

**T.C.
GALATASARAY ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI**

**TÜRKİYE’DE COVID-19 PANDEMİ KRİZİNDE DÖVİZ KURU
VOLATİLİTESİ**

YÜKSEK LİSANS TEZİ

ÖMER FARUK ALTUN

Tez Danışmanı: Doç. Dr. Ata ÖZKAYA

ENSTİTÜYE SUNULDUĞU TARİH: 02/2022

PREFACE

In this section, I would like to talk about the invisible heroes who helped me a lot in the writing of this thesis. First of all, the constant support of my life partner, my fiancée Tuana VATANSEVER, was one of my biggest motivations for writing this thesis, I always felt happy to have a wife like her. I am proud of my family as they have always supported me under all circumstances.

My thesis advisor, the esteemed Ata ÖZKAYA, provided me with detailed explanations even at his busiest time, and helped me spend the most productive time of my education and training life. I think I am really lucky to work with a teacher like Ata ÖZKAYA, he has contributed a lot to me with his deep knowledge of mathematics and his way of interpreting current economics. I will always be grateful to him.

Another hero is the venerable Serdar ALTAY. I cannot thank him enough. The things he contributed to me shed light not only on my education life, but also on my spiritual life. The conversations I had with him have always added quality to my life. I am grateful to him.

Although I have just joined, I would like to express my gratitude to the Garanti BBVA family. I am proud to be a part of Garanti BBVA family, which has my back in every sense and does not spare its support in data sharing. I am grateful to my friend Fatih BAKSIN and İbrahim ATİK who are more than just a friend, for always listening to me in every situation. I would like to thank my brother Halil İbrahim ALTUN and my cousin Berkay BENGİLER for always making me feel safe and secure.

Finally, I would like to express my endless thanks to all my Galatasaray University economics department teachers for the valuable information they have provided me for 2 years. I am sure that the 2 years I spent here formed a very good foundation for my future career. One of the best decisions I have made in my life was to come to this school and take lessons from these valuable teachers.

TABLE OF CONTENTS

PREFACE	II
TABLE OF CONTENTS	III
LIST OF ABBREVIATIONS	V
LIST OF SYMBOLS	VII
LIST OF FIGURES	IX
LIST OF TABLES	XI
ABSTRACT	XIV
1. INTRODUCTION	1
2. TURKEY'S PAST CRISIS EXPERIENCES AND PANDEMIC CRISIS.....	6
2.1. 1994 Economic Crisis	6
2.2. 2001 Economic Crisis	7
2.3. 2008 Global Economic Crisis.....	8
2.4. The World's Economy in the Pandemic Crisis	9
2.5. Turkish Economy in the Pandemic Crisis.....	9
3. LITERATURE REVIEW	12
3.1. The Volatility Measuring.....	12
3.2. The Volatility Measuring Models.....	13
3.3. Arch Class Conditional Volatility Models.....	14
3.3.1. Mathematical Definition of ARCH/GARCH Models	15
3.3.2. The General Problems of ARCH/GARCH Models	18
3.4. Some Basic Volatility Indexes and Their Mathematical Definitions	19
3.4.1. The Mathematical Definition of VIX.....	20
3.5. Can be VIX Model be Used to Gauge Emerging Markets Volatility Model?	21
3.6. The Comparison Between VIX Model, Implied Volatility Model and GARCH Model.....	21
3.7. ARCH/GARCH Usage Areas	22
3.8. The Volatility Decreasing Policies of Central Banks.....	23
3.9. Reel Effective Exchange Rate.....	25
3.10. FED Yield Curve Calculation and Its Interpretation	25
3.11. Biomedical Engineering and Epilepsy Literature	30
4. AN EXCHANGE RATE VOLATILITY MODELLING	32
4.1. The Regression Model.....	32
4.2. Graphical Representation.....	33
4.3. Non-Normality Distribution of Fat Tails (Skewness and Kurtosis Values)	34

4.4. Correlogram Analysis	37
4.5. Breusch-Pagan Test.....	44
4.6. White Test	45
4.7. Stationarity.....	45
4.8. GARCH (1,1) MODEL	53
5. CONCLUSION.....	56
5.1. Factors May Increase the Effects of VIX and CDS.....	56
5.2. Policy Recommendations	57
6. REFERENCES	59
7. APPENDIX	65
7.1. Augmented Dickey Fuller (ADF) and Phillips Perron (PP) Test Results on Stata.....	65
7.2. GARCH (1,1) MODEL	86
7.3. Autocorrelation Test Results (Breusch-Godfrey LM test) <i>Rt</i>	87
8. RESUME.....	90

LIST OF ABBREVIATIONS

ADF	: Augmented Dickey Fuller
AIC	: Akaike Information Criteria
AR	: Autoregressive
ARCH	: Autoregressive Conditional Heteroscedasticity
ARIMA	: Autoregressive Integrated Moving Average
ARMA	: Autoregressive Moving Average
BIS	: Bank for International Settlements
CA	: Current Account
CBRT	: Central Bank of the Republic of Turkey
CDS	: Credit Default Swap
CPI	: Consumer Price Index
DCDS	: The First Difference of Credit Default Swap
DF	: Dickey Fuller
ECB	: European Central Bank
EU	: European Union
FED	: Federal Reserve
FOMC	: Federal Open Market Committee
GARCH	: Generalized Autoregressive Conditional Heteroscedasticity
GDP	: Gross Domestic Product
GNP	: Gross National Product
HQ	: Hannan-Quinn Information Criteria
ILO	: International Labor Organization
IMF	: International Monetary Fund
INFDIF	: Inflation Difference
LM	: Lagrange Multiplier
MA	: Moving Average
OECD	: Organization for Economic Co-operation and Development
OLS	: Ordinary Least Squares

OPEC	: Organization of Petroleum Exporting Countries
PMI	: Purchasing Manager Index
PP	: Phillips Perron
PPI	: Producer Price Index
REER	: Reel Effective Exchange Rate
ROM	: Reserve Option Mechanism
RVIX	: Percentage Change of Volatility Index
SC	: Schwarz Information Criteria
TL	: Turkish Lira
TLREF	: Turkish Lira Reference Interest Rate
UK	: United Kingdom
USA	: United States of America
USD	: United States Dollar
USDX	: United States Dollar Index
VAR	: Variance
VIX	: Volatility Index
WB	: World Bank

LIST OF SYMBOLS

$E(INF_{At}^{t+k})$	: the daily inflation expectation of USA
H_0	: Hypothesis type 0
H_1	: Hypothesis type 1
K_i	: Strike price of i^{th} out-of-the-money option
K_0	: first strike below forward index level
P_{TUR}	: Turkey's price index
P_t	: USD/TL currency
$\bar{R}$	: Average expected return
R_t	: the percentage change of USD/TR currency
R_t^L	: 10-year government bond rate
R_t^S	: 3-month T-bill rate
S^2	: Skewness
$USDX_t$	: US dollar index at time t
Z_t	: Test Statistic value at time t
b_i	: coefficient of variance
$e_{i.TUR}$	: the exchange rate value of country "i" currency in TL
h_t	: Variance of error term at time t
u_i	: the error terms
u^2	: square of residual
w_i	: weight of country "i"
y_t	: dependent variable value at time t
y_{t-i}	: lagged dependent variable value
$\Delta TLREF_t$	: the reference interest rate of Turkish Lira at time t
δ_i	: coefficient of independent variables
ε_t	: error term at time t
σ_u^2	: the variance square of error
ψ_{t-1}	: Information set

μ	: expected value (mean)
F	: Forward index level derived from index option prices
C	: constant value of equation
$E(INF_t^{t+k})$	: the daily inflation expectation of Turkey
$E(\varepsilon_t)$	: Expected value of error term
K	: Kurtosis
N	: Number of observations
$RVIX_t$	: Percentage change of square rooted VIX
$Var(y_{t+1} x_t)$	: Conditional variance of y with respect to x
$Var(\varepsilon_t)$	: Variance of error term
Δ	: difference
ΔCDS_t	: the percentage change of Credit Default Swap at time t
$\Delta USDX_t$	: the percentage change of US Dollar Index at time t
Δy_t	: first difference of dependent variable at time t
α	: Constant term
β	: coefficient of independent variables
ρ	: unit root coefficient

LIST OF FIGURES

Figure 1.1: USD/TL currency in between 2019 and 2021

Figure 1.2: CBRT USD reserves in between 2019 and 2021

Figure 1.3: TL reference interest rate in between 2019 and 2021

Figure 2.1: USD/TL currency in between 1993 and 1994

Figure 2.2: USD/TL currency in between 1998 and 2001

Figure 2.3: VIX value in between 2006 and 2009

Figure 4.1: USD/TL currency in between 2019 and 2021

Figure 4.2: the percentage change of USD/TL currency

Figure 4.3: Histogram of the percentage change of USD/TL currency

Figure 4.4: Histogram of the percentage change of CDS

Figure 4.5: Histogram of the of RVIX

Figure 4.6: Histogram of the of inflation differences

Figure 4.7: Histogram of the of CBRT interest rates

Figure 4.8: Histogram of the of USDX

Figure 4.9: Autocorrelation curve of USD/TL

Figure 4.10: Partial Autocorrelation curve of USD/TL

Figure 4.11: Autocorrelation curve of percentage change of USD/TL

Figure 4.12: Partial Autocorrelation curve of percentage change of USD/TL

Figure 4.13: Autocorrelation curve of CDS

Figure 4.14: Partial Autocorrelation curve of CDS

Figure 4.15: Autocorrelation curve of percentage change of USDX

Figure 4.16: Partial Autocorrelation curve of percentage change of USDX

Figure 4.17: Autocorrelation curve of RVIX

Figure 4.18: Partial Autocorrelation curve of RVIX

Figure 4.19: Autocorrelation curve of inflation differences

Figure 4.20: Partial Autocorrelation curve of inflation differences

Figure 4.21: Autocorrelation curve of CBRT interest rates

Figure 4.22: Partial Autocorrelation curve of CBRT interest rates

Figure 4.23: The percentage change of USD/TL currency

Figure 4.24: RVIX value in between 2019 and 2021

Figure 4.25: CDS graph in between 2019 and 2021

Figure 4.26: The percentage change of USDX in between 2019 and 2021

Figure 4.27: Inflation difference graph in between 2019 and 2021

Figure 4.28: CBRT interest rate graph in between 2019 and 2021

Figure 4.29: The graph of the First Difference of CDS data

LIST OF TABLES

Table 1.1 The current macroeconomic indicators

Table 2.1 Literature Review Summary Table

Table 2.2 Literature Review Summary Table

Table 2.3 Literature Review Summary Table

Table 2.4 Literature Review Summary Table

Table 4.1 Breusch-Pagan test results

Table 4.2 White Test Results

Table 4.3 ARCH Effect Results

Table 4.4 Dickey Fuller Test Results for All Series

Table 4.5 Dickey Fuller Test results for DCDS

Table 4.6 The Coefficients of the Equations

Table 4.7 GARCH (1,1) Model Results

Table A.1 Lag Length for CDS

Table A.2 ADF for CDS with trend and constant

Table A.3 ADF for CDS with constant

Table A.4 PP test for CDS with trend and constant

Table A.5 PP test for CDS with constant

Table A.6 Lag Length for CBRTINT

Table A.7 ADF for CBRTINT with trend and constant

Table A.8 ADF for CBRTINT with constant

Table A.9 ADF for CBRTINT without trend and constant

Table A.10 PP for CBRTINT with trend and constant

Table A.11 PP for CBRTINT with constant

Table A.12 PP for CBRTINT without trend and constant

Table A.13 Lag Length for VIX

Table A.14 ADF for VIX with trend and constant

Table A.15 ADF for VIX with constant

Table A.16 ADF for VIX without trend and constant

Table A.17 PP for VIX with trend and constant

Table A.18 PP for VIX with constant

Table A.19 PP for VIX without trend and constant

Table A.20 Lag Length for USD/TL (R_t)

Table A.21 ADF for R_t with trend and constant

Table A.22 ADF for R_t with constant

Table A.23 PP for R_t with trend and constant

Table A.24 PP for R_t with constant

Table A.25 Lag Length for USDX

Table A.26 ADF for USDX with trend and constant

Table A.27 ADF for USDX with constant

Table A.28 ADF for USDX without trend and constant

Table A.29 PP for USDX with trend and constant

Table A.30 PP for USDX with constant

Table A.31 PP for USDX without trend and constant

Table A.32 Lag Length for INF.DIF

Table A.33 ADF for INF.DIF with trend and constant

Table A.34 ADF for INF.DIF with constant

Table A.35 PP for INF.DIF with trend and constant

Table A.36 PP for INF.DIF with constant

Table A.37 Lag Length for dCDS

Table A.38 ADF for dCDS with trend and constant

Table A.39 ADF for dCDS with constant

Table A.40 ADF for dCDS without trend and constant

Table A.41 PP for dCDS with trend and constant

Table A.42 PP for dCDS with constant

Table A.43 PP for dCDS without trend and constant

Table A.44 GARCH (1,1) MODEL

Table A.45 Autocorrelation Test for R_t

Table A.46 Autocorrelation Test for USDX

Table A.47 Autocorrelation Test for RVIX

Table A.48 Autocorrelation Test for INFDIF

Table A.49 Autocorrelation Test for CBRTINT

Table A.50 Autocorrelation Test for dCDS

University : Galatasaray University
Institute : Institute of Social Sciences
Science Programme : Economy
Programme : MA in Economy
Supervisor : Associate Professor Ata ÖZKAYA
Degree Awarded and date : MA –February 2022

ABSTRACT

TURKISH LIRA VOLATILITY AMID COVID-19 PANDEMIC CRISIS

ÖMER FARUK ALTUN

Understanding the reasons for the exchange rate movements, which are very popular in Turkey in recent days, is important in terms of ending this volatility that disrupts the welfare and social peace of the country in many areas. GARCH (1,1), one of the most widely used models in the literature, was used to find out which macroeconomic dynamics volatility originates from. The results obtained are that CDS premiums and VIX parameters affect exchange rate volatility during the COVID-19 pandemic period in between 2019 March and 2021 October. Moreover, it has been found that the volatility of the past period has a permanent and considerable effects on the volatility of today. In this case, policy makers are expected to prevent volatility by establishing a defense mechanism based on external dynamics rather than internal dynamics in cases of global crisis such as a pandemic.

Keywords : GARCH, Volatility, Exchange Rates, Covid-19

1. INTRODUCTION

In this study, the problem of exchange rate shocks brought about by the pandemic crisis in between 2019 March and 2021 October, which has taken the whole world under its influence, and what measures should be taken against these shocks are emphasized. Turkey has been chosen as the model country. It is known that the exchange rate volatility of Turkey is high, and this situation negatively affects the country's economy due to inflation, uncertainty, dollarization, poverty and many other reasons. Finding out what caused the exchange rate volatility will be a good starting point to reduce this volatility and the country's economy will perhaps have a chance to breathe for many years.

The GARCH (1,1) model, which is one of the most used models in the volatility modeling literature, was chosen in order to find out the severity of exchange rate volatility and what caused it. In this model, the CBRT overnight reference interest rates, the difference in inflation expectations calculated on a daily basis for Turkey and the USA, Turkey's CDS premiums, VIX rate and USD index are added to the model as independent variables, and the percent change in the USD/TL rate is included as the dependent variable in the model. According to the model results, the reason for the exchange rate volatility in Turkey between 2019 March and 2021 October, when the pandemic crisis was experienced, was determined as VIX and CDS. It has been observed that Turkey's exchange rate volatility is determined by external factors, not internal, at a time when conditions affecting the whole world such as the pandemic are taking place.

Since the main subject of the study is related to the pandemic crisis, it was thought that it would be necessary to briefly introduce the subject of economic crisis and to give information about how Turkey reacted to economic crisis situations and the level of macroeconomic indicators. Some of these crises are of local origin and some of them are of global origin. In order to distinguish them and to describe the relationship between the exchange rate volatility experienced in this period and the VIX, which is one of the significant parameters of our model, a brief introduction to the subject of economic crises will be made.

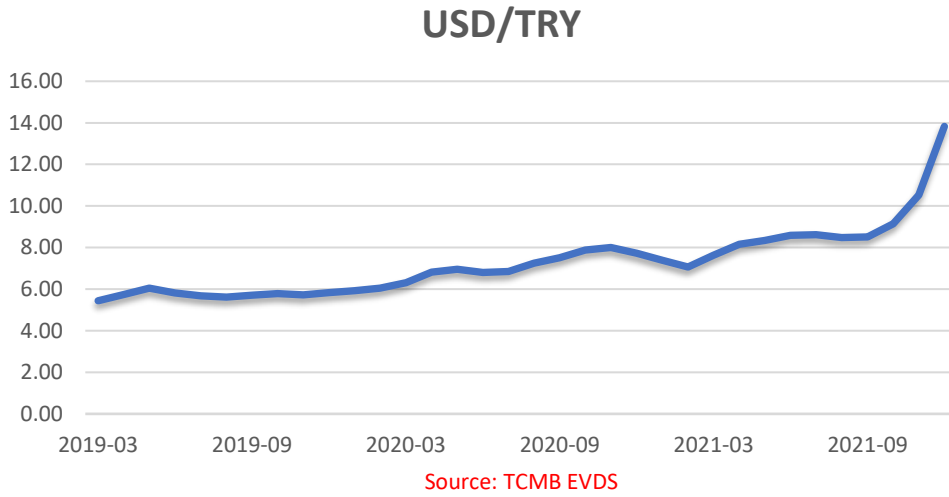
From past to present, one of the main problems observed in developing countries is the instability in these countries. Especially after the Covid 19 epidemic experienced by the whole world, not only developing countries, but also developed countries have lost their stability in macroeconomic areas such as growth, inflation and it does not seem to be able to recover for a long time. The concept of volatility stands out as a subject worth discussing for a country like Turkey, which is both in the developing country category and in the category of developing countries, where special emphasis is placed on the degree of sensitivity under the name "Fragile Five". Turkey stands before us as a plane tree with a past full of economic and political crises. An economic agenda that is shaken under the threat of economic and political crisis almost every 10 years makes it almost impossible to achieve economic stability in the country. Today, when any economist mentions Turkey's economic past, almost all of them will remember the 1994 economic crisis, the 2001 banking crisis, the 2008 Mortgage Crisis of American origin showing its global effect, and the pandemic-based crisis with a very fresh and global impact. In

fact, focusing a little on these crises and examining their causes will open a new window for the reader as to why such a topic has been chosen.

Two types of crises are generally mentioned in the literature of crisis economics: Monetary crises and Financial Crises (or Banking Crises). But sometimes these two types of crises can break out together. While talking about the currency crisis here, it should be emphasized that the excessive demand for foreign currency and the dollarization process, which is frequently used in Turkey, have great importance in this definition. Financial crises, on the other hand, are processes that result from systemic problems and ultimately result in the collapse of institutions and companies or rescue operations. Since the 1994 crisis and in the pandemic crisis we are currently experiencing, Turkey has an unmistakable rule: foreign currency reserves tend to decrease while exchange rates and interest rates rise (Ozatay, 2020).

This situation is graphically illustrated below.

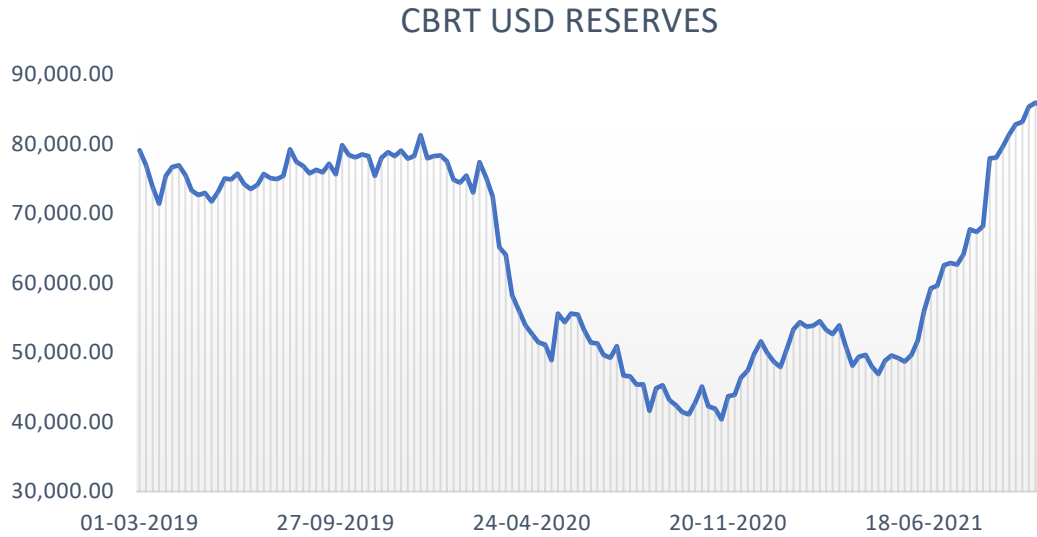
Figure 1.1



According to this chart, with the epidemic that started in March 2019, Turkey, which was not already in a good economic environment, started to enter into a foreign exchange bottleneck. The dollar, which was around 5 TL in March 2019, continued its upward trend over time and rose to 13 TL in December 2021.

This situation, as expected, caused a decrease in the dollar reserves of the Central Bank of the Republic of Turkey (CBRT). This is clearly seen in the chart below:

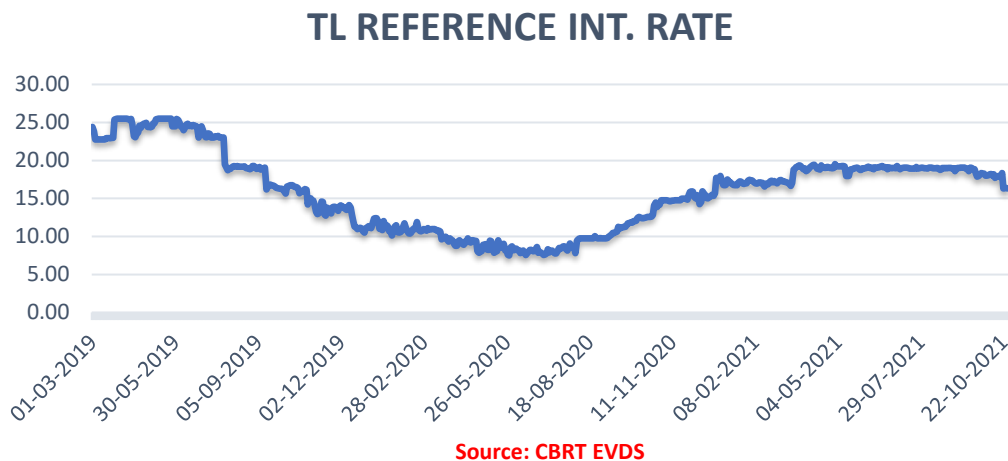
Figure 1.2



Because in such scenarios, citizens of developing countries see the currencies of more reliable and stable countries in terms of economy rather than their own money as a safe haven and invest in it. Dollar refers to the aforementioned safe haven for developing countries like Turkey. Even in the later stages of the crisis, a concept called dollarization manifests itself. Dollarization is when citizens of a country trade in dollars instead of their own national currency. At this stage, prices are indexed to dollars almost everywhere, house prices, goods, cars and similar assets increase and decrease with the dollar rate. Therefore, while the excessive demand for the dollar accelerates the upward momentum of the dollar, it also melts the Central bank reserves (Özatay, 2020).

In this scenario, in order to increase the domestic foreign exchange reserves, meet the demand for dollars, and increase the foreign investor's demand for the Turkish Lira, interest rates are increased, and the upward trend of the dollar is tried to be stopped.

Figure 1.3



On top of that, rising interest rates cause stagnation in the economy, because investors put their money in banks and start earning interest instead of opening businesses and jobs or investing in housing and similar real estate, stimulating the economy and increasing the circulation of money. Ultimately, unemployment rises, inflation rises, growth declines, and a crisis environment is entered. Focusing and examining the major economic crises that Turkey has experienced in the recent past will help to understand the main causes of dollar/TL volatility. Thus, without making volatility dependent only on a mathematical equation, it will be understood in a logical framework how the parameters of this equation exist in daily economic life.

As explained in more detail in the next section, it has been observed that the dynamics of global and local crises are very different from each other. Incompatible monetary and exchange rate policies constitute the main metrics of local crises. Factors such as inflation, interest rates, reserves and unemployment are known as the main indicators that the country is in crisis. In this sense, the factors that cause exchange rate volatility can be searched in these parameters. However, when it comes to a global crisis, it is necessary to look elsewhere for the exchange rate volatility that will emerge. One of the most basic indicators that the whole world is in a crisis is the VIX parameter. The fact that the VIX and CDS parameters are significant in the established GARCH (1,1) model indicates that the world is in a global crisis. Moreover, it is an indication that both the economic and political movements of Turkey have been met.

As in all crises Turkey has experienced, we are witnessing that the value of the usd/tl exchange rate has increased a lot in the pandemic crisis. However, in parallel with the findings of the model, the dynamics of global and local crises prove that the causes of this volatility vary.

All in all, In summary, we want to model Exchange rate volatility. We think that exchange rate volatility is important in developing countries where financial flows are free. Therefore, the following items have formed our motivation for exchange rate volatility modeling.

- We chose Turkey, we thought it would offer versatile policy implementation
- We chose GARCH (1,1) because the relevant country Central banks have studied this model in this regard.
- We looked at previous periods of high volatility 1994, 2001, 2008. Although 1994 and 2001 were fixed exchange rate regimes, a comparison can be made regarding the accumulated financial effects (error term variance). We took into account the 2008 financial crisis and the concentration of portfolio flows on developing countries during 2009-2011 and its relationship with the VIX index. Especially the studies after 2008 period are focused on GARCH.
- The period chosen to examine Turkey is March 2019-2021 December. We chose a 2-year time domain that includes the Covid Pandemics period. The reason for this is that since the economic policies implemented since 2015-2016 have moved away from orthodox approaches, there has been a problem of confidence in Turkish assets in global financial markets, and fluctuations occur in portfolio flows. Events such as treasury minister changes, MB president changes made us feel the need to include the pre-pandemic period in our data set. Descriptive statistical analyzes show that the effects of the Pandemic have increased the deviations in volatile processes.
- In particular, the fluctuation of risk appetite in the US Stock Exchange S-P 500 and related financial markets and the perception of uncertainty that rose with the

announcement of the pandemic on March 11, 2020, carried financial markets and monetary policy authorities to different extremes in the decision-making processes. The fact that the perception of uncertainty is different from the perception of risk has deviated the rational behavior elements in financial markets. Since this can be observed with the VIX index, it can be evaluated in terms of its effects on emerging markets.

In order to see the similarities and differences of the pandemic crisis with other crises, Turkey's past crises and crisis indicators are given in the second chapter, and at the end of the section, brief information about the roadmap followed in the pandemic crisis is given. In the literature review section, which is the third part of the study, information about the factors that are included or not included in the model but that may contribute to the explanatory power of the model are given from the perspectives of different authors. In the fourth chapter, the details of the GARCH (1,1) model applied in the model are entered and interpreted. In the last part, the findings were evaluated in the light of the expectations for 2022 and policy recommendations were made.

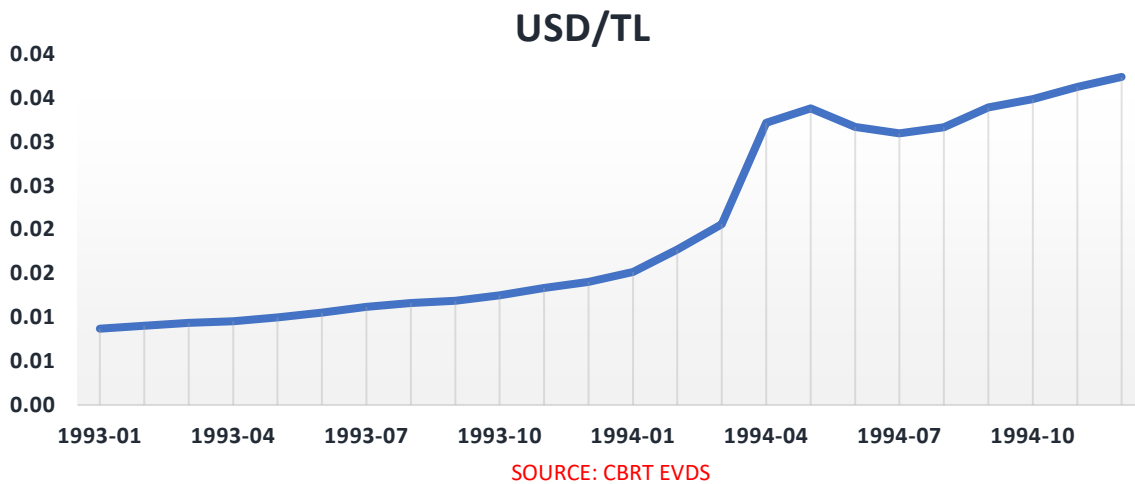


2. TURKEY'S PAST CRISIS EXPERIENCES AND PANDEMIC CRISIS

2.1. 1994 Economic Crisis

An idea of the origin and severity of the crisis can be obtained from the following usd/tl exchange rate chart:

Figure 2.1



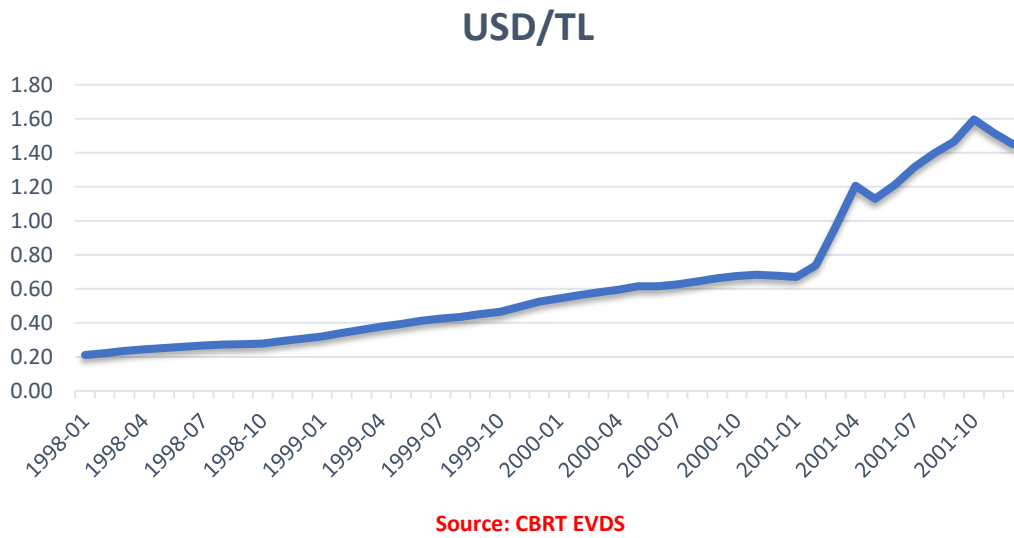
The economic crisis that Turkey experienced in 1994 fits perfectly within the theoretical framework known as first generation crisis models in the literature. In the first-generation crisis model, a monetary policy incompatible with the exchange rate regime is shown as the main reason for the formation of the crisis. The Republic of Turkey, which maintained a fixed exchange rate policy in those years, had to melt its reserves in order to meet the increasing exchange rate demand. However, since the decreasing reserves reduce the central bank's power of action, the interest weapon is activated. Thus, it increases the attractiveness of holding Turkish Lira in the market and aims to extinguish the fire of the dollar. Another reason for the increase in the demand for the dollar is that the increasing financial debts are met by printing Turkish lira. In a situation where there is high inflation and increasing domestic debt, citizens who have Turkish lira in their hands in case of printing money continue to rush to exchange offices and buy dollars. In such an environment, Turkish liras printed by the Central Bank are given to the Central Bank in exchange for foreign currency. Therefore, the printed coins are not kept in Turkish lira and the demand for foreign currency is increasing, and the promise of the government's fixed exchange rate policy is turning into a promise that is difficult or even impossible to keep. The central bank uses the interest weapon, but this interest weapon is not sustainable and stands out as one of the biggest obstacles to investment. If the treasury's budget deficit is indexed to short-term interest rates, the increase in interest rates by the central bank further increases the borrowing cost of the treasury. Borrowing costs of companies increase at the same rate and the probability of repayment of the loans they take decreases. At the same time, there may be decreases in the amount of goods they sell, and these increasing interest

loans can have a high cost to companies. In the end, in this toxic economic structure, banks are also damaged because the loans they give may not be returned. In such an environment, constantly raising interest rates becomes an unreasonable and unsuccessful policy, and a collapse occurs. The speed and acceleration of this collapse depend, in summary, on two basic economic terms. The first is the Central bank's foreign exchange reserves, and the second is the rate of printing money. These two fundamentals significantly affect exchange rate volatility and the stability of the economy (Özatay, 2020).

2.2. 2001 Economic Crisis

As in the 1994 crisis, it is possible to get an idea about the severity and onset of the crisis from the graph below:

Figure 2.2



One of the issues to be considered when talking about both the 1994 and 2001 crises is the global economic conditions of that period. What we want to understand is whether the crisis is global or domestic origin. In a global crisis environment, we see severe fluctuations in the VIX (Volatility Index), as we will see when we describe the 2008 crisis a little later, and this indicates that the global risk appetite has decreased and causes investors to invest their money in assets they see as safe haven. However, this was not the case in the 2001 crisis in Turkey. In this period, a policy that is heterodox, that is, in which exchange rate policy is integrated into the system as well as monetary and fiscal policies, was adopted. Due to the experiences in the 1994 economic crisis, the Central Bank was prevented from extending credit to the public, but monetary expansion was allowed only to the extent that foreign exchange reserves increased. Thus, it is aimed that monetary expansion will not cause a sudden jump in the exchange rate.

The 2001 crisis actually broke out as a banking crisis. One of the most basic problems of banks is related to foreign exchange. Banks' foreign currency liabilities are much higher than their foreign currency receivables, and the ratio of liquid assets in foreign currency to liquid liabilities in foreign currency is in a continuous decline. Another problem was that banks' debts were predominantly short-term while their receivables were long-term. Therefore, the system was quite vulnerable to any exchange rate increase. In this period, the public sector had huge duty

losses on its balance sheet because the state had given the public banks the task of supporting agriculture and small and medium-sized enterprises by providing low-interest loans. The support packages, which normally had to be handled by the treasury itself, came out of the treasury budget and were loaded on public banks, and debts not paid on time were a heavy burden on public banks. In 1999, the cumulative value of such receivables reached 16 percent of the total national income. When the increase in the number of non-performing loans was added to all these, the crisis became inevitable. On the other hand, the current account deficit is gradually increasing and corresponds to about 5 percent of the national income. In 1999, inflation was around 69 percent and at the end of 2000 it was around 39 percent. As a result of all these, banks were no longer able to find funds, could not close their own budget deficits, and therefore could not lend to companies. The central bank was reluctant to provide liquidity to banks due to bad experiences in the previous crisis. With the effect of all these, the borrowing costs of banks reached 315 percent per night. With the effect of the political crisis that followed, the overnight interest rate came to 2000 and 4000 percent. After the fixed exchange rate regime was abandoned and the floating exchange rate regime was introduced, the exchange rate increased almost one hundred percent within 4 days. In this crisis, it was seen how the banking sector, interest rates and government policies caused a crisis in the economy through the exchange rate.

2.3. 2008 Global Economic Crisis

Perhaps the best example that can be given to the crises that Turkey did not create and imported from abroad is the 2008 Mortgage crisis. The factors that led to the emergence of this crisis can be briefly stated as follows:

- Subprime loan market
- Shadow banking System
- Extreme increases (and later decline) in housing prices
- Rapid credit expansion

Figure 2.3



The Volatility Index chart given above is one of the most basic indicators of how the mortgage crisis affected the whole world. Again, in this crisis, exchange rate volatility increased, employment withdrawals were experienced, and growth rates decreased. This crisis is an important indicator to understand our country's response and resilience to economic shocks. In addition, it seems to confirm the results of our model linking exchange rate volatility to external shocks. In the modern economic system, countries have increasingly opened. Imports, exports and integration of banks with each other accelerated. As a result, countries have become more sensitive to external shocks. Therefore, even if their own internal dynamics did not deteriorate, shocks from other countries have come to destroy the economies of the countries.

The crisis period that spread first in the field of health and then in the field of economy due to the pandemic in 2019 should also be viewed from this perspective. Unlike other crises, external dynamics, not internal dynamics, are important in this crisis.

2.4. The World's Economy in the Pandemic Crisis

Since the beginning of the pandemic, the main policy of developing and developing countries has been to support the economy with expansionary monetary and fiscal policies. Central banks of many countries took dovish steps and chose to lower interest rates in order to be affected as little as possible by the economic negativities caused by the pandemic. The revived demand with increasing incentive packages and loose monetary policy, the acceleration of vaccination efforts, the rising commodity prices with the upward acceleration in global trade, the abnormal increases in food prices following global disasters and climate change have begun to feel the pressure on global inflation. Countries have started to decide to adopt a tight monetary policy, and in this sense, it is important to follow the FED closely. Disputes between Russia, Ukraine and the European Union continue to affect inflation through global energy prices. In this section, in order to be compatible with the results of our model (according to the model results, the parameters affecting the dollar volatility in Turkey are VIX and CDS premiums), important developments in the world, not in Turkey, will be examined and it will be tried to determine which events may affect the exchange rate volatility in the future, inside and outside the model.

2.5. Turkish Economy in the Pandemic Crisis

As the pandemic has affected many countries, it has also negatively affected Turkey both economically and socially. The rise in unemployment data, the possibility of economic contraction, the social unrest caused by increasing health problems, and the tension of health equipment with other countries are some of these negativities.

The decrease in the sales volume of firms and companies operating in the country, combined with the curfew, left deep and difficult wounds in the country's economy. The recession, which emerged especially in the tourism and services sector, which has an important place in Turkey's Gross National Product, showed itself with the channels of contraction and unemployment, and despite many measures taken, it caused many people to lose their jobs and the recruitment announcements of companies to stop. As in every crisis and global disaster, gold, which is seen as a safe haven, was in demand and increasing gold imports caused the country's current account deficit to grow. Turkey's response to the pandemic emerged with unemployment benefits and

credit channels. Turkey's credit and unemployment benefits remained above the G20 averages, but increased liabilities in the treasury balance sheet (The World Bank, 2021).

The negativities experienced by the country in foreign policy, combined with the imbalances in domestic policy, caused CDS premiums to rise and put the country in a foreign currency bottleneck. In the following periods, the successive appointments of the President of the Central Bank caused the deterioration of the environment of confidence and stability in the country and severe increases in the exchange rate volatility. Investments have been stopped or postponed. The economic revitalizing packages that emerged under the government guarantee in the fields of housing and automobiles worked and had a slightly revitalizing effect on the economy (The World Bank, 2021). However, low interest loans given by public banks will be a threat in the future for the banking sector.

The extreme volatility and devaluation of the Turkish lira greatly triggered the feeling of insecurity and drastically changed the priorities and consumption behavior of households. Continuing its upward movement with the effect of the pandemic and the decreasing confidence environment, the exchange rate made itself felt through the inflation pass-through. The rise in commodity prices, which are subject to international trade, and food prices also continued to put pressure on inflation. The difference between the producer price index and the consumer price index, which has increased in the coming days, and the core inflation indicators are the most basic indicators that show the bad situation of the country's economy and the permanent inflation. Turkey has become the country with the most unsuccessful inflation forecast among its counterparts in 2020 (The World Bank, 2021).

In order to protect itself from the negative conditions of the pandemic, the CBRT, like many countries' central banks, took steps to revive the economy by reducing interest rates for a while. However, with the policy rate lowering from 19 levels to 18 in 2021, it has been stated in the CBRT monetary policy meeting texts that the high interest rate brings the contractionary effect on commercial loans and interest rate cuts have been made to prevent this situation. The contractionary effect on these commercial loans and the negative impact on the economy were shown as the reason for the 200-basis point rate cut in October 2021. At the meeting held on November 18, 2021, the policy rate was reduced by 100 basis points and reduced to 15%. In the intervening period, 3 central bank governors have changed, and these changes have caused great volatility in the exchange rate and the deterioration of the environment of confidence and stability.

In the first place, the Covid-19 pandemic hit Turkey, as well as many other countries, deeply and lowered its growth rates. The growth data of the 2nd quarter of 2020, following the start of the pandemic, resulted in the shrinkage of the Turkish economy. However, as of the following quarter, it became one of the countries that positively differentiated from the rest of the world (The World Bank, 2021) and managed to grow for 4 consecutive quarters. In fact, a record was broken with a growth of 21.7% in the 2nd quarter of 2021 due to the base effect. One of the biggest dynamics of this growth was the export of goods and services originating from foreign demand.

At this point, almost all the macroeconomic indicators such as inflation, exchange rate, unemployment and CDS premiums reveal the economic crisis that the country is in. The current macroeconomic indicators table below explains the situation most clearly.

Table 2.1

INDICATOR	LAST ANNOUNCED	TIME
GDP GROWTH (TÜİK)	7,40%	Third Quarter
CPI (TÜİK)	19,60%	12-month average
PPI (TÜİK)	43,86%	12-month average
UNEMPLOYMENT (TÜİK)	11,20%	November 2021
IMPORT (TÜİK)	27,30%	November 2021
EXPORT (TÜİK)	33,70%	November 2021
INDUSTRIAL PRODUCTION (TÜİK)	11,40%	November 2021
ECONOMIC CONFIDENCE INDEX (TÜİK)	97,60%	December 2021
POPULATION (TÜİK)	83614362	2020
CONSUMER CONFIDENCE INDEX (TÜİK)	-3,10%	December 2021
FOREIGN TRADE DEFICIT (TCMB)	5,4 Billion USD	November 2021
CURRENT ACCOUNT BALANCE (TCMB)	3156 million USD Surplus	October 2021
REAL SECTION CONFIDENCE INDEX (TCMB)	106,80%	December 2021
CDS (Reuters)	554	December 2021

3. LITERATURE REVIEW

Since the 1950s, equity prices have attracted the attention of researchers, and a big proportion of the empirical research was supporting the two famous theories of the economy: random walk and efficient markets. According to the efficient market hypothesis, asset price returns are determined by a mean return (μ_t) for period t and a random disturbance (ε_t). Moreover, ε_t is not following any serial correlation (that is one of the main features of the efficient market hypothesis). It means that the past prices do not allow us to learn about the random component of the asset returns in period t . A random walk process necessitates that expected value of the asset returns, μ_t should be zero and the variance of the random component, ε should be constant for every time. Unfortunately, neither of them can give sufficient information about the asset price in reality (Figlewski, 1997). As it was demonstrated by the seminal and pioneering works of Mandelbrot (1963) and Fama (1965), the time series of stock returns have volatility clustering (large volatilities are following by large volatilities and the same is valid for the small volatilities) and they show serial correlation for short lags. It was not an insurmountable and an insuperable problem to cope with it, because the big proportion of the options trading was being made for short time intervals and although it was known that variances of the return are not expected to be constant over time, it was able to be ignored. The logic behind it was that variance changed stepwise in the short-term interval and this effect was not so effective that it could not be tolerated (Figlewski, 1997). Timely, the maturities of financial instruments have been lengthened and the constant variance has started to become a serious and thought-provoking problem for finance. Therefore, the constant variance was accepted to untenable thing in modern finance and some authors such Akgiray (1989) and Perry (1982) proved that daily stock return series do not conform to Gaussian (normal) distribution, and they exhibit significant levels of second-order dependence, and they cannot be modeled based on the linear strict white noise (random walk) assumptions. Furthermore, it was seen that asset returns differentiate from a normal distribution with their leptokurtic and fat tails features because sometimes prices can show tremendous increase or decrease that cannot be seen in a normal distribution (Akgiray, 1989; Figlewski, 1997).

3.1. The Volatility Measuring

In general, volatility is often synonymous with risk in people's minds. For instance, some of the option-based implied volatility indexes such as VIX are called as "fear index" (Yang & Liu, 2012). However, risk only measures negative effects while volatility shows positive and negative effects and therefore, they are not the same things. Volatility is simply known as the percentage changes in prices and the measure of change of the rate of return in financial markets (Schwert, 1990). The most general measurement way of the volatility is the standard deviation (Granger & Poon, 2003) and can be shown like this for the financial markets:

$$\hat{\sigma}^2 = \frac{1}{N-1} \sum_{t=1}^N (R_t - \bar{R})^2$$

where $\bar{R}$ is the sample average expected return, $\bar{R} = \sum R_t / T$.

Standard deviation is known as the distance from the mean. Hence, it is very useful for financial economists to be able to gauge the large positive and negative returns.

The place of volatility today is very important because they provide us with information about very important economic data, from stock markets to exchange rate returns and inflation expectations. In the modernized world, we live in, with the advent of technological progress, information is spreading very quickly, and people can react to these rumors immediately thanks to the computerized finance sector. On top of it, there are very useful and easy conditions for investors to take the money they need from the financial markets almost whenever they want. As almost everything has, it has pros and cons to discuss. Because of high liquidity conditions and fast communication opportunities, price change rates have accelerated, and this causes the financial markets to be more volatile than before. Furthermore, as the number of traders increases, the number of experts decreases, and the number of experts who have the right view and are stable market traders decreases. For these reasons, volatility can be seen as the side effect of technological advancement in financial sectors (Schwert, 1990). Generally, volatility increases are accompanied by terrible economic conditions. The 1929 and 1987 stock market crashes can be given as prominent examples of duration in which there were both high volatility and terrible economic conditions. To be able to prevent the increasing volatility, professionals proposed some precautions such as trading halts, increases in margin requirements, and limits on automated trading systems. Moreover, Schwert (1990) demonstrated that the volatility of equity prices is more intensified in economic recessions terms than in economic expansion terms. These asymmetric effects and notorious names of volatility led academicians and professionals to work more on this subject and to develop some volatility measurement techniques.

3.2. The Volatility Measuring Models

Policymakers are generally very sensitive and responsive to financial market volatilities to be able to see the potential power of the economies. Normally as with every model, the success of the volatility models depends highly on their explanatory power of out-of-samples. One of the first and groundbreaking studies in volatility modeling is Black and Scholes (1973). The Black & Scholes model has lost its functionality and has largely lost its validity today. However, it will still be very beneficial to see the mathematical logic behind it:

$$\frac{dS}{S} = \mu dt + \sigma dz$$

Where dS is the asset price change over time interval dt , μ is the mean return as it was mentioned above, dz is the time-independent random disturbance with mean 0 and variance $1 * dt$ (a stochastic process known as Brownian motion), and σ is the volatility term as we used above. As it can be seen from the equation above, this asset price process follows a normal distribution and has constant volatility σ . Since volatility is changing over time, the Black & Scholes model is not a sufficient estimator to give true information to investors. In real words' empirical researches show that the Black & Scholes model does not carry some important features which are vital to make good forecasts. They are **time variance in return distribution, serial correlation, and non-normality** (Figlewski, 1997). Moreover, Engle & Patton (2007) lists the features that a good volatility model should have as follows:

- **Volatility exhibits persistence.**

It was firstly demonstrated by Mandelbrot (1963) and Fama (1965) that large changes in the price of an asset are generally followed by large changes and the same rule is valid for the small changes in the price of an asset. The economic meaning of this theory is that the volatility shocks in the current time are very effective in the volatility expectations of the next time.

- **Volatility is mean reverting.**

It means that in a short time horizon, abnormal volatility changes can happen, but in the long-time interval, volatility will turn back to its normal volatility level (Whaley, 2009). It signifies that current information does not give precise information about the future.

- **Shocks may have an asymmetric impact on volatility.**

According to this subsection, positive and negative shocks are not the symmetric effects on volatility. One reasonable explanation of this matter is that as the price of an equity decreases, its debt-to-equity ratio increases, and because of its rising risk structure, its volatility rises as well. Since there is a risk aversion behavior in the financial markets, the demand for this equity will fall. All in all, if a volatility model suggests both positive and negative effects the same, this model is not very successful.

- **Exogenous variables can affect volatility intensity.**

If we want to bring our model closer to reality and give it credibility, we need to show that prices or other variables are affected by other exogenous variables.

- **Fat tail property**

As it was mentioned above, time series such as asset prices show non-normality features. One of the main determinations of this feature is fat tails. The kurtosis in between 4 and 50 means that there are non-normality conditions, and it should be added to the volatility model.

There are innumerable time series models to gauge volatility such as HA, $AR(p)$, $MA(q)$, $ARMA(p,q)$, $ARIMA(p,d,q)$, $ARCH(q)$, $GARCH(p,q)$, ES, EWMA, TAR, EGARCH(p,q) and so on (Xiao & Aydemir, 2007). Poon and Granger (2003) also have reviewed more than 90 published works and showed their relative advantages and disadvantages to each other. Since seeing all these models one by one will deflect the purpose of our study and waste a lot of space and time, only the details and comparative advantages of the models ($ARCH$, $GARCH$, and some other option-based volatility index models) will be interested in will be mentioned.

3.3. Arch Class Conditional Volatility Models

Most of the econometric analyses are being applied via Ordinary Least Squares method. It seems that it is normal because econometricians and other economists are generally trying to find how much one variable change in response to change in another variable. However, there is growing interest among econometricians in estimating the sum of unexplained data known as the error term. Two of the most widely used and effective way to measure the error term and its variance are $ARCH/GARCH$ models (Engle, 2001)

The main argument of the least squares is that the expected value of the error term is the same and its variance is constant over time (Gujarati, 2009):

$$E(\varepsilon_t) = 0$$

$$Var(\varepsilon_t) = \sigma^2$$

The name given to the time-invariant structure of the variance of the error term is homoscedasticity, and this is the assumption that ARCH/GARCH models are differentiating with. According to ARCH/GARCH models, the variance of the error term, ε_t , is not constant and changing over time, it is called as heteroscedasticity. For instance, the consumption behavior of the low-income family will be very different from the consumption behavior of the high-income family. Since high income family members' consumption bundles will be multifarious, their variances will presumably be higher than low-income family.

Despite the heteroscedasticity condition, the OLS coefficients are still unbiased. However, the standard errors and confidence intervals will probably be too narrow, and it causes forecasters to make some false assumptions about their estimations. Thanks to ARCH/GARCH models, heteroscedasticity is not a problem for time series data, because these models can be set in the presence of changing variance condition.

The ARCH model put forward by Engle (1982) has taken its place in history as the first formal model that considers the empirical findings of heteroscedasticity and autocorrelation. Engle (1982) proposed the Autoregressive Conditional Variance (ARCH) model, which relates the variance of the error term to the squares of the previous term error terms. Contrary to the common assumption in the literature, Engle (1982) proved by analyzing some macroeconomic data that the variance of error terms in time series models is not constant. Engle found that large and small forecast errors occur in clusters in inflation models, and as a result, the variance of forecast errors depends on the size of the error terms of the previous period.

3.3.1. Mathematical Definition of ARCH/GARCH Models

As one of the ways to model the observed volatility in time series, defining an independent variable related to volatility and estimating volatility through this variable comes to the fore. As a simple example reflecting the situation where volatility is modeled by defining an independent variable:

$$y_{t+1} = \varepsilon_{t+1}x_t$$

In this example, ε_{t+1} was defined as an error term with variance σ^2 , and x_t is defined as an independent explanatory parameter. If x takes the constant value which is time-independent, y_{t+1} will be white noise process with constant variance. In this model, the variance of y_{t+1} is not independent from the realized value of the x_t :

$$Var(y_{t+1}|x_t) = x_t^2 \sigma^2$$

In this case, the conditional variance of y_{t+1} will be increasing as x_t increases. One of the downsides of this model is that this model is assuming a specific reason for changing variance condition. However, there may be multiple reasons (not only one, as it was modeled by adding only x_t parameter) for the changing variance and we should not ignore them while building a model.

To be able to deal with this problem, Engle (1982), brought forward an idea according to which it is possible to model the mean and variance simultaneously. To reach ARCH model, a stationary autoregressive model is estimated:

$$y_t = a_0 + a_1 y_{t-1} + \varepsilon_t$$

In this case, conditional estimate of y_{t+1} will be:

$$E_t(y_{t+1}) = a_0 + a_1 y_t$$

If we use this conditional mean to estimate y_{t+1} , the variance of error term of the estimation can be shown like this:

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

On the other hand, unconditional estimation, and variance of y_{t+1} can be shown as:

$$E(y_{t+1}) = a_0 / (1 - a_1)$$

and

$$E[(y_{t+1} - a_0 / (1 - a_1))^2] = \sigma^2 / (1 - a_1^2)$$

As it can be seen from the equations above, the unconditional variance is much larger than conditional variance. Therefore, since it considers this period and known past period realizations, the conditional estimation has smaller variance and becomes preferable in this context.

Similarly, if the variance of the ε_t series is not constant, the ARMA model can be used to predict the continuous mobility in the variance in a given direction:

$$y_t = a_0 + a_1 y_{t-1} + \varepsilon_t$$

The conditional variance of y_{t+1} is:

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

At this point, it is necessary to establish a structure in which the conditional variance in equation above is not constant but changes over time. Modeling the conditional variance as an AR(p) process using estimated residual squares is considered a simple and logical strategy that can be used for this purpose:

$$\sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + a_2 \varepsilon_{t-2}^2 + \cdots + a_p \varepsilon_{t-p}^2$$

or shortly:

$$\sigma_t^2 = a_0 + \sum_{i=1}^p a_i \varepsilon_{t-i}^2$$

Finally, we arrived at the general equation of ARCH(p) that Engle (1982) found. There are some restrictions on autoregression parameters (a_0 and a_i) in ARCH models. Conditional variance must be positive for all actual values of ε_t . In order to satisfy this condition, it is determined that a_0 and a_i parameters in ARCH(p) equation will not be negative: (Engle, 1982; Granger & Poon, 2003; Figlewski, 1997)

$$a_0 > 0$$

and

$$a_i \geq 0$$

On top of it all, to be able to sustain the stationary condition of this autoregression model, the sum of all parameters used in ARCH model should be less than one: (Figlewski, 1997)

$$0 < \sum_{i=1}^p a_i < 1$$

After explaining the mathematical definition and limitations of the ARCH model, the GARCH model, which seems to be an upper version of this model, will be examined. In his study where he invented the GARCH model, Bollerslev (1986) states the fundamental superiority of the GARCH model over the ARCH model. Instead of the ARCH model, which includes a large number of lag lengths in order to add the long-term memory effect to the model, which is suggested in the empirical articles, Bollerslev (1986) offers the GARCH model which allows more flexible lag structure. The transformation of the ARCH model to GARCH model is very similar to transformation of the AR model to the ARMA model. Bollerslev (1986) compares his own GARCH model with the ARCH model used by Engle and Kraft to measure inflation volatility. As a result, he concludes that the GARCH model predicts more successfully than the ARCH model.

The mathematical definition of the GARCH model is as follows:

$$\varepsilon_t | \psi_{t-1} \approx N(0, \sigma_t),$$

$$\sigma_t = a_0 + \sum_{i=1}^q a_i \varepsilon_{t-i}^2 + \sum_{i=1}^p b_i \sigma_{t-i}$$

where, ε_t is the stochastic process, and ψ_{t-1} is the information set includes all of the information through time t. The GARCH model basically consists of two main parts, the first is to measure high frequencies from past error values, the other is the variance itself and is used to show long-term effects (Figlewski, 1997). In order for the GARCH model to be defined, the following constraints must be met:

$$a_0 > 0,$$

$$a_i \geq 0,$$

$$b_i \geq 0,$$

Lastly, the GARCH model we will use should ensure the stationary condition. It can be showed by using GARCH (1,1) model which is the most usable and the easiest GARCH model in economic literature (Figlewski, 1997; Engle, 2001; Granger & Poon, 2003):

$$\sigma_t^2 = C + a_1 \varepsilon_{t-1}^2 + b_1 \sigma_{t-1}^2$$

$$E_t(\sigma_t^2) = C + E_t(a_1 \varepsilon_{t-1}^2) + b_1 \sigma_{t-1}^2$$

Since the expected value of ε_{t-1}^2 is σ_t^2 , the long run steady state value of the variance is given by Figlewski as follows:

$$\sigma_t^2 = C + (a_1 + b_1) \sigma_t^2$$

$$\sigma_{Long Run}^2 = \frac{C}{1 - a_1 - b_1}$$

Then, the long run stationary condition: $a_1 + b_1 < 1$

We want to see if volatility actually returns to the average. For this, alpha and beta values must be less than 1, otherwise volatility will gradually move away from the average. However, if it is less than one, this effect is damped and there is a return to the mean (Engle, 2007).

3.3.2. The General Problems of ARCH/GARCH Models

One of the most obvious problems of arch and GARCH models is that they show the same reaction to positive and negative shocks. However, it has been observed empirically that negative shocks generally have greater effects than positive shocks. Not being able to include this asymmetric effect in the model is the biggest shortcoming of these ARCH and GARCH models (Figlewski, 1997; Granger & Poon, 2003; Bollerslev, 1992; Hafner & Herwartz, 2006). Nelson (1991) deals with the asymmetry problem of GARCH models and invented the EGARCH model. EGARCH model is very useful model to distinguish negative shocks from the positive shocks as expected.

In particular, the ARCH model needs many observations to make a successful prediction. This seems to be one of the problems encountered in model building. In the GARCH model, the model is established with fewer parameters compared to the ARCH model and increases the maximum likelihood of the model. So, in that sense it is better than the ARCH model. Moreover, they are subject to the general problem that the more complex any model is and the more parameters it contains, the better it will tend to fit a particular data sample and the faster it will tend to detach from the sample (Figlewski, 1997).

In addition, it becomes difficult to find maximum values in the likelihood process and the probability of the found values to be negative increases. In addition, the sum of the coefficients found may be greater than 1, resulting in the disruption of the stationarity assumption (Figlewski, 1997).

These ARCH-family models are being used to forecast only on step further, and they are not usable for long forecast horizons (Figlewski, 1997; Granger & Poon, 2003).

On the other hand, Akgiray (1989) makes use of the equity prices to compare the success rate of GARCH model with other time-series models such as ARMA, and he found that GARCH models are more successful than classical time series models to estimate future volatility of equity prices. According to him, the basic advantages of GARCH models over ARMA are that they include past variances, and it makes estimations simpler than that of time series models. Moreover, Akgiray (1989) shows that GARCH (1,1) model has superiority over all ARCH models regarding forecast the future volatility of equity prices.

Figlewski (1997), in his study, in which he models the monthly data of the S&P 500 index and treasury bill returns with GARCH, does not find any obvious superiority compared to historical volatility models. However, when he does the same study using daily data, he empirically finds the obvious superiority of the GARCH model and concludes that if the time to be estimated is 1 year or less, higher frequency data such as daily data should be used. In this way, the GARCH model will exhibit higher prediction success. According to Figlewski (1997), the most appropriate observation frequency to be used varies according to the time to be estimated, and forecast accuracy is more successful for longer forecast horizons than shorter ones because of mean reversion features of the GARCH models. Figlewski (1997) underlines the fact that the most recent historical data are most effective in GARCH models.

Figlewski (1997) and Bollerslev (1992) separately state that GARCH models are one of the most effective forecasting models especially in stock markets.

3.4. Some Basic Volatility Indexes and Their Mathematical Definitions

Traditionally used historical volatility models and GARCH models make use of past volatility information when making any volatility forecast and use this past information to predict the future. However, implied volatility models measure volatility by focusing on market prices instead of using historical volatility information. For this reason, they get rid of the weaknesses of GARCH and other volatility techniques and can make a more successful future prediction (Ryu, 2012).

There are some other variance estimation methods such as option implied volatility models. Option implied volatilities might be seen as the market's future volatility expectation according to the economic news. For this reason, it can be called as market-based volatility models (Granger & Poon, 2003). According to detailed works of Granger & Poon (2003), market-based volatility models are outperforming the historical volatility models in many ways, and they are equal with time series volatility models in terms of their performance rate. VIX can be given as a prominent example of the option based implied volatility models. The volatility index (VIX), which was created for the first time by the Chicago Options Exchange in 1993, is an index that measures the degree of fear in the markets (Kadioğlu, Kızılar, & Telçeken, 2019), and has become one of the important indicators followed around the world, as it provides information about the future uncertainties of financial markets. This volatility index is created by taking the weighted averages of stock prices, call and put options, and makes an estimate of the expected volatility of this market. As the index offers investors comprehensive information and trading guidance by observing the future volatility of the stock market, it soon became a risk index measure for the US stock markets and quickly became a primary indicator for the volatility of the stock markets in the US (Kadioğlu, Kızılar, & Telçeken, 2019). The VIX index makes use of the current option prices of the S&P 500 index and thus reflects investors' expectations of

30-day volatility in the stock markets (Whaley, 2009). A higher VIX means that the investors are expecting more volatile stock market than normal times (Liu & Yang, 2012). The 2002 WorldCom bankruptcy and the 2007 Mortgage Crisis might be given as confirmatory examples of this, because VIX level exceeded 40 and 80 thresholds respectively.

After the CBOE's volatility index example, other volatility indices started to be created by the CBOE and other country stock markets. The volatility index named VDAX based on DAX Index options by the Futures and Options Market of the German Stock Exchange (Deutsche Börse) in 1994; In 1997, the French Stock Exchange, French Marche des Options Negociables de Paris (MONEP), two volatility indices, VX1 and VX6, reflecting the implicit volatility of the CAC-40 synthetic index options at the break-even; In 2000, the CBOE created the Nasdaq volatility index (VXN), which is derived from the implicit volatility of the Nasdaq-100 Index (NDX) options (Kadioğlu, Kıyılar, & Telçeken, 2019).

The increased volatility index causes investors to demand higher returns. In this case, the prices of stocks with high return and therefore high-risk decrease. This is the rationale behind the volatility index and stock prices moving inversely (Whaley, 2009). That's why the VIX index has generally been called as investors' fear gauge.

After the VIX index was started to be calculated, the daily closing average of this index was calculated as 18. The VIX index has been between 14 and 23 50% of the time. It has a value between 12 and 29 at 75 percent of the time. finally, it has been rated between 11 and 37 90 percent of the time. The difference is clearest in the first ten months of 2008, when the financial crisis broke out. In this period, the VIX index took a value between 18 and 63 (Whaley, 2009). Moreover, if the VIX index stays above a certain threshold value permanently, there is tension and distress in that economy (Whaley, 2009). According to Whaley (2009), the most important information to keep in mind about the VIX is its ability to make short-term predictions, not long-term ones.

3.4.1. The Mathematical Definition of VIX

The VIX formula is as follows:

$$\sigma^2 = \frac{2}{T} \sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T} \left[\frac{F}{K_0} - 1 \right]^2$$

where:

σ VIX/100 => VIX = $\sigma * 100$

T Time to expiration

F Forward index level derived from index option prices

K_0 First strike below the forward index level, F

K_i Strike price of i^{th} out-of-the-money option; a call if $K_i > K_0$ and put if $K_i < K_0$; both put and call if $K_i = K_0$.

ΔK_i Interval between strike prices – half the difference between the strike on either side of K_i :

$$\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$$

R Risk-free interest rates to expiration

$Q(K_i)$ the average of the bid quote and ask quote for each option with strike K_i .

As it can be seen from the formula, if the gap between put and call options are big, VIX is increasing. If the gap between put and call options are small, VIX is decreasing (Öner, 2019).

Economists of the Central Bank of the Republic of Turkey (CBRT) always include VIX index data in their studies and call the VIX index as an indicator of uncertainty and risk appetite in global financial markets (Öner, 2019).

3.5. Can be VIX Model be Used to Gauge Emerging Markets Volatility Model?

Although the common idea according to which the world is very connected area, and for this reason, it is acceptable to expect that the VIX is useful measurement both for well-developed countries and emerging markets, there are various opinions regarding the accordance of VIX methods to emerging markets.

A fairly liquid market is needed to implement the VIX method. Therefore, this method is very difficult to apply for developing countries (Skiadopoulos, 2004; Ryu, 2012). However, Yang and Liu (2012) found that VIX is very effective and useful indicator to gauge Taiwan stock market's volatility level.

In his study, Öner (2019) investigated the relationship between the VIX and the 10-year bond market of 9 developing countries with the Granger causality method. According to this study, one-way causality was found between the VIX and the Russian and Mexican 10-year bonds. Bidirectional causality was found between VIX and Indonesian and South African 10-year bonds. Finally, there is no need to consider the VIX index as an indicator for bond interest rate movements in Brazil, China, India, Philippines and Turkey.

3.6. The Comparison Between VIX Model, Implied Volatility Model and GARCH Model

Yang and Liu (2012) found that the TVIX volatility model is more successful measure than the GARCH volatility model in regard to their predictive power of the future volatility level of Taiwan stock market.

Carr and Wu (2005) proved that the VIX volatility index is much more successful than the GARCH model in measuring the volatility of the S&P 500 index.

Yu et al. (2010) found that implied volatility models are more successful in predicting exchange market volatility than the classical historical volatility and GARCH models.

Poon and Granger (2003) scanned more than 90 articles from over 20 years and listed the successes of all volatility forecasting models. According to this ranking, implied volatility indices are in the first place and the GARCH type volatility prediction model is in the second place.

Engle (1993) showed that GARCH type models have more predictive power on measuring future volatility of the stock markets than historical volatility models.

Ryu (2012) has proven that if the KOSPI 200 index developed for the Korean financial market is included in the GARCH model, the volatility measurement success of the model increases.

3.7. ARCH/GARCH Usage Areas

Exchange rate volatility is of vital importance in determining the gross domestic product, inflation, employment rates, foreign trade, investments, interest rates and credit risk ratios of developing and developing countries. In addition, the negative effects of exchange rate volatility are more evident in developing countries. Because the financial depth and fiscal structures of developing countries, they are more vulnerable to such volatility than developed countries (Ozata, 2020).

Ozata (2020), in his study measuring the relationship between exchange rate volatility and growth with the GARCH (1,1) method, showed that the increase in exchange rate volatility had a negative effect on Turkey's economic growth.

Alexander and Lazar (2006), in their study modeling the dollar volatility based on 3 different currencies (British pound, euro and Japanese yen), compare the GARCH models with each other and say that the GARCH (1,1) model makes the most successful prediction according to the result.

Baillie, Chang and Tieslau (1996), used ARFIMA-GARCH model to estimate inflationary shocks and their persistence on ten countries. They especially used GARCH (1,1) model to be able learn long-time process of inflationary shock on G7 countries. They found that, inflationary shocks are mean reverting with long memory (except for Japan).

In the study of Chen, Hardle and Jeong (2009), in which daily forecasts of GBP currency volatilities and NYSE stock index are made, the support vector machine method is combined with the GARCH method, and this model is compared with the classical GARCH and asymmetric EGARCH models. In this study, it was determined that the SVM-GARCH model was more successful than other models in predicting beyond a period.

Chen, Hu, Meng and Zhang (2011) used the ARMA-GARCH model to measure intraday traffic flow levels, thus they are able to incorporate both linear conditional mean and non-linear conditional variance into the model. The similar work was made by Zhou, He and Sun (2006) for traffic prediction by using ARIMA-GARCH model.

Diebold and Nerlove (1989), investigated seven nominal exchange rates volatilities by applying ARCH family models, and they found that there is no random walk process for the error term and especially for the situations in which there is a non-linearity, ARCH family models are superior to other linear prediction models.

The constant variance assumption, which is the general problem of machine learning algorithms, poses a big problem for the estimation of financial time series. For this reason, integrating machine learning algorithms such as Lasso and SVM with ARCH/GARCH models with varying variance assumptions can greatly improve prediction efficiency. Dikheel and Sami (2021) tried to estimate the value of the Iraqi dinar against the dollar and showed that the predictions were more successful when GARCH models were included in the machine learning models.

While making stock market volatility estimation with GARCH, Perez-Cruz, Afonso-Rodriguez and Giner (2003) made parameter selection with the SVM method instead of using the maximum likelihood method, and he concluded that the estimations are more successful thanks to the parameters found. The causality for not using maximum likelihood is that the assumption that the data fit a normal distribution is not accepted.

Epaphra (2017) used the GARCH and EGARCH models in the study where he tried to measure the volatility of the Tanzanian currency against the dollar and discussed the symmetric and asymmetric effects and the leverage effect separately. In this study, it has been shown that past exchange rate volatility affects today's exchange rate volatility.

Kearney and Patton (2000) investigated the transmission effects of exchange rate volatility between European Union countries using the GARCH model and concluded that the German currency mark was the currency with the greatest transmission effect.

Kristjanpoller and Minutolo (2015) added the artificial neural network model to the GARCH model in order to more successfully measure the volatility of gold prices and observed that the success of the ANN-GARCH model they established increased by 25 percent compared to the normal GARCH model.

Abdalla (2012) also tried to find symmetrical and asymmetrical effects with GARCH and EGARCH models by using daily exchange rate data of 19 Arab countries between 2000 and 2011. In this study, it has been shown that there are asymmetric effects, that is, negative volatility has a greater effect than positive volatility in the future.

The fact that the prices in the electricity market have a great impact on the market directly and indirectly and the volatility of electricity prices is very high, necessitated a forecast for the market. Hua, Li and Li-zi (2005) applied the GARCH volatility measurement modeling in the electricity market to meet the need in this market.

ARCH and GARCH models are also frequently used in engineering and signal processing fields. Pham and Yang (2010) propose a hybrid model of autoregressive moving average (ARMA) and generalized autoregressive conditional variance of variance (GARCH) to predict machine condition based on vibration signal. The progress of the proposed model has been validated by empirical results when applied to a real methane compressor system in a petrochemical plant.

3.8. The Volatility Decreasing Policies of Central Banks

Especially after the 2008 financial crisis, as the capital inflows and outflows affected the developing and developing country markets negatively, countries considered some measures to reduce volatility in order to protect the values of their currencies and to ensure price and exchange rate stability. Financial stability has been added to the job descriptions of central banks in addition to price stability, because the 2008 financial crisis broke out during the low inflation period and the importance of financial stability came to light. The increased risk appetite in 2010 and 2011 provided hot money inflows to developing countries. The debt crisis that emerged in the European Union in 2011 and 2012 alarmed Turkey and a system called reserve option mechanism, unique to Turkey, was created in order to avoid the negative effects of capital outflow. According to the ROM mechanism, Turkish banks can hold a certain amount

of gold or foreign currency instead of Turkish Lira in required reserve ratios. Through this mechanism, the borrowing cost of the market in terms of Turkish lira is reduced and a foreign currency bottleneck is avoided (Oduncu, Akçelik & Ermişoğlu, 2013; Oduncu, Akçelik, Başçı & Ermişoğlu, 2013).

Oduncu, Akçelik, and Ermişoğlu (2013) investigated the volatility-reducing effect of the Reserve Option Mechanism on the Turkish Lira by using the GARCH (1,1) model. According to this study, ROM appears to be an important financial actor in reducing the volatility of the Turkish Lira.

Akardeniz and Engin (2019), in their study in which they examined the relationship between Central Bank interest rates and exchange rate volatility with GARCH, EGARCH, FIGARCH models, observed that the effect of interest rate changes on exchange rate volatility varies between times. This effect can sometimes be positive and sometimes negative. Also, in this study, it was determined by Granger causality analysis that the change in exchange rates was the cause of the change in interest rates.

Chang and Feunou (2013) obtained findings that the actions of the Bank of Canada reduce uncertainty and volatility in the markets. According to this study, the policy rate announcements of the Bank of Canada greatly reduced volatility. In addition, term purchases and resale transactions also play a role in reducing volatility.

Baillie and Osterberg (1997) investigated the effect of open market operations of G7 countries, Germany and the USA, on exchange rate volatility using the GARCH method. According to this study, it was observed that central bank interventions did not cause a high volatility in the exchange rates of these countries. The direction of the partial volatility found is upwards. In this case, contrary to the general belief, it was seen that the increasing central bank interventions did not have a relaxing effect on the market.

According to Bernanke and Gertler (2001), inflation targeting practices of central banks are important in terms of ensuring financial stability and price stability even when there is a bubble in asset prices. Thanks to the inflation targeting application, the markets will see the gain they will gain from asset prices, and therefore, speculative upward or downward movements in asset prices are prevented.

Dominguez (1998) also investigated the effect of foreign exchange interventions of central banks on exchange rate volatility for the years 1977-1994. According to this comprehensive study, interventions made in the 1970s had only a limited volatility-modifying effect. However, partial effects also increase volatility. In particular, secret market interventions increased volatility more, while open market interventions in the mid-1980s reduced exchange rate volatility. However, in general terms for all times, central bank interventions increase exchange rate volatility.

Another point that should be emphasized here is that the reaction of the central bank of each state to exchange rate changes is not the same. For example, Lubik and Schorfheide (2007) analyzed the interest rate responses of Australian and New Zealand central banks against the dollar using the Taylor rule, and according to this research, he found that these central banks do not respond to dollar changes. In the same study, it was found that the central banks of England and Canada responded to dollar volatility with interest rates.

In fact, even before the 2008 global financial crisis, it has been the subject of heated debate whether central banks should intervene against excessively high asset pricing or intervene as a regulatory agency after the bubbles burst. Bleich, Fendel and Rülke (2013) concluded that the Federal Reserve, the UK central bank and the European central bank responded to excessive asset price volatility by lowering interest rates.

Again, it has been shown that the changes in the balance of payments of major economies after the 2008 financial crisis can cause abnormal volatility in the prices in the markets of developing countries. On this occasion, the importance of the volatility spillover effect in emerging market markets was emphasized (Apostolou & Beirne, 2018).

3.9. Reel Effective Exchange Rate

The real effective exchange rate is calculated by finding the weighted average value of TL according to a basket consisting of the currencies of the countries that play an important role in Turkey's foreign trade. The weights of foreign currencies in this calculation are determined according to their volumes in the bilateral trade system with Turkey, and temporary price movements are ignored in this calculation and are not included in the calculation. The real effective exchange rate indices calculated by the Central Bank of the Republic of Turkey (CBRT) are calculated by taking the weighted geometric average of the ratio of the price level of our country to the price levels of the countries with which we do foreign trade (Kocakale & Toprak, 2015).

The general formula of reel effective exchange rate is as follows:

$$REER = \prod_{i=1}^N \left[\frac{P_{TUR}}{P_i * e_{i.TUR}} \right]^{w_i}$$

In the equation, w_i indicates the weight of country “i” in Turkey's REER index, P_{TUR} Turkey's price index, P_i price index of country “i”, $e_{i.TUR}$ the exchange rate value of country “i” currency in TL, and the number of countries N. The increase in the real effective exchange rate in the equation shows that the TL appreciated in real terms, in other words, the price of Turkish goods in terms of foreign goods increased. The method followed by the European Central Bank (European Central Bank - ECB) and Bank for International Settlements (BIS) was adopted in the real effective exchange rate indices calculated by the CBRT, and 45 countries were covered. The 2014 United Nations classification was used to group countries according to their level of development. Developed countries: USA, Germany, Austria, Belgium, Czech Republic, Denmark, Finland, France, Netherlands, England, Spain, Israel, Sweden, Switzerland, Italy, Japan, Canada, Korea, Norway, Portugal, Slovakia, Slovenia, Greece. Developing countries are Azerbaijan, Brazil, Bulgaria, Algeria, China, Indonesia, India, Iraq, Iran, Qatar, Kazakhstan, Hungary, Malaysia, Egypt, Poland, Romania, Russia, Saudi Arabia, Thailand, Ukraine and Jordan (Kocakale & Toprak, 2015).

3.10. FED Yield Curve Calculation and Its Interpretation

In its simplest definition, yield curves are a financial indicator that shows the returns of a debt securities of the same type in risk, liquidity and other areas with the help of a graph at different maturities. Yield curves are very important indicators for policy makers and especially for central bank policies. According to these indicators, clues are obtained about very important macro indicators such as inflation, growth and interest rate expectations. The yield curve depicts

how interest rates differ from each other over the short, medium and long terms. In this sense, the slope of the yield curves also indicates whether the returns increase as the maturity lengthens. Basically, there are 2 causalities why short-term and long-term interest rates differ from each other, they can be said as expectations regarding forward interest rates and maturity premium. According to the concept known as the theory of expectations in economics, the return of two different investment options should be equal. If one investment option yields more returns than the other, investors demand more of that investment to get more returns, which raises the price of that investment and lowers its return. Thus, the returns of both investment instruments are equalized (Mishkin, 1990).

Inflation expectations are also very important at this point. Since different inflation expectations in different maturities will also affect nominal interest rates, inflation can be very effective in the formation of yield differences between maturities. For example, if an increase in inflation is expected in the long run, the long-term yields of bonds are expected to be higher than the short-term interest yields. Since inflation expectations in developed countries will not change much in the medium and long term, it is expected that inflation expectations will not affect the yield slope much. On the other hand, the same is not the case for developing countries such as Turkey, whose inflation is very volatile. Another important factor that changes the yield slope is the maturity premium. Investors want to earn an additional return on long-term investment. Because, taking a positive position against long-term uncertainties is more costly, especially in periods when uncertainty increases and country risks increase, and this leads to an increase in the return of long-term investments (Mishkin, 1990).

The situation where the yield curves are horizontal or negative can be associated with a decrease in short-term interest rates in the future, a decrease in economic activities and a corresponding downward trend in inflation. In addition, the direction and severity of the yield slope give important clues about monetary policy. A positive yield slope indicates that the monetary policy stance gives dovish signals, while a horizontal or negatively sloping yield curve indicates a hawkish monetary policy stance.

In economic literature, there are many works according to which negative yield curves means the decreasing economic turnover and probably a recession (Mishkin, 1990; Estrella & Hardouvelis, 1991). In fact, according to some authors, recessions can be predicted much more successfully by using yield slopes than professional macroeconomic forecasting methods (Rudebusch & Williams, 2019; Wright, 2006; Haubrich & Dombrosky, 1996).

For instance, Estrella & Hardouvelis (1991) set up a regression model in between 1955-1988 to predict real GNP rate 1 or 2 quarter ahead by taking yield curve's slope as independent variable as follows:

$$Y_{t,t+k} = a_0 + a_1 SPREAD_t + \sum_{i=1}^N \beta_i X_{it} + \varepsilon_t$$

Where $Y_{t,t+k}$ is the real GNP coefficient, X_{it} is another information about market, and $SPREAD$ is defined as follows:

$$SPREAD_t = R_t^L - R_t^S$$

Where R_t^L and R_t^S are 10-year government bond rate and 3-month T-bill rate respectively. Hence, the slope of the yield curve is given by the difference of them. According to this study, in line with the generally accepted theory, a steeper positive slope indicates a recovery in the economy, while a more horizontal or negative slope indicates a possible recession in the economy (Estrella & Hardouvelis, 1991).

In general, the underlying causality for this finding is that the tightening monetary policy increased the short-term interest rates above the long-term interest rates, pulling inflation down and negatively affecting long-term interest rate expectations.

Today, the opposing view on whether a negative slope will cause a recession in developed countries is that the main causality for the decline in long-term interest rates is that central banks reduce maturity premiums with expansionary monetary policies, apply verbal guidance and reduce uncertainties about the future, and in this case, interest rates actually fall to “**new normal**” levels (Williams, 2017).

On the other hand, when the extreme volatility of inflation and import costs in developing countries are evaluated together with the uncertainty about the future, the hawkish monetary policy may create a more stable and positive-looking economy in the long run. In this case, the economy may paint a more stable and reliable economy picture in the long run rather than implying any recession. In addition, the rise of short-term interest rates above long-term interest rates in developing countries may accelerate the short-term capital inflows, causing the deficiency in foreign exchange reserves of such countries to be eliminated and the economic growth to be revived through investment.

Gürcihan & Özel (2010), investigated the transmission mechanism of policy rate changes on the rate of government debt securities in between 2008-2009 and they found that the decreasing policy rate caused government debt securities' interest rates to fall. Both short-term and long-term interest rates of government debt securities decreased together with policy rate falling and it was very effective to bounce back the Turkish economy after the plummet of demand in the global financial crisis.

Turker and Cakir (2019) investigated the predictive power of yield curve on Turkey's GDP growth rate by setting up a linear regression model in which yield curve coefficient was given as explanatory variable of the real GDP. According to this study, yield curve coefficient is significant, and every 1 percent increase of yield curve coefficient leads to 1 percent rising on GDP.

A summary of the literature review is given in the tables below.

Table 2.1

AUTHOR	TOPIC	MODEL	RESULT
Akgiray (1989)	The estimation comparison of the different forecast techniques to predict future volatilities of the equity prices by using daily data in between 1963-1986.	ARCH(2), GARCH(1,1), ARMA, EWMA, H	The basic advantages of GARCH(1,1) models over ARCH and ARMA are that they include past variances, and it makes estimations simpler than that of time series models
Figlewski (1997)	Measuring the S&P 500 index and T-Bills' returns by using their monthly and daily data in between 1974-1994.	HIS, BS, GARCH(1,1)	The superiority of GARCH models over historical volatility models is existing when the daily data is used and when the forecast horizon is relatively long.
Bollerslev (1986)	The superiority of the GARCH model over the ARCH model and its empirical evidence for measuring inflation uncertainty by using quarterly data in between 1946-1983	ARCH(8), GARCH(1,1)	GARCH(1,1) is the better forecast technique to predict the inflation uncertainty than ARCH types models.
Yang & Liu (2012)	The predictive power of VIX in emergin markets for the period of December 2006 to March 2010. (daily data was used.)	VIX, GARCH	TVIX is superior forecast success over the GARCH as regards forecasting the Taiwan stock market's activities.
Carr & Wu (2005)	To measure the S&P 500 index return innovatives by using daily data in between 1990-2005	VIX.GARCH(1,1)	The author sets up a regression in which the VIX and GARCH models are taken as independent variables, and accordingly the VIX parameter gives 10% more successful results.
Ryu (2012)	To gague the volatility of Korean index options (KOSPI200) in between 2003-2012 by using monthly data.	VKOSPI, GARCH,GJR-GARCH-VKOSPI	Including VKOSPI as independent variable in GARCH equation increases the forecast power of regression.

Table 2.2

Whaley (2009)	to forecast the next 30 days volatility of S&P 500 index by including 274 months as sapmle.	VIX	A high VIX index and staying at those levels for a long time usually depicts a negative panic atmosphere in the economy.
Engle (2001)	The aim of this essay is to make comprehensive explanation of ARCH/GARCH models, and their usage areas by using daily data of NYSE, Dow Jones and T-Bills in between 1990 - 2000.	GARCH(1,1)	ARCH/GARCH volatility models are very successful in measuring the volatility of equity prices and interst rates. However, the biggest downside of GARCH model is not to be able to measure the asymmetric effects of volatility.
Engle (1982)	To estimate the variance of inflation by using British data from 1968 to 1977 as taken by quarterly.	ARCH(4), OLS	the ARCH model is more successful than OLS model to forecast variance of inflation.
Engle (2007)	The aim of this paper is to show how the good volatility model should be. Daily price data was collected from Dow Jones index in between 1988 - 2000.	ARCH(1,1), TARCH(1,1), GARCH(1,1)-	According to Engle, GARCH family models are very effective to make good estimations. However, they should be updated every passing time to obtain results which are more successful.
Nelson (1991)	The new method to estimate a model of the risk premium on the CRSP Value-Weighted Market Index from 1962 to 1987.	EGARCH, ARMA(2,1)	The restrictions and disadvantages of using GARCH model were explained, and the new method was evaluated to include asymmetric effects of volatility samples.
Oduncu, Akçelik & Ermişoğlu (2013)	To see the effectiveness of the Reserve Option Mechanism. The study used daily data in between 2010-2012.	GARCH(1,1)-X	According to the results, ROM is very effective tool in decreasing the volatility of Turkish Lira against foreign exchanges in the sample period.

Table 2.3

Alexander & Lazar (2006)	The main objective of this paper is to show that GARCH(1,1) model performs better for modelling exchange rates than other GARCH models with higher components. Data consists of daily prices of pound, euro and yen from 1989 to 2002.	GARCH(1,1), NM(2), t-GARCH	According to this study, GARCH(1,1) and NM(2) are the preferred specification for exchange rates.
Dikheel & Sami (2021)	The aim is to predict exchange rate of Iraqi dinar against USD by combining machine learning methods with GARCH. Data was collected monthly	SVM-GARCH(1,0)	The results suggest that SVM based GARCH models are more effective to estimate future exchange rate values for IQD/USD. This study uses Lasso, SVM and RT machine learning algorithms.
Baillie & Chung (1996)	Monthly post-World War 2 CPI inflation for ten countries were taken as data. The aim was to show the persistence of inflation.	ARFIMA (0,d,1)- GARCH (1,1)	There is a strong evidence that data has long memory and mean reverting behaviour. Furthermore, an inflationary shock will have long memory and persistence
Chen, Härdle & Jeong (2009)	This paper aims to combine SVM with GARCH model and forecast the future volatilities of GBP exchange rate and NYSE stock indexes. The daily GBP exchange rates and NYSE composite index were used.	SVM-GARCH(1,1)	the SVM-GARCH is a better model than simple GARCH and EGARCH models for estimating future volatilities and daily returns of GBP exchange rates and NYSE index.
Diebold & Nerlove (1989)	To measure seven major dollar spot rates' (Canadian Dollar, Deutsche Mark, French franc, Italian lira, Japanese yen, British pound and Swiss franc) volatilities, data were taken from 1973 to 1985 as weekly and ARCH model was used.	ARCH(12)	They found that exchange markets are very efficient and sensitive to news, because economic actors are reacting these news instantaneously. According to them, ARCH model is reflecting all of them properly.
Perez-Cruz, Afonso-Rodriguez & Javier (2003)	They are using GARCH model by finding its parameters via SVM rather than maximum likelihood method. As empirical evidence, they make use of S&P 500, NIKKEI and FTSE100 index prices as daily in between 1995 and 2000.	GARCH(1,1)	Making use of SVM rather than ML to choose parameters caused prediction success to increase.
Hua, Li & Li-Zi (2005)	To forecast electricity prices by making use of GARCH model. Data was taken hourly in May 1999.	GARCH(1,1)	According to the results, the electricity prices with high volatility can be forecasted via GARCH model properly, and this model provides transparency for this market.
Kristjanpoller & Minutolo (2015)	The hybrid ANN-GARCH model is used to forecast the gold price volatility. The sample period for this forecast is from 199 to 2014. The data was taken as daily and total of 3836 observations.	ANN-GARCH	The results show that using ANN-GARCH model rather than simply GARCH is improving estimation results as far as %25.
Kearney & Patton (2000)	To gauge the exchange rate volatility transmission across the important European Monetary System currencies by collecting both daily and weekly data from 1979 to 1997.	GARCH(1,1)	According to this model, Deutsche Mark has dominant role to transmit its own volatility to the other important currencies.

Table 2.4

Abdalla (2012)	This paper considers the generalized autoregressive conditional heteroscedastic approach in modelling exchange rate volatility in a panel of nineteen of the Arab countries using daily observations over the period of 1st January 2000 to 19th November 2011.	GARCH(1,1), EGARCH(1,1)	These results show that 10 out of 19 currencies the sum of estimated persistent coefficients exceed one implying that volatility is an explosive process.
Pham & Yang (2010)	The aim of this paper is to estimate machine state based on vibration signal by using hybrid ARMA-GARCH model. The data were recorded every 6 hours from September 2005 to November 2005.	ARMA(1,1)-GARCH(1,1)	The results show the adequacy of the proposed model which used to estimate monitoring machine condition system.
Akardeniz & Engin (2019)	THE ARTICLE INVESTIGATION OF THE EFFECT OF THE CENTRAL BANK'S INTEREST DECISIONS ON EXCHANGE VOLATILITY IS BASED ON THE MONTHLY DATA BETWEEN 2002-2017.	GARCH(1,1), EGARCH(1,1), FIGARCH	According to this essay, CBRT's interest decision sometimes increases and sometimes decreases the volatility of the currency.
Baillie & Osterberg (1997)	This paper focused on the effectiveness of the foreign exchange interventions (\$/Yen and \$/DM) on market. Daily nominal dollar exchange returns were used in between 1985-1990.	Martingale-GARCH(1,1)	There is some evidence that foreign currency intervention via open market operations are slightly increasing the volatility of the exchange rate returns. Furthermore, this effect varies according to exchange rate changes.
Dominguez (1998)	The effects of Japan, German and US monetary and intervention policies on the dollar/mark and dollar/yen exchange rate volatility over 1977-1994.	GARCH(1,1), Implied Volatility	This paper concluded that interventions are increasing the exchange rate volatilities in general.
Doroodian & Caporale (2001)	The impact of Federal Reserve intervention on US exchange rates. Daily yen/dollar and mark/dollar exchange rates from 1985 to 1997 were used.	GARCH(1,1)	This study shows that intervention is increasing uncertainty and volatility for both bilateral spot exchange rates (yen/dollar and mark/dollar).
Chen, Härdle & Jeong (2009)	This paper aims to combine SVM with GARCH model and forecast the future volatilities of GBP exchange rate and NYSE stock indexes. The daily GBP exchange rates and NYSE composite index were used.	SVM-GARCH(1,1)	the SVM-GARCH is a better model than simple GARCH and EGARCH models for estimating future volatilities and daily returns of GBP exchange rates and NYSE index.

3.11. Biomedical Engineering and Epilepsy Literature

Mohamadi, Yeganegi & Nasrabadi (2019) used the ARIMA-GARCH hybrid model for use in predicting the highly fluctuating signals observed in epileptic seizures and heart attacks in humans. According to this model, the ARIMA parameter displays the normal status signals, while the GARCH parameter indicates the probability of detecting abnormal conditions. Moreover, according to this model, the situation where the GARCH parameter, that is, the volatility, exceeds a certain threshold is seen as a forerunner of the crisis. A similar study was done by Mihandoost, Amirani & Varghahan (2011). Electroencephalogram (EEG) signals were classified according to the GARCH model, and signals sent by healthy people and people with epilepsy or other seizures were estimated.

Mohamadi, Amindavar & Hosseini (2017) also modeled Electroencephalogram signals with GARCH in order to predict epilepsy crises before the onset and tried to understand the normal-abnormal state differences with the ARIMA-GARCH model. The data were processed with

samples taken in pre-crisis and non-crisis situations and the GARCH (1,1) model was established. Almost the same works made by Follis & Lai. (2020).

Kalbkhani, Shayesteh & Zali-Vargahan (2013) modeled the magnetic resonance image of the brain and the volatility of brain waves with GARCH (1,1) and modeled the wavelengths and images of 7 different disease types, including Alzheimer's, with KNN and SVM machine learning algorithms.

Rasool, Bouaynaya & Iqbal (2012) used myoelectric (EMG) signals to obtain information about temporary muscle activity and, considering that these signals carry information about muscle diseases and disorders, they tried to observe the health status of muscle activities with the AR-GARCH hybrid model. The AR model was used to generate the normal process, while the GARCH process was used to identify the abnormal processes. According to the Akaike Information Criteria, the AR-GARCH hybrid model outperformed the AR model.



4. AN EXCHANGE RATE VOLATILITY MODELLING

4.1. The Regression Model

$$R_t = \beta_0 + \beta_1 RVIX + \beta_2 E(INF_t^{t+k} - INF_{At}^{t+k}) + \beta_3 \Delta USDX_t + \beta_4 \Delta CDS_t + \beta_5 \Delta TLREF + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

where,

$$R_t = \text{the percentage change of USD/TR currency} = \ln\left(\frac{P_t}{P_{t-1}}\right),$$

$$P_t = \text{USD/TL currency}$$

$$RVIX_t = \text{the Volatility Index} = \ln\left(\frac{\sqrt{VIX_t}}{\sqrt{VIX_{t-1}}}\right)$$

$$E(INF_{t-k}^t) = \text{the daily inflation expectation of Turkey}$$

$$E(INF_{At-k}^t) = \text{the daily inflation expectation of USA}$$

$$\Delta USDX_t = \text{the percentage change of US Dollar Index} = \ln\left(\frac{USDX_t}{USDX_{t-1}}\right)$$

$$\Delta CDS_t = \text{the percentage change of Credit Default Swap} = CDS/100$$

$$\Delta TLREF_t = \text{the reference interest rate of Turkish Lira} = \ln\left(\frac{TLREF_t}{TLREF_{t-1}}\right)$$

In the regression model established above, the main purpose is to learn the causalities for the volatility shock created by the pandemic crisis in the usd/tl exchange rate. In this sense, triggering parameters of both global and local crises are given among the factors that will cause volatility. The VIX index, known as the fear index all over the world, is included in this model because it is a harbinger of a global crisis. In the pandemic crisis, the position of the official currency of America, one of the most important actors of the world, against other strong currencies, is another parameter likely to be affected by the volatility of usd/tl. Inflation, which has been the nightmare of all developing countries from the past to the present, has been compared with the inflation expectation of a developing country's economy and it has been examined whether this effect contributes to the exchange rate volatility. CDS premiums, known as the pricing of a country's economic and political stance, national security and stability by the outside world, are also included with the idea that it will contribute to the model. Finally, interest, which is one of the most effective weapons of the country's central banks and plays an important role in almost all crises, has been added to the model as a parameter.

The first of the necessary conditions for constructing the Garch model is that the series are stationary. After the non-stationary series are made stationary, it should be examined whether these series are compatible with Arch and Garch models. For this reason, it should be determined by looking at the skewness and kurtosis values whether the series show a normal distribution feature. In this section, after the statistical properties of all data are given, the

compatibility of the dependent variable USD/TL series with ARCH/GARCH models will be examined.

4.2. Graphical Representation

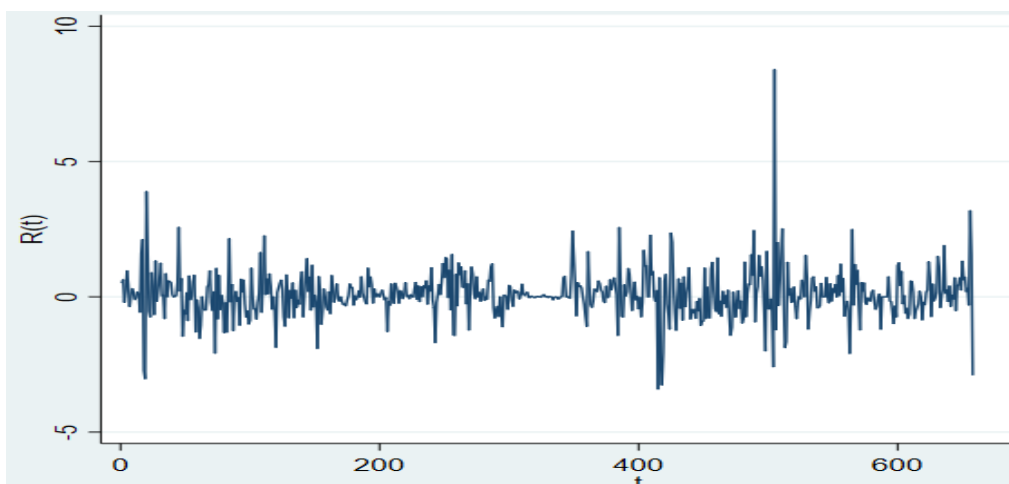
As Mandelbrot (1963) and Fama (1965) mentioned, volatility clustering, which is a feature generally seen in financial time series, is a situation that occurs as a result of positive shocks and negative shocks following each other in clusters. As seen in the graph of the original version of the exchange rate series used as the dependent variable in the model, there are sharp ups and downs over time.

Figure 4.1



In order to see it more clearly, the graph of the series with the logarithm showing the change in the exchange rate was used. As can be seen from the chart, while the volatility was very low in some periods, it was very high in some periods, and positive volatility shocks were followed by positive shocks, and negative volatility shocks were followed by negative shocks. This is a sign that volatility is autocorrelated. In addition, the fact that negative and positive volatilities are not symmetrical is one of the issues mentioned in the literature.

Figure 4.2



4.3. Non-Normality Distribution of Fat Tails (Skewness and Kurtosis Values)

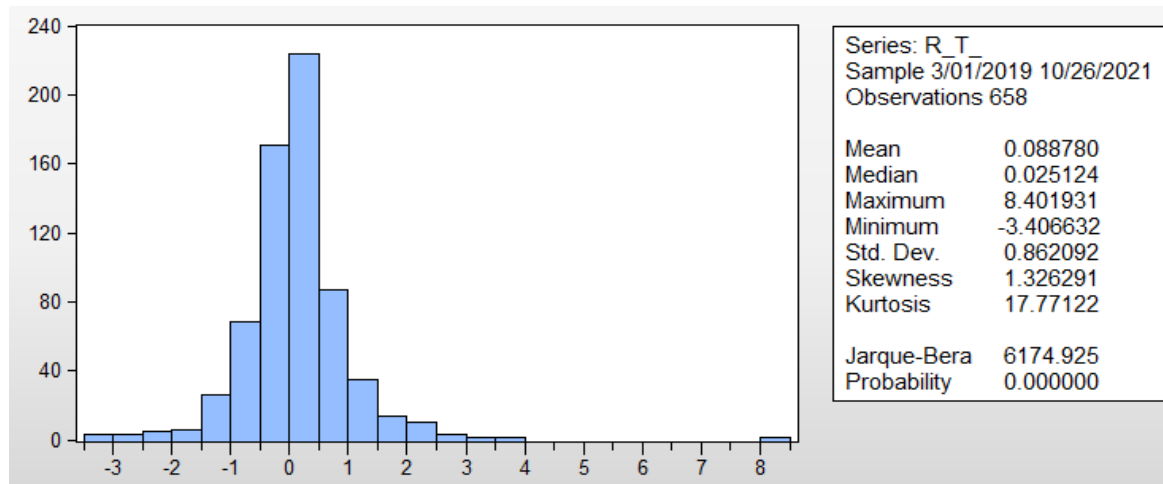
The model established by Jarque & Bera (1982) to test the fat tail property is given below.

$$JB = \frac{T}{6} \left(S^2 + \frac{(K-3)^2}{4} \right)$$

According to this normality assumption, skewness should take the value 0 and kurtosis should take the value 3 (Gujarati, 2019). In the descriptive statistics section given below, it will be examined whether the series have these features.

$R_t(\text{USD/TL})$

Figure 4.3

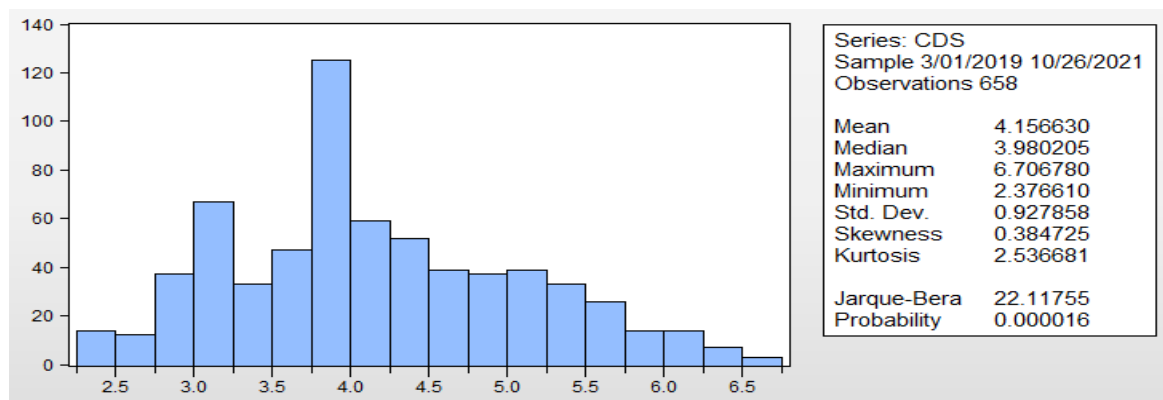


The graph above indicated that exchange rate series are not normally distributed because distribution is more peaked than the normal distribution and it seems that it has fat tail property which is one of the main features of non-normal distributions. As mentioned in detail in the literature review, the value of kurtosis between 4 and 50 is one of the evidences showing that the series does not comply with the normality assumption (Engle & Patton, 2007). As seen in the table given in the descriptive statistic section above, the kurtosis value of the exchange rate series is given as 17.77. This proves that the series has non-normal properties (fat tail property).

The descriptive statistics of other variables are given below:

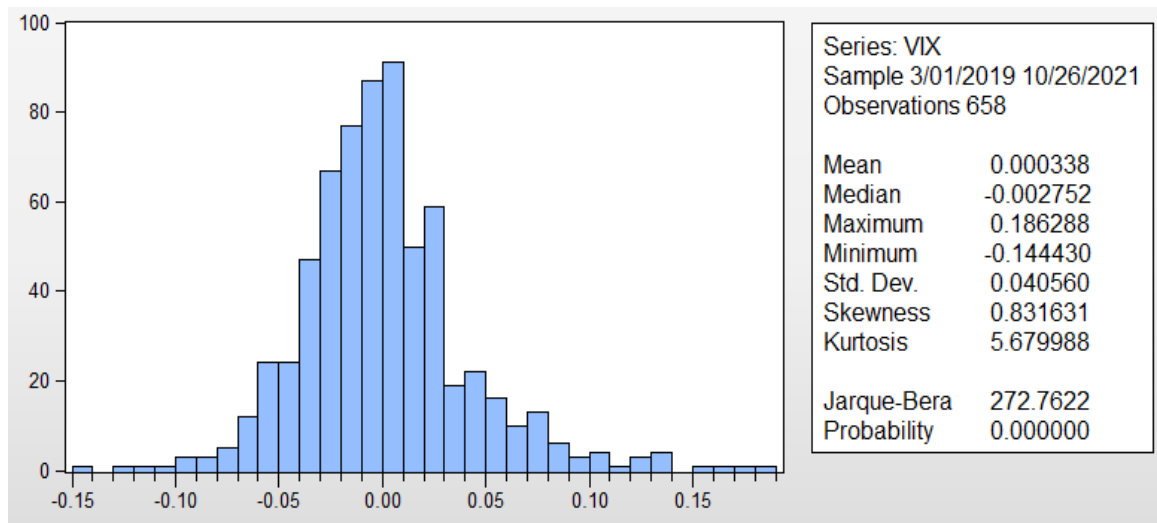
CDS

Figure 4.4



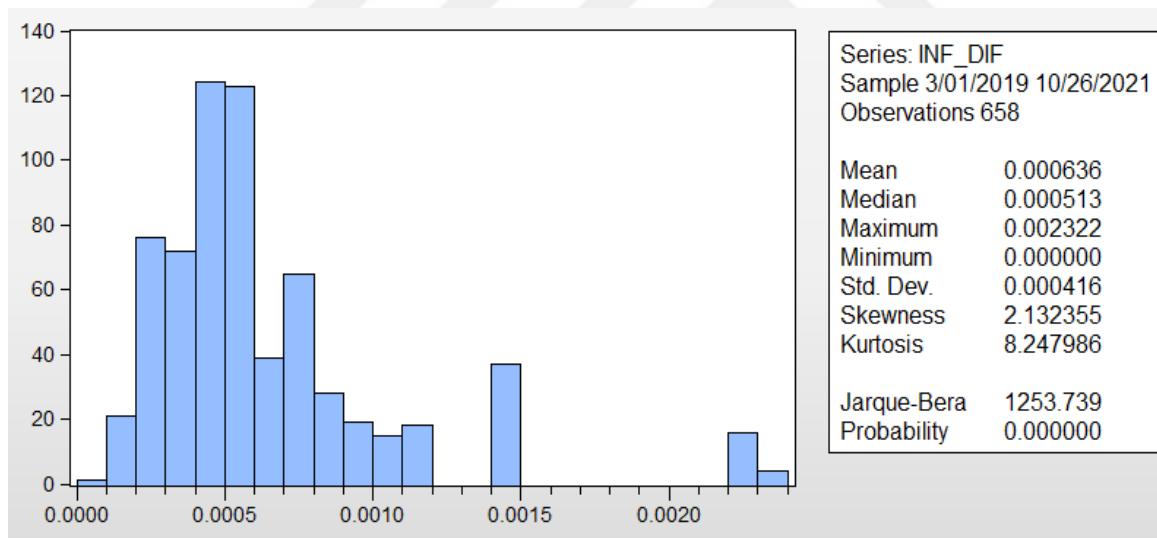
RVIX

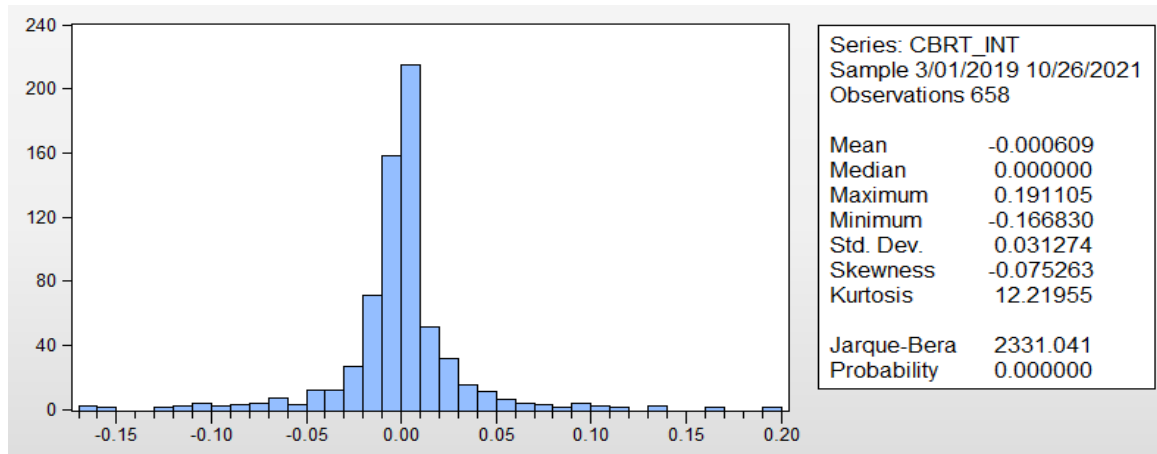
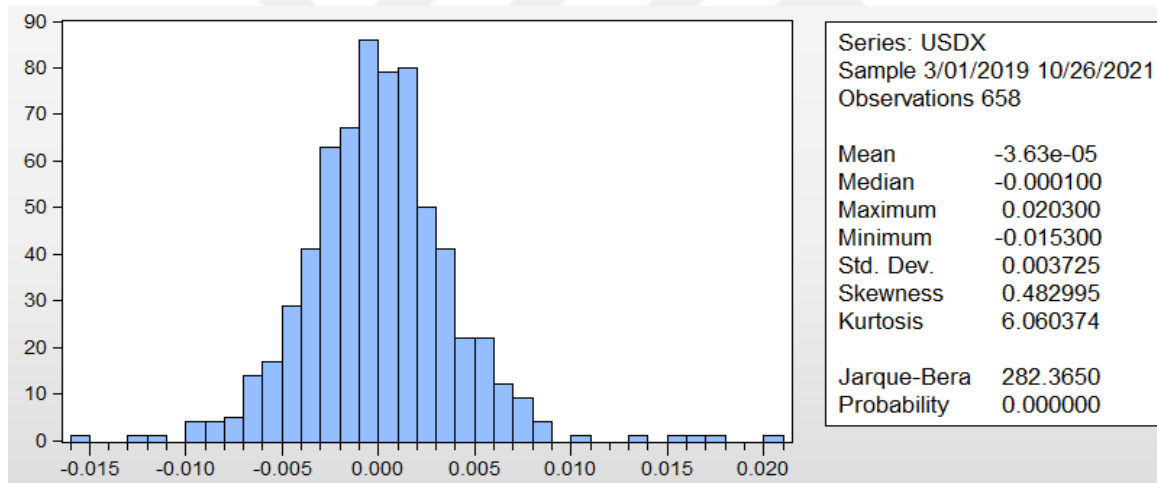
Figure 4.5



INF.DIF

Figure 4.6



CBRT.INT**Figure 4.7****USDX****Figure 4.8**

4.4. Correlogram Analysis

The results of the correlogram analysis, which are used to see whether the series are affected by the past values and give important clues about whether the series is stationary before performing the stationarity tests, are shared below.

USD/TL

Figure 4.9

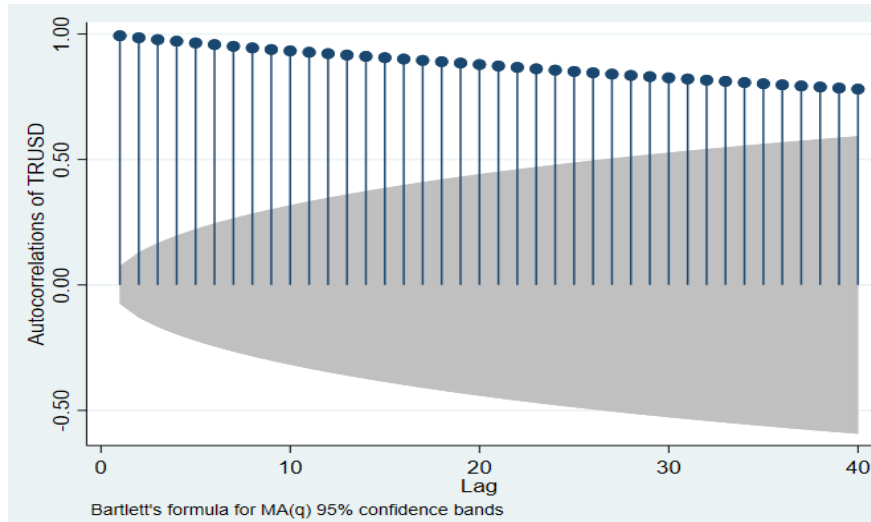
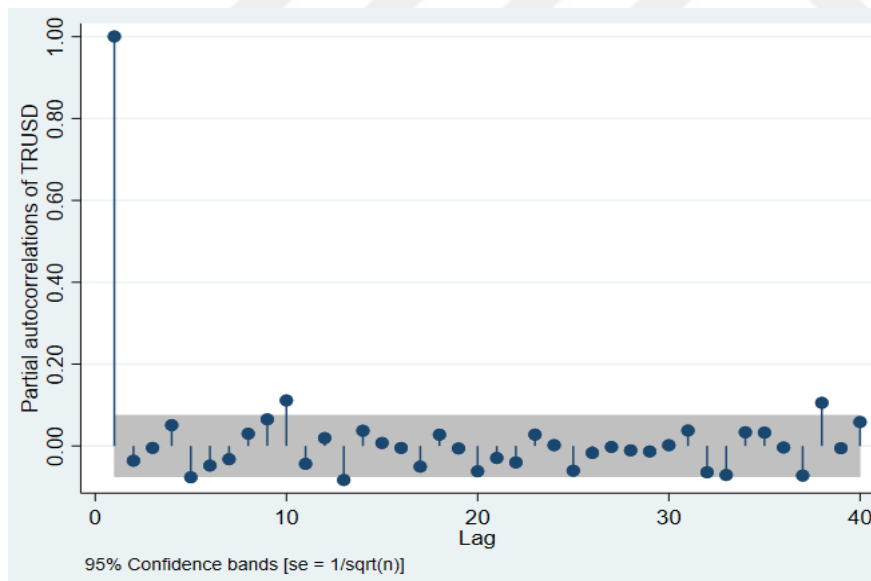


Figure 4.10



As can be seen from the charts above, the original series of the exchange rate (not logged) follows both AR and MA processes. It is seen that they follow the ARMA (1,1) process, as they exceed the confidence intervals at the first lag. It means they are affected from their own past values.

R_t (Logged value of USD/TL)

The autocorrelation graphs of the logarithm of the exchange rate series are given below. As can be seen from these graphs, almost all values are within the confidence interval, and it can be claimed that they are not affected by the historical values.

Figure 4.11

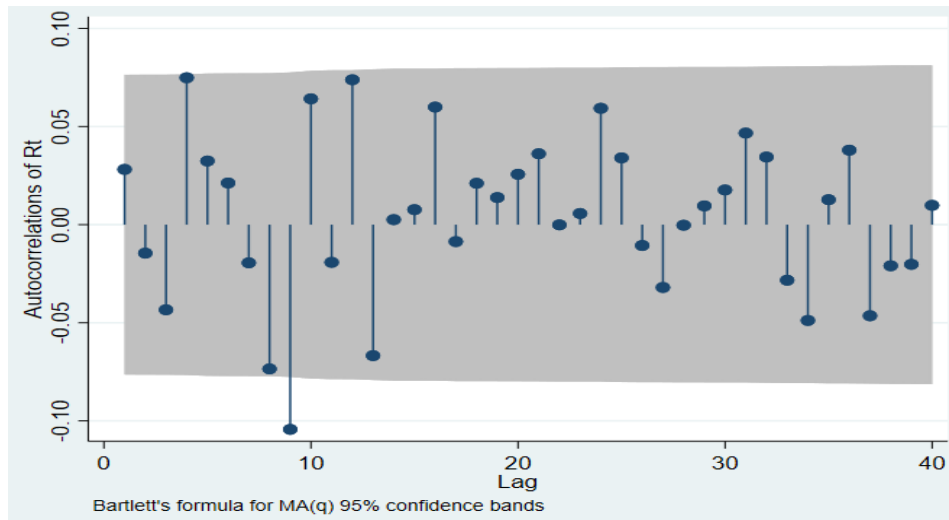
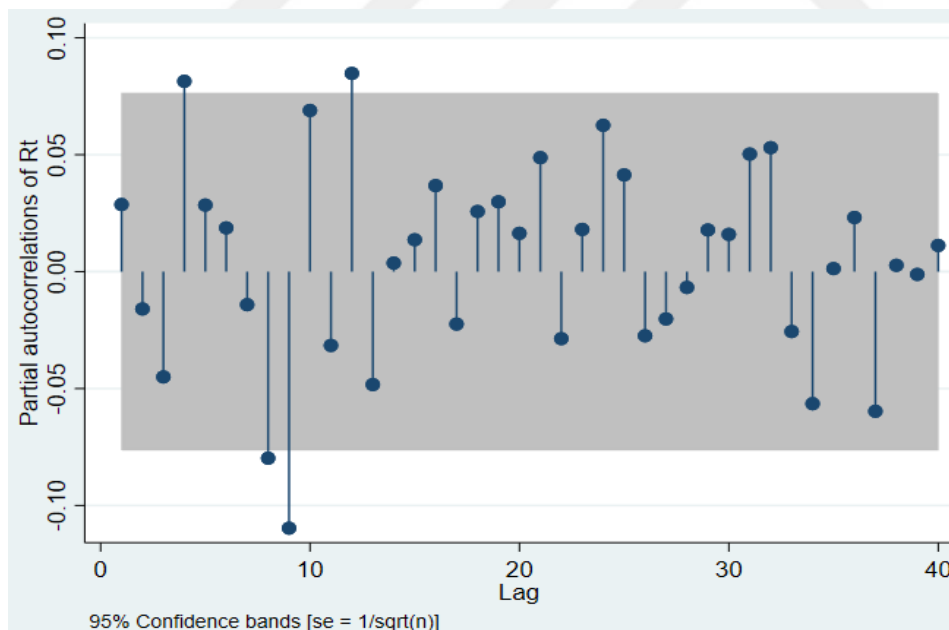


Figure 4.12



CDS

Figure 4.13

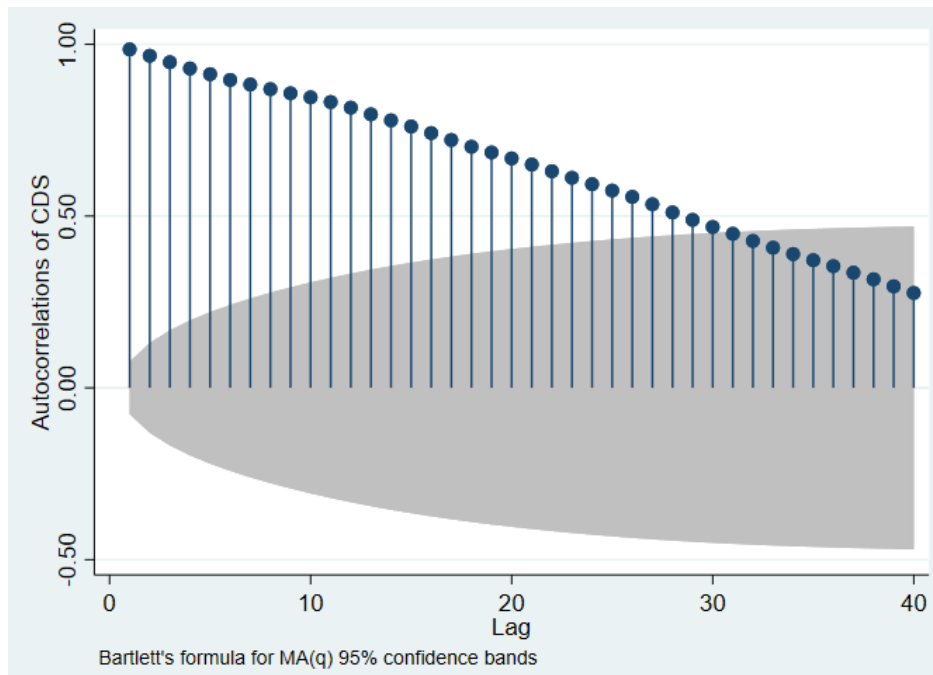
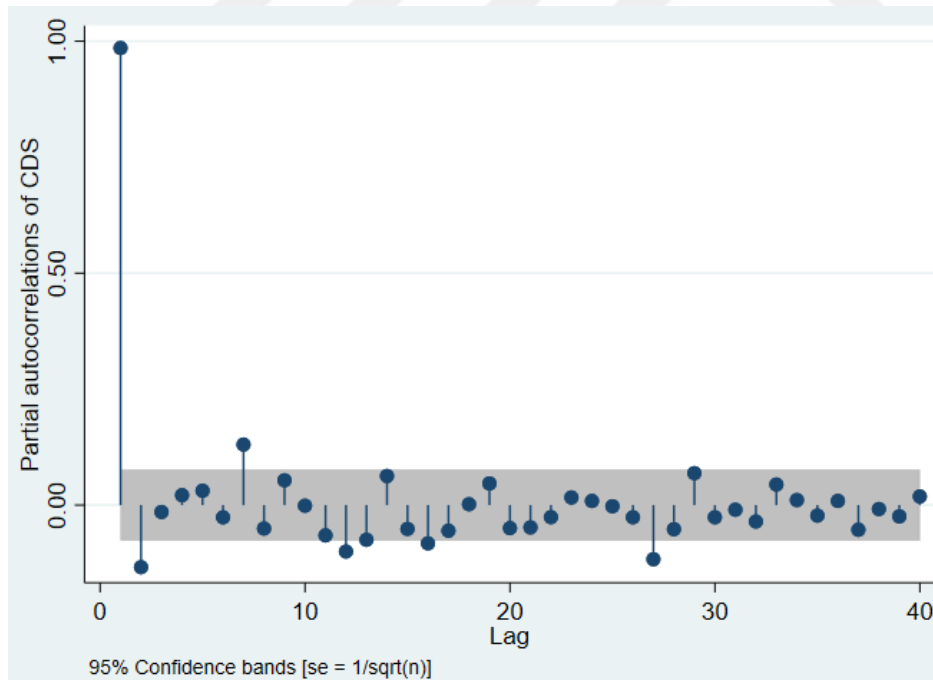
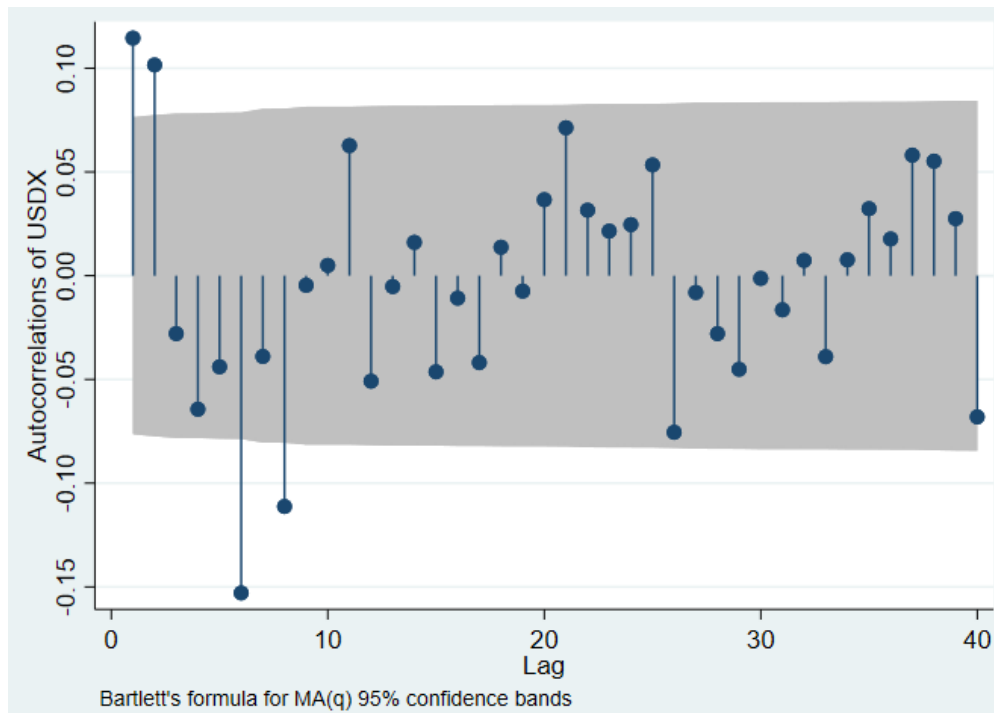
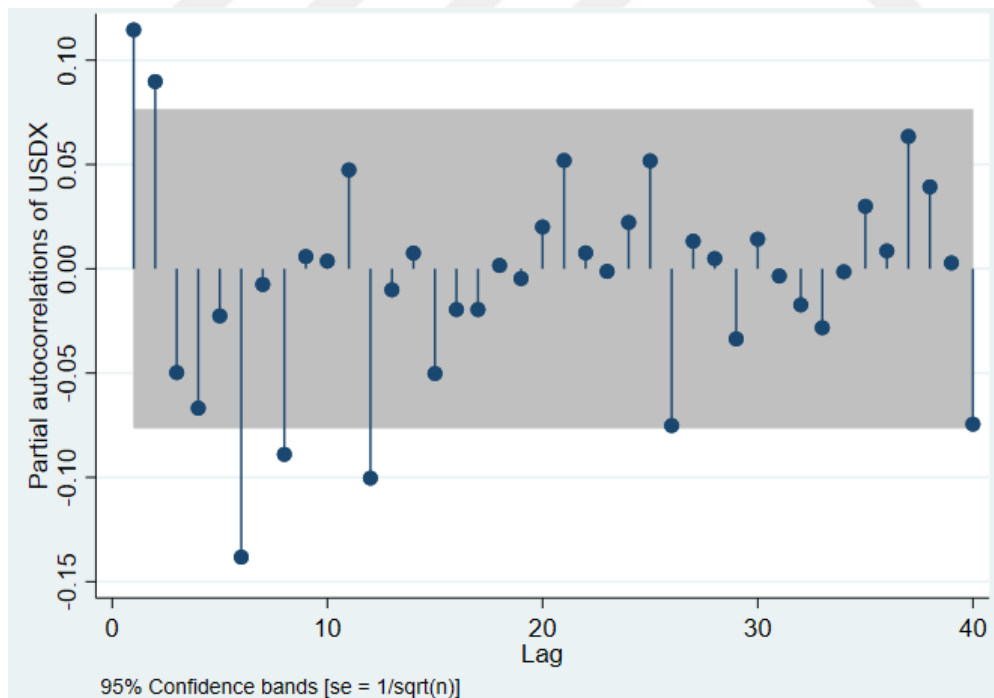


Figure 4.14



As can be seen from the charts above, the CDS series follow both AR and MA processes. It is seen that they follow the ARMA (1,1) process, as they exceed the confidence intervals at the first lag. It means they are affected from their own past values.

Δ USDX**Figure 4.15****Figure 4.16**

As can be seen from the charts above, the USDX series follow both AR and MA processes. It is seen that they follow the ARMA (1,1) process, as they exceed the confidence intervals at the first lag. It means they are affected from their own past values.

RVIX

Figure 4.17

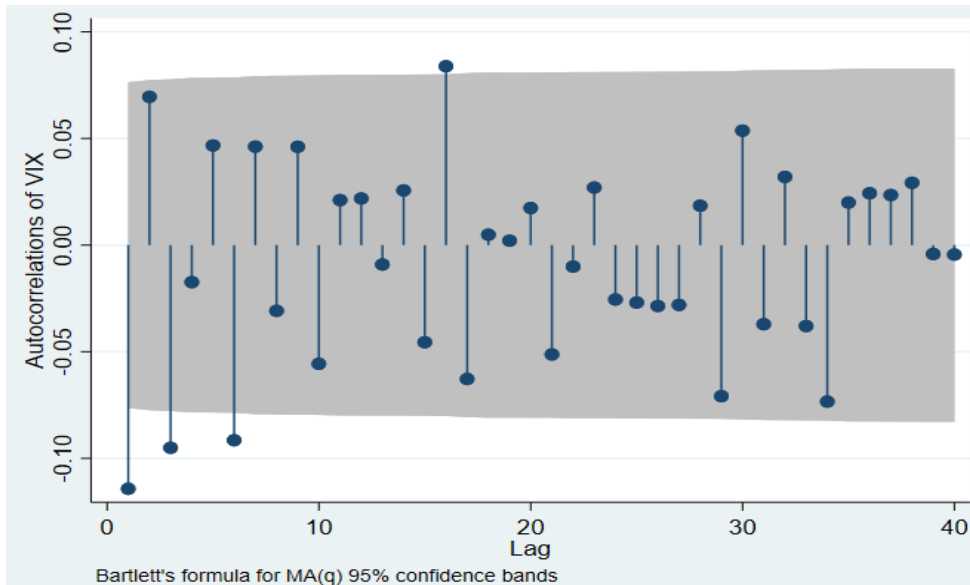
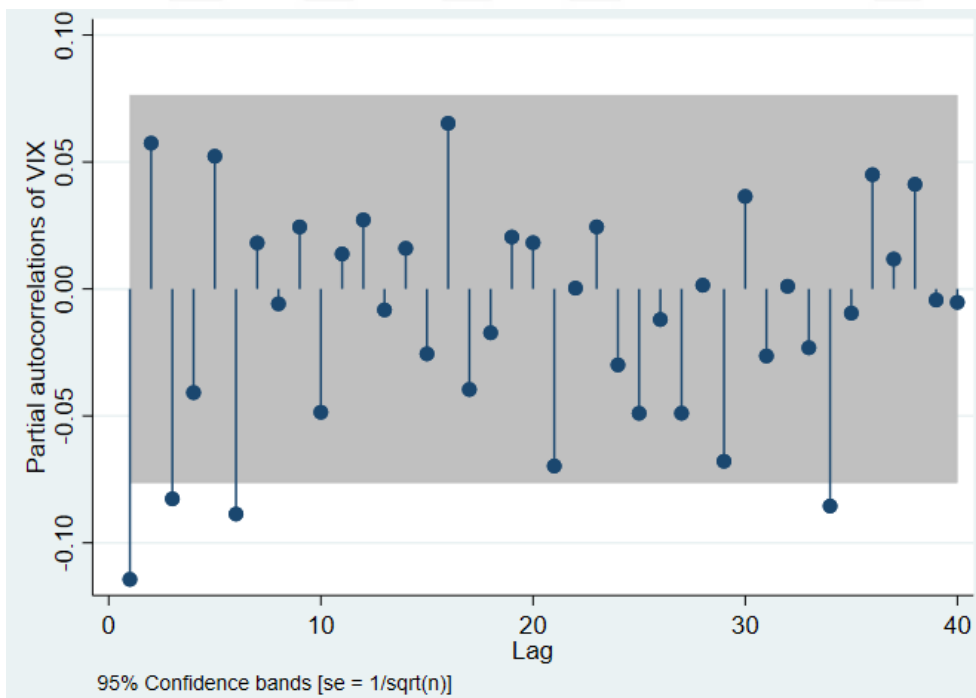
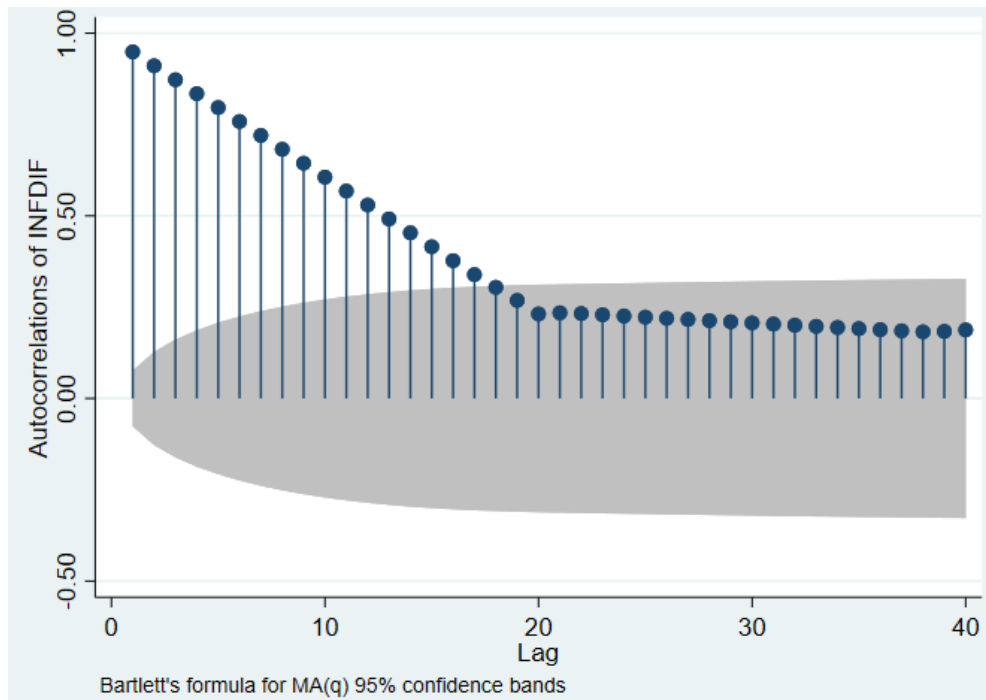
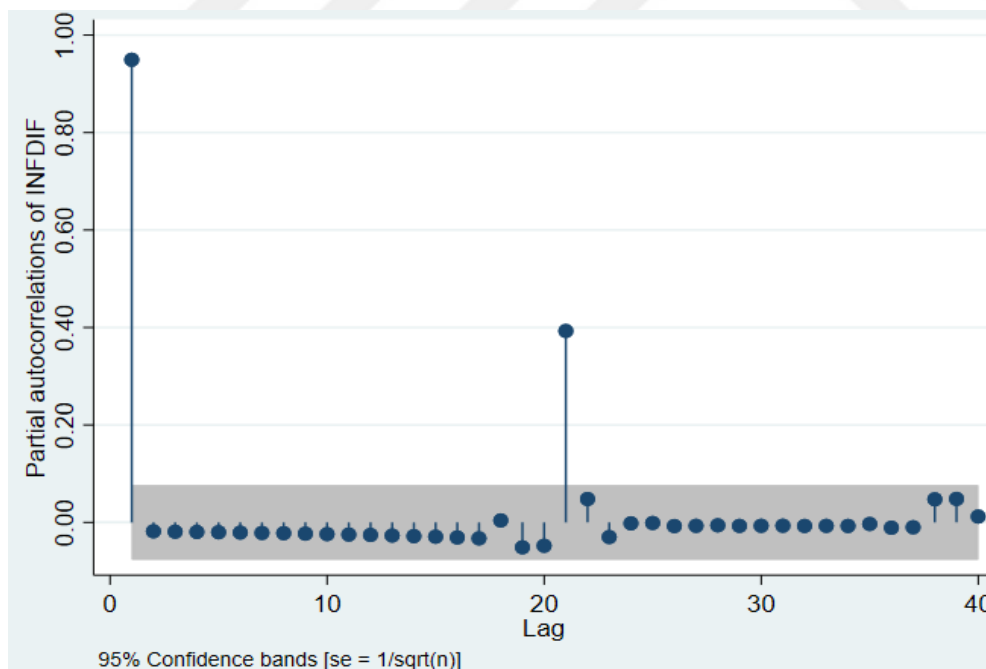


Figure 4.18



As can be seen from the charts above, the RVIX series follow both AR and MA processes. It is seen that they follow the ARMA (1,1) process, as they exceed the confidence intervals at the first lag. It means they are affected from their own past values.

INF.DIF**Figure 4.19****Figure 4.20**

As can be seen from the charts above, the INF.DIF series follow both AR and MA processes. It is seen that they follow the ARMA (1,1) process, as they exceed the confidence intervals at the first lag. It means they are affected from their own past values.

CBRTINT

Figure 4.21

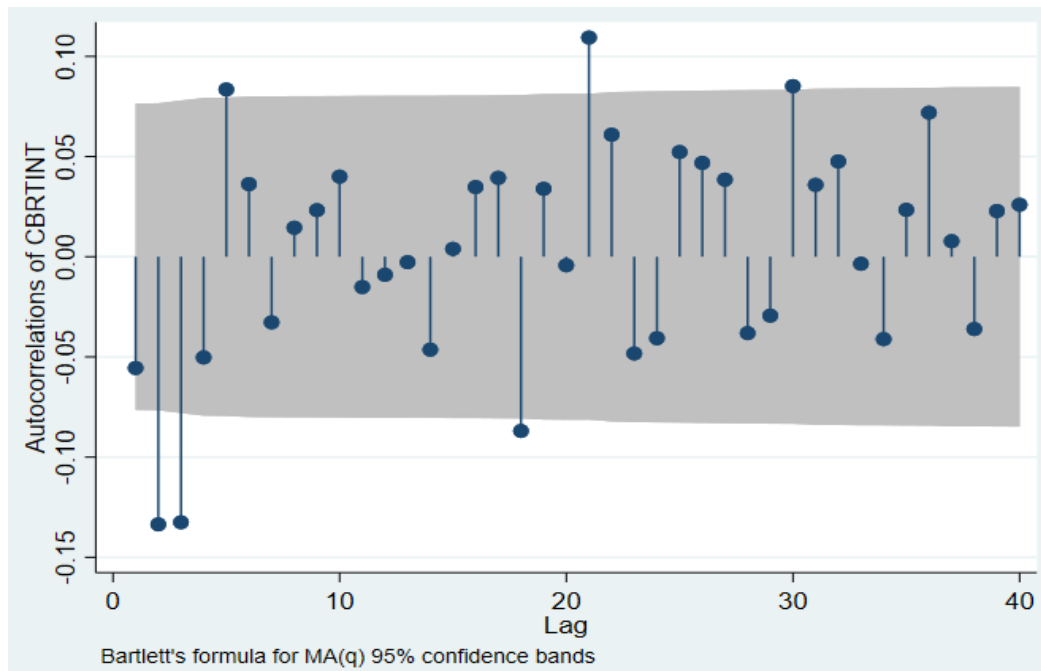
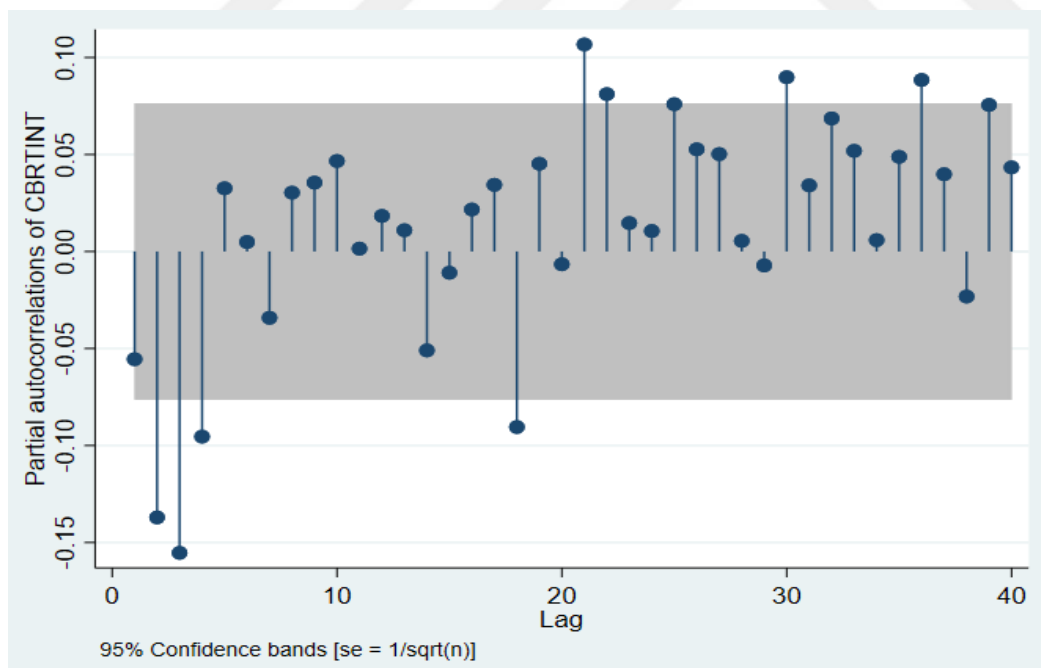


Figure 4.22



As it is known, the constant variance assumption given under the normality assumption of the error term in multiple regression analysis is one of the key points that enable the OLS (Ordinary Least Squares) method to give the most effective results. If the variance of the error term changes according to the different values of the explanatory (independent) variables, the constant variance assumption does not work. When the constant variance rule is broken, the t and F tests and confidence intervals used to measure the consistency of the regression obtained by the OLS method will not give reliable results. Before starting to build the model, regression should be established, and it should be tested whether the variance of the error term in the model is constant. Having varying variance will provide a suitable environment for building ARCH/GARCH models. In this study, first the Breusch - Pagan test statistic and then the White test statistic will be used to find the existence of the varying variance (Wooldridge, 2019).

4.5. Breusch-Pagan Test

- 1) The model is estimated by the OLS method using the determined dependent and independent variables. OLS error terms (u^2) are obtained for each observation.
- 2) A regression is obtained showing the functional relationship of the error terms with the independent variables. An $R_{u^2}^2$ value is obtained from this regression.
- 3) LM test is used, and p value is calculated. If the calculated p value is small enough to be below the chosen significance level, the null hypothesis suggesting the constant variance hypothesis is rejected and it is concluded that there is varying variance (Wooldridge, 2019). Breusch-Pagan test results can be seen below:

Table 4.1

Source	SS	df	MS	Number of obs	=	657
Model	104.213171	5	20.8426341	F(5, 651)	=	35.34
Residual	383.905251	651	.589716207	Prob > F	=	0.0000
				R-squared	=	0.2135
				Adj R-squared	=	0.2075
Total	488.118422	656	.74408296	Root MSE	=	.76793

Rt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CBRTINT	.28879	.9616057	0.30	0.764	-1.599433	2.177013
dCDS	2.325574	.2010579	11.57	0.000	1.930774	2.720374
INFDF	-10.64993	72.26177	-0.15	0.883	-152.5442	131.2443
USDx	-1.444347	8.255685	-0.17	0.861	-17.65533	14.76664
VIX	2.825323	.7630705	3.70	0.000	1.326947	4.3237
_cons	.0893549	.0548977	1.63	0.104	-.0184431	.1971528

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of Rt

chi2(1) = 137.28

Prob > chi2 = 0.0000

The figure above shows that the probability value of the chi-square statistic is less than 0.05. Therefore, the null hypothesis of constant variance can be rejected at 5% level of significance. It implies the presence of heteroscedasticity in the residuals.

4.6. White Test

The starting point of the White Test is that the square of the error term, which is one of Gauss-Markov's constant variance assumptions, is uncorrelated with all independent variables and cross products of all independent variables. In order to test this situation, in addition to the regression established in the Breusch-Pagan test, explanatory variables in the form of cross products were added. In the White test, it is tested whether the coefficients of the explanatory variables in this regression model are 0. F and LM statistics are generated, and the p value is calculated. If the P value is small enough to be below the chosen significance level, the H_0 hypothesis is rejected, and it is understood that the error terms do not show constant variance (Wooldridge, 2019). White Test results can be seen below:

Table 4.2

White's test for H_0 : homoskedasticity
against H_a : unrestricted heteroskedasticity

chi2(20) = 240.37
Prob > chi2 = 0.0000

Cameron & Trivedi's decomposition of IM-test

Source	chi2	df	p
Heteroskedasticity	240.37	20	0.0000
Skewness	49.38	5	0.0000
Kurtosis	4.11	1	0.0426
Total	293.86	26	0.0000

Similar to the results of the Breusch-Pagan test, here too $\text{prob} > \text{chi2} = 0.000$. The null hypothesis of constant variance can be rejected at 5% level of significance. The implication of the above finding is that there is heteroscedasticity in the residuals.

4.7. Stationarity

If the relationship between two variables (let's call them x and y) changes randomly every time period, we can't say for sure how the change in one variable affects the other variable in just a specified time period (Wooldridge, 2019).

Stationarity requires that the existing correlation mechanism between consecutive terms does not change over time and therefore depends on the following 3 basic conditions (Wooldridge, 2019):

- The expected value of the series should not change over time.
- The variance of the series should not change over time.
- The covariance of the series with its different and consecutive terms should not change over time.

In order to make the stationarity issue understandable, let's consider an equation following an AR (1) process, given by the equation below.

$$y_t = \rho y_{t-1} + u_t$$

In this case, the condition $\rho < 1$ must be met. Otherwise, it will be examined whether the series will comply with the 3 basic conditions of stationarity mentioned above.

Let's consider $\rho = 1$.

$y_t = y_{t-1} + u_t$ this equation can be called as random walk.

Let's consider a y-series starting from 0 and going up to the value t (considering that the ρ value is equal to 1).

$$y_t = y_{t-1} + u_t = y_{t-2} + u_{t-1} + u_t = \dots = y_0 + \sum_{i=1}^t u_i$$

In such a case where the ρ value is equal to 1, the y_t series will be equal to the sum of all the error terms in the past with the y_0 series (i.e., the y value at $t=0$). That is, all past values will have a permanent effect on present value. In this case, if the error term u_t follows a white noise process, its expected value is zero and its variance is constant (Gujarati, 2009; Korurek & Ozkaya, 2009). Therefore, the expected value of y_t will be equal to y_0 and the variance of y_t can be written like this:

$$Var(y_t) = t \cdot Var(u_t) = t \cdot \sigma_u^2$$

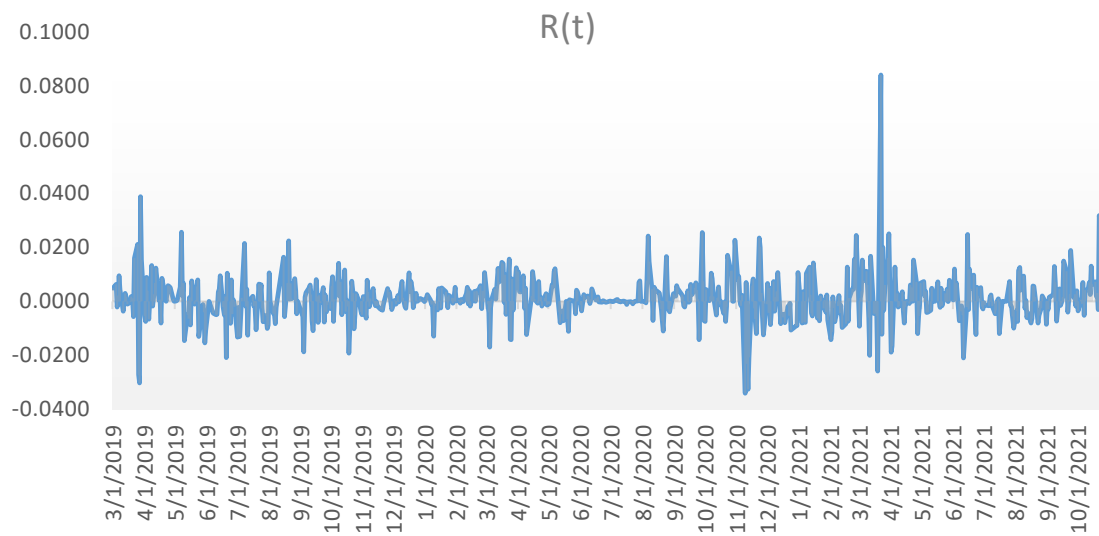
In this case, the variance of the y_t series will change with time and go to infinity, and in this case, it will not match with the constant variance, which is one of the stationarity conditions (Korurek & Ozkaya, 2009).

The way to fix this situation and make the series stationary is as follows (Gujarati, 2009; Wooldridge, 2019):

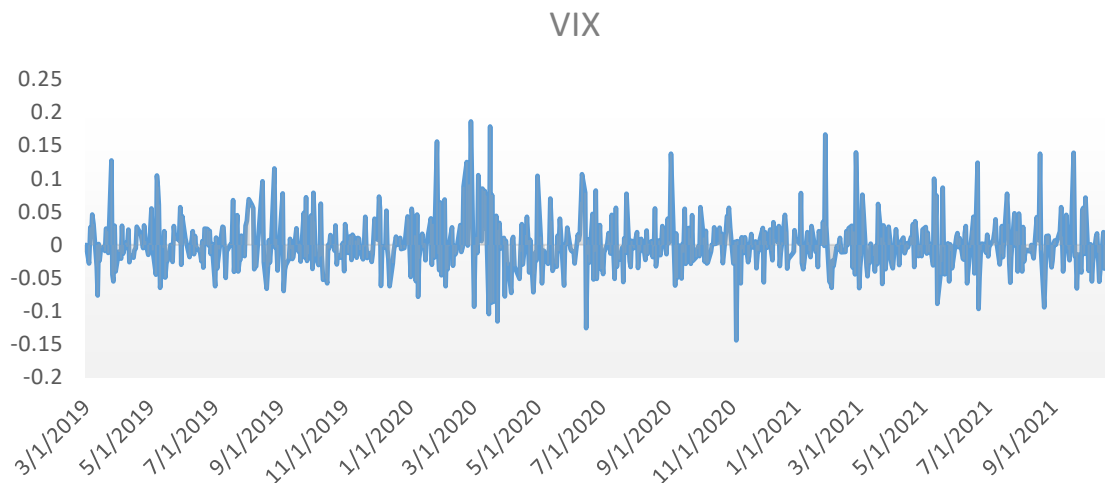
$$\Delta y_t = y_t - y_{t-1} = e_t, \quad t = 2, 3 \dots$$

Moreover, taking the first difference of the series allows for the disappearance of the trends in the series and more consistent predictions (Wooldridge, 2019).

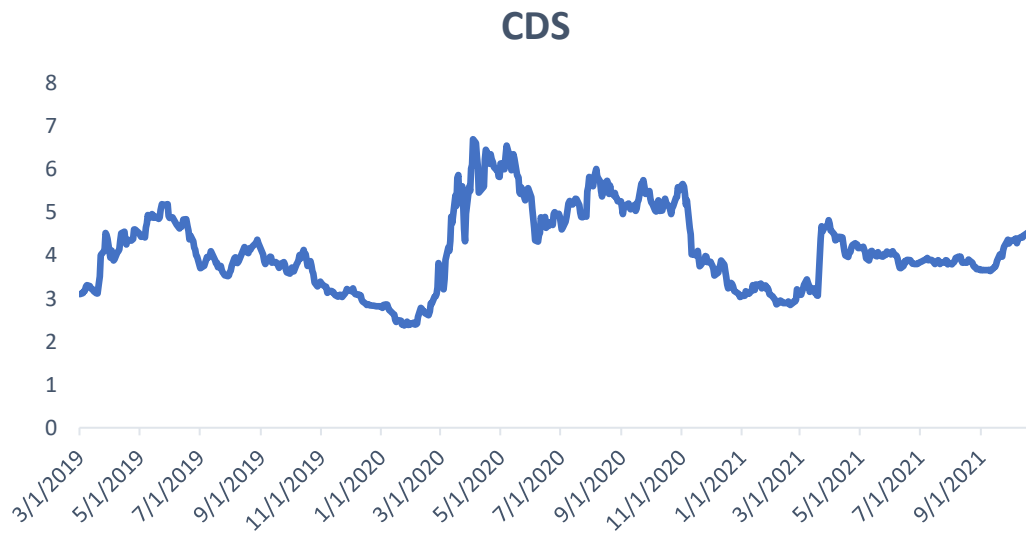
As it is known in the academic world, the stationary condition of data can be measured basically by 2 methods which are drawing the graph of data and applying stationarity tests such as Dickey Fuller and Phillips Perron. In this study, firstly, the graph drawing method will be discussed. After that, more formal and conclusive methods will be applied to be sure whether the data we use are stationary or not. But before, appropriate lag length should be chosen to reach real and accurate results. Excessive lag length and too short lag length will avoid us to make accurate forecasts. Akaike (AIC), Schwarz (SC) and Hannan-Quinn (HQ) information criterions will be indicator of this study to determine true lag length (results can be seen in appendix). By finding appropriate lag length, the error term which follows white noise process will be found (Gujarati, 2009).

USD/TL GRAPH:**Figure 4.23**

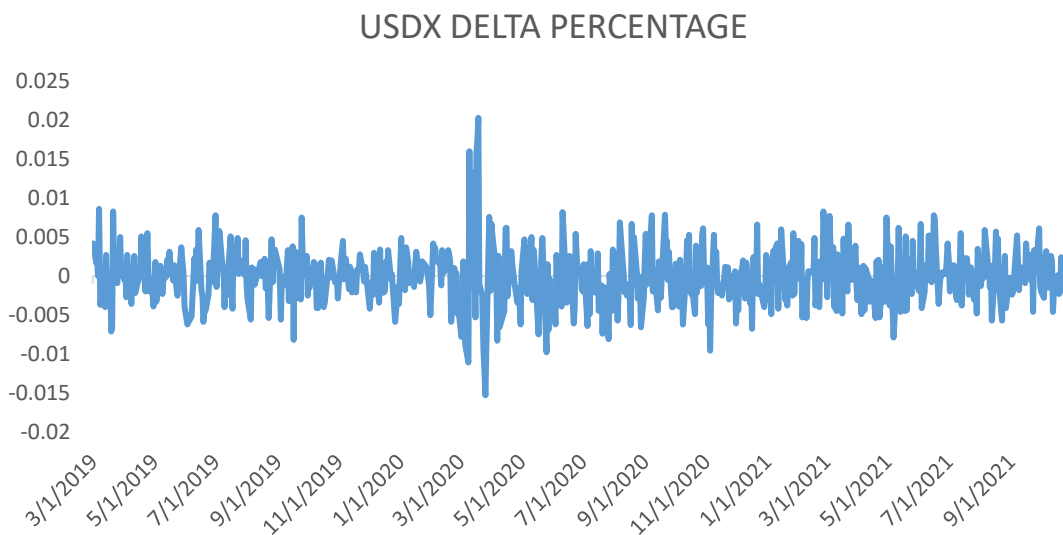
As it can be seen from the graph above, there is no clear trend or any other thing which indicates that the data is non-stationary. According to the graph above, it can be asserted intuitively that the data is stationary. It means variance and mean of the data is not changing over time.

RVIX GRAPH:**Figure 4.24**

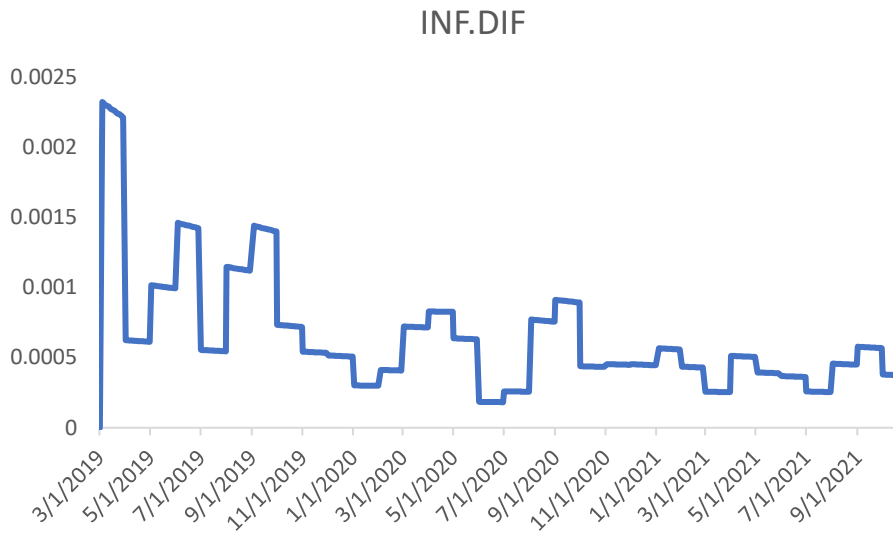
As it can be seen from the VIX graph above, there is no clear trend or any other thing which indicates that the data is non-stationary. According to the graph above, it can be asserted intuitively that the data is stationary. It means variance and mean of the data is not changing over time.

CDS GRAPH:**Figure 4.25**

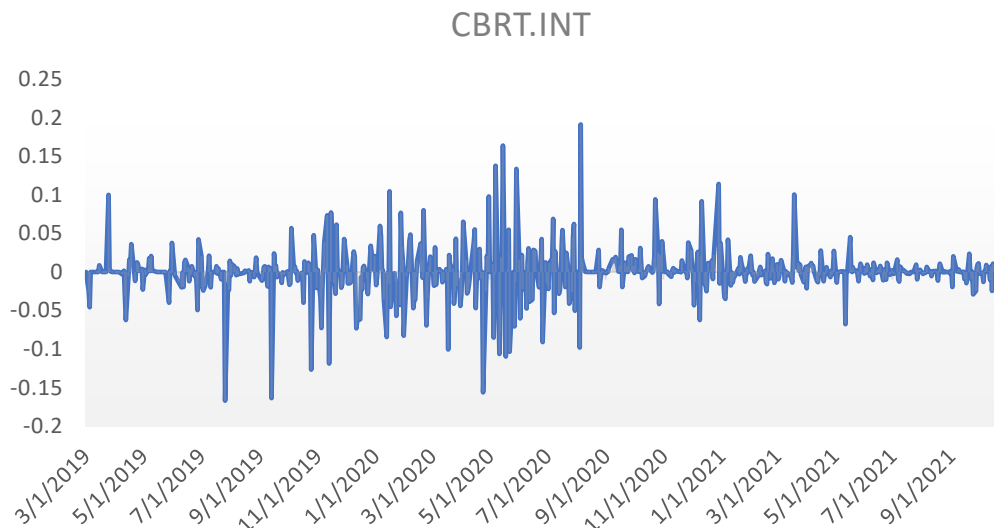
It might be asserted intuitively that CDS data is not stationary because it looks like its mean and variance are time changing. Therefore, it will be clear when stationary tests are applied to CDS data.

USDX GRAPH:**Figure 4.26**

As it can be seen from the USDX graph above, there is no clear trend or any other thing which indicates that the data is non-stationary. According to the graph above, it can be asserted intuitively that the data is stationary. It means variance and mean of the data is not changing over time.

INFLATION DIFFERENCE GRAPH:**Figure 4.27**

The chart above shows the difference between the US and Turkey's daily inflation expectations. Although it is meaningless to precisely determine whether the series is stationary according to this graph, since this difference is taken as a percentage, it is expected that the variance and mean of the series will remain constant over time in the stationarity test.

CBRT INTEREST RATE GRAPH:**Figure 4.28**

As it can be seen from the CBRT INTEREST RATE graph above, there is no clear trend or any other thing which indicates that the data is non-stationary. According to the graph above, it can be asserted intuitively that the data is stationary. It means variance and mean of the data is not changing over time.

DICKEY FULLER TEST RESULTS FOR ALL SERIES

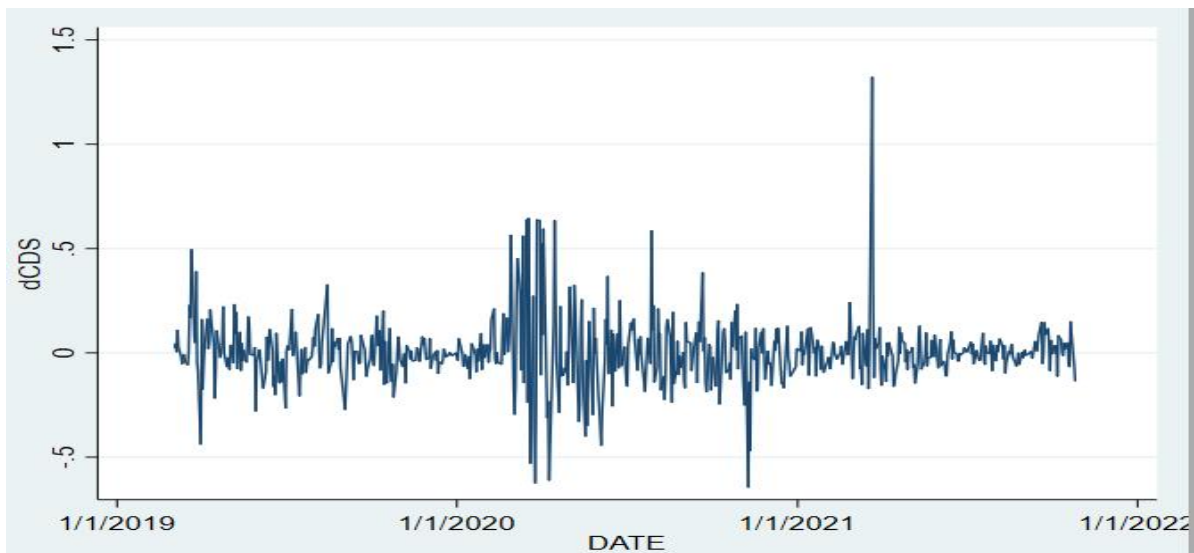
Table 4.3

DICKEY FULLER TEST RESULTS				
Series	%1 Critical Value	%5 Critical Value	%10 Critical Value	Test Statistic
Rt	-3,430	-2,860	-2,570	-24,643
CDS	-3,43	-2,860	-2,570	-2.275
INF.DIF	-3,43	-2,860	-2,570	-4,186
USDX	-3,43	-2,860	-2,570	-22,832
CBRT.INT	-3,43	-2,860	-2,570	-27,055
VIX	-3,43	-2,860	-2,570	-28,691

As it can be seen from the table above, the only data which is not stationary is CDS, because the absolute value of its Test Statistic Value (Z_t) is smaller than all critical values'. Before we set the GARCH (1,1) model, CDS data should be stationary. For this reason, the first difference of CDS data will be taken to make CDS series stationary. After that, stationary CDS data is going to be put into the regression.

The Graph of the First Difference of CDS data:

Figure 4.29



As it can be seen from the dCDS graph above, there is no clear trend or any other thing which indicates that the data is non-stationary. According to the graph above, it can be asserted intuitively that the data is stationary. It means variance and mean of the data is not changing over time.

After taking the first difference of CDS data to make CDS data stationary, Dickey Fuller test was applied, and the test results are above. As it can be seen from table, the absolute value of test statistic of dCDS is greater than the value of other critical values. It means the variance and the mean of dCDS value is not time changing anymore. For this reason, dCDS value can be put into the regression equation and to the GARCH model.

Table 4.4

DICKEY FULLER TEST RESULTS				
Series	%1 Critical Value	%5 Critical Value	%10 Critical Value	Test Statistic
dCDS	-3,43	-2,860	-2,570	-22,515

As can be seen in detail in the appendix section, the following procedures were examined in order to observe the stationarity of each data used in the model:

First of all, it was questioned whether the trended state of the data was stationary or not, if the trend was meaningless, the trend was removed from the model and model 2 was started. In Model 2, it has been observed whether the constant term of the series is stationary. In cases where the constant term is not significant, Model 3 was used, the constant term was removed from the model, and it was decided whether the model without trend and without constant term was stationary. The mathematical definition of the explanation above is given below in 3 equations:

1. $\Delta y_t = \alpha + \beta \cdot t + \sum_{i=1}^p \delta_i \cdot \Delta y_{t-i} + \varepsilon_t$
2. $\Delta y_t = \alpha + \sum_{i=1}^p \delta_i \cdot \Delta y_{t-i} + \varepsilon_t$
3. $\Delta y_t = \sum_{i=1}^p \delta_i \cdot \Delta y_{t-i} + \varepsilon_t$

As stated above and in the appendix, the stationary states of the data and their equations are given below:

dCDS:

$$\Delta CDS_t = -\delta_1 CDS_{t-1} + \varepsilon_t$$

The coefficients and test results of the above equation are given in detail in the appendix. As it is known, CDS (Credit Default Swap) is a credit risk premium, a valuation instrument that enables the determination of the risk of non-repayment of a loan and the insurance of the loan against this risk. In this equation, it seems that the CDS premium is included in the equation with a single lag length. Accordingly, the CDS premiums of the previous period are effective on the CDS premiums of this period. Also, as can be seen in the appendix, the coefficient of CDS premiums at time t-1 is negative, which means that an increase in past CDS values will decrease today's CDS value.

CBRTINT:

$$\Delta CBRTINT_t = \delta_1 CBRTINT_{t-1} + \beta_1 \Delta CBRTINT_{t-1} + \beta_2 \Delta CBRTINT_{t-2} + \varepsilon_t$$

The CBRT overnight reference interest rate equation is given above. According to this equation, the values of the overnight reference interest rate at time t-1 and t-2 affect the present value of

this rate. Therefore, policy makers should consider the interest rate decisions up to 2 periods before making their decisions. According to the equation, interest rates of the past period have a decreasing effect on today's interest rates.

VIX:

$$\Delta RVIX_t = -\delta_1 RVIX_{t-1} + \varepsilon_t$$

Extensive information about the volatility index is given in the literature review section. However, to be explanatory, the Volatility index (VIX) is an index traded on the Chicago Stock Exchange, called the fear index in the markets, to measure the volatility of the markets. A high index of this index indicates that the tension in the markets is dominant, and the risk appetite has decreased. As can be seen in the equation, the VIX value is inversely proportional to the VIX value of the previous period. In this case, a high past VIX value will have a lowering effect on the present VIX value.

USD/TL (R_t)

$$\Delta R_t = \alpha - \delta_1 R_{t-1} + \varepsilon_t$$

As can be seen from the equation, the amount of change in the dollar/tl rate in period t depends only on a constant term lag 1 and an error term. Therefore, it has already become impossible for the change in the dollar/tl rate to be 0. This means that apart from the policy and will of the Republic of Turkey, some political, social, and natural conditions, which are not shown in this model, have an impact on this exchange rate. The fact that the constant term is positive proves that these conditions have an increasing effect on the change in the dollar/tl exchange rate. On the other hand, last term dollar/tl currency change has decreasing effect on current term dollar/tl.

USDX:

$$\Delta USDX_t = \delta_1 USDX_{t-1} + \beta_2 \Delta USDX_{t-2} + \varepsilon_t$$

As it is known, the dollar index is an instrument that is used to measure the value of the dollar in the world markets in general. There are 6 main currencies used to calculate the dollar index. These currencies are Euro, Yen, Frank, Pound, Canadian Dollar and Swedish Krona. The dollar index is calculated by taking the current geometric mean of the dollar against these 6 currencies. In the given equation, it is seen that the dollar index is affected by t-1 periods. At this point, it is understood that the present value of the dollar in the world market cannot be determined independently from the past periods.

INF.DIF:

$$\Delta INF DIF_t = \alpha - \delta_1 INF DIF_{t-1} + \varepsilon_t$$

According to this equation, which deals with the difference between the US inflation expectation and Turkey's inflation expectation on a daily basis, the increase in the past inflation expectation difference reduces the current inflation expectation gap. Moreover, the inclusion of the constant term in the equation indicates that inflation expectations will never be the same. This situation indirectly indicates that the volatility in the exchange rate will never decrease to 0.

The coefficients of the equations above are given with table in detail:

Table 4.5

COEFFICIENTS				
Parameters	constant	L1 (the first lag)	LD	LD2
dCDS	no constant	-0,8687539	no	no
TLREF	no constant	0,3724895	0,3724895	0,2163707
RVIX	no constant	-1,050263	no	no
USD/TL (Rt)	0,0854807	-0,9712974	no	no
USDX	no constant	-0,9296913	no	0,1316376
INF.DIF	0,0000216	-0,0385473	no	no

Whether all the series are stationary or not has been examined empirically, firstly by graphics and then by Dickey Fuller and Phillips Perron tests. Non-stationary series (CDS) were made stationary by taking their first difference. The stationary states of these series should be included in the GARCH model to be installed. The installed GARCH (1,1) model and the parameters of this model are given in detail below:

4.8. GARCH (1,1) MODEL

Consistent with many previous studies (see for example, Oduncu, Akçelik & Ermişoğlu, 2013; Alexander & Lazar, 2006; Kearney & Patton, 2000; Abdalla, 2012; Akardeniz & Engin, 2019; Baillie & Osterberg, 1997; Dominguez, 1998; Doroodian & Caporale, 2001) the GARCH (1,1) model was applied in this study to show that ARCH/GARCH family model is one of the best models to determine exchange rate volatility.

There are other areas that GARCH (1,1) model was used to be able describe volatility of different variables (see for example, Akgiray, 1989; Figlewski, 1997; Bollerslev, 1986; Engle, 2001; Engle, 2007; Hua, Li & Li-Zi, 2005; Pham & Yang, 2010).

This GARCH (1,1) model of the daily percentage change in the exchange rate, is estimating using data from March 1, 2019 through October 26, 2021. The coefficients of both the lagged squared residual and (u_{t-1}^2) and lagged conditional variance (σ_{t-1}^2) terms in the conditional variance equation are individually statistically significant at the 1 percent significance level because their p values are less than 0.05. According to these results, the volatility that comes from the previous period has explanatory power on the volatility of the current period.

According to Stock & Watson, one way to test the persistence and long-term effects of variance σ_{t-1}^2 and shocks u_{t-1}^2 in the GARCH model is to interpret the sums of these coefficients (2007). The sum of 0.70 is large and indicating that changes in the conditional variance have long-term effect. To put it more precisely, large sums of these coefficients mean that large positive and

large negative shocks will have a large variance to be estimated in the future (Epaphra, 2017). This explanation also confirms the volatility clustering situation that should be in GARCH models. According to results, exchange rate behaviour in Turkey is generally influenced by previous volatilities and shocks of exchange rate.

Only CDS and VIX parameters are statistically significant (because their p values are smaller than 0,05), it means that CDS and VIX changes are influencing the volatility of exchange rate today. USDX, INFDIF, TLREF variables are not statistically significant. For this reason, it cannot be said that these variables affect the dollar exchange rate volatility during the period determined in the model.

The presence of a significant constant term in the model indicates that volatility cannot be 0 even if the variables determined in this model are 0. This is evidence that some parameters not shown in this model are also effective in the formation of volatility.

Table 4.6

Rt	COEF.	STD.ERROR	Z	P > Z	
VIX	0.0227753	0.004955	4,60	0.000	
USDX	0.0816053	0.0592249	1,38	0.168	
INFDIF	-0.3033618	0.6411786	-0,47	0.636	
TLREF	0.0005759	0.0055955	0,1	0.918	
dCDS	0.0185708	0.001264	14,69	0.000	
cons	0.0009493	0.0004845	1,96	0.050	
ARCH L1.	0.379643	0.0528733	7,18	0.000	
GARCH L1	0.3137865	0.0807268	3,89	0.000	
cons	0.000018	3.26e-06	5,54	0.000	

As shared in detail in the literature review section, the Garch model has certain parameter constraints, these constraints are (Bollerslev, 1986; Figlewski, 1997; Engle, 2001; Granger & Poon, 2003):

- **Constant term should be greater than zero.**
- **Arch coefficient must be greater than or equal to zero.**
- **Garch coefficient must be greater than or equal to zero.**
- **The sum of Arch and Garch coefficients should not be greater than 1.**

The constant term coefficient in the model is 0.000018 and is greater than 0. ARCH and GARCH coefficients are 0.379643 and 0.3137865, respectively, greater than 0 and met the non-negativity condition. Finally, the Arch and GARCH coefficients add up to 0.6933, a value less than 1. Therefore, it can be said that the coefficients of the model fit all the constraints of the GARCH model.



5. CONCLUSION

In this study, the effect of the pandemic crisis, which affected the years 2019 and 2021, on Turkey's exchange rate volatility was examined. CBRT overnight reference rate, USD index, Turkey's CDS premiums, VIX rate and daily differences in inflation expectations between Turkey and USA are the explanatory variables in the model. The percentage change in USD/TL rate was included in the model as a dependent variable. The obtained data were first tested for stationarity and the non-stationarity ones were made stationary by finding the appropriate lag lengths. The GARCH (1,1) method was used for volatility modelling. In the established model, parameters such as VIX and CDS, which are based on external dynamics rather than internal dynamics, were found to be significant and it was observed that dollar/tl exchange rate volatility was affected by past shocks and volatilities, and these effects were permanent in the long term. Therefore, in this section, will be focused on the trajectory of the world and the global factors that may affect the dollar/TL volatility in the future and will be made policy recommendations on a subject-by-subject basis.

A country like Turkey, where both volatility is high and the impact of economic policies is great, has been specially chosen in order to put the theoretical assumptions of the model into concrete assumptions. After the 2008 financial crisis, portfolio flows towards developing countries between the years 2009-2011 and the relationship of this situation with the VIX index were taken into account. Taking advantage of the experiences of the 1994 and 2001 economic crises in the past, we included the CDS parameter as an independent variable in the model, considering that exchange rate volatility in Turkey cannot be independent of political effects. In this sense, we have included the model for about 1 year before the date of March 11, 2020, when the pandemic was declared in Turkey. As a matter of fact, the significant CDS variable confirms these observations.

5.1. Factors May Increase the Effects of VIX and CDS

As a result of the established model, it has been observed that the exchange rate volatility in Turkey during the pandemic period is dependent on external factors such as VIX and CDS. For this reason, the factors that threaten the world, and therefore may cause exchange rate volatility in Turkey, are given.

Covid-19 virus and its variations

One of the main risks that the world will experience in 2022 is still the covid-19 virus and its mutants. Because this virus, together with itself and its variations, always continues to pose a threat to the country's economies and does not give a sigh of relief to the states. Delta variant, which dominates 2021, is one of the most important examples of this. As we enter the year 2022, the world is under the influence of a brand-new variant of covid, the omicron variant, which is spreading at an incredible rate. Many countries, especially European countries, have already started to show signs of closure again, and this is one of the most undesirable scenarios for economies. According to The Economist Magazine (2021), shutdowns will be a thing of the past and a pandemic will become a normal epidemic rather than a dangerous kind of flu.

Undoubtedly, since Covid-19 variants will increase uncertainty all over the world, it will have an increasing effect on our country's exchange rate volatility through the VIX channel.

US - China Tension

America's arrogant attitude towards China has begun to give way to a multipolar world management approach. Just like in the cold war period of 90 years, both states are trying to prove their superiority against each other. On the one hand, China intends to implement the new silk road project and establish a road connection with Europe. It is in an effort to dominate the countries with the 5G internet technology infrastructure it will establish, especially in Eastern Europe and the Caucasus. It seems that vaccination policies, which returned to the struggle for supremacy during the pandemic period, resulted in favor of China. Just like the Marshall aid applied by the USA during the cold war, China is trying to attract these countries to its side by helping countries with vaccine, internet, road and similar infrastructure projects and not interfering in their internal affairs. According to the Foreign Affairs magazine, which is one of the most famous magazines in America and said to direct foreign policy, the USA has lost its political power with Donald Trump. In the past, the USA, which attracted countries with monetary aid like Marshall and largely prevented the formation of the Soviet Union, is trying to market democracy instead of economic aid these days and meddling in the internal affairs of countries. This policy, on the other hand, causes the USA to lose power against China and the developing countries are increasingly siding with China (Foreign Affairs, 2021).

The area where the competition for dominance will hit the hardest will be the economy, as always. According to the forecasts of The Economist magazine (2021), the annual growth of the USA will be around 4% and the annual growth of China will be around 5%. However, the fines and restrictive regulations imposed by the Chinese State on technology giants in the near future will undermine the trust in the Chinese State in 2022 and cause companies to be more cautious about investment (The Economist, 2021).

Measures and policies regarding Covid-19 are also among the areas where competition is the subject. While the USA and Europe want to create an economic order that learns to live with the pandemic, China acts with a zero-case policy and shows its determination in this area by taking drastic measures (The Economist, 2021).

The tense environment between China and America will cause tension on the entire world financial market. For this reason, the China-USA tension should be followed closely, as the VIX coefficient is likely to increase, and this will likely affect Turkey's exchange rate volatility.

5.2. Policy Recommendations

All these external factors and much more will continue to have a significant impact on Turkey's exchange rate volatility. In this respect, one of the most important policies for Turkey will be to establish a defense mechanism against excessive volatility due to external factors. For this reason, instead of reducing foreign exchange and gold reserves with constant interventions, it is necessary to act more cautiously and intervene when the market needs it most. Swap agreements should be made with more states and financial instruments such as reserve option mechanism should be used. An environment of political stability should be ensured, and foreign relations should improve day by day. There should be an urgent transition to domestic vaccine production and use, and the import cost in this area should be reduced. In addition, it should be ensured that re-closures are not on the agenda with the production and use of domestic vaccines,

and possible threats that will disrupt foreign trade volume should be eliminated. Green energy and green transformation policies should be accelerated against global climate change. Nowadays, it is expected that the European Union and other regional unions will impose export restrictions on products that contain fossil fuels and harm the global climate, in order to accelerate the transition to green energy. The decrease in exports resulting from these export restrictions will upset Turkey's newly established economic system based on exports and production. With the expectation that Turkey's increasing current account deficit will decrease foreign exchange reserves, an increase in country CDS premiums may be observed. Increasing CDS premiums may cause volatility in the country's exchange rate as part of the model's consequences.

According to the results we obtained in the established model, Volatility Index (VIX) and CDS premiums are among the factors affecting the dollar exchange rate volatility in the country. Therefore, increasing the treasury burden of the country and signaling that it will have difficulty in paying its debts and the deterioration of relations with other neighboring countries will increase the volatility of the dollar exchange rate through the CDS channel. On the other hand, global movements should be closely monitored, and caution should be exercised in the face of events that will increase global volatility. It should be considered that a past volatility in the exchange rate will also affect the current exchange rate volatility, and it should be known that this volatility effect will be permanent for a long time.

In the model established in this study, it was observed that volatility during the pandemic period was more dependent on external factors such as the Volatility Index and CDS, rather than internal factors. Therefore, it should not be overlooked that this mechanism may impose an extra burden on the treasury and disrupt the internal balances after the exchange rate increase. Moreover, constantly making market interventions and melting foreign exchange reserves will make our country more vulnerable to shocks caused by external reasons, and with the increase in CDS premiums and the increase in the global Volatility Index, it will increase the volatility of the dollar/tl exchange rate.

Foreign relations should be improved and the country's CDS premiums should be reduced. It should not be forgotten that the effect of a possible increase in volatility will be long-lasting and policy makers should take immediate action. As can be clearly seen from the model results, exchange rate volatility in Turkey during the pandemic period is not fed by economic dynamics, but by political and global problems that may affect the whole world. In this sense, foreign relations have become more and more important. Politics and diplomacy are critical points that shape economic dynamics through CDS.

According to the results of the model presented in this study, the reason for the exchange rate volatility experienced in the years of the pandemic crisis in Turkey is completely attributed to external factors. However, the realities we see in practical economic life (central bank governor change, political discourses, political conflicts, instability, and so on) show that exchange rate volatility may also depend on internal factors. Filling the gap created in this study in the future and adding internal variables to the model will enable Turkey to use its power in reducing volatility more efficiently. Moreover, another shortcoming of this model is that all negative and positive shocks seem to affect volatility equally. It is very important for the academicians who will work on this model in the future to show sensitivity on these issues in order to complete this model that I have started.

6. REFERENCES

- Abdalla, S. Z. S. (2012). Modelling Exchange Rate Volatility using GARCH Models: Empirical Evidence from Arab Countries. *International Journal of Economics and Finance*, 4(3).
- Akardeniz, E, Engin, C. (2019). TCMB FAİZ KARARLARININ DÖVİZ KURU VOLATİLİTESİNE ETKİSİ. *Finansal Araştırmalar ve Çalışmalar Dergisi*, 11 (20), 1-27. DOI: 10.14784/marufacd.599086
- Akçelik, Y., Başçı, E., Ermişoğlu, E. ve Oduncu, A. (2013). The Turkish Approach to Capital Flow Volatility. *TCMB Çalışma Tebliği* 13/06.
- Akgiray, Vedat. (1989), Conditional Heteroscedasticity in Time Series of Stock Returns: Evidence and Forecasts, *The Journal of Business*, 62, issue 1, p. 55-80.
- Alexander, C., & Lazar, E. (2006). Normal mixture GARCH (1,1): applications to exchange rate modelling. *Journal of Applied Econometrics*, 21(3), 307–336.
- Alper, K., Kara, H. ve Yörükoğlu, M. (2012). Rezerv Opsiyonu Mekanizması. *TCMB Ekonomi Notu* No: 12/28
- Amirmazlaghani, M., & Amindavar, H. (2009). EMG signal denoising via Bayesian wavelet shrinkage based on GARCH modeling. *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*. doi:10.1109/icassp.2009.4959622
- Apostolou, A., & Beirne, J. (2018). Volatility spillovers of unconventional monetary policy to emerging market economies. *Economic Modelling*. doi: 10.1016/j.econmod.2018.10.006
- Arif Oduncu & Yasin Akcelik & Ergun Ermisoglu, 2013. "Reserve Options Mechanism and FX Volatility," *Working Papers 1303, Research and Monetary Policy Department, Central Bank of the Republic of Turkey*.
- Baillie, R. T., & Osterberg, W. P. (1997). Why do central banks intervene? *Journal of International Money and Finance*, 16(6), 909–919.
- Baillie, R. T., Chung, C.-F., & Tieslau, M. A. (1996). Analysing inflation by the fractionally integrated ARFIMA-GARCH model. *Journal of Applied Econometrics*, 11(1), 23–40.
- Bernanke, B., & Gertler, M. (2000). Monetary Policy and Asset Price Volatility. doi:10.3386/w7559.
- Bernanke, Ben, S., and Mark Gertler. 2001. "Should Central Banks Respond to Movements in Asset Prices?" *American Economic Review*, 91 (2): 253-257.
- Black, Fischer and Myron Scholes. 1973. "The Pricing of Options and Corporate Liabilities." *Journal of Political Economy* 81: 637–54.

Bleich, Dirk and Fendel, Ralf and Rülke, Jan-Christoph, Monetary Policy and Stock Market Volatility (2013). *Bundesbank Discussion Paper* No. 45/2013, Available at SSRN: <https://ssrn.com/abstract=2796936>

Bo Young Chang & Bruno Feunou, 2014. "Measuring Uncertainty in Monetary Policy Using Realized and Implied Volatility," *Bank of Canada Review*, Bank of Canada, vol. 2014(Spring), pages 32-41.

Bo Zhou, Dan He, & Zhili Sun. (n.d.). Traffic predictability based on ARIMA/GARCH model. *2006 2nd Conference on Next Generation Internet Design and Engineering, 2006. NGI'06.*

Bollerslev, T. 1986. "Generalized Autoregressive Conditional Heteroscedasticity." *Journal Of Econometrics* 31: 307–327. [https://doi.org/10.1016/0304-4076\(86\)90063-1](https://doi.org/10.1016/0304-4076(86)90063-1)

Bollerslev, T., Chou, R. Y. ve Kroner, K. F. (1992). ARCH Modelling in Finance. *Journal of Econometrics*, 52, 5-59.

Carr, P. P., & Wu, L. (2005). A Tale of Two Indices. *SSRN Electronic Journal*.

Chen, C., Hu, J., Meng, Q., & Zhang, Y. (2011). Short-time traffic flow prediction with ARIMA-GARCH model. *2011 IEEE Intelligent Vehicles Symposium (IV)*.

Chen, S., Härdle, W. K., & Jeong, K. (2009). Forecasting volatility with support vector machine based GARCH model. *Journal of Forecasting*, 29, 406-433.

Chris Brooks & Simon P. Burke (2003) Information criteria for GARCH model selection, *The European Journal of Finance*, 9:6, 557-580, DOI: 10.1080/1351847021000029188

Diebold, Francis X & Nerlove, Marc, 1989. "The Dynamics of Exchange Rate Volatility: A Multivariate Latent Factor Arch Model," *Journal of Applied Econometrics*, John Wiley & Sons, Ltd., vol. 4(1), pages 1-21.

Dominguez, K. (1993). Does Central Bank Intervention Increase the Volatility of Foreign Exchange Rates? doi:10.3386/w4532

Dominguez, K. M. (1998). Central bank intervention and exchange rate volatility. *Journal of International Money and Finance*, 17(1), 161–190.

Doojin Ryu (2012) Implied Volatility Index of KOSPI200: Information Contents and Properties, *Emerging Markets Finance and Trade*, 48:sup2, 24-39.

Doroodian, K., Caporale, T. Central bank intervention and foreign exchange volatility. *International Advances in Economic Research* 7, 385–392 (2001). <https://doi.org/10.1007/BF02295768>

Engle, R. (2001). GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. *Journal of Economic Perspectives*, 15(4), 157–168.

Engle, R. F. (1993). Statistical Models for Financial Volatility. *Financial Analysts Journal*, 49(1), 72–78.

Engle, R. F., & Patton, A. J. (2007). What good is a volatility model? Forecasting Volatility in the Financial Markets, 47–63.

- Engle, Robert. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica* 50: 987–1000.
- Epaphra, M. (2017) Modeling Exchange Rate Volatility: Application of the GARCH and EGARCH Models. *Journal of Mathematical Finance*, 7, 121-143.
<https://doi.org/10.4236/jmf.2017.71007>
- Estrella, A., & Hardouvelis, G. A. (1991). The Term Structure as a Predictor of Real Economic Activity. *The Journal of Finance*, 46(2), 555.
- Fama, E.F. (1965). "The Behaviour of Stock-Market Prices." *Journal of Business* 38, 34-105.
- Figlewski, S. (1997). Forecasting Volatility. *Financial Markets, Institutions and Instruments*, 6(1), 1–88.
- Follis, Jack L., and Dejian Lai. (2020). "Modeling Volatility Characteristics of Epileptic EEGs using GARCH Models" *Signals* 1, no. 1: 26-46. <https://doi.org/10.3390/signals1010003>
- G. W. Schwert, "Stock Market Volatility," *Financial Analysts Journal*, Vol. 46, No. 3, May/June 1990, pp. 23-34.
- Glosten, L. R., R. Jagannathan, and D. E. Runkle. 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* 48: 1779-1801.
- Gujarati, D. N., & Porter, D.C. (2009). *Basic econometrics* (5th ed.). McGraw – Hill international edition.
- Gujarati, N.D. and Porter, D.C. (2009) *Basic Econometrics. International Edition* McGraw-Hill/Irwin, A Business Unit of The McGraw-Hill Companies, Inc., New York.
- Gürcihan, B., & Özel, Ö. (2010). *Küresel Finans Krizi Döneminde Para Politikası Kurulu Kararlarının Piyasa Getirileri Üzerindeki Etkisi*. Ankara: TCMB.
- Hafner, C. M., & Herwartz, H. (2006). Volatility impulse responses for multivariate GARCH models: An exchange rate illustration. *Journal of International Money and Finance*, 25(5), 719–740.
- Haubrich, Joseph & Dombrosky, Ann. (1996). Predicting Real Growth Using the Yield Curve. *Economic Review*. 32. 26-35.
- Kadıoğlu, E., Kıyılar, M., & Telçeken, N. (2019). Volatilite Endeksleri: Gelişimi, Türleri, Uygulamaları ve TRVIX Önerisi. *Journal of Research in Economics, Politics & Finance*, 204-228.
- Kalbkhani, H., Shayesteh, M. G., & Zali-Vargahan, B. (2013). Robust algorithm for brain magnetic resonance image (MRI) classification based on GARCH variances series. *Biomedical Signal Processing and Control*, 8(6), 909–919.
- Kearney, C., & Patton, A. J. (2000). Multivariate GARCH Modeling of Exchange Rate Volatility Transmission in the European Monetary System. *The Financial Review*, 35(1), 29–48.

- Kocakale, Y., Toprak, H.H. 2015. Türkiye'nin Reel Efektif Döviz Kuru Endekslerinin Güncellenmesi. *TCMB Ekonomi Notları*, No. 15/06.
- Kristjanpoller, W., & Minutolo, M. C. (2015). Gold price volatility: A forecasting approach using the Artificial Neural Network–GARCH model. *Expert Systems with Applications*, 42(20), 7245–7251.
- Londono, Juan M. and Beth Anne Wilson (2018). "Understanding Global Volatility," IFDP Notes. Washington: *Board of Governors of the Federal Reserve System*, January 2018, <https://doi.org/10.17016/2573-2129.40>.
- Lubik, T. A., & Schorfheide, F. (2007). Do central banks respond to exchange rate movements? A structural investigation. *Journal of Monetary Economics*, 54(4), 1069–1087.
- Lubik, T. A., & Schorfheide, F. (2007). Do central banks respond to exchange rate movements? A structural investigation. *Journal of Monetary Economics*, 54(4), 1069–1087.
- Mandelbrot, B. (1963). The Variation of Certain Speculative Prices. *Journal of Business*, 36, 394-419.
- Mihandoost, S., Amirani, M. C., & Varghahan, B. Z. (2011). A new approach for feature extraction of EEG signal using GARCH variance series. *2011 5th International Conference on Application of Information and Communication Technologies (AICT)*.
- Mihandoost, S., Mazlaghani, M., Amirani, M., & Mihandoost, A. (2012). Automatic feature extraction using generalised autoregressive conditional heteroscedasticity model: an application to electroencephalogram classification. *IET Signal Processing*, 6(9), 829–838.
- Mishkin, Frederic S., Yield Curve (December 1990). *NBER Working Paper*, No. w3550, Available at SSRN: <https://ssrn.com/abstract=226841>
- Mohamadi, S., Amindavar, H., & Hosseini, S. M. A. T. (2017). ARIMA-GARCH modeling for epileptic seizure prediction. *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*.
- Mohamadi, Salman & Yeganegi, Farhang & Nasrabadi, N.M. (2019). Detection and Statistical Modeling of Birth-Death Anomaly.
- Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, 59, 347–370.
- Newman, A., & Farrell, H. (2021). The New Age of Protectionism. *The Foreign Affairs*.
- Öner, H. (2019). Korku Endeksi ile Gelişmekte Olan Ülke Tahvil Piyasaları Arasındaki İlişkinin Ampirik Analizi. *Muhasebe Bilim Dünyası Dergisi*, 140-154.
- Ozata, E., (2020). The effect of exchange rate volatility on economic growth in Turkey. *Journal of Business, Economics and Finance (JBFEF)*, V.9(1), p.42-51.
- Ozatay, F., (2020) *Finansal Krizler ve Türkiye*. İstanbul: Doğan Yayıncılık
- Papadamou, S., Sidiropoulos, M., & Spyromitros, E. (2014). Does central bank transparency affect stock market volatility? *Journal of International Financial Markets, Institutions and Money*, 31, 362–377.

- Perez-Cruz, Fernando & Afonso-Rodriguez, Julio A. & Rubio, Javier. (2003). Estimating GARCH models using support vector machines. *Quantitative Finance*, 3, 163-172.
- Perry, P. R. (1982). The Time-Variance Relationship of Security Returns: Implications for the Return-Generating Stochastic Process. *The Journal of Finance*, 37(3), 857–870.
- Pham, H. T., & Yang, B.-S. (2010). Estimation and forecasting of machine health condition using ARMA/GARCH model. *Mechanical Systems and Signal Processing*, 24(2), 546–558.
- Poon, S.H. and Granger, C.W.J. (2003) Forecasting Volatility in Financial Markets A Review. *Journal of Economic Literature*, 41, 478-539.
- Rasool, G., Bouaynaya, N., & Iqbal, K. (2012). Muscle activity detection from myoelectric signals based on the AR-GARCH model. 2012 IEEE Statistical Signal Processing Workshop (SSP). doi:10.1109/ssp.2012.6319721
- Rudebusch, G.D., & Williams, J.C. (2009). Forecasting Recessions: The Puzzle of the Enduring Power of the Yield Curve. *Journal of Business & Economic Statistics*, 27, 492 - 503.
- Skiadopoulos, G. (2004) The Greek Implied Volatility Index: Construction and Properties. *Applied Financial Economics*, 14, 1187-1196.
- Stock, J.H. and Watson, M.W. (2007) Why Has U.S. Inflation Become Harder to Forecast? *Journal of Money, Credit and Banking*, 39, 3-33. <https://doi.org/10.1111/j.1538-4616.2007.00014.x>
- Tahir R Dikheel and sura H Sami 2021 Journal of Physics.: Conference. Ser. 1897 012013.
- The World Bank. (2021). Turkey Economic Monitor, Navigating the Waves (pp. 1-113). Washington DC.
- Turker, I., & Cakir, B. (2019). Reading Macroeconomics from the Yield Curve: The Turkish Case. *General Economics*.
- Wagner, H., & Berger, W. (2004). Globalization, Financial Volatility and Monetary Policy. *Empirica*, 31(2-3), 163–184.
- Whaley, R. E. (2009). Understanding the VIX. *The Journal of Portfolio Management*, 35(3), 98–105.
- Williams, John C. (2017), “Interest Rates and the ‘New Normal.’” FRBSF Economic Letter 29.
- Wooldridge, J. M. (2019). Introductory Econometrics - A Modern Approach (4 b., Cilt 1). (E. Ç. Akay, Dü.) Ankara: Nobel Yayıncılık. Şubat 2019 tarihinde alındı.
- Wright, J.H. (2006). The Yield Curve and Predicting Recessions. *Econometrics eJournal*.
- Xiao, L., & Aydemir, A. (2007). Volatility modelling and forecasting in finance. *Forecasting Volatility in the Financial Markets*, 1–45.

Yang, M. J., & Liu, M.-Y. (2012). The Forecasting Power of the Volatility Index in Emerging Markets: Evidence from the Taiwan Stock Market. *International Journal of Economics and Finance*, 4(2).

Yang, M. J., & Liu, M.-Y. (2012). The Forecasting Power of the Volatility Index in Emerging Markets: Evidence from the Taiwan Stock Market. *International Journal of Economics and Finance*, 4(2).

Yu, W. W., Lui, E. C. K., & Wang, J. W. (2010). The Predictive Power of the Implied Volatility of Options Traded OTC and on Exchanges. *Journal of Banking and Finance*, 34. 1-11.

Zheng Hua, Xie Li, & Zhang Li-zi. (2005). Electricity price forecasting based on GARCH model in deregulated market. *2005 International Power Engineering Conference*.



7. APPENDIX

7.1. Augmented Dickey Fuller (ADF) and Phillips Perron (PP) Test Results on Stata

CDS

Before applying ADF and PP tests, the appropriate lag length will be found for every data.

Table A.1

Selection-order criteria

Sample: 5 - 658

Number of obs = 654

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-878.13				.86122	2.68847	2.69113	2.69533
1	295.504	2347.3	1	0.000	.023863	-.897567	-.892251	-.883857
2	301.415	11.821*	1	0.001	.023507*	-.912584*	-.90461*	-.89202*
3	301.487	.14352	1	0.705	.023574	-.909746	-.899113	-.882326
4	301.637	.30011	1	0.584	.023635	-.907146	-.893856	-.872872

Endogenous: CDS

As it can be seen from the table A.1, the appropriate lag length for CDS is 2.

ADF for CDS with trend and constant

Table A.2

Augmented Dickey-Fuller test for unit root				Number of obs = 655	
	Test Statistic	1% Critical Value	Interpolated Dickey-Fuller	5% Critical Value	10% Critical Value
Z(t)	-2.559	-3.960		-3.410	-3.120
MacKinnon approximate p-value for Z(t) = 0.2989					
D.CDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
CDS					
L1.	-.016625	.0064957	-2.56	0.011	-.02938 -.00387
LD.	.1319104	.039134	3.37	0.001	.0550661 .2087548
L2D.	.0146842	.0392121	0.37	0.708	-.0623134 .0916818
_trend	-8.07e-06	.0000316	-0.26	0.799	-.0000702 .000054
_cons	.0734316	.0294889	2.49	0.013	.0155265 .1313367

ADF for CDS with constant

Table A.3

Augmented Dickey-Fuller test for unit root Number of obs = **655**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.563	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = **0.1008**

D.CDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CDS						
L1.	-.0166379	.0064908	-2.56	0.011	-.0293834	-.0038925
LD.	.1320071	.0391041	3.38	0.001	.0552218	.2087924
L2D.	.0147742	.0391823	0.38	0.706	-.0621647	.0917132
_cons	.0708215	.0276376	2.56	0.011	.016552	.125091

PP test for CDS with trend and constant

Table A.4

. pperron CDS , lags(2) trend regress

Phillips-Perron test for unit root Number of obs = **657**
Newey-West lags = **2**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-11.407	-29.500	-21.800	-18.300
Z(t)	-2.454	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = **0.3512**

CDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CDS						
L1.	.985302	.0064761	152.15	0.000	.9725856	.9980184
_trend	-9.69e-06	.0000317	-0.31	0.760	-.0000719	.0000525
_cons	.0663146	.0293673	2.26	0.024	.008649	.1239802

PP test for CDS with constant

Table A.5

Phillips-Perron test for unit root Number of obs = **657**
 Newey-West lags = **2**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-11.407	-29.500	-21.800	-18.300
Z(t)	-2.454	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = **0.3512**

CDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CDS						
L1.	.985302	.0064761	152.15	0.000	.9725856	.9980184
_trend	-9.69e-06	.0000317	-0.31	0.760	-.0000719	.0000525
_cons	.0663146	.0293673	2.26	0.024	.008649	.1239802

CBRTINT

Table A.6

Selection-order criteria

Sample: **5 - 658** Number of obs = **654**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1337.95				.000982	-4.08854	-4.08588	-4.08169
1	1339.03	2.157	1	0.142	.000981	-4.08878	-4.08347	-4.07507
2	1345.28	12.498	1	0.000	.000966	-4.10483	-4.09686	-4.08427
3	1353.14	15.714	1	0.000	.000946	-4.1258	-4.11517	-4.09838*
4	1356.08	5.8751*	1	0.015	.00094*	-4.13173*	-4.11844*	-4.09745

Endogenous: CBRTINT

As it can be seen from the table A.6, the appropriate lag length for CBRTINT is 4.

ADF for CBRTINT with trend and constant

Table A.7

Augmented Dickey-Fuller test for unit root Number of obs = **653**

	Test Statistic	1% Critical Value	Interpolated Dickey-Fuller 5% Critical Value	10% Critical Value
Z(t)	-13.650	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = **0.0000**

D.CBRTINT	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CBRTINT						
L1.	-1.499966	.1098844	-13.65	0.000	-1.71574	-1.284192
LD.	.3967554	.0940183	4.22	0.000	.212137	.5813739
L2D.	.235157	.0768751	3.06	0.002	.0842019	.3861122
L3D.	.0713579	.0589031	1.21	0.226	-.0443068	.1870226
L4D.	-.0268236	.0397525	-0.67	0.500	-.1048834	.0512361
_trend	.000011	6.40e-06	1.72	0.087	-1.58e-06	.0000236
_cons	-.0043775	.0024399	-1.79	0.073	-.0091686	.0004135

ADF for CBRTINT with constant

Table A.8

Augmented Dickey-Fuller test for unit root Number of obs = **653**

	Test Statistic	1% Critical Value	Interpolated Dickey-Fuller 5% Critical Value	10% Critical Value
Z(t)	-13.524	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = **0.0000**

D.CBRTINT	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CBRTINT						
L1.	-1.473063	.1089246	-13.52	0.000	-1.686951	-1.259174
LD.	.3747478	.0932802	4.02	0.000	.1915793	.5579163
L2D.	.2180367	.07634	2.86	0.004	.0681326	.3679408
L3D.	.0600049	.0586187	1.02	0.306	-.0551009	.1751107
L4D.	-.0325686	.039671	-0.82	0.412	-.110468	.0453308
_cons	-.0007266	.0011975	-0.61	0.544	-.003078	.0016248

ADF for CBRTINT without trend and constant

Table A.9

Augmented Dickey-Fuller test for unit root Number of obs = **653**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-13.517	-2.580	-1.950	-1.620

D.CBRTINT	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CBRTINT						
L1.	-1.470225	.1087711	-13.52	0.000	-1.683811	-1.256639
LD.	.3724895	.0931605	4.00	0.000	.1895566	.5554224
L2D.	.2163707	.0762534	2.84	0.005	.0666371	.3661043
L3D.	.0588607	.0585598	1.01	0.315	-.0561291	.1738505
L4D.	-.0331341	.0396407	-0.84	0.404	-.1109737	.0447056

PP for CBRTINT with trend and constant

Table A.10

. pperron CBRTINT , lags(4) trend regress

Phillips-Perron test for unit root Number of obs = **657**
Newey-West lags = **4**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-586.817	-29.500	-21.800	-18.300
Z(t)	-27.951	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = **0.0000**

CBRTINT	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CBRTINT						
L1.	-.0578912	.0390383	-1.48	0.139	-.1345467	.0187643
_trend	8.27e-06	6.44e-06	1.28	0.199	-4.37e-06	.0000209
_cons	-.0033643	.0024449	-1.38	0.169	-.0081651	.0014366

PP for CBRTINT with constant

Table A.11

. pperron CBRTINT , lags(4) regress

Phillips-Perron test for unit root Number of obs = **657**
 Newey-West lags = **4**

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-587.978	-20.700	-14.100	-11.300
Z(t)	-27.854	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = **0.0000**

CBRTINT	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CBRTINT L1.	-.0555039	.0390133	-1.42	0.155	-.1321102	.0211025
_cons	-.0006429	.0012203	-0.53	0.598	-.0030391	.0017532

PP for CBRTINT without trend and constant

Table A.12

. pperron CBRTINT , lags(4) noconstant regress

Phillips-Perron test for unit root Number of obs = **657**
 Newey-West lags = **4**

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-588.072	-13.800	-8.100	-5.700
Z(t)	-27.860	-2.580	-1.950	-1.620

CBRTINT	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
CBRTINT L1.	-.0551074	.0389846	-1.41	0.158	-.131657	.0214423

VIX

Table A.13

Selection-order criteria

Sample: 5 - 658

Number of obs = 654

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	1167.07				.001655	-3.56596	-3.5633	-3.5591
1	1171.35	8.5739	1	0.003	.001639	-3.57601	-3.57069*	-3.5623*
2	1172.45	2.1955	1	0.138	.001638	-3.57631	-3.56833	-3.55574
3	1174.69	4.475*	1	0.034	.001632*	-3.58009*	-3.56946	-3.55267
4	1175.24	1.0902	1	0.296	.001634	-3.5787	-3.56541	-3.54443

Endogenous: VIX

As it can be seen from the table A.13, the appropriate lag length for VIX is 1

ADF for VIX with trend and constant

Table A.14

Augmented Dickey-Fuller test for unit root

Number of obs = 656

Test Statistic	Interpolated Dickey-Fuller		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-18.027	-3.960	-3.410

MacKinnon approximate p-value for Z(t) = **0.0000**

D.VIX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
VIX						
L1.	-1.052499	.0583857	-18.03	0.000	-1.167145	-.9378522
LD.	-.0563796	.0391139	-1.44	0.150	-.133184	.0204249
_trend	-6.95e-06	8.33e-06	-0.83	0.404	-.0000233	9.40e-06
_cons	.0026956	.0031642	0.85	0.395	-.0035175	.0089088

ADF for VIX with constant

Table A.15

Augmented Dickey-Fuller test for unit root		Number of obs =		656		
Test Statistic	Interpolated Dickey-Fuller		5% Critical Value	10% Critical Value		
	1% Critical Value					
Z(t)	-18.012	-3.430	-2.860	-2.570		
MacKinnon approximate p-value for Z(t) = 0.0000						
D.VIX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
VIX						
L1.	-1.050471	.0583216	-18.01	0.000	-1.164992	-.9359508
LD.	-.0574166	.0390851	-1.47	0.142	-.1341643	.019331
_cons	.0004047	.001575	0.26	0.797	-.002688	.0034973

ADF for VIX without trend and constant

Table A.16

. dfuller VIX ,noconstant regress lags(1)

Augmented Dickey-Fuller test for unit root		Number of obs =		656		
Test Statistic	Interpolated Dickey-Fuller		5% Critical Value	10% Critical Value		
	1% Critical Value					
Z(t)	-18.023	-2.580	-1.950	-1.620		
D.VIX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
VIX						
L1.	-1.050263	.0582743	-18.02	0.000	-1.16469	-.9358358
LD.	-.0575165	.0390553	-1.47	0.141	-.1342054	.0191723

Table A.17

Phillips-Perron test for unit root	Number of obs	=	657
	Newey-West lags	=	1

MacKinnon approximate p-value for $Z(t) = 0.0000$

PP for VIX with constant

Table A.18

Test Statistic	Interpolated Dickey-Fuller		
	1% Critical Value	5% Critical Value	10% Critical Value

MacKinnon approximate p-value for Z(t) = 0.0000

VIX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
VIX L1.	-.1143981	.0388407	-2.95	0.003	-.1906655	-.0381307
_cons	.0003841	.0015745	0.24	0.807	-.0027076	.0034758

PP for VIX without trend and constant**Table A.19**

```
. pperron VIX , lags(1) noconstant regress
```

Phillips-Perron test for unit root Number of obs = **657**
 Newey-West lags = **1**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-734.230	-13.800	-8.100	-5.700
Z(t)	-28.701	-2.580	-1.950	-1.620

VIX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
VIX L1.	-.114306	.0388111	-2.95	0.003	-.1905149	-.0380972

USD/TL (R_t)**Table A.20**

Selection-order criteria

Sample: 5 - 658

Number of obs = **654**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-832.053				.748028*	2.54756*	2.55022*	2.55442*
1	-831.788	.52873	1	0.467	.749713	2.54981	2.55513	2.56352
2	-831.708	.16127	1	0.688	.751823	2.55262	2.5606	2.57319
3	-831.068	1.2803	1	0.258	.752651	2.55372	2.56436	2.58114
4	-828.984	4.1668*	1	0.041	.750162	2.55041	2.5637	2.58468

Endogenous: R_t

As it can be seen from table A.20, the appropriate lag length for R_t is 0.

ADF for R_t with trend and constant**Table A.21**

Dickey-Fuller test for unit root			Number of obs =		657	
			Interpolated Dickey-Fuller			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value		
Z(t)	-24.635	-3.960	-3.410	-3.120		
MacKinnon approximate p-value for Z(t) = 0.0000						
D.Rt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
Rt						
L1.	-.971934	.0394538	-24.63	0.000	-1.049405	-.8944626
_trend	.0000955	.0001777	0.54	0.591	-.0002534	.0004444
_cons	.0541333	.0674718	0.80	0.423	-.0783543	.1866208

ADF for R_t with constant**Table A.22**

Dickey-Fuller test for unit root		Number of obs =		657	
	Test Statistic	Interpolated Dickey-Fuller			
		1% Critical Value	5% Critical Value	10% Critical Value	
Z(t)	-24.643	-3.430	-2.860	-2.570	
MacKinnon approximate p-value for Z(t) = 0.0000					
D.Rt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
Rt					
L1.	-.9712974	.0394146	-24.64	0.000	-1.048692 - .8939032
_cons	.0854807	.0338658	2.52	0.012	.0189821 .1519793

PP for R_t with trend and constant

USDX

Table A.25

Selection-order criteria

Sample: 5 - 658

Number of obs = 654

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	2728.98				.000014	-8.34244	-8.33978	-8.33559
1	2733.23	8.5001	1	0.004	.000014	-8.35238	-8.34706	-8.33867*
2	2735.84	5.2239*	1	0.022	.000014	-8.35731	-8.34934*	-8.33674
3	2736.65	1.6179	1	0.203	.000014	-8.35673	-8.34609	-8.32931
4	2738.11	2.9296	1	0.087	.000014*	-8.35815*	-8.34486	-8.32387

Endogenous: USDX

As it can be seen from table A.25, appropriate lag length for USDX is 4.

ADF for USDX with trend and constant

Table A.26

Augmented Dickey-Fuller test for unit root			Number of obs = 653			
Test Statistic		Interpolated Dickey-Fuller				
		1% Critical Value	5% Critical Value	10% Critical Value		
Z(t)	-12.004	-3.960	-3.410	-3.120		
MacKinnon approximate p-value for Z(t) = 0.0000						
D.USDX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
USDX						
L1.	-.9311385	.077567	-12.00	0.000	-1.083452	-.7788245
LD.	.0341813	.0691132	0.49	0.621	-.1015323	.169895
L2D.	.1323837	.0608285	2.18	0.030	.0129383	.2518292
L3D.	.0910271	.0524486	1.74	0.083	-.0119631	.1940174
L4D.	.0226657	.0391492	0.58	0.563	-.0542094	.0995408
_trend	3.54e-07	7.64e-07	0.46	0.644	-1.15e-06	1.85e-06
_cons	-.0001746	.0002913	-0.60	0.549	-.0007466	.0003973

ADF for USDX with constant

Table A.27

Augmented Dickey-Fuller test for unit root			Number of obs =		653	
Test Statistic	Interpolated Dickey-Fuller					
	1% Critical Value	5% Critical Value		10% Critical Value		
Z(t)	-12.005	-3.430	-2.860	-2.570		
MacKinnon approximate p-value for Z(t) = 0.0000						
D.USDX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
USDX						
L1.	-.9304965	.0775075	-12.01	0.000	-1.082693	-.7782998
LD.	.033732	.0690644	0.49	0.625	-.1018854	.1693494
L2D.	.1320782	.060788	2.17	0.030	.0127127	.2514437
L3D.	.0908447	.0524152	1.73	0.084	-.0120798	.1937692
L4D.	.022575	.039125	0.58	0.564	-.0542522	.0994023
_cons	-.0000575	.000144	-0.40	0.690	-.0003404	.0002253

ADF for USDX without trend and constant

Table A.28

Augmented Dickey-Fuller test for unit root				Number of obs =		653
Test Statistic	Interpolated Dickey-Fuller					
	1% Critical Value	5% Critical Value	10% Critical Value			
Z(t)	-12.007	-2.580	-1.950	-1.620		
D.USDX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
USDX						
L1.	-.9296913	.077431	-12.01	0.000	-1.081737	-.7776454
LD.	.0331177	.0690025	0.48	0.631	-.1023777	.1686131
L2D.	.1316376	.0607385	2.17	0.031	.0123696	.2509057
L3D.	.0905324	.0523754	1.73	0.084	-.0123135	.1933784
L4D.	.0224241	.0390977	0.57	0.566	-.0543495	.0991977

PP for USDX with trend and constant

Table A.29

Phillips-Perron test for unit root Number of obs = **657**
 Newey-West lags = **4**

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-595.862	-29.500	-21.800	-18.300
Z(t)	-22.878	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = **0.0000**

USDX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
USDX					
L1.	.1144752	.0388104	2.95	0.003	.0382672 .1906832
_trend	1.86e-07	7.62e-07	0.24	0.807	-1.31e-06 1.68e-06
_cons	-.0000995	.0002895	-0.34	0.731	-.0006679 .0004689

PP for USDX with constant

Table A.30

Phillips-Perron test for unit root Number of obs = **657**
 Newey-West lags = **4**

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-595.914	-20.700	-14.100	-11.300
Z(t)	-22.893	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = **0.0000**

USDX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
USDX					
L1.	.1145334	.0387818	2.95	0.003	.0383818 .190685
_cons	-.0000384	.0001445	-0.27	0.791	-.000322 .0002453

PP for USDX without trend and constant**Table A.31**

Phillips-Perron test for unit root				Number of obs =	657
				Newey-West lags =	4
	Test Statistic	Interpolated Dickey-Fuller			
		1% Critical Value	5% Critical Value	10% Critical Value	
Z(rho)	-595.949	-13.800	-8.100	-5.700	
Z(t)	-22.908	-2.580	-1.950	-1.620	
USDX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
USDX L1.	.1146399	.0387522	2.96	0.003	.0385465 .1907332

INF.DIF**Table A.32**

Selection-order criteria

Sample: 5 - 658

Number of obs = **654**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	4189.24				1.6e-07	-12.8081	-12.8054	-12.8012
1	5148.14	1917.8*	1	0.000	8.6e-09*	-15.7374*	-15.7321*	-15.7237*
2	5148.18	.07504	1	0.784	8.6e-09	-15.7345	-15.7265	-15.7139
3	5148.22	.08345	1	0.773	8.6e-09	-15.7316	-15.7209	-15.7041
4	5148.46	.4898	1	0.484	8.6e-09	-15.7292	-15.716	-15.695

Endogenous: INF DIF

As it can be seen from table A.32, the appropriate lag length for INF.DIF is 1.

ADF for INF.DIF with trend and constant

Table A.33

Augmented Dickey-Fuller test for unit root Number of obs = **656**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-4.685	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = **0.0007**

D.INFDIF	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
INF DIF						
L1.	-.051047	.0108956	-4.69	0.000	-.0724417	-.0296524
LD.	.0230469	.0280628	0.82	0.412	-.0320575	.0781512
_trend	-4.57e-08	2.36e-08	-1.94	0.053	-9.20e-08	6.61e-10
_cons	.0000446	.0000136	3.27	0.001	.0000178	.0000713

ADF for INF.DIF with constant

Table A.34

Augmented Dickey-Fuller test for unit root Number of obs = **656**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-4.383	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = **0.0003**

D.INFDIF	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
INF DIF						
L1.	-.0385473	.008794	-4.38	0.000	-.0558152	-.0212794
LD.	.0181972	.0280094	0.65	0.516	-.0368023	.0731966
_cons	.0000216	6.66e-06	3.24	0.001	8.50e-06	.0000347

PP for INF.DIF with trend and constant

Table A.35

Phillips-Perron test for unit root

Number of obs = 657

Newey-West lags = 1

		Interpolated Dickey-Fuller		
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-56.064	-29.500	-21.800	-18.300
Z(t)	-5.646	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.0000

INFDIF	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
INFDIF						
L1.	.9184618	.0147272	62.36	0.000	.8895435	.9473802
_trend	-1.16e-07	3.23e-08	-3.61	0.000	-1.80e-07	-5.31e-08
_cons	.0000908	.0000185	4.92	0.000	.0000545	.000127

PP for INF.DIF with constant

Table A.36

Phillips-Perron test for unit root

Number of obs = 657

Newey-West lags = 1

		Interpolated Dickey-Fuller		
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-34.188	-20.700	-14.100	-11.300
Z(t)	-4.242	-3.430	-2.860	-2.570

MacKinnon approximate p-value for $Z(t) = 0.0006$

INFDIF	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
INFDIF L1.	.9494091	.0120851	78.56	0.000	.925679	.9731392
_cons	.0000328	9.18e-06	3.57	0.000	.0000147	.0000508

dCDS**Table A.37**

Selection-order criteria

Sample: 6 - 658

Number of obs = 653

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	292.246				.023995	-.892025	-.889364	-.885162
1	297.468	10.444*	1	0.001	.023687*	-.904956*	-.899633*	-.89123*
2	297.478	.01896	1	0.890	.023759	-.901922	-.893938	-.881333
3	297.781	.60674	1	0.436	.02381	-.899788	-.889143	-.872336
4	298.284	1.0064	1	0.316	.023846	-.898267	-.884959	-.863951

Endogenous: dCDS

As it can be seen from table A.37, the appropriate lag length for dCDS is 1.

ADF for dCDS with trend and constant**Table A.38**

Augmented Dickey-Fuller test for unit root

Number of obs = 655

Test Statistic	Interpolated Dickey-Fuller		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-16.760	-3.960	-3.410

MacKinnon approximate p-value for Z(t) = 0.0000

D.dCDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dCDS						
L1.	-.8692238	.0518631	-16.76	0.000	-.971063	-.7673847
LD.	-.005577	.0392164	-0.14	0.887	-.0825829	.0714289
_trend	-8.70e-06	.0000318	-0.27	0.784	-.0000711	.0000537
_cons	.0045178	.0120563	0.37	0.708	-.0191562	.0281918

ADF for dCDS with constant

Table A.39

Augmented Dickey-Fuller test for unit root Number of obs = **655**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-16.770	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = **0.0000**

D.dCDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dCDS						
L1.	-.8690358	.0518217	-16.77	0.000	-.9707934	-.7672781
LD.	-.0056665	.0391872	-0.14	0.885	-.0826149	.0712818
_cons	.0016547	.0060031	0.28	0.783	-.0101329	.0134424

ADF for dCDS without trend and constant

Table A.40

Augmented Dickey-Fuller test for unit root Number of obs = **655**

	Test Statistic	Interpolated Dickey-Fuller		
		1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-16.779	-2.580	-1.950	-1.620

D.dCDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dCDS						
L1.	-.8687539	.051775	-16.78	0.000	-.9704195	-.7670884
LD.	-.0058125	.0391559	-0.15	0.882	-.0826991	.0710742

PP for dCDS with trend and constant**Table A.41**

Phillips-Perron test for unit root		Number of obs = 656			
		Newey-West lags = 1			
	Test Statistic	1% Critical Value	Interpolated Dickey-Fuller 5% Critical Value	10% Critical Value	
Z(rho)	-573.147	-29.500	-21.800	-18.300	
Z(t)	-22.500	-3.960	-3.410	-3.120	
MacKinnon approximate p-value for Z(t) = 0.0000					
dCDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dCDS					
L1.	.1259369	.0388447	3.24	0.001	.0496613 .2022126
_trend	-9.24e-06	.0000316	-0.29	0.771	-.0000714 .0000529
_cons	.0047592	.0120008	0.40	0.692	-.0188055 .028324

PP for dCDS with constant**Table A.42**

Phillips-Perron test for unit root		Number of obs = 656			
		Newey-West lags = 1			
		Interpolated Dickey-Fuller			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	
Z(rho)	-573.060	-20.700	-14.100	-11.300	
Z(t)	-22.514	-3.430	-2.860	-2.570	
MacKinnon approximate p-value for Z(t) = 0.0000					
dCDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dCDS L1.	.1260573	.0388154	3.25	0.001	.0498395 .2022751
_cons	.0017251	.0059892	0.29	0.773	-.0100352 .0134854

PP for dCDS without trend and constant

Table A.43

Phillips-Perron test for unit root		Number of obs =		656	
		Newey-West lags =		1	
	Test Statistic	Interpolated Dickey-Fuller			
		1% Critical Value	5% Critical Value	10% Critical Value	
Z(rho)	-572.944	-13.800	-8.100	-5.700	
Z(t)	-22.528	-2.580	-1.950	-1.620	
dCDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dCDS L1.	.1262205	.0387841	3.25	0.001	.0500644 .2023766

7.2. GARCH (1,1) MODEL

Table A.44

Sample: 2 - 658				Number of obs = 657		
Distribution: Gaussian				Wald chi2(5) = 362.17		
Log likelihood = -672.7495				Prob > chi2 = 0.0000		
Rt	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
Rt						
VIX	2.279115	.4954345	4.60	0.000	1.308081	3.250149
USDx	8.155774	5.921642	1.38	0.168	-3.45043	19.76198
INFDF	-30.46724	64.11545	-0.48	0.635	-156.1312	95.19674
dCDS	1.856964	.1263809	14.69	0.000	1.609262	2.104666
CBRTINT	.0585471	.5595714	0.10	0.917	-1.038193	1.155287
_cons	.0950306	.0484424	1.96	0.050	.0000852	.189976
ARCH						
arch						
L1.	.379823	.0529027	7.18	0.000	.2761357	.4835103
garch						
L1.	.3133087	.0807617	3.88	0.000	.1550187	.4715987
_cons	.1803857	.0325587	5.54	0.000	.1165717	.2441996

7.3. Autocorrelation Test Results (Breusch-Godfrey LM test) R_t

Table A.45

```
. reg Rt
```

Source	SS	df	MS	Number of obs	=	658
Model	0	0	.	F(0, 657)	=	0.00
Residual	488.284669	657	.743203454	Prob > F	=	.
				R-squared	=	0.0000
				Adj R-squared	=	0.0000
Total	488.284669	657	.743203454	Root MSE	=	.86209

Rt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
_cons	.0887798	.0336079	2.64	0.008	.022788 .1547716

```
. estat bgodfrey
```

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.532	1	0.4658

H0: no serial correlation

USDX

Table A.46

```
. reg USDX
```

Source	SS	df	MS	Number of obs	=	658
Model	0	0	.	F(0, 657)	=	0.00
Residual	.009117642	657	.000013878	Prob > F	=	.
				R-squared	=	0.0000
				Adj R-squared	=	0.0000
Total	.009117642	657	.000013878	Root MSE	=	.00373

USDX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
_cons	-.0000363	.0001452	-0.25	0.803	-.0003215 .0002488

```
. estat bgodfrey
```

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	8.630	1	0.0033

H0: no serial correlation

RVIX

Table A.47

. reg VIX

Source	SS	df	MS	Number of obs	=	658
Model	0	0	.	F(0, 657)	=	0.00
Residual	1.08086402	657	.001645151	Prob > F	=	.
				R-squared	=	0.0000
				Adj R-squared	=	0.0000
Total	1.08086402	657	.001645151	Root MSE	=	.04056

VIX	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
_cons	.0003385	.0015812	0.21	0.831	-.0027663 .0034433

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	8.601	1	0.0034

H0: no serial correlation

INFDIF

Table A.48

. reg INFDIF

Source	SS	df	MS	Number of obs	=	658
Model	0	0	.	F(0, 657)	=	0.00
Residual	.000113452	657	1.7268e-07	Prob > F	=	.
				R-squared	=	0.0000
				Adj R-squared	=	0.0000
Total	.000113452	657	1.7268e-07	Root MSE	=	.00042

INFDIF	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
_cons	.0006358	.0000162	39.25	0.000	.000604 .0006676

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	592.748	1	0.0000

H0: no serial correlation

CBRTINT

Table A.49

. reg CBRTINT

Source	SS	df	MS	Number of obs	=	658
Model	0	0	.	F(0, 657)	=	0.00
Residual	.642576285	657	.000978046	Prob > F	=	.
				R-squared	=	0.0000
				Adj R-squared	=	0.0000
Total	.642576285	657	.000978046	Root MSE	=	.03127

CBRTINT	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_cons	-.0006085	.0012192	-0.50	0.618	-.0030025	.0017854

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	2.027	1	0.1545

H0: no serial correlation

dCDS

Table A.50

. reg dCDS

Source	SS	df	MS	Number of obs	=	657
Model	0	0	.	F(0, 656)	=	0.00
Residual	15.6343489	656	.023832849	Prob > F	=	.
				R-squared	=	0.0000
				Adj R-squared	=	0.0000
Total	15.6343489	656	.023832849	Root MSE	=	.15438

dCDS	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
_cons	.0020393	.0060229	0.34	0.735	-.0097872	.0138658

. estat bgodfrey

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	10.427	1	0.0012

H0: no serial correlation

TEZ ONAY SAYFASI

Üniversite : T.C. GALATASARAY ÜNİVERSİTESİ
Enstitü : SOSYAL BİLİMLER ENSTİTÜSÜ
Hazırlayanın Adı Soyadı :Ömer Faruk ALTUN
Tez Başlığı : Türkiye’de Covid-19 Pandemi Krizinde Döviz Kuru Volatilitesi
Savunma Tarihi : 23 / 02 / 2022
Danışman :Doç. Dr. Ata ÖZKAYA

JÜRİ ÜYELERİ:

Unvan, Ad-Soyadı

İmza

Prof. Dr. Sahir KARAKAYA

Prof. Dr. Ali ARI

Doç. Dr. Ata ÖZKAYA

Prof. Dr. M. Yaman ÖZTEK
Enstitü Müdürü