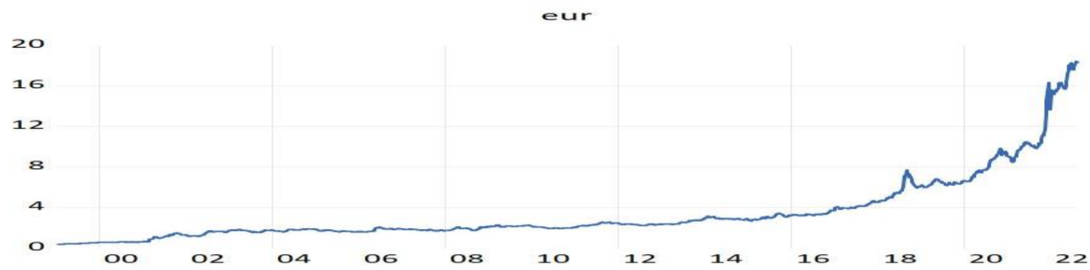


Figure 2. Graph of Raw Data of variable eur

Source: It was created by us using the raw data obtained from the TCMB (2022).

Figure 2 illustrates the weekly fluctuations in the Euro exchange rate, which constitutes the second variable under investigation, spanning the period from 1999 to 2022.

Table 3: Descriptive Statistics of Raw Data

Variables	Obs.	Mean	Std. dev.	Min.	Max.
usd	1232	2.895779	2.973301	.321082	17.97826
eur	1232	3.389645	3.263606	.3730846	18.40044

The descriptive statistics pertaining to the initial data are summarized in Table 3 above. Following the exposition of the raw data's characteristics, we applied the time series analysis approach that will be employed in the subsequent application section. This processing entailed conducting a logarithmic transformation subsequent to differentiation, rendering the data prepared for application. The resulting post-processed series of variables have been restructured to form two new variables: "r_usd" representing the weekly return of the USD, and "r_eur" representing the weekly return of the EUR

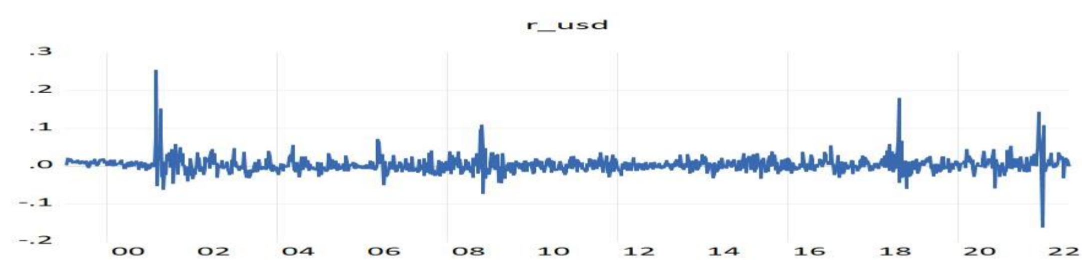


Figure 3. Graph of r_usd Variable

Source: It was created by us after processing the raw data of the variable.

In Figure 3, the graph of the r_usd variable, which was prepared for analysis, between the dates 1999-2022 is given.

Figure 4. Graph of r_eur Variable

Source: It was created by us after processing the raw data of the variable.

In Figure 4, there is a graph showing the change in the 1999-2022 date range of the r_eur variable, which is the other variable to be used in the analysis.

Table 4: Descriptive Statistics of Variables Prepared for Analysis

Variables	Obs.	Mean	Std. dev.	Min.	Max.
r_usd	1232	.0032699	.020546	-.1621555	.2583455
r_eur	1232	.0031639	.0203897	-.1603222	.2524696

In Table 4, descriptive statistics of the variables prepared for analysis that will be used in the application part are given.

4. THEORETICAL FRAMEWORK AND METHODOLOGY

Since the data of the variables used in the research are time series, the Augmented Dickey Fuller (ADF) unit root test was first performed to determine the stationarity of the variables. In the next stage, autoregressive conditional variance (ARCH) and generalized autoregressive conditional variance (GARCH) models used in estimating the volatility of financial assets were estimated and the most appropriate model for the variables was selected. Then, diagnostic tests (White Noise condition, Corregram Q test and Heteroskedasticity test) of the most appropriate model estimated for the variables were performed and the validity of the model was decided. Finally, Static Estimation was applied on the validated model.

4.1. Augmented Dickey Fuller Unit Root Test

In time series analysis, determining the stationarity of the series of variables constitutes the first step of the analysis process. For this reason, Dickey and Fuller (1979) first introduced the Dickey Fuller unit root test to test the stationarity of the variables. However, after a while, she stated that the error terms cannot be used if they contain autocorrelation and that there is a “p” order relationship between them (Dickey and Fuller, 1981).

$$\varepsilon_t = \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2}+.....+ \theta_3\varepsilon_{t-3}+ \varepsilon_t \quad \textbf{(1)}$$

In response to this situation, Dickey and Fuller developed the Extended Dickey Fuller (ADF) test, a new method in which the lagged value of the dependent variable is included in the model as independent variables, as expressed in equation (1). This developed test has eliminated the autocorrelation problem in error terms (Holden and Perman, 1994:61). Three different models are estimated for the ADF unit root test (Endres, 1995: 225). These;

$$\Delta Y_t = \beta_1 Y_{t-1} + \sum_{i=1}^{k} \lambda_i \, \Delta Y_{t-1} + \varepsilon_t \quad \textbf{(2)}$$

As expressed in equation (2), it is the first model in which there is no constant or trend (none).

$$\Delta Y_t = \beta_0 + \beta_1 Y_{t-1} + \sum_{i=1}^{k} \lambda_i \, \Delta Y_{t-1} + \varepsilon_t \quad \textbf{(3)}$$

The second model is in the form of an equation in which the constant parameter is present but the trend is not, as seen in equation (3).

$$\Delta Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 \,\text{trend} + \sum_{i=1}^{k} \lambda_i \, \Delta Y_{t-1} + \varepsilon_t \quad \textbf{(4)}$$

Equation (3), on the other hand, expresses the equation of the last model in which both the constant parameter and the trend take place together.

In the post-estimation hypothesis tests of these models, it was determined that the main hypothesis was that the series had a unit root, and the alternative hypothesis was that the series was stationary. If the test statistic of the estimated model is greater than the table critical value, the main hypothesis is rejected and the alternative hypothesis is accepted. If the calculated test statistic and table are less than the critical value, the alternative hypothesis is accepted and the test is performed.

4.2. Autoregressive Model AR (p)

The AR(1) model used in time series analysis is statistically accepted as the simplest first-order model in time series.

$$Y_t = \phi Y_{t-1} + u_t \quad \textbf{(5)}$$

Equation (5) represents an example of first-order AR (1) model. Here |ϕ| While < 1 represents the constant number, "ut" represents the Gaussian White Noise error term. The basic assumption in the AR (1) model is based on the fact that the change in the "Yt" time series is largely dependent on its past values. Therefore, what happens in the "t" period largely depends on what happens in the "t-1" period. Alternatively, what will happen in the "t+1" period will be determined by the behavior of the series at the current "t" time (Asteriou and Hall, 2011: 267-268).

4.3. Autoregressive Conditional Variance Model ARCH (p)

In her model, Engel suggested that the residual variances at time "t" depend on the square of the error terms in the past periods. Simply, it proposes modeling by estimating the mean and variance of a series together in order to obtain more efficient and unbiased results when the conditional variance is not constant. This situation is explained by a simple model as follows.

$$Y_t = \alpha + \beta' X_t + u_t \quad \textbf{(6)}$$

While "Xt" in Equation (6) is the "kx1" vector of explanatory variables, "β^" refers to the vector of slopes in "kx1" number.

$$u_t \sim N(0, \sigma^2) \quad \textbf{(7)}$$

Normally, ut is assumed to have a zero mean and a constant variance, σ^2, as in notation (7). Engel states that the residual variance changes with time and this causes the problem of varying variance, thus allowing the variance to change as a function of the square of the lagged Errors

$$\sigma_t^2 = \gamma 0 + \gamma 1\, u_{t-1}^2 \quad \textbf{(8)}$$

As a result of the function that emerged with this change, the basic ARCH (1) process represented by the equation in equation (8) emerged. As stated before, mean and variance equations are estimated together in the ARCH (1) model.

$$Y_t = \alpha + \beta' X_t + u_t \quad \textbf{(9)}$$

$$u_t \mid \psi_{t-1} \sim N(0, h_t)$$

$$h_t = \gamma 0 + \gamma 1\, u_{t-1}^2 \quad \textbf{(10)}$$

While equation (9) represents the mean equation to be estimated in the ARCH (1) model, equation (10) represents the variance equation. In the last equation, the symbol "ht" is now used instead of the symbol previously used for variance "σ^2". Here, "ht" is the conditional function of the information set "ψ_(t-1)". In the ARCH model, the increase in the value of "ut" (because its squares are taken) becomes larger and positive in the face of a possible shock in the "t-1" period. Therefore, since the variance is positive, the estimated coefficient "γ1" should also be positive, that is, 0<γ1. This is the accepted assumption that the model coefficients are 0<γ0 and 0<γ1<1 in the ARCH (1) process. (Engel, 1982)

4.3.1. Testing for the Presence of the ARCH Effect

Before estimating the ARCH model, which model should be used instead of the least squares method (OLS) depends on the presence of the ARCH effect. That is, if the AR (p) model estimated by OLS management has ARCH effect, this model is estimated by ARCH method. Lagrange Multiplier (LM) is one of the frequently used tests to investigate the presence of ARCH effect. This method is as follows:

$$Y_t = \alpha + \beta\ X_t + e_t \quad \textbf{(11)}$$

The model is estimated with the help of OLS as shown in Equation (11). Then, the error term "e_t" and the square of the error term "e_t^2" of this model are estimated.

$$e_t^2 = \gamma 0 + \gamma 1\, e_{t-1}^2 + v_t \quad \textbf{(12)}$$

Then, as seen in equation (12), the regression line consisting of the error term and the lagged value of the error term is estimated, and the existence of the ARCH effect is tested. For this, the LM test statistic LM= (T-q) R2 is calculated and a decision is made about the hypotheses created by comparing the calculated test statistic with the table value "χ_q^2".

$H_0 : \gamma 1 = 0 \qquad H_0 : \gamma 1 \neq 0$ **(13)**

The main and alternative hypotheses created for the test are as in the illustration (13). In case the basic hypothesis is rejected, the existence of ARCH effect in the model will be accepted. Afterwards, the ARCH model will be estimated (Hill, Griffiths and Lim, 2011: 523).

4.4. Generalized Autoregressive Conditional Variance Model GARCH (p,q)

According to Engel (1995), one of the disadvantages of the ARCH (p) model is that the process resembles a moving mean estimation process rather than an autoregression. While this situation causes the need for "px"1 parameter, it also affects the accuracy of the prediction model as the "p" value gets larger (parsimony principle). Therefore, T. Bollerslev (1986) developed a new model with lagged conditional variance terms as autoregressive terms. In this regard, the Generalized autoregressive conditional variance model has become a special generalization and alternative of the ARCH model to capture long-lagged effects using fewer parameters.

$Y_t = \alpha + \beta' X_t + \varepsilon_t$ **(14)**

$\varepsilon_t | \psi_{t-i} \sim N(0, h_t)$

$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \, h_{t-j}$ **(15)**

In short, the equation in equation (14) represents the mean equation of the GARCH (p,q) model, which is the extended version of the ARCH model. The error term of this equation has zero mean under the information set "ψ_(t-i)" and the conditional variance of "ht" and normal distribution. Starting from here;

$p > 0, \; q \geq 0$

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

$\beta_j \geq 0 \qquad j = 0,1,2,...q$

It is seen that the GARCH (p,q) model is equal to the ARCH (p) model when q = 0. If "p" and "q" take the value of zero at the same time in the model, the error term "ε_t" will be white noise. On the other hand, if p = 1 and q = 1, the GARCH (1,1) model will be obtained.

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \, h_{t-1}$ **(16)**

Equation (16) represents the variance equality of the above-mentioned GARCH (1,1) model (Bollerslev, 1990: 501). The assumption regarding the parameters of this model is accepted as α_0 >0, α_i≥0, β_j ≥0 as in the ARCH (p) model. And again, as in the ARCH (p) model, the sum of "α_i" and "β_j" must be less than one. If these conditions are met, the error terms will become weakly stationary. (Bollerslev, 1986: 310-311). In addition, ARCH LM test is used to investigate the GARCH effect while estimating the model (Bera and Higgins, 1993).

4.5. Predictive Performance for the GARCH (p,q) Model

GARCH (p,q) gives information about the conditional variance and volatility of the predicted model in a model. Considering any GARCH (1,1) model;

$\varepsilon_t = h_t z_t$ **(17)**

$z_t \sim iid\,(0,1)$

$h_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + b h_{t-1}^2$ **(18)**

As shown in equation (17), according to the unit variance assumption in the change process, “z_t” transforms “h_t” into the variance of “ε_t”, the process depends on the information set “F_(t-1)”, which includes the historical information set until the “t-1” period. In the equation estimated in Equation (18), the parameters “α”, “ω” and “b” have positive values.

$$E_{t-1}(\varepsilon_t^{2r+1}) = 0, \qquad r = 0,1,2,....K-1 \qquad \textbf{(19)}$$

$$E_{t-1}(\varepsilon_t^{2r}) = k_r(h_t^{2r}), \qquad r = 0,1,2,....K$$

As expressed in notation (19) above, the conditional distribution of "ε_t" is assumed to be symmetrical with all available even-order moments proportional to the corresponding powers of the conditional variance given in the information set "F_(t-1)". That is, here “k_r” is the conditional density of “ε_t” “r.” represents the cumulative sum of degrees.

$$\widetilde{h_{t+s}^2} = E_t(h_{t+s}^2) = \omega \sum_{i=1}^{s-1}(\alpha + b)^{i-1} + (\alpha + b)^{s-1} h_{t+1}^2 \qquad \textbf{(20)}$$

The optimal estimator of the conditional variance for the prediction line “s” in equation (20) is the conditional expected value of “(h_(t+s)^2)̃ , h_(t+1)^2”. Here, h_(t+1)^2= ω + αε_t^2 + bh_t^2 corresponds to the known equal time “t”.

$$\sigma^2 := \mathrm{Var}(\varepsilon_t) = \frac{\omega}{1-\alpha-b} \qquad \textbf{(21)}$$

The only thing necessary and sufficient for the existence of unconditional variance is the variance value belonging to "ε_t" in the notation (21). It is known that the estimator will tend to have an unconditional variance when the “s” value of the prediction line goes to infinity (s→∞).

$$\widetilde{h_{t+s}^2} = \omega\ (s-1) + h_{t+1}^2 \qquad \textbf{(22)}$$

On the other hand, when the sum of the parameters "α" and "b" is equal to one, the estimator shown in equation (22) is obtained (Caporale et al., 2005).

5. ANALYSIS AND EMPIRICAL FINDINGS

In practice, before moving on to ARCH and GARCH model estimations in time series of high frequency (hourly, daily, weekly, etc.) variables, some prerequisites must be met in order to be able to predict these models. If these prerequisites are met, the estimation phase is started for ARCH and GARCH models. These;

1) Volatility (Clustering) Clustering: Existence and collection of high or low fluctuation clusters experienced in the frequency series,

2) Fat Tails: Frequency series shows thick double tails compared to normal distribution and histogram table is leptokurtic,

3) Stationarity: It consists of prerequisites such as the long-term variances of the frequency series being stationary (Kozhan, 2010: 84).

The application of the research will be done separately for both variables. In the first step, ARCH and GARCH models will be estimated for the r_usd variable and then the most suitable model for the variable will be accepted. Afterwards, diagnostic tests of the accepted model will be applied and the validity of the model will be decided. If the validity of the model is accepted, static prediction will be applied for the model. In the second stage, the same analysis made for the r_usd variable will be applied to the r_eur variable. Thus, both variables will be analyzed separately and compared with each other. Eviews 12 and STATA 17 package programs were used in the application part of the research.

5.1. Implementation of the r_usd Variable

After the preconditions for the time series of the variable subject to the application are met, ARCH and GARCH model predictions of the variable will be started.

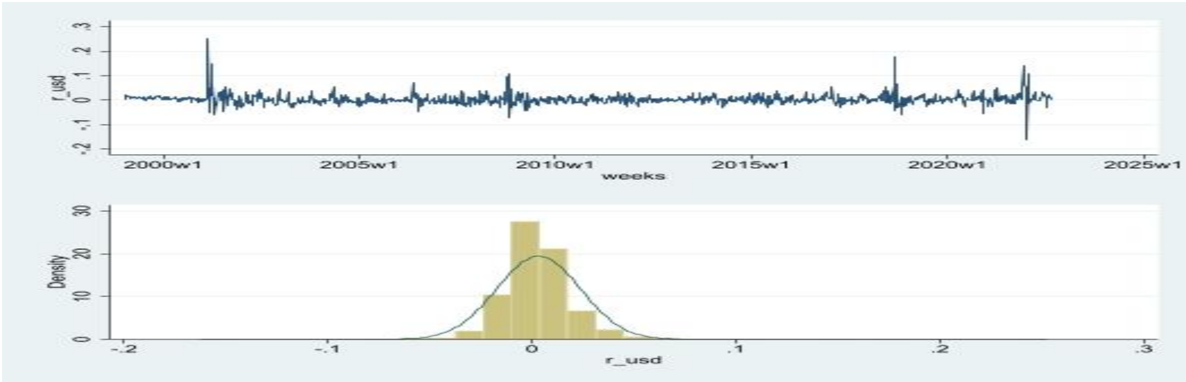


Figure 5. Time Series Prerequisite Graphs of r_usd Variable

Source: It was created by us using the STATA 17 package program.

Figure 4 shows the combined graph for investigating the volatility clustering and fat tails conditions of the r_usd variable. At the top of the graph, in the series of the variable, the volatility experienced in 2001, 2008, 2018 and 2022 is seen, and it is seen that it is clustered in these years. That is, the first condition of the variable is satisfied. In the lower part of the graph, the frequency distribution of the series of the variable is given. It is seen that this scatter plot of the series has a double thick tail feature compared to the normal distribution and the histogram table is leptokurtic, and it is accepted that the second prerequisite is met.

Table 5: ADF Unit Root Test for r_usd Variable

Variables	Augmented Dickey Fuller Unit Root Test		
	Intercept	**Trend & Intercept**	**None**
usd	-3.435453 -2.863681 (6.473017)	-3.965524 -3.413469 (5.037343)	-2.566843 -1.941081 (6.952624)
r_usd	-3.435462* -2.863685** (-16.27500)	-3.435462* -2.863685** (-16.27500)	-2.566846* -1.941081** (-15.76086)

*%1, **5%,***%10% Significance Level Stable, () Test Statistic Value in Parenthese

In Table 5, unit root test results of both the time series usd belonging to the raw values and r_usd belonging to the weekly dollar return used in the application are given for the dollar variable. As seen in the table, usd has unit root at 1% and 5% significance level for all three models. However, it is seen that the ready-to-use r_usd variable of the weekly return of the dollar provides the stagnation condition at the 1% and 5% significance level for all three models (it is sufficient for none model in the literature). Thus, three prerequisites for ARCH and GARCH model estimation are provided for the r_usd variable.

5.1.1. ARCH Model Estimation for the r_usd Variable

As mentioned in the theory part, the AR (p) model will be estimated for the r_usd variable, which is the subject of the research. Afterwards, ARCH-LM test will be applied to determine whether the AR (p) model has ARCH effect. In case of ARCH effect, ARCH (p) model will be estimated and the model will be accepted according to the diagnostic test results.

Table 6: Auto-Regressing (1) Model Estimation for the r_usd Variable

Depented Variable: r_usd			**Auto Regressive (1) Model**	
Variables	**Coefficient**	**Std. Error**	***t-Statistic***	*Prob.*
C	0.002525	0.000578	4.368022	0.0000*
r_usd (-1)	0.227677	0.027787	8.193582	0.0000*
R-squared	0.051836		Akaike info criterion	-4.982277
Log likelihood	3066.100		Schwarz criterion	-4.973960
F-statistic	67.13478		Hannan-Quinn criter	-4.979148
Prob(F-statistic)	0.000000		Durbin-Watson stat	2.008120

*%1, **5%,***10% Significance Level.

As a result of the estimation, it was decided that the most suitable model for the r_usd variable was the AR (1) model. As it is seen in the estimation output of the AR (1) model in Table 4, since the coefficients meet the t statistical value (t >|1.96| for n > 30) (Newblod, 2016), the basic hypothesis is rejected and it is seen that the coefficients of the model are statistically significant.

Table 7: ARCH-LM Test for Auto Regressive (1) Model the r_usd Variable

Depented Variable: RESID^2			**ARCH-LM TEST**	
Variables	**Coefficient**	**Std. Error**	***t-Statistic***	*Prob.*
C	0.002525	0.000578	4.368022	0.0000*
RESID^2(-1)	0.227677	0.027787	8.193582	0.0000*
F-statistic	143.7710		Prob. F(1,1227)	0.0000*
Obs*R-squared	128.9016		Prob. Chi-Square(1)	0.0000*

*%1, **5%,***10% Significance Level.

Table 7 shows the ARCH-LM test result to determine whether the predicted AR (1) model has ARHC effect. According to the output, the coefficient of the square of the error term was statistically significant, and according to the F statistic and χ^2 test statistics in the lower right corner of the output, the basic hypothesis was rejected and the alternative hypothesis that the ARCH effect existed was accepted.

Table 8: ARCH (1)[1] Model Estimation for the r_usd Variable

Depented Variable: r_usd			**ARCH (1) Model**	
Variables	**Coefficient**	**Std. Error**	***z-Statistic***	*Prob.*
C	0.000817	0.000378	2.162753	0.0306**
r_usd (-1)	0.194864	0.011517	16.91981	0.0000*
Mean Equation :	**$r\_usd_t = 0.000817 + 0.194864\ r\_usd_{t-}$**			
C	0.000174	4.63E-06	37.50233	0.0000*
RESID(-1)^2	0.642125	0.034784	18.46016	0.0000*
Variance Equation :	**$r\_usd_t = 0.000174 + 0.642125\ u_{t-1}^2$**			
R-squared	0.042952		Akaike info criterion	-5.348508
Log likelihood	3293.333		Schwarz criterion	-5.331875
Adj. R^2	0.042173		Hannan-Quinn criter	-5.342250
Durbin-Watson stat	1.924951			

*%1, **5%,***10% Significance Level.

The output of the ARCH (1) model estimation is shown in Table 8. The coefficients of the mean equation and variance equation according to the output are statistically significant since $p < 0.05$. In addition, the parameters in the variance equation provide the assumption of $0<\gamma0$ and $0<\gamma1<1$. The average return of the variable r_usd according to the constant parameter in the average equation is $\gamma0 = 0.000817$. Therefore, it is possible to say that the ARCH (1) model estimated for r_usd is statistically significant and meets the model assumptions (in accordance with the principle of disposition).

5.1.2. ARCH (1) Model Diagnostic Tests for the r_usd Variable

For the validity of the estimated ARCH (1) model, it must pass diagnostic tests as well as providing the model assumptions. Otherwise, the predicted model will not be accepted because it will not be valid. The first of the diagnostic tests is the heteroskedasticity test. Since the statistical values for this test (Prob. F(1, 1227) = 0.8910 and Probe. χ^2 (1) = 0.8909) F >

[1] For the variable that is the subject of the research, the ARCH (p) model was estimated separately from different orders, and it was decided that the order that fulfills the ARCH (p) model assumptions is (1). In other model estimations, such as ARCH (2), ARCH (4) and ARCH (8) models, the parameters were greater than 1 or negative, and the ARCH model assumptions could not be met. In order not to take up much space in the study, the model outputs of the estimations made for other levels are not included.

0.005 and χ^2 >0.005, the basic hypothesis that there is no variance for this test was accepted. . That is, the predicted model fulfilled the heteroskedasticity condition, which is the first of the diagnostic tests. Another diagnostic test is the Corregram Q Test, which is the test for the error term to have the property of white noise. In this test, the Q statistics of autocorrelation and partial autocorrelation values and Prob. are decided according to their values (Box and Jenkins, 1976).

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.108	0.108	14.443	0.000
		2	0.018	0.006	14.843	0.001
		3	0.078	0.076	22.307	0.000
		4	0.014	-0.002	22.566	0.000
		5	0.063	0.062	27.491	0.000
		6	0.047	0.028	30.193	0.000
		7	-0.067	-0.078	35.714	0.000
		8	0.020	0.027	36.231	0.000
		9	-0.032	-0.044	37.471	0.000
		10	-0.019	-0.005	37.937	0.000
		11	-0.049	-0.055	40.930	0.000
		12	0.001	0.026	40.932	0.000
		13	0.010	0.013	41.064	0.000
		14	0.057	0.061	45.179	0.000
		15	-0.045	-0.053	47.693	0.000
		16	-0.022	-0.012	48.279	0.000
		17	0.030	0.029	49.418	0.000
		18	-0.006	-0.018	49.467	0.000
		19	0.014	0.016	49.729	0.000
		20	0.007	-0.004	49.795	0.000
		21	-0.051	-0.037	53.077	0.000
		22	-0.004	-0.011	53.096	0.000
		23	-0.015	-0.009	53.369	0.000
		24	-0.001	0.012	53.371	0.001
		25	0.014	0.015	53.633	0.001
		26	0.060	0.064	58.114	0.000
		27	0.007	-0.006	58.180	0.000
		28	0.048	0.046	61.136	0.000
		29	0.035	0.023	62.714	0.000
		30	0.028	0.016	63.734	0.000
		31	0.005	-0.021	63.768	0.000
		32	0.016	0.006	64.073	0.001
		33	0.021	0.017	64.624	0.001
		34	0.048	0.036	67.519	0.001
		35	0.027	0.032	68.423	0.001
		36	-0.021	-0.034	69.007	0.001

Figure 6. Corregram Q Table for ARCH (1) Model for Variable r_usd

Source: It was created by us using the Eviews 12 package program.

In Figure 5 and Figure 7, there is 36 delayed Corregram Q table of the estimated model. As can be seen in the figures, Q statistics and Prob. Since the model could not provide the white noise feature according to the ($p<0.05$) values, the estimated model was deemed invalid.

5.1.3. GARCH Model Estimation for the r_usd Variable

Since the ARCH model estimated for the variable r_usd, which is the subject of the research, did not meet the white noise condition from the diagnostic tests, the GARCH model was estimated for this variable.

Table 9: GARCH (1.1)[2] Model Estimate for the r_usd Variable (Generalized Error Distribution)[3]

Depented Variable: r_usd			**GARCH (1,1) Model**	
Variables	**Coefficient**	**Std. Error**	***z-Statistic***	*Prob.*
C	0.001134	0.000333	3.404242	0.0007*
r_usd (-1)	0.355102	0.028231	12.57844	0.0000*

[2] GARCH (p,q) models of different orders were estimated separately as GARCH (1,2), GARCH(1,4), GARCH (1,6) and GARCH (2,1) for the variable that was the subject of the research. These estimated models, only the GARCH (1,1) model provides the assumptions for the parameters explained in the theory part. Therefore, only the output of the GARCH (1,1) model estimation is included in the study.

[3] While estimating the model, one of three different distribution types is preferred for the error term. These; Gaussian (Normal) Distribution is Student's t Distribution and Generalized Error Distribution. The model has been estimated separately for all three distribution types by us, and the model has been subjected to diagnostic test tests for these three distributions that can be preferred. As a result of the diagnostic test test, heteroskedasticity problem arose in the model estimated using Student's t Distribution, and the model estimated using Gaussian Distribution and Generalized Error Distribution passed the diagnostic tests. Log likelihood value for the model estimated using Gaussian Distribution and Generalized Error Distribution, Adj. R^2 value, Akaike Information Criteria and Schwarz Information Criteria were compared, and the most appropriate distribution model was accepted for the estimated model, and the output of this model was included.

Mean Equation :	**$r\_usd_t = 0.001134 + 0.355102\ r\_usd_{t-1}$**			
C	2.70E-05	5.64E-06	4.781302	0.0001*
RESID(-1)^2	0.274560	0.037565	7.308845	0.0000*
GARCH (-1)	0.652082	0.043673	14.93112	0.0000*
Variance Equation :	**$r\_usd_t = 0.00000270 + 0.652082\ r\_usd_{t-1} + 0.274560\ u^2_{t-1}$**			

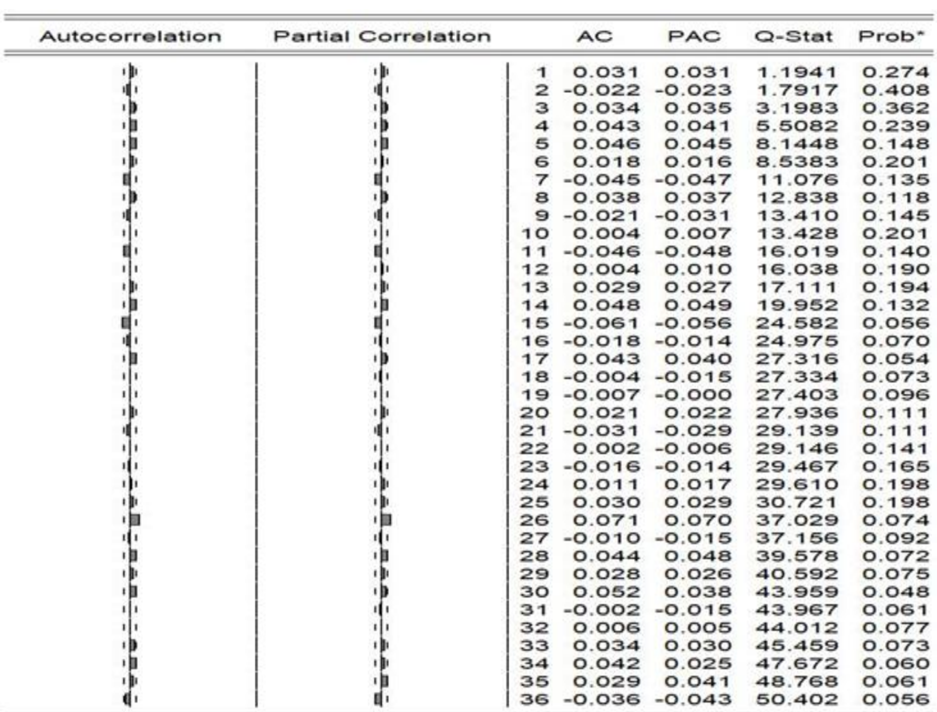
R-squared	0.033350	Akaike info criterion	-5.614013
Log likelihood	3458.618	Schwarz criterion	-5.589063
Adj. R^2	0.032563	Hannan-Quinn criter	-5.604626
Durbin-Watson stat	2.250442		

*%1, **5%,***10% Significance Level.

Table 9 shows the GARCH (1,1) model prediction output of the r_usd variable. According to the output, it is understood that the coefficients in the average equation are $p<0.05$ and are statistically significant at the $\alpha=0.001$ significance level. According to the average equation parameters, the average return of the r_usd variable is 0.001134, while the current value of the variable from past values is 0.355102. The parameters of the variance equation are the coefficient of the constant variance term, and the ARCH and GARCH parameters are significant at the $\alpha = 0.001$ level. The constant of time-varying variance is 0.00000270, and the current value of the variable is estimated to be 0.652082 from past values, while 0.274560 of this is based on past errors. In other words, it shows that a possible shock effect on the r_usd variable will be included in the variance estimates for the next period. The parameters in both equations satisfy the condition $\alpha\_0 >0$, $\alpha\_i \geq 0$, $\beta\_j \geq 0$. In addition, if the parameters in the variance equation meet the condition $\alpha\_i + \beta\_j < 1$, it shows that all assumptions of the GARCH model (including the principle of parsimony) are met.

5.1.4. GARCH (1,1) Model for r_usd Variable Diagnostic Tests and Static Prediction

After the estimated GARCH (1,1) model satisfies the necessary model assumptions, the diagnostic test results to decide its validity: Heteroskedasticity test result (Prob. F(36, 1157) = 0.1720 and Prob. χ^2 (36) = 0.1739) According to F > 0.005 and χ^2 >0.005, the basic hypothesis of this test was accepted and it was decided that there was no problem of varying variance in the model.

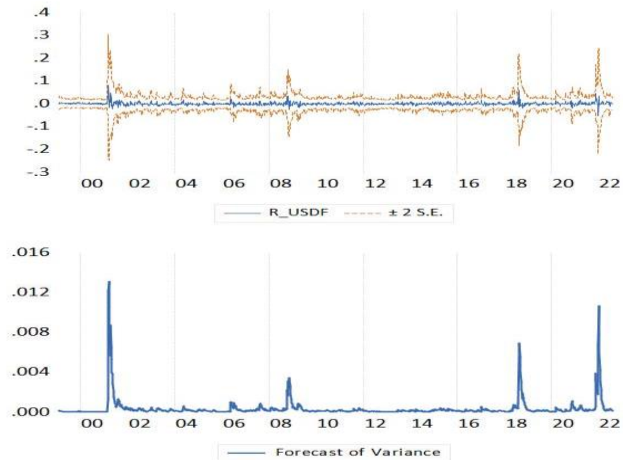


	AC	PAC	Q-Stat	Prob*
1	0.031	0.031	1.1941	0.274
2	-0.022	-0.023	1.7917	0.408
3	0.034	0.035	3.1983	0.362
4	0.043	0.041	5.5082	0.239
5	0.046	0.045	8.1448	0.148
6	0.018	0.016	8.5383	0.201
7	-0.045	-0.047	11.076	0.135
8	0.038	0.037	12.838	0.118
9	-0.021	-0.031	13.410	0.145
10	0.004	0.007	13.428	0.201
11	-0.046	-0.048	16.019	0.140
12	0.004	0.010	16.038	0.190
13	0.029	0.027	17.111	0.194
14	0.048	0.049	19.952	0.132
15	-0.061	-0.056	24.582	0.056
16	-0.018	-0.014	24.975	0.070
17	0.043	0.040	27.316	0.054
18	-0.004	-0.015	27.334	0.073
19	-0.007	-0.000	27.403	0.096
20	0.021	0.022	27.936	0.111
21	-0.031	-0.029	29.139	0.111
22	0.002	-0.006	29.146	0.141
23	-0.016	-0.014	29.467	0.165
24	0.011	0.017	29.610	0.198
25	0.030	0.029	30.721	0.198
26	0.071	0.070	37.029	0.074
27	-0.010	-0.015	37.156	0.092
28	0.044	0.048	39.578	0.072
29	0.028	0.026	40.592	0.075
30	0.052	0.038	43.959	0.048
31	-0.002	-0.015	43.967	0.061
32	0.006	0.005	44.012	0.077
33	0.034	0.030	45.459	0.073
34	0.042	0.025	47.672	0.060
35	0.029	0.041	48.768	0.061
36	-0.036	-0.043	50.402	0.056

Figure 7. Corregram Q Table for GARCH (1.1) Model for Variable r_usd

Source: It was created by us using the Eviews 12 package program.

The autocorrelation and partial autocorrelation limits up to 36 lags of the model estimated in Figure 6 and Figure 7, Q statistics and Prob. There is a Corregram Q statistics table showing the values. According to the table, autocorrelation and partial autocorrelation limits were not violated for all 36 lags. Since all of the values ($p>0.001$ for the 30th delay only) are $p>0.05$, the model satisfies the white noise condition. Thus, it is concluded that the estimated GARCH (1,1) model is valid.

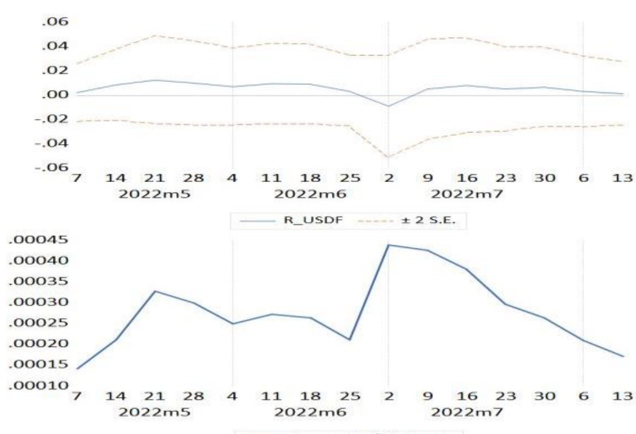


Forecast: R_USDF	
Actual: R_USD	
Forecast sample: 1/09/1999 8/13/2022	
Adjusted sample: 1/23/1999 8/13/2022	
Included observations: 1230	
Root Mean Squared Error	0.020138
Mean Absolute Error	0.012220
Mean Abs. Percent Error	181.0409
Theil Inequality Coef.	0.718608
Bias Proportion	0.001830
Variance Proportion	0.465628
Covariance Proportion	0.532541
Theil U2 Coefficient	0.962647
Symmetric MAPE	140.0076

Figure 8. Prediction of Variance for the r_usd Variable

Source: It was created by us using the Eviews 12 package program.

Figure 7 shows the static forecasting application using all the data belonging to the r_usd variable. Although the figure above shows that the return of the r_usd variable is stable within the estimation limits, it is seen that the volatility is extremely high, especially in 2001, 2018 and 2022, as seen in the variance prediction in the lower figure.



Forecast: R_USDF	
Actual: R_USD	
Forecast sample: 5/07/2022 8/13/2022	
Included observations: 15	
Root Mean Squared Error	0.016047
Mean Absolute Error	0.012877
Mean Abs. Percent Error	100.7799
Theil Inequality Coef.	0.588710
Bias Proportion	0.206893
Variance Proportion	0.410710
Covariance Proportion	0.382398
Theil U2 Coefficient	0.975356
Symmetric MAPE	103.4941

Figure 9. Static Forecast for r_usd Variable

Source: It was created by us using the Eviews 12 package program.

Figure 8 represents the modified static prediction graph for the r_usd variable. By using the values of the variable three months ago (07/05/2022), the volatility prediction for the period (13/08/2022) three months after its historical values was estimated. As can be seen in the figure above, while the return of the r_usd variable is stable, it is seen that the volatility after three months has increased (especially for June). Thus, it is possible to say that the prediction made based on the variable's own historical data is successful.

5.2. Implementation of the r_eur Variable

Under this title, which is the second part of the application part, the analysis of the r_eur variable will be made. All of the analysis for the previous variable will be applied within the r_eur variable. Therefore, in order not to repeat the same things, only the analysis outputs and values will be interpreted in the analysis for the r_eur variable.

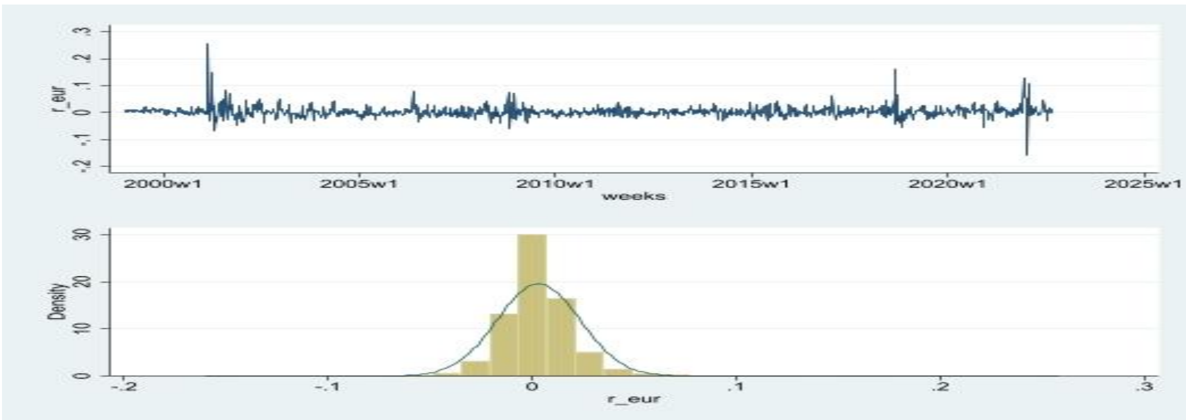


Figure 10. Time Series Prerequisite Graphs of r_eur Variable

Source: It was created by us using the STATA 17 package program.

Figure 9 shows the composite chart for investigating pre-analysis prerequisites for the r_eur variable. As seen in the upper part of the chart, there are clusters of volatility experienced in 2001, 2008, 2018 and 2022. In the lower part of the graph, it is seen that the frequency distribution of the variable is fat tail compared to the normal distribution and the prerequisites for the histogram table to have leptokurtic characteristics are met.

Table 10: ADF Unit Root Test for r_eur Variable

Variables	Augmented Dickey Fuller Unit Root Test		
	Intercept	**Trend & Intercept**	**None**
	-3.435453	-3.965524	-2.566843
eur	-2.863681	-3.413469	-1.941081
	(4.943802)	(3.397407)	(5.653552)
	-3.435453*	-3.965524*	-2.566843*
r_eur	-2.863681**	-3.413469**	-1.941081**
	(--27.72632)	(-27.71700)	(-27.21199)

*%1, **5%,***%10% Significance Level Stable, () Test Statistic Value in Parentheses

The ADF unit root test results of the variable r_eur are shown in Table 10. According to the test results, the main hypothesis was rejected at the 1% significance level in the null model for the r_eur variable and the series was decided to be stationary. Thus, the variable r_eur satisfies all the prerequisites for analysis.

5.2.1. ARCH Model Estimation for the r_eur Variable

After the prerequisite research, the ARCH model estimation phase was started for the r_eur variable.

Depented Variable: r_eur			**Auto Regressive (1) Model**	
Variables	**Coefficient**	**Std. Error**	***t-Statistic***	*Prob.*
C	0.002432	0.000573	4.243654	0.0000*
r_eur (-1)	0.229970	0.027773	8.280475	0.0000*
R-squared	0.052883		Akaike info criterion	-4.998689
Log likelihood	3076.194		Schwarz criterion	-4.990373
F-statistic	68.56626		Hannan-Quinn criter	-4.995560
Prob(F-statistic)	0.000000		Durbin-Watson stat	1.997992

*%1, **5%,***%10% Significance Level

Table 11 shows the output of the estimated AR (1) model. The t statistics of the coefficients in the output and the Prob. values were determined to be statistically significant. In the next process, the ARCH effect of the predicted AR (1) model will be investigated.

Table 12: ARCH-LM Test for Auto Regressive (1) Model for the r_eur Variable

Depented Variable: RESID^2			**ARCH-LM TEST**	
Variables	**Coefficient**	**Std. Error**	***t-Statistic***	*Prob.*
C	0.000287	6.09E-05	4.709931	0.0000*
RESID^2(-1)	0.272619	0.027467	9.925401	0.0000*
F-statistic	98.51358		Prob. F(1,1227)	0.0000*
Obs*R-squared	91.34059		Prob. Chi-Square(1)	0.0000*

*%1, **5%,***%10% Significance Level

In Table 12, there is the ARCH-LM test output to investigate the ARCH effect of the estimated AR (1) model. t statistics of the square of the error term according to the output and Prob. values were statistically significant. According to the F statistics and χ^2 table values in the lower right corner of the table, the basic hypothesis of this test was rejected and the alternative hypothesis that there was ARCH effect was accepted.

Table 13: ARCH (1)[4] Model Estimation for the r_eur Variable

Depented Variable: r_eur			**ARCH (1) Model**	
Variables	**Coefficient**	**Std. Error**	***z-Statistic***	*Prob.*
C	0.000830	0.000384	2.163024	0.0305**
r_eur (-1)	0.336195	0.017231	19.51106	0.0000*
Mean Equation :	$\mathbf{r\_eur_t = 0.000830 + 0.336195\ r\_eur_{t-1}}$			
C	0.000167	3.73E-06	44.75549	0.0000*
RESID(-1)^2	0.630704	0.037318	16.90080	0.0000*
Variance Equation :	$\mathbf{r\_eur_t = 0.000167 + 0.630704\ u_{t-1}^2}$			
R-squared	0.037750		Akaike info criterion	-5.377651
Log likelihood	3311.255		Schwarz criterion	-5.361018
Adj. R^2	0.036966		Hannan-Quinn criter	-5.371393
Durbin-Watson stat	2.192843			

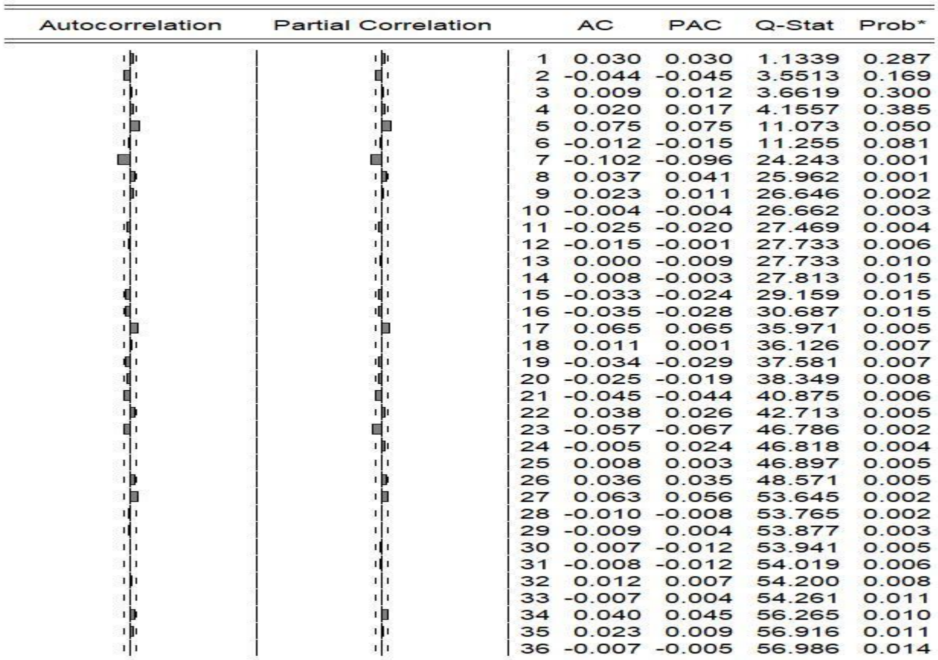
*%1, **5%,***%10% Significance Level

The output of the ARCH (1) model estimation is shown in Table 13. It is seen that the coefficients of the mean equation and variance equation according to the output are statistically significant at the 1% significance level. The constant parameter $\gamma 0$=0.00830 in the average equation shows the average return of the r_eur variable. Again, the parameters in both equations provide the assumption of $0<\gamma 0$ and $0<\gamma 1<1$ of the ARCH (p) model.

5.2.2. ARCH (1) Model Diagnostic Tests for the r_eur Variable

The predicted ARCH (1) model must pass the diagnostic test tests, is the validity condition, as well as satisfying the necessary assumptions. For this, first of all, heteroskedasticity test was performed. Since the values (Prob. F(1, 1227) = 0.9483 and Probe. χ^2 (1) = 0.9482) according to this test result, F > 0.005 and χ^2 >0.005, the basic hypothesis that there is no variance for this test was accepted. In addition, the predicted model passed this test.

[4] It was decided that the most appropriate model estimation among the model estimation results made from different orders for the variable that was the subject of the research was the ARCH (1) model (in accordance with the parsimony principle), and only the output of this model estimation was included.



	AC	PAC	Q-Stat	Prob*
1	0.030	0.030	1.1339	0.287
2	-0.044	-0.045	3.5513	0.169
3	0.009	0.012	3.6619	0.300
4	0.020	0.017	4.1557	0.385
5	0.075	0.075	11.073	0.050
6	-0.012	-0.015	11.255	0.081
7	-0.102	-0.096	24.243	0.001
8	0.037	0.041	25.962	0.001
9	0.023	0.011	26.646	0.002
10	-0.004	-0.004	26.662	0.003
11	-0.025	-0.020	27.469	0.004
12	-0.015	-0.001	27.733	0.006
13	0.000	-0.009	27.733	0.010
14	0.008	-0.003	27.813	0.015
15	-0.033	-0.024	29.159	0.015
16	-0.035	-0.028	30.687	0.015
17	0.065	0.065	35.971	0.005
18	0.011	0.001	36.126	0.007
19	-0.034	-0.029	37.581	0.007
20	-0.025	-0.019	38.349	0.008
21	-0.045	-0.044	40.875	0.006
22	0.038	0.026	42.713	0.005
23	-0.057	-0.067	46.786	0.002
24	-0.005	0.024	46.818	0.004
25	0.008	0.003	46.897	0.005
26	0.036	0.035	48.571	0.005
27	0.063	0.056	53.645	0.002
28	-0.010	-0.008	53.765	0.002
29	-0.009	0.004	53.877	0.003
30	0.007	-0.012	53.941	0.005
31	-0.008	-0.012	54.019	0.006
32	0.012	0.007	54.200	0.008
33	-0.007	0.004	54.261	0.011
34	0.040	0.045	56.265	0.010
35	0.023	0.009	56.916	0.011
36	-0.007	-0.005	56.986	0.014

Figure 11. Corregram Q Table for ARCH (1) Model for Variable r_eur

Source: It was created by us using the Eviews 12 package program.

Figure 9 shows the 36 delayed Corregram Q statistical table of the estimated ARCH (1) model. In the model estimated according to the figure, both according to the limits of autocorrelation and partial autocorrelation, as well as Q statistics and Prob. According to the ($p<0.005$) values, the white noise condition cannot be met in some delays. That is, the predicted model did not meet the validity criterion because it did not pass this test.

5.2.3. GARCH Model Estimation for the r_eur Variable

As the ARCH (1) prediction model was not accepted by failing the diagnostic tests, the GARCH (1,1) model was estimated.

Table 14: GARCH (1.1) Model Estimation for the Variable r_eur (Gaussian Distribution)

Depented Variable: r_eur			**GARCH (1,1) Model**	
Variables	**Coefficient**	**Std. Error**	***z-Statistic***	*Prob.*
C	0.001504	0.000360	4.176119	0.0000*
r_eur (-1)	0.322188	0.034070	9.456675	0.0000*
Mean Equation :	$\mathbf{r\_eur_t = 0.001504 + 0.322188\ r\_eur_{t-1}}$			
C	3.15E-05	3.56E-06	8.860449	0.0001*
RESID(-1)^2	0.393046	0.023911	16.43815	0.0000*
GARCH (-1)	0.560549	0.024157	23.20487	0.0000*
Variance Equation :	$\mathbf{r\_eur_t = 0.00000315 + 0.560549\ r\_eur_{t-1} + 0.393046\ u^2_{t-1}}$			
R-squared	0.043407		Akaike info criterion	-5.534854
Log likelihood	3408.935		Schwarz criterion	-5.514062
Adj. R^2	0.042628		Hannan-Quinn criter	-5.527031
Durbin-Watson stat	2.173719			

*%1, **5%,***%10% Significance Level

Table 14 shows the GARCH (1,1) model prediction output. The coefficients of the average equation were considered statistically significant at the $\alpha = 0.001$ significance level. While the return of the r_eur variable in the average equation according to its fixed parameter is 0.001504, the coefficient that predicts the current value of the variable from past values is 0.322188. The constant parameters of the variance equation, ARCH, and GARCH parameters were considered statistically significant at the $\alpha=0.001$ significance level. While the fixed parameter of the time-varying variance is 0.00000315, the coefficient of estimating the current value of the variable from its past values is 0.560549, and 0.393046 of this value is explained by the error term. It is seen that the parameters in both the mean and variance equations satisfy the conditions α_0 >0, α_i≥0, β_j ≥0. In addition, as another assumption, if the parameters in the variance equation meet the condition α_i + β_j < 1, it shows that all assumptions of the GARCH model (including the attitude principle) are met.

5.2.4. GARCH (1,1) Model Diagnostic Tests and Static Prediction for r_eur variable

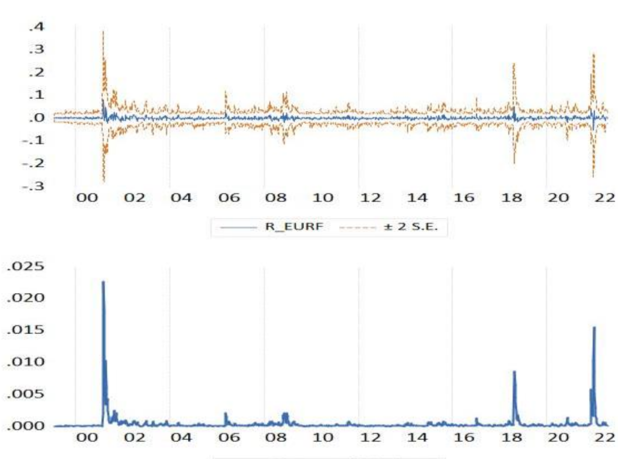
According to the heteroskedasticity test results (Prob. F(36, 1157) = 0.0568 ve Prob. χ^2 (36) = 0.0592) F > 0.005 and χ According to ^2 >0.005, the basic hypothesis of this test was accepted and it was decided that there was no problem of varying variance in the model.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.036	0.036	1.6051	0.205
		2	-0.019	-0.020	2.0334	0.362
		3	0.036	0.038	3.6689	0.300
		4	0.044	0.041	6.0101	0.198
		5	0.048	0.047	8.8938	0.113
		6	0.018	0.015	9.3090	0.157
		7	-0.047	-0.050	12.071	0.098
		8	0.037	0.036	13.752	0.088
		9	-0.020	-0.030	14.271	0.113
		10	0.002	0.005	14.275	0.161
		11	-0.046	-0.048	16.858	0.112
		12	0.004	0.011	16.876	0.154
		13	0.030	0.028	17.995	0.158
		14	0.052	0.053	21.349	0.093
		15	-0.059	-0.055	25.677	0.042
		16	-0.016	-0.012	26.003	0.054
		17	0.043	0.040	28.343	0.041
		18	-0.004	-0.016	28.364	0.057
		19	-0.007	-0.001	28.434	0.075
		20	0.021	0.022	28.988	0.088
		21	-0.032	-0.030	30.306	0.086
		22	0.002	-0.007	30.311	0.111
		23	-0.016	-0.014	30.644	0.132
		24	0.010	0.017	30.781	0.160
		25	0.029	0.029	31.807	0.164
		26	0.069	0.069	37.854	0.062
		27	-0.010	-0.015	37.986	0.078
		28	0.043	0.046	40.339	0.062
		29	0.027	0.025	41.290	0.065
		30	0.051	0.037	44.598	0.042
		31	-0.000	-0.014	44.599	0.054
		32	0.006	0.005	44.638	0.068
		33	0.034	0.030	46.112	0.064
		34	0.042	0.024	48.309	0.053
		35	0.029	0.041	49.410	0.054
		36	-0.034	-0.042	50.913	0.051

Figure 12. Corregram Q Table for GARCH (1.1) Model for Variable r_eur

Source: It was created by us using the Eviews 12 package program.

While it is seen that the autocorrelation and partial autocorrelation boundary lines in the 36 lagged Corregram Q statistics test table in Figure 10 are not violated, the Q statistics values and Prob. According to the values (14. lag, 17. lag and 30. lag at p>0.01 significance level), most of the delays have white noise characteristics since p>0.05. According to these test results, the validity of the GARCH (1,1) estimation model was decided.



Forecast: R_EURF	
Actual: R_EUR	
Forecast sample: 1/09/1999 8/13/2022	
Adjusted sample: 1/23/1999 8/13/2022	
Included observations: 1230	
Root Mean Squared Error	0.019942
Mean Absolute Error	0.012349
Mean Abs. Percent Error	NA
Theil Inequality Coef.	0.720753
Bias Proportion	0.001015
Variance Proportion	0.480510
Covariance Proportion	0.518475
Theil U2 Coefficient	NA
Symmetric MAPE	141.5882

Figure 13. Prediction of Variance for the r_usd Variable

Source: It was created by us using the Eviews 12 package program.

Figure 11 shows the static forecasting application using all the historical data of the r_eur variable. Although the figure in the upper part shows that the return of the r_eur variable is stable within the estimation limits, as seen in the prediction of the variance in the lower figure, it is seen that the volatility is extremely high, especially in 2001, 2018 and 2022.

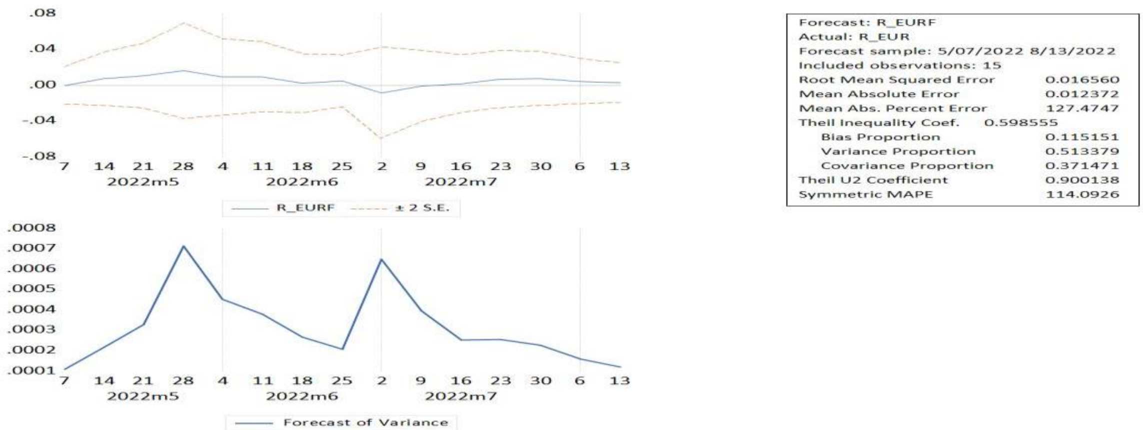


Figure 14. Static Forecast for r_usd Variable

Source: It was created by us using the Eviews 12 package program.

Figure 12 represents the modified static prediction chart for the variable r_usd. Using the values of the variable three months ago (07/05/2022), the volatility estimate for the period three months after (13/08/2022) was estimated from its historical values. As seen in the figure above, while the return of the r_usd variable is stable, it is seen that volatility increases after three months (especially in May and June). Therefore, it is possible to say that the prediction made based on the variable's own historical data is successful in this variable.

6. CONCLUSION

Exchange rate is one of the important mechanisms that shape macroeconomic variables. Within the framework of this importance, the volatility of the US Dollar and Euro in Türkiye and how they affected financial assets in the period from 1999, when the EU adopted the common currency Euro, to 2022 was investigated. Today, the demand for foreign exchange, which is seen as financial return by investors, is affected by developments both domestically and abroad. This study makes a significant contribution to the literature by examining Euro and US Dollar volatility in Türkiye between 1999 and 2022 with ARCH and GARCH models.

In the study, the sample of the research includes 1243 observations using weekly data between the dates 09.01.1999-19.08.2022. The series of the variables are expressed as follows; US dollar yield series: r_usd; The yield series of Euro is shown as: r_eur. Before proceeding to ARCH and GARCH modeling, preconditions such as volatile clustering, thick tails and stationarity were tested and the results were statistically significant.

In ARCH and GARCH model estimation, it is decided that the valid model for both r_usd return series and r_eur return series is GARCH (1,1). While the return of the r_usd variable, which shows the dollar return series, was stable, it was observed that its volatility increased in May and June of 2022. In addition, it was observed that the volatility in the return series of the r_eur variable was extremely high in 2001, 2018 and 2022.

Therefore, it supports the studies of Bekar (2023), Demir and Kesekler (2019), Gün (2019), Uysal and Özşahin (2012), who observed that volatility increased during the period of economic crisis and inflationary fluctuations in the literature.

In summary, it has been concluded that Türkiye, which is both an exporter and an importer in foreign trade, has increased the volatility in the exchange rate as a result of the economic crises experienced both at home and abroad. In this sense, it makes an important contribution to the literature.

AUTHOR DECLARATIONS

Declarations of Research and Publication Ethics: This study has been prepared in accordance with scientific research and publication ethics.

Ethics Committee Approval: Since this research does not include analyzes that require ethics committee approval, it does not require ethics committee approval.

Author Contributions: The author has done all the work alone.

Conflict of Interest: There is no conflict of interest arising from the study for the author or third parties.

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