AN ANALYSIS BETWEEN CRYPTOCURRENCIES AND A NATIONAL CURRENCY: A CASE STUDY OF TURKEY

CAN CANLI

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CAN CANLI

THESIS ADVISOR: PROF. DR. BERNA AYDOĞAN

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ETHICAL DECLARATION

I hereby declare that I am the sole author of this thesis and that I have conducted my work in accordance with academic rules and ethical behaviour at every stage from the planning of the thesis to its defence. I confirm that I have cited all ideas, information and findings that are not specific to my study, as required by the code of ethical behaviour, and that all statements not cited are my own.

Name, Surname:
Can Canlı

Date:
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ABSTRACT

AN ANALYSIS BETWEEN CRYPTOCURRENCIES AND A NATIONAL CURRENCY: A CASE STUDY OF TURKEY

Canlı, Can

Master's Program in Business Administration

Advisor: Prof. Dr. Berna Aydoğan

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This thesis conducts an empirical analysis of the causality and volatility spillovers to investigate the relationship between national currency and three most traded cryptocurrencies, namely Bitcoin, Ethereum and Ripple from March 10th, 2016, to December 31st, 2021. Utilizing Granger causality test and VAR-BEKK-GARCH models, the empirical findings demonstrate that unidirectional causality exists from $/TRY to all the selected cryptocurrencies while the findings suggests that there is no evidence of causality from cryptocurrencies to $/TRY. Furthermore, this thesis reveals a unidirectional transmission of volatility from $/TRY to all selected cryptocurrencies. The analysis also indicates the strong impact of $/TRY on Ripple's returns. This thesis contributes to the limited existing literature with a unique investigation on volatility spillover and causality between $/TRY and cryptocurrencies over a broad period and offers insights and implications on understanding the interconnectedness and risks between a national currency and cryptocurrencies for researchers, investors and policymakers.

Keywords: (Cryptocurrencies, Turkish Lira, National currency, Granger causality, Volatility spillover, VAR-BEKK-GARCH)

ÖZET

KRİPTO PARA BİRİMLERİ VE ULUSAL PARA BİRİMİ ARASINDA ANALİZ: TÜRKİYE ÖRNEĞİ

Canlı, Can

İşletme Yüksek Lisans Programı

Tez Danışmanı: Prof. Dr. Berna Aydoğan

Haziran, 2023

Bu tez, Türk Lirası ve 10 Mart 2016-31 Aralık 2021 tarihleri arasında piyasa değerleri en yüksek olan kripto para birimleri; Bitcoin, Ethereum, Ripple arasındaki nedensellik ve oynaklık yayılmalarının ampirik bir analizini yapmaktadır. Granger nedensellik testi ve VAR-BEKK-GARCH modeli kullanılarak elde edilen analiz sonuçları, Türk Lirasının seçilen tüm kripto para birimi getirilerine doğru tek yönlü bir nedensellik ilişkisi içerisinde olduğunu göstermektedir. Ayrıca, bu çalışma, Türk Lirası getirilerindeki oynaklığın tek yönlü olarak kripto para birimi getirilerine önemli ölçüde yayıldığını ve Türk Lirasının Ripple getirileri üzerindeki güçlü etkisini de ortaya koymaktadır. Bu tez, kripto para birimleri ile Türk Lirası arasındaki oynaklık yayılımı ve nedensellik üzerine geniş bir zaman aralığında benzersiz bir analiz yaparak sınırlı sayıdaki literatüre katkı sağlamaktadır. Elde edilen sonuçlar, araştırmacılara, politika yapıcılara ve yatırımcılara ulusal bir para birimi ile kripto para birimleri arasındaki bağlılığı ve riskleri anlamaya yönelik çıkarımlar ve fikirler sunmaktadır.

Anahtar Kelimeler: (Kripto paralar, Türk Lirası, Ulusal para birimi, Granger nedenselliği, Oynaklık yayılımı, VAR-BEKK-GARCH)

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey Fuller
ARCH	Autoregressive Conditional Heteroskedasticity
BEKK	Baba, Engle, Kraft and Kroner model
BTC	Bitcoin
ETH	Ethereum
GARCH	General Autoregressive Conditional Heteroskedasticity
JB	Jarque-Bera test
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LM	Lagrange Multiplier
PP	Phillips-Perron
TRY	Turkish Lira
US	United States
USD	United States Dollar
$/TRY	United States Dollar to Turkish Lira Exchange Rate
VAR	Vector autoregression
XRP	Ripple

CHAPTER 1: INTRODUCTION

In recent years, cryptocurrencies have gained significant popularity due to their decentralized and secure structure, which distinguishes them from traditional national currencies. Blockchain technology and its decentralized nature facilitates less manipulated, more efficient and transparent transaction structure for cryptocurrencies. Festa & Schaupp (2018) noted that blockchain technology makes data transactions easier and more secure than current conventional methods. The pioneer and most well-known cryptocurrency, Bitcoin, played a crucial role in the increasing popularity and mainstream adoption of cryptocurrencies. Bitcoin was originally published in a white paper by an anonymous group or individual called Satoshi Nakamoto in 2008. Bitcoin altered the concept of decentralization, enabling users to make transactions without the need for intermediaries. DeVries (2016) indicated that cryptocurrencies could change digital trade by making it possible to make transactions without fees. Since the introduction of Bitcoin, many other cryptocurrencies have emerged over the years, offering a variety of features and intricate mechanisms. Ethereum, for instance, is a blockchain-based software platform with smart contract capabilities, while Ripple is a financial transaction network well known for its novel selling concept that enables people to exchange money with ease. As of December 2022, the market value of Bitcoin, Ethereum, and Ripple represents 46%, 19%, and 3% of the total market share, respectively. These three cryptocurrencies hold a combined market dominance of 68%, demonstrating their noteworthy influence in the cryptocurrency market (CoinMarketCap, 2022). In recent times, there has been a notable growth in the quantity of new cryptocurrencies emerging in the market. As stated by coinmarketcap.com, currently there are over twenty-two thousand cryptocurrencies listed, and their valuation in total has exceeded $750 billion on more than five hundred markets as of December 2022. This phenomenon has contributed to an increase in the diversity of investment alternatives available to investors and intensified competition among digital assets.

The increasing popularity and widespread adoption of cryptocurrencies have led to a rapid expansion of cryptocurrency markets. Cryptocurrency markets are online platforms that enable users to buy, sell, and trade a variety of cryptocurrencies using national currencies or other cryptocurrencies as means of exchange. Some of these platforms not only facilitate trades between buyers and sellers but also allow individuals to exchange cryptocurrencies with one another.

The history of cryptocurrency markets can be traced back to 2010, the initial stages of Bitcoin and other pioneer cryptocurrencies. In the early days of these markets, cryptocurrencies were traded on small, specialized exchanges that were unregulated and vulnerable to hacks and frauds, which made it risky for investors to participate. As the popularity of cryptocurrencies grew, so did the number of markets, and regulatory measures were put in place to ensure security and protection for investors. The adoption of cryptocurrency in Turkey has been on the rise recently, as individuals and businesses have started to recognize the potential benefits of cryptocurrencies as an investment and payment method. As of September 2022, the average daily trading volume of cryptocurrencies in Turkish markets reached more than $361 million (CoinMarketCap, 2022). Cryptocurrencies have gained popularity in Turkey due to a variety of reasons, such as the increasing prevalence of digital payments, investment opportunities, the ability to facilitate anonymous transactions, economic instability and national currency devaluation.

National currencies, also known as fiat currencies or fiat money, are forms of money that are issued and regulated by governments without backed by physical commodities. These currencies are used by individuals and corporates within a certain country or region and are recognized as a means of payment within that country or region’s borders. The US dollar, Euro, British pound, and Turkish Lira are examples of these types of national currencies. National currencies of developed countries, such as US Dollar, Euro, and British pound, are perceived as stable financial instruments. The national currencies of emerging countries are more prone to significant volatility than the national currencies of developed countries due to a variety of factors. These may include declining economic conditions, less stable environments and weakened investor trust. Volatility refers to the fluctuation in the value of a currency over a specified period of time. The volatility of a national currency is fundamentally affected by the economic conditions of the country. A strong economy tends to have less volatile currency. Yet, an uncertain economy could cause currency volatility. Furthermore, the volatility of one currency may be affected by outside forces and may spread to other currencies, resulting in a phenomenon known as volatility spillover effect.

Volatility spillover is an important phenomenon with many implications in finance including risk management, asset pricing, financial model development, measuring the instruments stability. Volatility spillover does not only occur in conventional instruments. Newly emerging instruments such as cryptocurrencies also have a tendency of volatility spillovers between themselves and with other conventional instruments due to their volatile nature. Examining and understanding the volatility spillovers on cryptocurrencies is very crucial to assess the complexities of the cryptocurrencies and measure the potential impacts of the cryptocurrencies on certain instruments. This phenomenon of volatility spillovers on cryptocurrencies has gained significant attention by academics, researchers, financial authorities and investors. The rapidly rising attention to cryptocurrencies has led to extensive research efforts by academics and researchers. While some papers have concentrated on the volatility spillovers within cryptocurrencies, others concentrated on volatility spillovers between cryptocurrencies and other instruments like national currencies, financial indices and other conventional instruments. There are numerous studies on volatility spillovers between cryptocurrencies in the existing literature. Certain ones examined the major cryptocurrencies volatility characteristics including, Corbet et al. (2018), Yi et al. (2018), Huynh (2019), Katsiampa et al. (2019), Kyriazis (2019), Palamalai et al. (2019), Sensoy et al. (2021). These investigations show a common result that the major cryptocurrencies spillover their volatilities to other cryptocurrencies in the market. However, the studies concentrated on volatility spillovers involving conventional instruments and cryptocurrencies are more limited. Therefore, the principal goal of this thesis is to examine the interconnectedness between three major cryptocurrencies and a national currency by analyzing the volatility spillovers. This thesis seeks to demonstrate the effects of the changes in the cryptocurrency's prices on a national currency and national currencies on cryptocurrencies. This thesis aims to offer valuable insights into the relationship between cryptocurrencies and a conventional financial instrument to literature.

This thesis contributes to literature in three aspects. Primarily, it offers a unique contribution to literature by being the first to investigate the volatility spillovers and causalities between the three most traded cryptocurrencies, namely Bitcoin, Ethereum and Ripple, in the selected period and a national currency, Turkish Lira. Secondly, utilizing Granger causality test and VAR-BEKK-GARCH model, this study spans a wide range of data from March 10th, 2016, to December 31st, 2021, which enhances the robustness of the findings. Third, with the current and wide analysis, it provides useful information to investors, policymakers and researchers that can assist them in comprehending the risks and opportunities of investing in cryptocurrencies or the Turkish Lira.

The other parts of the thesis are arranged as follows: Second chapter reviews previous relevant literature on the nexus between cryptocurrencies and national currency and highlights the key findings of previous studies. The third chapter describes the methodologies used in this thesis and provides in-depth explanation of the models and other tests. The fourth chapter offers a general outline of the data and the summarized statistics of the variables. The fifth chapter covers empirical findings and interpretations of models and tests. Finally, the conclusions and implications of the thesis are presented in the last chapter.

CHAPTER 2: LITERATURE REVIEW

In recent years, cryptocurrencies have emerged as both a popular investment instrument and a potential currency alternative. While national currencies remain the primary elements of the financial system and dominant as a medium of exchange, the emergence of cryptocurrencies has opposed traditional notions of financial instruments and fiat money. The literature review aimed to explore the existing research on various aspects related to cryptocurrencies, including their legal frameworks, market efficiency, instability, volatility and volatility spillovers, investment behaviors, and relationships with traditional currencies in the context of Turkish markets and Turkish Lira. In general, many studies have provided evidence of a volatility presence and spillovers in the cryptocurrency market.

Cryptocurrencies have appeared with a framework that naturally challenges the traditional legal frameworks. Dibrova (2016) suggested that despite the potential for growth, the construction of a legal framework for cryptocurrencies and their markets is essential to ensure their stability and credibility. The regulatory policies and the legal framework for cryptocurrencies vary between countries, as Shchepeleva & Stolbov (2020) evaluated the legal frameworks and regulatory policies of 134 countries and found that higher values of free expression, financial responsibility, and governance quality increase the free flow of cryptocurrencies in the markets. A study that combines the legal investor behavior aspects of cryptocurrencies and investor behaviors analyzed by Werbach & Feinstein (2021) indicated that the rapid growth of the worldwide cryptocurrency markets gives different challenges to the regulators, although the findings showed that there is no scientific evidence to suggest that regulatory procedures cause investors to flee from the cryptocurrency markets. In contrast, Alfieri & Chokor (2021) stated that news about the possibility of regulation implementation on cryptocurrencies results negative anomalous returns for these currencies.

Efficient market hypothesis is a critical area of research that has been of interest to investors and regulators. ElBahrawy et al. (2017) found that several statistical aspects of the markets have remained consistent for years and are efficient in terms of those aspects, even though new cryptocurrencies arise and disappear on a regular basis. An opposite study of Caporale et al. (2018) found evidence of market inefficiency, suggesting that the market is predictable and causes anomalous profits. Al-Yahyaee et al. (2020) likewise stated inefficiency of the cryptocurrency markets while pointing out the reasons of the inefficiency of the markets as the liquidity and volatility. Manavi et al. (2020), contrarywise, argued that the control and absence of control in cryptocurrency markets resemble the destabilizing effects of network hubs; hence, the cryptocurrency market may be considered as either a traditional or semi-efficient market.

Another concerning issue for investors is the instability of cryptocurrencies. Allenykh (2021) studied the instability of the cryptocurrencies and stated that cryptocurrencies are not yet fully developed currencies or private money as defined by the Austrian school, and therefore they are currently unstable. Rao & De Pace’s (2022) study on the instability of cryptocurrencies further supports this notion, highlighting the frequent concurrent instability seen in various cryptocurrencies during the last three quarters of 2018 and the third and fourth quarters of 2019.

Similar to cryptocurrencies, their markets are also acknowledged for their significant volatilities which can cause spillover effects within or between the markets. This means that the price movements of one cryptocurrency may affect the price movements of others. Numerous studies have examined the phenomenon of volatility spillovers in the cryptocurrency markets and many of these studies have found evidence of such spillovers.

Yi et al. (2018) evaluated the association of cryptocurrencies and the transmission of volatility between them and found that all cryptocurrencies are strictly interrelated and that those with larger market caps have a higher tendency to spread volatility shocks to other cryptocurrencies. Similarly, Kyriazis's (2019) research on the presence of volatility spillovers in their markets showed that there were bidirectional characteristics in the volatility spillovers between the leading cryptocurrencies. In addition, the research highlighted that there were instances of volatility shock transmission between Bitcoin and national currencies. Palamalai et al. (2019) conducted a similar study and found mutuality and bidirectional volatility among several sets of cryptocurrency markets using Diagonal BEKK and Multivariate GARCH models which are uniform with the observations of the other studies. The investigation by Canh et al. (2019) presented similar results and found that strong volatility spillovers between cryptocurrencies have been observed and that structural breaks can cause larger cryptocurrencies to be more susceptible to fluctuations than smaller ones. In a more specific study, Huynh (2019) analyzed the potential receiver of the volatility spillover effects in cryptocurrency markets and found that Bitcoin tended to be the recipient of spillover effects, while Ethereum tended to be independent. Serletis et al. (2019) adopted a wider perspective and examined the volatility spillovers from cryptocurrency markets to various markets in the world and found volatility spillover evidence from cryptocurrency markets to other markets of developed countries like the US. Bouri et al. (2019) conducted a Granger causality test on cryptocurrencies and found substantial evidence on causality between the volume of trading, returns and the volatility of the largest cryptocurrencies. Analogously, Elsayed et al. (2020) found strong dependencies between Bitcoin, Litecoin and the Chinese Yuan, while other national currencies had no significant impact on cryptocurrencies. Smales (2021) focused on the returns and transmissions of volatility among the cryptocurrencies and found a bidirectional correlation on Bitcoin and Ethereum, while only a unidirectional effect existed from Bitcoin to Ethereum in the short term.

Investors have expressed concerns over the volatility of cryptocurrencies as it leads to higher risks and difficulty in making accurate forecasts. Sterninski (2018) analyzed the volatilities of Ethereum, Bitcoin, Ripple, Euro, Japanese Yen and British Pound and indicated a significant result that cryptocurrencies are substantially more volatile than the national currencies. In another study, Baur et al. (2018) combined the behavioral finance with cryptocurrencies volatilities and found that the shocks with positive characteristics provide more significant effect on price volatility than negative characteristics because of the trader's fear of missing out. Antonakakis et al. (2019) investigated the reasons behind cryptocurrency volatility and discovered that the price volatility of cryptocurrencies is linked to increasing uncertainty in cryptocurrency markets. Alternatively, Ozyesil (2019) analyzed the volatility relationships between cryptocurrencies and stated that price changes in several cryptocurrencies impact other cryptocurrencies' values. More inquiring study by Katsiampa et al. (2019) inspected the potential reasons for the volatility in cryptocurrencies and found that the volatility of cryptocurrencies is highly correlated with the major news and that negative news, and the positive news have an asymmetrical influence on, Bitcoin, Ethereum, Ripple and Litecoin. In addition, Katsiampa et al. (2019) analyzed dynamics of conditional volatility and interlinkages among the most traded cryptocurrencies and retrieved noteworthy evidence of bidirectional transmission of shock between them. Similarly, Fakhfekh et al. (2020) analyzed the asymmetrical effect of shocks on cryptocurrencies and attributed this to the presence of uneducated investors in the market. Additionally, Rehman (2020) found that volatility is affected by the positive shocks more than negative shocks. Cheng & Yen (2021) investigated the linkage between the future volatility of Bitcoin and uncertainty in economic policy in China and indicated that economic policy uncertainty of China is significantly related to cryptocurrency volatility. On another perspective, Tang & You (2021) explored the interconnectedness between the investor behaviors and price changes and noted that the value of the Bitcoin increases when investors show more skepticism towards other cryptocurrencies which is consistent with Hayek's (1937) theory of investor's excitement and optimism leading to bubbles in asset prices.

The examination of investor behavior is a frequently explored topic in the field of cryptocurrency research. The behaviors of investors may have an important influence on the performance and volatility of cryptocurrencies and assessing these behaviors may provide insight for investors, researchers and the cryptocurrency market's dynamics.

To assess the characteristics of cryptocurrency investors, Ozdemir et al. (2015) examined the perceptions of Bitcoin among well-educated individuals and found that it was viewed as a trustable electronic cash flow structure. To measure the investor's behaviors on risk, Lammer et al. (2019) analyzed the investments choices of cryptocurrency investments and found that cryptocurrency investors are more likely to make risky investments and involved in the cryptocurrency markets. It is supported with the investigation of Hackethal et al. (2021) which investigated a similar behavior and reported that price hikes or volatility increases on cryptocurrencies attract investors and following their initial investments, investors are more prone to make riskier investments in cryptocurrencies. Additionally, Sonkurt et al. (2021) observed that the age group of 18-25 years old is more likely to invest in cryptocurrencies, with approximately one in two of them engaging in investments with a gambling-like behavior.

Lately, there has been a significant rise in the interest in cryptocurrencies, resulting in their emergence as highly popular and widely invested financial instruments. Teker & Deniz (2021) discovered that robust performance in terms of returns has attracted significant attention from investors towards cryptocurrencies. Lin (2021) also found equivalent results, indicating that previous returns of cryptocurrencies drastically influenced the subsequent attention of investors to the cryptocurrencies. Building upon these findings, Li et al. (2021) conducted a more specific study and discovered a symmetric causality from the cryptocurrencies returns to investor attention. As the interest in cryptocurrencies has increased in recent years, a variety of outcomes have followed. Al Guindy (2021) analyzed the consequences of increased investors interest in cryptocurrencies and stated that the rising attention of investors to cryptocurrencies has the consequence of expanding volatility. Additional study conducted by Koch & Dimpfl (2022) on investors' attention and its outcomes showed that attention to cryptocurrencies Granger causes price co-movement and Google search volume index or number of tweets in Twitter Granger causes a rise in price synchronization of Bitcoin and Ethereum. Ozdamar et al. (2022) analyzed the outcomes of investor behavior on cryptocurrency markets through examining the cryptocurrency returns and attention of investor and demonstrated the negative influence of investor's behavior on the returns of cryptocurrencies, thereby increasing the risk of volatility and instability on cryptocurrency markets.

Herding behavior, which is a phenomenon where small investors tend to follow the actions of larger investors rather than making their own decisions, has been observed in the context of cryptocurrencies. O'Loughlin & Gurdgiev (2020) found that market sentiment can predict the trend of cryptocurrencies values and identified the direct influence of anchoring and herding behaviors. In parallel research, Mansour et al. (2020) found that the market for cryptocurrency is significantly influenced by herding behavior among investors with their actions having a direct effect on cryptocurrencies values. In a similar vein, but within a different time span, Waked & Youssef (2022) conducted an analysis investigating the herding behaviour in the context of cryptocurrencies during the pandemic of COVID-19, based on a sample of the forty-three major cryptocurrencies by their market capitalization and found substantial evidence of herding from 2013 to 2020 in cryptocurrency markets.

Cryptocurrencies and national currencies are often compared in literature and studies on their relationship tend to concentrate on major currencies rather than minor ones. Numerous investigations have been performed to examine the association between cryptocurrencies and national currencies, as well as indexes from various aspects.

According to Dyhrberg (2015), the cryptocurrency market has undergone significant expansion and by utilizing the GARCH model, the research discovered that cryptocurrencies present similarities with traditional instruments such as gold and the US dollar. This suggests that cryptocurrencies may have hedging properties and can serve as a viable form of investment instrument or exchange. Corelli (2018) conducted an analysis between national currencies and cryptocurrencies and found that cryptocurrencies can perform as substitutes for national currencies in certain situations, as demonstrated through a multivariate regression analysis that revealed correlated bidirectional relationships between cryptocurrencies and certain national currencies such as the Taiwan dollar, and Chinese Yuan. Similarly, but in a more specific way, Shahzad et al. (2022) analyzed the hedge effect of national currencies on cryptocurrencies and identified the Japanese yen as the most stable hedging currency, tailed by the British pound. Study also revealed that the Euro, British pound, and Chinese yuan can function as a "port in a storm" for cryptocurrencies during times of market volatility. Benigno et al. (2022) also analyzed national currencies along with cryptocurrencies and stated that globally used cryptocurrency may significantly alter the whole financial system. Ajmi & Mokni (2021) similarly explored the correlation between cryptocurrencies and national currencies, particularly analyzing the causal impacts between the US dollar index and leading cryptocurrencies by employing the Granger causality test. Findings demonstrated a vastly significant causal association between the US dollar and cryptocurrencies, especially throughout the first quarters of the COVID-19 pandemic.

There are several literatures that investigates the associations relating cryptocurrencies and other instruments in the perspective of Turkey. Research conducted by Taskinsoy (2019) reviewed the comparison of volatility of Turkish Lira and cryptocurrencies and showed that the \$/TRY was more volatile than the average volatility of the top ten cryptocurrencies between January 2018 and December 2018. In a unique perspective, Sivrikaya (2020) analyzed the inflation dynamics with cryptocurrencies and concluded that there exists a nonlinear association between Bitcoin’s trade volume at the markets in Turkey and uncertainty of inflation, suggesting that investors should consider inflation forecasts when making investment decisions. In a parallel study, Akdag et al. (2021) found that there is a strong motivation on the usage of cryptocurrencies as an alternative to the local currency in times of macroeconomic or political uncertainty in Turkey. Furthermore, Ozturk (2021) discovered that the values of Bitcoin and Ethereum in Turkish Lira are correlated positively with GDP and CCI but correlated negatively with M2. Finally, Ustaoglu (2022) analyzed the volatility spillovers among Turkish main stock market index and top cryptocurrencies. The findings revealed unidirectional transmission of shock from the Turkish main stock market index to Bitcoin and Ripple. Findings also revealed the unidirectionally transmitted volatility from Turkish main stock market index to Bitcoin and Ethereum.

CHAPTER 3: METHODOLOGY

This thesis estimates the causality and volatility spillovers by employing Granger Causality and Multivariate GARCH models. Before engaging these methodologies, ADF, Phillips-Perron and KPSS unit root tests are applied to measure stationarity. And then, ARCH Lagrange Multiplier test is implemented to detect ARCH effects on variables.

3.1. Augmented Dickey-Fuller Unit Root Test

The Augmented Dickey-Fuller (ADF hereafter) test (Dickey and Fuller, 1981) is a test that is utilized to validate stationarity of the selected series and an upgraded type of the initial Dickey Fuller test (Dickey & Fuller, 1979). The ADF test allows for higher-order autoregressive methods by including the lagged value of the time series,

$$\Delta y_{t-p} \qquad (1)$$

Where involved as an explanatory variable to detect autocorrelation. The null hypothesis in the model posits that there is a unit root.

$$\gamma = 0 \qquad (2)$$

The model without constant and trend shown as,

$$\Delta y_t = \alpha + \beta_t \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \cdots \qquad (3)$$

Where the dependent variable of the first difference is (Δy_t) and term of error is depicted by (ϵ_t).

3.2. Phillips-Perron Unit Root Test

Phillips-Perron (PP henceforth) test (Phillips & Perron, 1988) is a wider unit root test which builds on Dickey Fuller test (Dickey & Fuller, 1979) with a non-parametric approach and auto-correlated residuals. The modified statistics represented Z_t and Z_δ are measured as,

$$Z_t = \sqrt{\frac{\hat{\alpha}^2}{\hat{\beta}^2}} t_{\hat{\delta}} - \frac{1}{2}\left(\frac{\hat{\beta}^2 - \hat{\alpha}^2}{\hat{\beta}^2}\right)\left(\frac{T(SE(\hat{\delta}))}{\hat{\alpha}^2}\right) \qquad (4)$$

$$Z_{\delta} = T\hat{\delta} - \frac{1}{2}\frac{T^2(SE(\hat{\delta}))}{\hat{\alpha}^2}\left(\hat{\beta}^2 - \hat{\alpha}^2\right) \quad (5)$$

The terms $\hat{\alpha}^2$and $\hat{\beta}^2$ are consistent estimates of variance parameters.

$$\hat{\alpha}^2 = \lim_{T \leftarrow \infty} T^{-1} \sum_{t=1}^{T} E(\varepsilon_t^2) \quad (6)$$

$$\hat{\beta}^2 = \lim_{T \rightarrow \infty} \sum_{t=1}^{T} E(\frac{1}{T}\sum_{t=1}^{T} \varepsilon_t^2) \quad (7)$$

The sample size denoted with the (T) while standard error denoted with ($SE(\widehat{\delta})$). Z_t and Z_{δ} statistics exhibit the equivalent asymptotic distributions as the Augmented Dickey Fuller test statistics.

3.3. Kwiatkowski–Phillips–Schmidt–Shin Unit Root Test

Kwiatkowski-Phillips-Schmidt-Shin (KPSS hereafter) test (Kwiatoski et al., 1992) is a test which introduces an alternative approach for investigating the presence of the unit roots. Rejection of null hypothesis indicates the presence of unit root in a time series which signifies, series is non-stationary. The null hypothesis of the model written as,

$$\sigma_u^2 = 0 \ \rightarrow Y_t \sim I(0) \quad (8)$$

KPSS test's model expressed as follows,

$$Y_t = \alpha_0 + \alpha_1 t + r_t + \varepsilon_t \quad (9)$$

$$r_t = r_{t-1} + u_t, u_t \sim IID(0, \sigma_u^2) \quad (10)$$

The constant term denotes α_0, linear time trend depicted by $\alpha_1 t$, the r_t stands for random walk and u_t is the model's disturbance term.

3.4. ARCH Lagrange Multiplier Test

The ARCH Lagrange Multiplier (ARCH-LM henceforth) test (Engle, 1982) is used on detection of autoregressive conditional heteroscedasticity which is applied before GARCH models to make the examinations applicable. The null hypothesis regression of no ARCH(q) represented as,

$$e_t^2 = \hat{\delta}_0 + \sum_{s=1}^{q} \hat{\delta}_s e_{t-s}^2 + \upsilon_t \tag{11}$$

The ARCH LM test is estimated by total observations (T) multiplied by (R^2) the regression.

$$LM = R2 * T \tag{12}$$

It follows a p degree of freedom on an asymptotic chi-squared distribution.

3.5. Jarque–Bera Test

The Jarque-Bera (JB hereafter) test is employed to analyze the time series distribution's normality with its kurtosis and skewness. The written equation of the Jarque-Bera test is presented as,

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right) \tag{13}$$

3.6. Granger Causality Test

The Granger causality test (Granger, 1969) tests the statistical causality among the variables to predict each other. Rejection of the null hypothesis exhibits a Granger causal relationship among the variables. Test is conducted to examine the Granger causality between the $/TRY exchange rate and three cryptocurrencies, followed as,

$$Y_t = \mu_0 + a_1 Y_{t-1} + \cdots + a_p Y_{t-p} + b_1 X_{t-1} + \cdots + b_p X_{t-p} + u_t \tag{14}$$

Where dependent variable is depicted by a_1 to a_p and c_1 to c_p, independent variable represented by the coefficients of b_1 to b_p and d_1 to d_p.

3.7. Vector Autoregression Model

Vector Autoregression (VAR hereafter) (Sims, 1980) is a random process model which is used to relate the present observations of a variable with its and other variables past observations to measure and forecast the behaviors of the variables. To analyze the relationship between $/TRY exchange rate and three cryptocurrencies, the VAR (1) model is utilized. Equations of the model with two variables is written as,

$$Y_{1,t} = \alpha_1 + \beta_{11,1} Y_{1,t-1} + \beta_{12,1} Y_{2,t-1} + \varepsilon_{1,t} \tag{15}$$

$$Y_{2,t} = \alpha_2 + \beta_{21,1} Y_{1,t-1} + \beta_{22,1} Y_{2,t-1} + \varepsilon_{2,t} \tag{16}$$

Where, $Y_{1,t-1}$ and $Y_{2,t-1}$ respectively are the initial lags of the variables. Using VAR model as a single model is not sufficient to gather the information. However, combining VAR model with other models like GARCH can be more effective.

3.8. Multivariate VAR-BEKK-GARCH Model

GARCH model with BEKK approach (Engle and Kroner, 1995) is a suitable method to assess the volatility spillovers between the variables as it does not demand any limitation on the correlation. The mean equation used is the VAR (1) model which is shown as,

$$R_t = \mu + \Phi R_{t-1} + \varepsilon_t \tag{17}$$

$$\varepsilon_t = H_t^{\frac{1}{2}}, \eta_t \, , \tag{18}$$

where $R_t = (r_t^B, r_t^A)'$ represents the return value of $/TRY exchange rate and three cryptocurrencies, Bitcoin, Ethereum and Ripple, respectively. While μ depicts the vector of constant coefficients, $\varepsilon_t = (\varepsilon_t^B, \varepsilon_t^A)'$ signifies the terms of error in the conditional mean equation of the $/TRY rate and three cryptocurrencies.

Φ represents the lagged variables in the mean equation by a (2x2) matrix,

$$\Phi = \begin{pmatrix} \Phi_{11} & \Phi_{12} \\ \Phi_{21} & \Phi_{22} \end{pmatrix} \tag{19}$$

The conditional covariance matrix (H_t) of BEKK-GARCH model stated as follows,

$$H_t = C'C + A' \varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{20}$$

where, A, B and C indicates the parameters of the (2x2) matrices and ε_t represents the error terms. Lower triangular constant matrix to assess positive confidence of H_t is represented by C. While Matrix A exhibits the ARCH coefficients, Matrix B demonstrates the GARCH coefficients. Matrix A coefficients represent both own and cross variable shocks, Matrix B coefficients characterizes own volatility and the transmission of the volatility between the returns of $/TRY exchange rate, Bitcoin, Ethereum and Ripple. The parameters of matrices, A, B and C written as follows,

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, B = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}, C = \begin{bmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{bmatrix} \tag{21}$$

The bivariate model of BEKK-GARCH can be written as,

$$\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} \times \begin{bmatrix} c_{11} & 0 \\ c_{12} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \times$$
$$\begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \times \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \times \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \times$$
$$\begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} \tag{22}$$

CHAPTER 4: DATA AND SUMMARY STATISTICS

In this chapter, the variables of the dataset are described, the summary statistics are applied to analyze whether the variables are stationary to apply further tests and models. The econometric software RATS 9.0 and Eviews 12 are utilized in the examination of the variables.

4.1. Data Overview

In this study, the dataset consists of daily prices and daily returns of cryptocurrencies; Bitcoin, Ripple, Ethereum, and a national currency, US Dollar / Turkish Lira exchange rate ($/TRY hereafter). The sample spanning from March 10th, 2016, to December 31st, 2021, corresponds to a total of 1517 observations. To evade data discrepancies and ensure consistency, the weekend data are excluded from the sample. The data for cryptocurrency prices and $/TRY exchange rate is gathered from investing.com. Returns, $\mathcal{R}_{i,t}$ is calculated as $\mathcal{R}_{i,t} = ln\,(P_{i,t}) - ln\,(P_{i,t-1})$, where $P_{i,t}$ denotes prices of cryptocurrencies and exchange rate at time t.

Figures 1 through 4 depict the changes in the prices of most traded three cryptocurrencies, and the $/TRY, respectively. Meanwhile, Figures 5 through 8 illustrate the returns and volatility of these cryptocurrencies and the $/TRY exchange rate over time through line graphs.

Figure 1. Bitcoin Pricing Chart (2016-2021)

Figure 1 illustrates the fluctuation of the value of Bitcoin over time, with the highest peak occurring at the end of 2020 and continuing through 2021. Prior to this, in the early days of 2018 and mid-2019 significant rises in the price were observed.

Figure 2. Ethereum Pricing Chart (2016-2021)

Figure 2 depicts the price movement of Ethereum over time, exhibiting a similar trend to that of Bitcoin with notable peaks and decreases. However, the volatility of Ethereum appears to be less erratic compared to that of Bitcoin, particularly during the year of 2019. Additionally, the increase in Ethereum's value observed in the second quarter of 2021 appears to be more short-lived in comparison to the sustained upward trend seen in the Bitcoin's price throughout the same period.

Figure 3. Ripple Pricing Chart (2016-2021)

Figure 3 illustrates the fluctuation of the price of Ripple over time, with the most significant peak and subsequent decrease occurring at the end of 2017. Throughout the years, Ripple has experienced continuous volatility. The sharp increase and the decrease in the value of Ripple at the end of 2017 are the highest of all variables.

Figure 4. $/TRY Pricing Chart (2016-2021)

Figure 4 illustrates the changes of the $/TRY exchange rate over time, demonstrating a general trend of depreciation in the value of the Turkish Lira. The peak in the $/TRY exchange rate occurred at the end of 2021, although a notable increase was also observed in the third quarter of 2018.

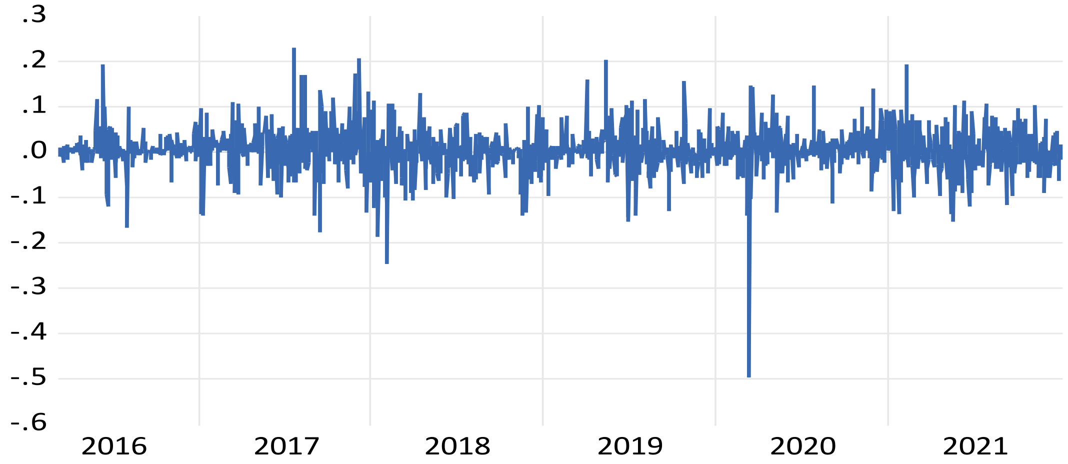

Figure 5. Bitcoin Return Graph (2016-2021)

Figure 5 demonstrates the returns of Bitcoin between 2016 to 2021, with the most dramatic fluctuations occurring in the early months of 2020, concurring with the initiation of the COVID-19 pandemic. Additionally, the figure illustrates a continuous period of high volatility from the second half of 2017 through the first days of 2018.

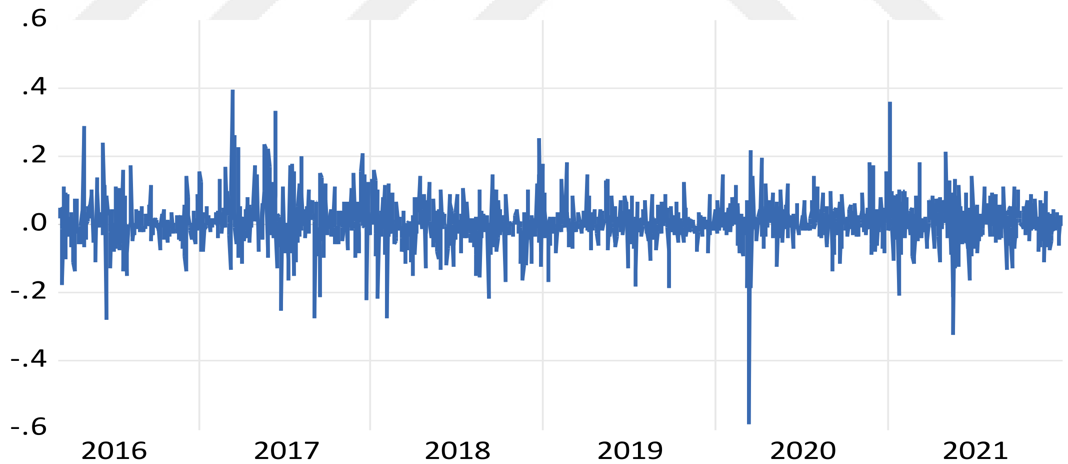

Figure 6. Ethereum Return Graph (2016-2021)

Figure 6 presents the returns of Ethereum over the period from 2016 to 2021, revealing a pattern of significant volatility, especially in the 2020's first months when the COVID-19 pandemic began just like Bitcoin.

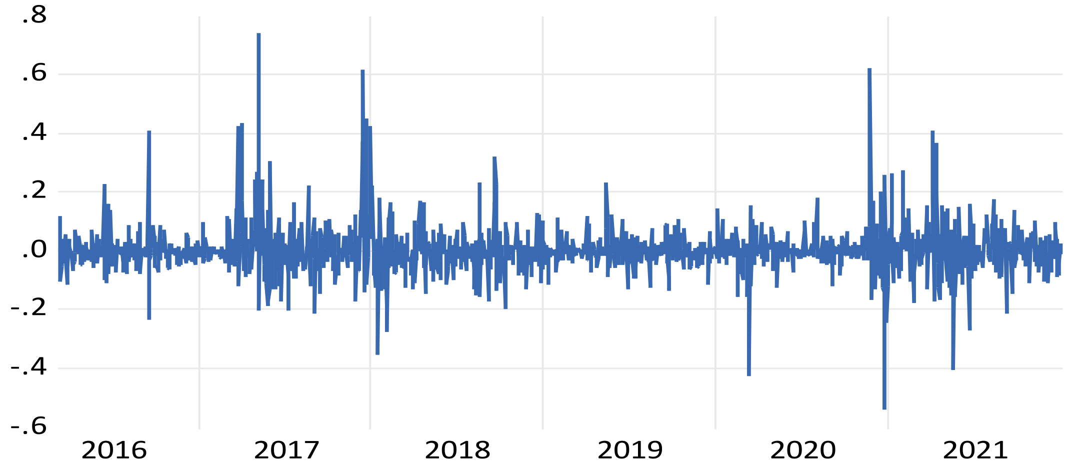

Figure 7. Ripple Return Graph (2016-2021)

Figure 7 displays the returns of Ripple, highlighting the volatility of this cryptocurrency and instances of significant volatility, as well as moments of relative stability. Interestingly, the period of highest volatility for Ripple does not happen together with the start of the pandemic as was seen with Bitcoin and Ethereum, but rather begins at the end of 2020.

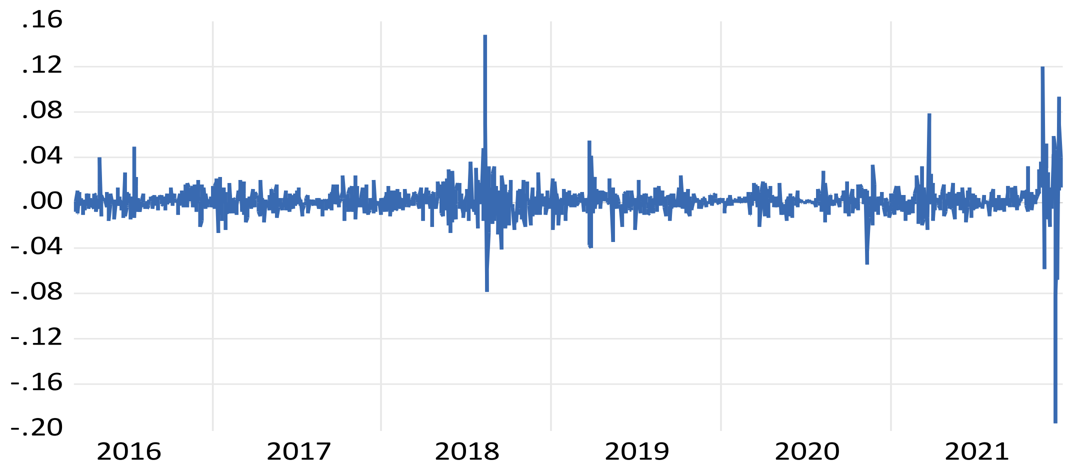

Figure 8. $/TRY Return Graph (2016-2021)

Figure 8 shows the return changes in the $/TRY exchange rate. The Turkish Lira experienced its most volatile period in the end of summer of 2018 and the final quarter of 2021, with fluctuations in value that were generally lower in comparison to cryptocurrencies but higher than those typically observed in traditional national currencies.

4.2. Descriptive Statistics

Descriptive statistics demonstrated in Table 1. $/TRY has the least average return, followed by Bitcoin, Ripple, and Ethereum, which have slightly higher average returns from each other. $/TRY has the lowest standard deviation, followed by Bitcoin, Ethereum, and Ripple, which have slightly larger standard deviations. This states that the $/TRY returns are relatively consistent, while the returns of cryptocurrencies are more volatile.

Based on the skewness values, the distribution of the returns of the $/TRY, Ethereum and Bitcoin are skewed negatively. This means that there are relatively more values on the left side of the mean, and the distribution on the left side has a longer tail and the mean is pulled to the left side. However, the distribution of the returns of Ripple is skewed positively, therefore, there are more values on the right side of the mean, and the distribution has a longer tail on the right side and the mean is pulled to the right side. In addition to this outcome, it is observed that all kurtosis values are larger than 3, representing that all results indicates a heavy tail and peak relative to a normal distribution, kurtosis of all returns surpass a normal distribution (kurtosis=3), denoted as leptokurtic distribution. Jarque-Bera (JB) Lagrange Multiplier test assesses the normality, and it is strongly rejected in all variables.

Table 1. Descriptive Statistics of $/TRY and Cryptocurrencies.

Descriptive Stats	$ / TRY	Bitcoin	Ethereum	Ripple
Mean	0.001007	0.003107	0.003790	0.003046
Standard Deviation	0.013477	0.047266	0.067507	0.081017
Max	0.147563	0.227605	0.392521	0.740796
Min	-0.195044	-0.497278	-0.589639	-0.541017
Skewness	-0.568522	-0.800131	-0.251872	1.59847
Kurtosis	51.02833	13.79132	10.38979	18.03817
Jarque-Bera	145789.5	7517.677	3465.493	14930.51
Probability	(0.000) *	(0.000) *	(0.000) *	(0.000) *

Note: “*” signifies the statistical significance at 1% level.

Table 2. Unit Root Tests Results of $/TRY and Cryptocurrencies Returns (ADF, KPSS, PP).

Variables	Level						First Difference					
	ADF		KPSS		PP		ADF		KPSS		PP	
	Intercept	Trend + Int.	Intercept	Trend + Int.	Intercept	Trend + Int.	Intercept	Trend + Int.	Intercept	Trend + Int.	Intercept	Trend + Int.
$/TRY	-34.103	-34.117	0.1534	0.0677	-33.823	-33.831	-21.851	-21.839	0.1684	0.1675	-422.416	-424.533
Prob.	(0.000) *	(0.000) *			(0.000) *	(0.000) *	(0.000) *	(0.000) *			(0.000) *	(0.000) *
Bitcoin	-40.269	-40.268	0.1290	0.0905	-40.279	-40.276	-20.286	-20.280	0.3239	0.3184	-558.74	-558.85
Prob.	(0.000) *	(0.000) *			(0.000) *	(0.000) *	(0.000) *	(0.000) *			(0.000) *	(0.000) *
Ethereum	-39.526	-39.513	0.1534	0.1523	-39.567	-39.554	-20.308	-20.301	0.0500	0.0500	-652.47	-651.45
Prob.	(0.000) *	(0.000) *			(0.000) *	(0.000) *	(0.000) *	(0.000) *			(0.000) *	(0.000) *
Ripple	-36.878	-36.881	0.1247	0.0653	-37.892	-37.875	-36.878	-36.881	0.1247	0.0653	-37.892	-37.875
Prob.	(0.000) *	(0.000) *			(0.000) *	(0.000) *	(0.000) *	(0.000) *			(0.000) *	(0.000) *

Note: "*" implies statistical significancy at 1% level. Significance levels for the ADF and Phillips-Perron tests without trend at 1%, 5% and 10% are -3.4345, -2.8632 and -2.5677 respectively. Significance levels for the ADF and Phillips-Perron tests with trend at 1%, 5% and 10% are -3.9641, -3.4128 and -3.1284 respectively. Significance levels for the KPSS test without trend at 1%, 5% and 10% are 0.7390, 0.4630 and 0.3470, respectively. Significance levels for the KPSS test with trends at 1%, 5% and 10% are 0.2160, 0.1460 and 0.1190, respectively.

Table 2 depicts findings of unit root tests applied on return variable sets, allowing an estimation of unit root existence in these variables. The returns series' stationarity is analyzed utilizing the ADF, KPSS and Phillips-Perron unit root tests. These unit root tests with two specifications (intercept and trend) are implemented both on the level and first difference. The unit root test results of the return series show statistical significancy which signifies the absence of a unit root on level and first difference.

The ARCH-LM test is employed prior to analyzing volatility spillovers between $/TRY and three cryptocurrencies to assess the existence of any ARCH effect.

Table 3. Heteroscedasticity Test Results of $/TRY and Cryptocurrencies Returns. (ARCH-LM)

Variable	ARCH-LM Statistics	Prob. Chi-Square
Bitcoin	5.5884	0.0181 **
Ethereum	17.1180	0.0000 *
Ripple	44.8441	0.0000 *
$/TRY	46.2104	0.0000 *

Note: "*" and "**" imply statistical significance at 1% and 5% level, respectively.

Table 3 represents the ARCH-LM test results which were employed to investigate the ARCH effect existence in the model for return series residuals. According to the result, it has been specified that it is appropriate to predict the return series of each variable by using alternative ARCH specifications.

CHAPTER 5: EMPIRICAL RESULTS

The chapter of empirical results examines the Granger causalities and volatility spillover effects between $/TRY and three most traded cryptocurrencies namely, Bitcoin, Ethereum and Ripple by utilizing Granger causality test and VAR-BEKK-GARCH model.

5.1. Granger Causality Test

The test is conducted to investigate Granger causalities between the $/TRY and cryptocurrencies and validate the effectiveness of one to predict the other. Table 4 summarizes the Granger Causality test results between $/TRY exchange rate and three cryptocurrencies. The first column within the table indicates the null hypothesis for each pair of variables. The second column of the table represents the lags employed to the variables which is selected “2” as an appropriate length for all in the test. In the third and fourth column, the existence and direction of the Granger causality is examined by the f-statistic and its p-value while fifth column specifies the existence of causality of the pair.

According to the Granger causality test results, none of the cryptocurrencies show any significancy to provide evidence of causal relationship to $/TRY. However, $/TRY exhibits Granger causality to all three cryptocurrencies. The most substantial finding of the test is the unidirectional causality from $/TRY to Ripple’s returns with the p-value of 0.07%. Furthermore, $/TRY exhibits causal relationship to the returns of Bitcoin and Ethereum unidirectionally with p-values of 6% and 5,02% respectively.

Overall, three of the six variable pairs show causal relationships, all of which are from $/TRY to the cryptocurrencies. According to the test results, $/TRY have been found to be the most influential variable since it exhibits Granger causality to all the variables. Additionally, Ripple is found to be the most affected cryptocurrency by the $/TRY while Bitcoin is the least.

5.2. Volatility Spillover: VAR-BEKK-GARCH Model

The return spillovers, shock transmissions and transmissions of volatilities between the returns of \$/TRY and most traded three cryptocurrencies, namely, Bitcoin, Ethereum, and Ripple examined by VAR (1) BEKK-GARCH (1,1) model. The findings of the VAR-BEKK-GARCH model are stated on the panels A, B of Table 5 while the summarized findings which demonstrate the existence and the directions of the return spillovers, shock transmissions and volatility spillovers are depicted in Table 6.

The coefficients on the Panel A of the Table 5 which represents mean equation of the model, $\varphi(1)_{11}$and $\varphi(1)_{22}$ indicate the VAR results of own lagged mean spillovers. While $\varphi(1)_{21}$ displays the result of the return spillovers from cryptocurrencies to the \$/TRY, $\varphi(1)_{12}$ presents the return spillovers from the \$/TRY to cryptocurrencies. The coefficients of variance equation on Panel B c_{11}, c_{21} and c_{22} indicate the constants, a_{11}, a_{12}, a_{21} and a_{22} show the shocks, while b_{11}, b_{12}, b_{21} and b_{22} exhibit volatility transmissions between the variables. a_{12}, a_{21}, b_{12} and b_{21} demonstrate the cross-market shocks and spillovers, a_{11}, a_{22}, b_{11} and b_{22} depict the own-market shocks and spillover persistence of the variables. While (1) represents the dependent variable which is the \$/TRY's returns, (2) denotes the returns of Bitcoin, Ethereum and Ripple.

The empirical results regarding the mean equation of the model state a unilateral return spillover from all three cryptocurrencies to the \$/TRY, represented in Table 5. In the context of \$/TRY, the results indicate the absence of significancy to prove any return spillovers to cryptocurrencies.

The variance equation results regarding the shock spillovers indicates that there is no evidence of shock transmission from cryptocurrencies to \$/TRY as shown in Table 5. However, the estimations provide considerable evidence of shock transmissions from \$/TRY to Bitcoin and Ripple, meaning that present returns in Bitcoin and Ripple are affected by previous period returns of \$/TRY. There is no significant evidence of shock spillovers from \$/TRY to Ethereum, unlike the other cryptocurrencies. While the empirical findings regarding the volatility spillovers provide significant indication of volatility transmission from \$/TRY to the cryptocurrencies, estimations demonstrated absence of statistical significancy to prove any volatility transmissions from cryptocurrencies to \$/TRY. The estimations of the model show no evidence of bidirectional spillovers between the pairs. Among the analyzed pairs, the estimation results reveal that \$/TRY and Ripple exhibit the most statistically significant spillover relationship in the model which is similar to Granger causality test results. Another result which is like the Granger causality findings is the order of pairs in terms of statistical significancy.

To summarize the empirical results of VAR-BEKK-GARCH model, several important insights and implications have emerged from the analysis illustrated in Table 6. Firstly, the results demonstrate that there is a volatility transfer from \$/TRY to all selected cryptocurrencies. The presence of these unidirectional spillovers highlights the necessity of monitoring cryptocurrencies for the investors who are interested in \$/TRY and the policymakers. \$/TRY transmits shocks to all selected cryptocurrencies except for Ethereum. Secondly, it has been observed that volatility spillover from \$/TRY to Ripple is strongly significant which signifies the potential influences of national currencies on cryptocurrency. These findings hold significant importance for both market participants and policymakers in shaping their asset allocation strategies and policy frameworks, respectively. Investors must exercise caution and remain vigilant regarding the potential fluctuations and transmission of volatility between cryptocurrencies and national currencies when structuring their investment portfolios. The findings offer substantial implications to policymakers as well. Policymakers should monitor the cross-market interconnections and examine spillovers to mitigate the potential volatilities and employ efficient policies to increase stability and protect investors from the risks associated with the volatility spillovers. Future studies which investigate cryptocurrencies and national currencies may consider the empirical results and implications of this study.

Table 4. Granger Causality Test Results

Null Hypothesis (H0)	Lag	F-stat	P-value	Granger Causality
(Bitcoin) return does not Granger Cause ($/TRY)	2	1.515	0.220	NO CAUSALITY
(Ethereum) return does not Granger Cause ($/TRY)	2	0.079	0.924	NO CAUSALITY
(Ripple) return does not Granger Cause ($/TRY)	2	0.475	0.622	NO CAUSALITY
($/TRY) return does not Granger Cause (Bitcoin)	2	2.823	0.060 ***	CAUSALITY
($/TRY) return does not Granger Cause (Ethereum)	2	2.997	0.0502 ***	CAUSALITY
($/TRY) return does not Granger Cause (Ripple)	2	4.746	0.0089 *	CAUSALITY

Note: *, **, *** represents rejection of null hypothesis at 1%, 5%, 10% respectively. The abbreviation $/TRY, stands for US Dollar / Turkish lira exchange rate.

Table 5. Estimated findings of volatility spillovers between $/TRY and most traded three cryptocurrencies based on VAR-BEKK-GARCH model.

$/TRY	Bitcoin	Ethereum	Ripple
Panel A - Mean Equation (Mean Spillovers)			
$\varphi(1)_{11}$	0.1300 [5.0934] *	0.1306 [5.1157] *	0.1305 [5.1185] *
$\varphi(1)_{12}$	-0.0051 [-0.7022]	-0.0005 [-0.1080]	-0.0014 [-0.3338]
μ_1	0.0009 [2.6058] *	0.0009 [2.5651] **	0.0009 [2.5743] **
$\varphi(1)_{21}$	-0.2037 [-2.2610] **	-0.2803 [-2.1771] **	-0.4277 [-2.7787] *
$\varphi(1)_{22}$	-0.0371 [-1.4427]	-0.0184 [-0.7156]	0.0527 [2.0580] **
μ_2	0.0034 [2.8086] *	0.0041 [2.3733] **	0.0032 [1.5554]
Panel B - Variance Equation (Volatility Spillover Effect)			
c_{11}	0.0029 [9.1889] *	0.0024 [7.4468] *	0.0025 [8.6101] *
c_{21}	-0.0035 [-1.6813] ***	0.0003 [0.0839]	-0.0148 [-3.1403] *
c_{22}	0.0117 [9.5627] *	0.0142 [6.8619] *	0.0233 [6.6090] *
a_{11}	0.5573 [17.6980] *	0.5242 [17.5086] *	0.5260 [16.5973] *
a_{12}	-0.1382 [-2.0892] **	-0.1435 [-1.6289]	-0.3547 [-2.7863] *
a_{21}	-0.0053 [-0.8208]	0.0037 [1.0140]	-0.0002 [-0.0521]
a_{22}	-0.3010 [-9.5879] *	-0.2521 [-10.5735] *	-0.5007 [-5.9940] *
b_{11}	0.8185 [37.9274] *	0.8506 [45.2613] *	0.8514 [46.0365] *

Table 5. (continued)

b_{12}	0.0680 [1.8799] ***	0.1202 [2.5176] **	0.4123 [3.7539] *
b_{21}	0.0003 [0.0924]	-0.0030 [-1.4845]	0.0005 [0.2357]
b_{22}	0.9238 [70.0434] *	0.9474 [97.1446] *	0.8164 [13.7311] *

Note: T-stats are given within the parenthesis. $\mu 1$ and $\mu 2$ are the constants, $\varphi(1)_{11}$ and, $\varphi(1)_{22}$ signifies the own lagged means of the variables.$\varphi(1)_{12}$ and, $\varphi(1)_{21}$ states the mean spillovers from the $/TRY to cryptocurrencies and from cryptocurrencies to the $/TRY. Variance equation's constant terms are c_{11}, c_{12} and c_{22}. a_{11} and a_{22} shows the ARCH effects on the variables. a_{12} is used to determine the spillover effect of a preceding shock in $/TRY 's return on the current volatility of Bitcoin, Ripple and Ethereum's returns. The opposite of this denotes as a_{21}. b_{11} and b_{22} are the GARCH parameter estimates. b_{12} examines spillover effects of preceding period's variance of the $/TRY 's return on the current variance of Bitcoin, Ripple and Ethereum's returns. The opposite of this effect denotes as b_{21}. The numbers in square brackets represent t-statistics associated with the variables. Significance levels are respectively denoted as "***" for 10% "**" for 5% and "*" for 1%.

Table 6. Estimated results of the conditional variance equations and the directions of mean, volatility spillovers and shock transmissions

	Bitcoin	Ethereum	Ripple
Mean Spillovers			
$/TRY	←	←	←
Shock Transmission			
$/TRY	→	-	→
Volatility Spillovers			
$/TRY	→	→	→

Note: "←" specifies that the variable on the column is the unidirectional mean, volatility or shock transmission taker, "→" indicates that the variable on the column is the transmitter of unidirectional mean, volatility or shock transmissions, "↔" signifies that the variables are bidirectionally transmitting and taking mean, volatility or shock, "-" shows that there isn't evidence to any transmission of volatility, mean or shock.

CHAPTER 6: CONCLUSION

In this thesis, the causal relationship and spillover effects between three major cryptocurrencies and a national currency are examined using daily data spanning from March 10th, 2016, to December 31st, 2021. The three cryptocurrencies, Bitcoin, Ethereum, Ripple, are selected due to their market capitalization rankings during the specified period. The empirical tests and models employed in this study have yielded statistically significant results, shedding light on the interrelationships and presence of volatility spillovers between the cryptocurrencies and the exchange rate of the $/TRY.

The findings of the Granger causality test show the existence of causalities between three major cryptocurrencies and a national currency. While the test results do not confirm causal relationships from cryptocurrencies to the $/TRY, there is a causal relationship from $/TRY to each of the cryptocurrencies unidirectionally. The empirical analysis reveals a robust unidirectional causal association between the $/TRY and Ripple, indicating that changes in the $/TRY tend to have a substantial influence on Ripple. Conversely, the causality between the $/TRY and Bitcoin, as well as Ethereum, is comparatively weaker in comparison.

As a further investigation, the findings from the VAR-BEKK-GARCH model imply the existence of cross-market shock effect from $/TRY to both Bitcoin and Ripple unidirectionally. The results obtained from the Multivariate GARCH model exhibit similar findings to those obtained from the Granger causality test. This correspondence in results provides additional support and consistency to the observed relationships. Besides, there is a unidirectional spillover effects from $/TRY to all selected cryptocurrencies, highlighting that conditional volatility and past shocks in the $/TRY are significant in the explanation of the conditional volatility of three most traded cryptocurrencies. The analysis reveals that the volatility spillover effects originating from $/TRY to Ripple exhibit the highest level of statistical significance compared to other pairs considered in the model, aligning with the findings of the Granger causality test. Overall, the findings specify that the returns of these cryptocurrencies are influenced by the volatility of $/TRY's returns, however, it is noteworthy that the returns of these cryptocurrencies' returns do not exert the same effect on the returns of $/TRY.

In conclusion, this thesis provides a distinct and novel contribution to the current literature in terms of the relationships between the top three cryptocurrencies and a national currency across an extensive period. Findings of this thesis offer numerous implications for both investors and policymakers. Investors with an interest in both \$/TRY exchange rate and cryptocurrencies should consider the potential spillover effects of the \$/TRY on their investment decisions. The analysis demonstrates that the returns of the \$/TRY not only affect the volatilities of the most widely traded cryptocurrencies but also spill over to their returns. This highlights the importance of considering the interplay between cryptocurrency and national currency markets and exploring their potential cross-market influences. Furthermore, it is vital for investors to make their own decisions, considering the inherent unpredictability of cryptocurrencies attributable to their decentralized and unregulated nature. As for the results of the existence of significant causal relationships in tails and spillover effects imply that investors might encounter challenges in effectively mitigating risks across different cryptocurrencies, thereby develop volatility-hedging strategies and building a diverse cryptocurrency portfolio to constantly manage the risk. Policymakers should prioritize investor and market protection by monitoring the cryptocurrencies and national currencies mutually to avoid potential risks associated with the volatility spillovers. Further research with alternative national currencies and cryptocurrencies should be conducted to provide extended information on the subject. Therefore, this thesis serves as a notable foundation to guide future research to assess further relationships of national currencies and cryptocurrencies.

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