IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF ECONOMICS

MASTER THESIS

EXAMINING THE EFFECT OF THREAT OF INTERVENTION IN CRYPTO MARKET: A CASE STUDY OF BITCOIN AND RIPPLE

OUSMAN DRAMMEH

THESIS SUPERVISOR

ASST. PROF. ASAD UL ISLAM KHAN

ISTANBUL, 2021

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by

OUSMAN DRAMMEH

A thesis submitted to the School of Graduate Studies in partial fulfilment of the requirements for the degree of Master of Arts in Economics

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APPROVAL PAGE

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Arts in Economics

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This is to confirm that this thesis complies with all the standards set by the School of Graduate Studies of Ibn Haldun University.

Date of Submission   Seal/Signature

ACADEMIC HONESTY ATTESTATION

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ÖZ

KRİPTO PAZARINDA MÜDAHALE TEHDİTİNİN ETKİSİNİN İNCELENMESİ: BITCOIN VE RIPPLE ÖRNEĞİ

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Son yıllarda çoğu kripto paranın fiyatlarındaki oynaklık diğer para birimlerine veya menkul kıymetlere göre artmıştır. Bu tez, Bitcoin ve XRP'nin oynaklığını değerlendirmek için Eşik veya GJR-GARCH modelinin formülasyonu ile çalışılan para birimlerinin fiyat ve hacim getiri oynaklığını etkileyebilecek değişikliklere yol açabilecek kripto para piyasasına müdahale tehdidinin araştırılması ile ilgilidir. Piyasadaki fiyatlar ve hacimler geri döner. Veri seti 1 Ocak 2014 ile 15 Şubat 2021 arasında başlar. GJR-GARCH modelinden elde ettiğimiz sonuçlar, haber şokları ile Bitcoin'in fiyat getirisi oynaklığı arasında negatif anlamlı bir ilişki bulunmaktadır. Aksi taktirde, haber şokları ile XRP'nin fiyat getirisi oynaklığı arasında istatistiksel olarak anlamlı olmayan bir ilişki bulunmaktadır. Öte yandan, XRP'nin hacim getirileri, haber şokları ile pozitif olarak anlamlı bir ilişkiye sahipken, Bitcoin'in hacim getirileri anlamlı bir ilişkiye sahip değil. Geçmişteki şoklar ve koşullu varyans şoklarının tümü, bugünün getiri oynaklığının önemli belirleyicileridir. Bu bulgular, Ripple Company'nin madeni parayı piyasadan uzak tutarak XRP fiyatlarının artmasını kontrol ettiğini doğruluyor. Bitcoin yatırımcıları, her zaman Bitcoin'in değerini kazanacağına inandıkları için şoklara fazla dikkat etmezler, dolayısıyla daha yüksek riskler daha yüksek kazanç sağlar.

Anahtar Kelimeler: Bitcoin, GJR-GARCH, kripto para birimi, müdahale tehdidi, XRP

ABSTRACT

EXAMINING THE EFFECT OF THREAT OF INTERVENTION IN CRYPTO MARKET: A CASE STUDY OF BITCOIN AND RIPPLE

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In recent years, the volatility in the prices of most cryptocurrencies has increased relative to other currencies or securities. This thesis is concerned with the investigation of the threat of intervention in the cryptocurrency market and how it may lead to changes that affect the price and volume return volatility of the currencies under study with the formulation of the Threshold or GJR-GARCH model to assess the volatility of Bitcoin and XRP prices and volumes returns in the market. The data set begins from 1 January 2014 to 15 February 2021. Our results from the GJR-GARCH model shows a negatively significant relationship between news shocks and Bitcoin’s price returns volatility, whereas the relationship between news shocks and XRP’s price returns volatility isn't significant. On the other hand, volume returns of XRP have a positively significant relationship with news shocks whilst volume returns of Bitcoin do not have a significant relationship. Past shocks and conditional variance shocks are all significant determinants of today’s return volatility. These findings confirm that, Ripple Company controls the prices of XRP from surging by keeping the coin off the market. Investors of Bitcoin don’t pay much attention to shocks because they always believe Bitcoin will gain its value, hence higher risks yield higher gains.

Keywords: Bitcoin, cryptocurrency, GJR-GARCH, the threat of intervention, XRP

DEDICATION

This dissertation is dedicated to the memory of my father, Ahmad Kajally Drammeh. Although he was my inspiration to pursue my higher degrees, he was unable to see my graduations from high school and tertiary level educations.

It is also dedicated to the two most incredible women (Fatoumata Sillah and Jaha Tida Jabbi) who have been the biggest support to me in life and to the entire family for their unwavering support and unconditional love to me throughout my life.

Most importantly, all this is made possible by Allah's decree through one person, Lamin K. Drammeh, who has loved me as if I'm his very own, never made me feel the pain of not having a father around me. He is a father and best friend, advisor, role model, mentor, source of guidance and inspiration to me.

This is for him too.

Thank you to my academic adviser who guided me in this process and the committee who kept me on track.

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I must acknowledge as well the many friends, colleagues, students, and lecturers, who counselled, advised, and supported my research and avail me the privacy over the months. Especially, I need to express my gratitude and deep appreciation to all my family, hospitality, knowledge, and wisdom who have supported, enlightened and entertained me over the many years of our lives. They have consistently helped me keep perspective on what is important in life and shown me how to deal with reality.

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Ousman Drammeh

ISTANBUL, 2021

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CHAPTER I

INTRODUCTION

Mostly due to their revolutionary characteristic, cryptocurrencies are fast becoming a key instrument in the modern financial arena. It has fast and comfortable means of payment with worldwide scope. They are private and anonymous enough to serve as a means of payment for some outlawed economic activities and black markets. They give rise to a fast-growing and incredibly dynamic market for investors and speculators. The trading volumes in the cryptocurrencies market exceeds major European Stock Exchanges daily (Rosic, 2020). Some of them are highly volatile and may gain from 10 to 100 per cent a day and may lose by the same margin the next day. In 2009, Bitcoin was the only cryptocurrency in the world but it grew up to 1,658 in 2018 and the total number of cryptocurrencies add up to 4000+ by the end of 2019 (Rosic, 2020). Cryptocurrencies leverage blockchain technology to gain decentralization, transparency and immutability. The demand for cryptocurrencies may increase due to their use by money launderers, extortionists, human traffickers, weapons and drugs sellers as well as the desire to evade tax, and the high expectations or speculations surrounding it (Gruber, 2013). A Blockchain system enables us to store and share the history of all transactions of a network on computers (Halpin & Piekarska, 2017). The blockchain is presumed to improve the efficiency of the crypto market by reducing transaction costs via counterparty risk minimization, reduce settlement duration, and eliminating unnecessary middlemen, consensus algorithms etc. Miners are availed of their financial rewards for their work on generating a block of transactions to add to the end of the blockchain (Abramowicz, 2016). The programmers centrally coordinate the cryptocurrency protocol and regulate it via their blocking and forking decision interactions from addresses of specific characters (Gervais et al., 2014). With regards to Bitcoin, several programmers contribute to the codebase and some commenters propose changes to the codebase (Azouvi et al., 2018).

Cryptocurrencies can be exchanged, each transaction is logged and distributed through a network of miners and these miners use the technology of blockchain to facilitate all these. This is why it is not controlled by any government or officials (Vaddepalli & Antoney, 2018). One good thing about cryptocurrencies is that, the system is not controlled by any government and authority and due to its decentralized nature, it is theoretically unaffected by government control or interference.

There have been many failed attempts to create a currency that could be more flexible than even fiat money. Many have tried and failed in the process and yet there lives one person who was ready to take up the challenge of making this idea a reality, Satoshi Nakamoto. Nakamoto tried his luck at creating a cryptocurrency money system without any central entity to control it. A system that is more like a Peer-to-Peer network for sharing files. And that idea gave rise to cryptocurrency (Rosic, 2020). Cryptocurrencies may prove to be a bit technical but once you understand how it works, life becomes easy for you.

Nakamoto was the first person to describe Bitcoin in 2008 and later in the year make an introduction to the world a network he refers to as Bitcoin network (Kjærland, et al., 2018). Since its creation in 2009, the price of Bitcoin has risen from $0.07 to approximately $37,000 in January 2021 but it has again been hitting a new record high prices in the subsequent weeks. In his announcement regarding the creation of Bitcoin in late 2008, Satoshi Nakamoto, the unknown inventor of Bitcoin, the first and still the most important cryptocurrency, said he has developed a "Peer-to-Peer Electronic Cash System" to prevent double-spending. In the new global economy, Bitcoin has become a central issue for many investors and governments alike, even in countries like Turkey, China, the USA, Canada, Netherlands, UK and El Salvador. Bitcoin miners use a machine called Application Specific Integrated Circuit (ASIC) to mine Bitcoin by solving the mining algorithm and creating new blocks on the blockchain; the block reward is currently at 12.5 BTC (Griffith, 2018). It is on the verge of being adopted by the second largest bank in Spain, BBVA (Allison, 2020), and another bank in Switzerland. Gazprom bank, Switzerland has already executed their first trades using Bitcoin (Sinclair, 2020). Interestingly, the Swiss Canton Zng will be accepting Bitcoin or Ether as a form of tax payments starting from 2021

(Baker, 2020). There is a growing body of literature that recognizes the importance of Bitcoin as a safe haven for most investors and this can be evidenced by the financial crisis during the COVID-19 pandemic. Despite the financial struggles, the price of Bitcoin seemed to take a hugely increasing trend and the prices are reportedly hitting record heights in the subsequent weeks that followed until it reached $30, 000 per Bitcoin, and it is predicted to be increasing in the year 2021 (Faridi, 2021). One of the main things which attract most investors to cryptocurrencies, especially Bitcoin, is due to their extreme volatility, exceptionally high return averages, less correlation with the normal traditional assets as well as accessibility daily (Rufino, 2019). This is coupled with their lack of correlation to traditional securities, bonds and other stocks (Baur & Dimpfl, 2018).

A couple of years after Bitcoin led the way in the cryptocurrency era. Ripple became OpenCoin after changing tracks. OpenCoin is a money transfer network where large financial services companies act as counterparties to transactions (Reiff, 2020). Their cryptocurrency, XRP, was launched in late 2012 with the aim of serving as an intermediate channel of exchange between two different networks or currencies. OpenCoin was changed to Ripple Labs in the early fourth quarter of 2013.

XRP is developed by Ripple Company, a group of investors in 2012, Ripple have offices in Luxemburg, the UK and Australia. On their website *Timeline of XRP Evolution*, (2021), Ripple characterized itself as a global network for payments and enumerated some major banks and financial services amongst their customers. XRP is used in facilitating fast and easy conversion between different currencies. They have emerged as powerful platforms for interbank transfers and provided competition for SWIFT transfers because of their reliability, ease of transaction and low cost. It is additionally developed to be used as currency exchange and payment settle for two currencies that can't be directly exchanged (*Ripple Vs. Bitcoin: Key Differences*, 2019). One hundred billion XRP are pre-mined and only 38 billion of them are in the market, the rest are kept in Ripple Labs (Reiff, 2020). How Ripple controls XRP remains unclear but one method is clear according to most studies, it is believed that they control it by reducing the supply of XRP in times of high greed or fear in the cryptocurrency market, this is because the Ripple company still holds the largest amount of XRP token and they can decide when to release them for sale or keep them. Ripple relies on the technology of an **iterated consensus** ledger coupled with validating servers' network to accept and validate XRP transactions within seconds. It hit its record high in the early days of 2018 at $3.31, but the market was corrected shortly after and it has had a stable price ever since of below $1. This may be because it has been involved with banks which boosts its popularity but this could also be the reason it has a low stable price and it may also be a limitation since decentralization is the main idea of cryptocurrencies (Goryunov, 2020). Ripple labs initially had five validating servers and also enables other institutions to arrive at a consensus concerning the financial transactions' fate (Armknecht et al., 2015). Ripple is a syndicate of 200 or more financial institutions based in at least 40 countries to allow for the ease of facilitation of cross-border payments (Reiff, 2020).

1.1 Some Key Differences: Ripple Versus Bitcoin

XRP was found by CEO Bradley Garlinghouse and co-founder Christian Larsen who also owned Ripple Company. They founded XRP as a system to be utilized mostly by payment networks and banks to settle payments, exchange currencies, and transfer money (Bursztynsky, 2020). Whereas, the development of Bitcoin, which was created by an unidentified group or person called Satoshi Nakamoto, was mainly created for payment of services and goods as a digital currency (*Ripple Vs. Bitcoin: Key Differences*, 2019). The nature of XRP helps greatly in providing transparent, secure and cheap real-time direct asset transfers than the predominant payment methods such as SWIFT.

Bitcoin is an equivalent of real-world USD for purchases whereas, XRP is its equivalent for inter-bank transfers (Reiff, 2020). The transaction cost for Bitcoin is $40 but it's $0.004 for XRP which translates the inflationary and deflationary nature of Bitcoin and XRP respectively (Reiff, 2020). Bitcoin has a total supply of 21 million tokens whilst XRP has 100 billion out of which only 38 billion are available in the market. Bitcoin is mostly used by organizations or individual investors whilst XRP payments are commonly used by banks and payment networks.

Bitcoin tokens are spread all around the world while Ripple owns at least 60% of XRP tokens. On average, XRP transactions only take five minutes to complete whereas, it takes minutes for Bitcoin transactions to be completed (Reiff, 2020). While Ripple's main goal is to use XRP for currencies and commodity transfers such as gold, or oil over the network, Bitcoin is used to buy goods and services in the capacity of fiat money.

This study systematically reviews the volatility trends for Bitcoin and XRP aiming to examine the emerging role of the company Ripple in the context of controlling XRP prices by intervening in the cryptocurrency market using the **Threshold GARCH or GJR GARCH Model**.

This paper has been divided into five parts. The first part deals with the introduction of the main currencies used in the study, the second aspect of the study highlighted the past research works related to this study, the third chapter is concerned with the data and methodology used for this study, the fourth is centred around the analysis of results, discussion and the final aspect is the conclusion.

CHAPTER II

LITERATURE REVIEW

In their early years, there was an increasing amount of literature on cryptocurrencies and their market, many researchers touched on different aspects of these currencies and their market from price dynamics to factors affecting the prices to their relationship with other markets such as the stock markets, gold, and oil markets. Several studies have examined the price volatility in the cryptocurrency market as the most fundamental characteristic of cryptocurrencies is that they are volatile and can change at any time within a short period of time.

To date, several studies have investigated the impact of news on cryptocurrency prices or returns or the response of volatility to economics news surrounding the market amongst these studies include Yeoh (2017) who examined the main regulatory challenges that affect the blockchains and innovative distributed technologies with the United States and European Union and found out that the smart regulatory laid-back approach that was adopted in both regions bodes well for the future innovative contributions of the blockchains within the financial services and related sectors to enhance financial inclusion.

Othman et al. (2019) checked for the effects of symmetric and asymmetric information on cryptocurrency volatility using the GARCH models and indicated that Bitcoin returns and volatility is informatively symmetric. There is the existence of long memory in future volatility, and it is further discovered that symmetric volatility is largely sensitive to its lagged (past) values than to the recent shock of market values. On the contrary, there is no evidence of a volatility response to asymmetric information if there are no positive or negative shocks in the Bitcoin market, which, to put it in other words, there is no leverage effect. The result also suggests that there is harmony between the efficient market hypothesis and the Bitcoin market with regards to asymmetric information but not with respect to symmetric information. For short-term investments, Bitcoin return cannot be easily predicted using past market information. Also, in the mean equation of the

GARCH-in-Mean (1,1) model, the coefficient of the risk premium was positive but not statistically significant which shows that the trade-off of risk-return doesn't lead to an increase in market returns. Overall, their paper suggests that cryptocurrency markets are good for risk-averse investors and not for risk-taking investors. Corbet et al. (2020) checked whether the cryptocurrency price dynamics react to interventions and if so whether the reaction depends on the blockchain architecture or not. Using volatility analysis of Exponential GARCH, EGARCH between blockchain-based and DAG-based currencies found that, DAG-based cryptocurrencies are more responsive to shocks in the market as they reach maturity. Directed Acyclic Graph or DAG-based currencies do not use blockchain but rather use something else but in a form of a graph. Some examples of these currencies include; IOTA, Nano and ByteBall (Obyte) and are very successful since their creation (Comben, 2019). These behaviours resemble that of the well-established cryptocurrencies such as Bitcoin, Litecoin and Ethereum which can confirm that DAG-based currencies now share close features to the traditional blockchain-based cryptocurrencies.

Furthermore, Maiti et al. (2020) and Demir et al. (2020) carried out a study to research volatility dynamics during the COVID-19 period among cryptocurrencies with Maiti et al. (2020) focusing on the non-linear dynamics of Tether during the COVID-19 pandemic by comparing it to XRP, Bitcoin, Bitcoin Cash and Ethereum using Smooth Transition Autoregression (STAR) and the Threshold Autoregression (TAR) models with a maximum lag of 1. Their study revealed that the daily average returns of Tether are chaotic and highly nonlinear in nature with the other four cryptocurrencies showcasing a contradictory nature in their daily average return time series which showed that they are all linear. As for the study of Demir et al. (2020) who utilized the Wavelet Coherence Analysis to check the relationship between COVID-19 and cryptocurrencies during the period of the pandemic, this study found that the relationship between reported cases and deaths and Bitcoin was initially negative, which could be due to fear factors of investors, but the economic links become positive in the later period which can be evinced by the highly increasing Bitcoin prices during recent months with prices hitting new all-time highs week in week out. This further proved that cryptocurrencies can be used for hedging purposes in times of uncertainties raised by the novel COVID-19 pandemic. Interestingly, Ripple and Ethereum showed a similar relationship but have weaker interactions. Katsiampa, (2019) empirically investigated the cryptocurrency market volatility dynamics using the Asymmetric Diagonal BEKK model and found the volatility dynamics of cryptocurrencies like Bitcoin, Stella, Ripple and Litecoin to be reactive to major news but exhibiting a structural break-point in their conditional variances and also, they are affected by their past volatility shocks. He further proved that there exists a time-varying correlation among the currencies but these are positive. This study has important implications for users and investors in cryptocurrency markets. Despite these advanced encryption techniques of cryptocurrencies, many investors and governments alike, continue to take cautious procedures toward them due to their lack of consumer protection against fraud, regulations, large mining cost, insufficient recognition and lack of a central controlling unit (Sidel, 2013). As most banks haven't been dealing with cryptocurrencies before, but have now started adopting them in numbers (Browne, 2020).

Walther et al. (2019) did a study on the volatility of cryptocurrencies using GARCH-MIDAS and also checked for the exogenous drivers of volatility and found that, Global Real Economic Activity performs better than all the other economic and financial components they have investigated and also the content of the information of these exogenous factors is time-varying and the averaging approach of the model has a diversifying effect on each driver. Bitcoin daily returns exhibit regime changes in their volatility dynamics (Ardia et al. 2019). Kjærland et al. (2018) have worked on the dynamics of Bitcoin's prices using the same method as (Adrian & Rosenberg, 2008) to predict the unconditional variances of Bitcoin prices. From their study, the ARCH showed positive effects and is significant at the 1% level, which means that, a collapse in the conditional variance a fortnight ago will have a 56.2% on approximation on the volatility in the subsequent weeks. On the other hand, GARCH effects show significance at a 5% critical value. This indicates that 31.5% of the volatility in the previous week has an impact on volatility in the following week. Katsiampa, (2017) determined that the perfect model would be AR-CGARCH in their study on the volatility of Bitcoin prices using a GARCH type of model, but (Ječmínek et al., 2020) conducted a study to check which method would best be used for value-at-risk estimation of cryptocurrencies using a comparison between parametric and non-parametric methods (GARCH and historical Var) and Monte Carlo simulation. They concluded that Monte Carlo simulation is the best method because of the stochastic process and the results' robustness. Sapuric et al. (2020), using an asymmetric GARCH model or EGARCH to be specific, studied the nexus of volume, volatility and returns, and the volatility's asymmetric response to economic news and found a positive relationship among volume, volatility and returns after 2013 (when Bitcoin becomes popular) and before the Mt. Gox hack respectively. This is supported by the unprecedented rise in the price returns of Bitcoin which led to an increase in volatility of Bitcoin beyond expectation from the early days of 2013 towards the Mt. Gox hack (the euphoric period).

Gemici & Polat (2019) found a cointegration relationship between Bitcoin prices and the trading volume. In their study using the symmetric and asymmetric causality test, there is a unilateral causality link between negative and positive shocks in prices and trading volume from both directions. Dhamija & Bhalla, (2010) also stressed in their study that, this method can be utilized when modelling for volatility dynamics of exchange rates and find out that, Integrated-GARCH (IGARCH) and Threshold GARCH (TGARCH) outperformed the other models in forecasting the volatilities of the daily rates of five currency in question namely; German mark, British Pound, Japanese Yen, Euro and Indian Rupee respectively. Hayek & Naimy, (2018) modelled and predicted Bitcoin/ US Dollar exchange rates volatility by comparing the standard GARCH (1,1) model, EWMA (Exponential Weighted Moving Average) and the Exponential GARCH (EGARCH), and the GARCH (1,1) and EWMA were outperformed by the EGARCH model in both sample and out of sample estimation with even higher accuracy in out of sample period. Their results also proved that; Bitcoin behaves differently from traditional currencies.

An asymmetric analysis of GARCH family models was made amongst normal errors, GED and Student's t-errors by (Miron & Tudor, 2010) and discovered that, the latter two provides a better presentation of conditional volatility and that, the former isn't capable of capturing the leptokurtosis fully in time series. This finding is in agreement with the study of Abdullah et al. (2017) using the same GARCH family models with AR(2)—GARCH (1,1) model is considered the best of the tried ones. Miron & Tudor, (2010) further highlighted that some conformed features of volatility aren't captured by the symmetric ARCH and GARCH models but were considered by the asymmetric ARCH and GARCH models to document their existence in the empirical time series. Amongst the asymmetric GARCH family models studied, Exponential GARCH otherwise EGARCH, presents generally lower forecasted errors and hence it was confirmed as the most accurate estimation given the other asymmetric models. This study was made on daily stock returns with the main aim of finding the most accurate forecasted result.

CHAPTER III

DATA AND METHODOLOGY

3.1 Data Source

The currencies under study were selected based on the market capitalization criteria in the cryptocurrency market. The data set ranges from January 01, 2014, to February 15, 2021. The data on closing prices with daily frequency has been obtained from www.coinmarketcap.com. The modelling framework of the econometrical discussions covers various unit root tests namely; Augmented Dickey-Fuller (D. A. Dickey & Fuller, 1979), Phillips Perron Test developed by (Phillips & Perron, 1988) and The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) Test by (Kwiatkowski et al., 1992), Threshold GARCH (TGARCH) model which is developed by Glosten et al. (1993) and the post estimation test analysis such as ARCH-LM test and the correlogram of Squared Residual plots. All analyses and empirical models were carried out using E-views. The prices were then converted to returns series which will be used to estimate the volatilities for this study. The series graphs, as well as the descriptive statistics table, are in the result discussion section. In a good number of financial studies, researchers used returns instead of assets' price and Campbell et al. (1997) has two reasons for this; the first of which being that, returns gives a complete and a free scale summary of investment opportunities for average investors, and also, it is easier to handle returns than price simply because return series have a better attractive statistical feature (Tsay, 2005). The return series for both currencies are calculated as:

$$r_t = \ln(1 + R_t) = ln\left({}^{X_t}/_{X_{t-1}}\right) = x_t - x_{t-1}$$

$$p_t = \ln(X_t)$$

Econometrically,

$R_t = \sum_{i=1}^{N} w_i R_{it},$ $\qquad$ R_{it}= Simple Return of cryptocurrency i

Hence

$$r_t \approx \sum_{i=1}^{N} w_i r_{it}$$

Where *r* is the price return at time t and *x* represent the cryptocurrency price or volume at time *t*.

3.2 Methods

3.2.1 Unit Root Tests

The most vital assumption is the stationarity of the data. The basic idea of stationarity is that the probability laws that govern the behaviour of the process do not change over time in other words, the value doesn't increase with time. In essence, the process is in statistical equilibrium (Degtyarev et al., 1983). The most common unit root testing tool is the Augmented Dickey-Fuller Test (D. A. Dickey & Fuller, 1979). Another test to be carried out is the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test which was developed by (Kwiatkowski et al., 1992) and it has a different null hypothesis from the rest. It has stationarity as its null hypothesis whilst Augmented Dickey-Fuller (DF) developed by (D. A. Dickey & Fuller, 1979) and Phillips Perron (PP) test of the unit root which was developed by Phillips & Perron (1988) have unit root as the null hypothesis. Since a serial correlation will do well to present a shortcoming in the Dickey-Fuller test, which depends on OLS, Phillips-Perron involves fitting models; he proposed two alternatives; the first is to view it as a robust DF to serial correlation using the (Newey-Wey (1987)) heteroskedasticity (Phillips & Perron, 1988). A stationary data may also mean that the variance of the data does not change with time and even if it does, it will regularize with time.

3.2.1.1 Augmented Dickey-Fuller Test:

The Augmented Dickey-Fuller test is derived from the normal Dickey-Fuller test which is based on the first-order autoregressive process (Box & Jenkins, 1970):

$$y_t = \phi_1 y_{t-1} + \varepsilon_t, \qquad t = 1, \ldots, T$$

ϕ_t represents the autoregression parameter for the past value y_{t-1}, $\varepsilon_t$is the white noise process. This process has a unit root as the null hypothesis => H_0: $\phi_1 = 1$, in essence, this means the process is a non-stationary process because it has a unit root in it denoted as $I(1)$. The alternative hypothesis, $H_1: \phi_1 < 1$, means that the process doesn't contain a unit root in it and hence, the process is stationary and is denoted as $I(0)$.

We can calculate the test statistic by subtracting y_{t-1} from both sides of the equation above;

$$y_t - y_{t-1} = \phi_1 y_{t-1} - y_{t-1} + \varepsilon_t$$

$$\Delta y_t = (\phi_t - 1)y_{t-1} + \varepsilon_t$$

Let $\delta = \phi_1 - 1$. And the test statistic can be defined as:

$$t_{DF} \frac{\widehat{\phi_1} - 1}{se_{\widehat{\phi_1}}}$$

Where $se_{\widehat{\phi_1}}$ represents the standard error estimate, $se_{\widehat{\phi_1}}$ is the OLS estimate of ϕ_t. This test statistic follows a Dickey-Fuller distribution under the null hypothesis and the critical values obtained by simulation, are tabulated in D. Dickey (1976) and Fuller (1976).

Using a constant or linear trend the above model can be expanded:

$$y_t = \delta_0 + \phi_1 y_{t-1} + \varepsilon_t,$$

$$y_t = \delta_0 + \delta_1 t + \phi_1 y_{t-1} + \varepsilon_t,$$

Then the Augmented Dickey-Fuller test can be constructed if a non-symmetric component in the Dickey-Fuller models is autocorrelated. And therefore, the above equation is transformed as:

$$y_t = \phi_1 y_{t-1} + \sum_{i=1}^{p-1} \gamma_i \Delta y_{t-i} + \varepsilon_t,$$

Just as we do with the DF, the test statistic for the ADF test is illustrated as:

$$\Delta y_t = (\phi_1 - 1)y_{t-1} + \sum_{i-1}^{p-1} \gamma_i \Delta y_{t-i} + \varepsilon_t \,.$$

The practical shortcoming of the above test lies with the lag choice of p. Schwert (1989) made a suggestion of choosing the maximum lag $p_{max} = 12\left({}^{T}\!/_{100}\right)^{\frac{1}{4}}$, because he believed that, the test will suffer from autocorrelation if there is a very low p, and a very large p will lead to a reduction in the power of the test. So, tests are used based on the following model and hence the Augmented Dickey-Fuller test is illustrated as:

$$y_t = d_t + \phi_1 y_{t-1} + \sum_{i=1}^{p-1} \gamma_i \Delta y_{t-i} + \varepsilon_t \quad ,$$

Where $d_t = \sum_{i=0}^{p} \delta_i t^i \,,\ for\ p = 0{,}1,$ contains within it the deterministic parts of the equations above.

3.2.1.2 Phillips-Perron:

This model is not much different from the Dickey-Fuller test, it is also based on the equations above with only the linear trend of the DF test been replaced by a centred time variable. This test differs from the previous test because it doesn't use differentiated equations to calculate the test statistics, but it is derived from them eventually.

The test statistic Z for the model bearing a constant is written as follows (Arltová & Fedorová, 2016; Pesaran, 2015):

$$Z_\phi = \left(\widehat{\phi_T} - 1\right) - \frac{1}{2}\,\frac{T^2 \times se_{\hat{\phi}}^2}{se_T^2}\left(se_{LT}^2 - se_T^2\right)$$

$$Z_T = \left(\frac{se_T}{se_{LT}}\right) t_{DF} - \frac{1}{2}\left(se_{LT}^2 - se_T^2\right)\frac{1}{se_{LT}}\,\frac{T \times se_{\hat{\phi}}}{se_T} \,,$$

Where:

$$t_{DF} = \frac{\widehat{\phi_T} - 1}{se_{\widehat{\phi}}}, se_T^2 = \frac{1}{T}\sum_{t=1}^{T}\widehat{\varepsilon_t^2}, se_{LT}^2 = se_T^2 + 2\sum_{j=1}^{q}\left(1 - \frac{j}{q+1}\right)\widehat{\gamma_{J,T}} \; and \; \widehat{\gamma_{J,T}} = \frac{1}{T}\sum_{t=j+1}^{T}\widehat{\varepsilon_t}\widehat{\varepsilon_{t-J}}$$

t_{DF} is the original test statistics of the Dickey-Fuller test, se_T^2 represents the Ordinary Least Square estimator of the unsystematic component variance, $\widehat{\gamma_{J,T}}$ is the ML estimator of the component variance and q is the number of covariates' lags. $\gamma_{j,T} = 0$ when there is no correlation in the residuals ε_t, for $j > 0, and\ se_{LT}^2 = se_T^2$, the test statistic's limiting distribution t is therefore nondependent on autoregressive parameters of the residual process ε_t (Arltová & Fedorová, 2016).

3.2.1.3 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

This test was built on the notion that, the stationarity of the time series occurs around a deterministic trend and is calculated as the sum of a random walk, deterministic trend and stationary random error or white noise. And the model is as follows:

$$y_t = d_t + r_t + \varepsilon_t,$$

$$r_t = r_{t-1} + u_t,$$

Where $d_t = \sum_{i=0}^{p}\delta_i t^i,\ for\ p = 0{,}1,$ contains within it the deterministic parts of the above equations (trend and constant), ε_t are iid N$(0,\ \sigma_\varepsilon^2), r_t$ is a random walk having a variance $\sigma_u^2\ and\ u_t\ are\ iid\ N(0, \sigma_u^2)$.

Moreover, KPSS relies on Lagrange Multiplier (LM) test with a null hypothesis that, the random walk has a variance of zero; $H_0\colon \sigma_u^2 = 0,$ meaning that, r_t is constant, against the alternative; $H_1\colon \sigma_u^2 > 0$. The test statistic of KPSS is written as:

$$\boldsymbol{LM} = \sum_{t=1}^{T}\frac{se_t^2}{\widehat{\boldsymbol{\sigma_t^2}}},$$

Where $se_t = \sum_{t=1}^{T} \widehat{\varepsilon_t}$, $t = 1, 2, \dots, T$ and $\widehat{\sigma_t^2}$ is the variance estimate of residual process ε_t from the initial equation. The critical values for the test were derived via simulation process and were listed in Kwiatkowski, Phillips, Schmidt and Shin, (1992).

Furthermore, we used the Threshold GARCH model (Glosten et al., 1993) as the main statistical tool for this study. This method was chosen for this study because there is a strong persistence in volatility (long memory), and it can be used to explain price volatilities which are caused by factors that can't be calculated such as news or sentiments, using the leverage component of it. The results from the study of Baur & Dimpfl, (2018) has shown that the majority of the 20 cryptocurrencies exhibit a negative leverage effect. These negative leverage effects post a positive impact on the volatility of the returns of cryptocurrency prices.

The expected results from this test are that, Bitcoin volatility is expected to be very sensitive to outside news or organizational intervention as compared to XRP that has been controlled by an entity and their prices are stabilized as the market experiences shocks from the outside interventions. Historically, Bitcoin prices are highly volatile compared to other assets or securities. XRP on the other hand, only experienced high volatility in their prices in 2017 and toward the beginning of 2018 until they were stabilized by the Ripple company and the price has since 2020 been below $1 (Goryunov, 2020).

3.2.2 Selection of the Model

This study relied on the wisdom of EViews to test for the adequate autoregressive (AR) and moving-average (MA) terms of the tentative ARMA models in choosing the most appropriate ARMA model as the mean equation. Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) were used to select the best-of-fit model among the tentative ARMA models. The lower the information criteria value, the better the model (Brockwell & Davis, 2009; Burnham & Anderson, 2004). AIC by definition=$-2\ln(L) + 2k$ whereas, BIC= $-2\ln(L) + k\ln(T)$. L represents the maximized value of the likelihood function, k equals the number of parameters plus the constant; mathematically, $k = p + q + 1$ (Ayele et al., 2017).

The objective of financial time series analysis is to establish a good model for the basic stochastic process. These models are to be used for analyzing to obtain optimal predictions for the time series, and ARMA has been a very familiar statistical technique used in the literature by financial researchers. ARMA relies on the lag order process resulting from the past values of the series or the past shocks to predict future occurrences. It is a combination of Autoregressive (AR) and Moving Average (MA) lag orders interactions and it is illustrated as follows:

Infinite moving average of ε_t: MA(q)

$$r_t = \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_t \ ,$$

Autoregressive order of ε_t : AR(p)

$$r_t = \sum_{i=1}^{p} \delta_i r_{t-i} + \varepsilon_t \ ,$$

$$\begin{Bmatrix} \epsilon_t \sim (WN) \\ \epsilon_t \sim IID(0, \sigma^2) \end{Bmatrix}$$

Where MA(q) is always a stationary process and ε_t is an independently identified distribution with mean zero and variance σ^2. Hence ARMA (p, q) is written as:

$$r_t = \mu + \sum_{i=1}^{p} \delta_i r_{t-i} + \sum_{j=1}^{q} \varphi_j \varepsilon_{t-j} + \varepsilon_t$$

3.2.3 Identifying ARCH Effect

To identify the appropriate ARMA model for our test, the correlogram was used and thereby checking for the significant spikes with statistically significant Q-stats. Q-stats check for serial correlation in the mean equation and the specification of the mean equation. The selected ARMA models were ARMA (5,4) and (2,1) for Bitcoin and XRP price returns respectively; ARMA (4,6) for Bitcoin volume returns and ARMA (6,5) for XRP volume returns.

The ARCH-LM test is calculated from the auxiliary regression. Testing the null hypothesis that, there is no ARCH effect up to order q in the residuals, the regression is run as:

$$\epsilon_t^2 = \beta_0 + \left(\sum_{i=1}^{q} \beta_1 \epsilon_{t-1}^2 \right) + v_t$$

Where ϵ represents the residual at time t and the regression takes the squared residuals bearing an intercept and sum of the lagged squared residual order of q. Two test statistics are reported by EViews, the omitted variable tests for the combined significance of all the past squared residuals, F-statistic and the Obs*R-squared stats which is Engle's, (1982) maximum likelihood statistic, measured using total observation multiplied by the R^2 from the regression's R^2. Where T is the total observation, ARCH-LM can also take the form as follows:

$$ARCH_{LM}(q) = TR^2$$

3.3 Model Specification

The basic idea governing the study of volatility phenomena is that the series, r_t is either serially-uncorrelated or with minimal lower-order serial correlations, but of course a dependent series (Tsay, 2005). The first model to provide a fundamentally systemic framework for volatility modelling in econometrics analysis is the ARCH model of Engle, (1982). The essential idea of ARCH models is that; (i) the shock ε_t of an asset return is serially uncorrelated thus dependent, and (ii) this dependency of ε_t can be described by the simple quadratic function of its past returns. Economically, an ARCH(q) model is assumed to be constructed as follows:

Consider the returns series: - $r_t = \mu_t + \epsilon_t,$

where μ_t denotes the conditional mean of the process and ϵ_t is the shock or innovation process having a mean of 0 at time t.

Supposed the shocks are generated as:

$$\epsilon_t = \sigma_t z_t$$

Let $\boldsymbol{H_t}$ represent the process' history at time t. the conditional variance of the return's series, r_t is;

$$Var(r_t|H_{t-1}) = Var(\epsilon_t|H_{t-1}) = E(\epsilon_t^2|H_{t-1}) = \sigma_t^2$$

Hence ARCH(q):

$$\sigma_t^2 = \omega + \alpha_1\epsilon_{t-1}^2 + \cdots + \alpha_q\epsilon_{t-q}^2;$$

And the residual series is defined as;

$$\varepsilon_t = r_t - \widehat{\mu_t}$$

where $\{z_t\}$ is a sequence of independent and identically distributed (IID) random variables with a mean zero and a variance of 1 (Tsay, 2005). From the structure of the model, it can be seen that, large past squared shocks $\{\epsilon_{t-1}^2\}$ imply a big conditional variance σ_t^2 for the innovation ϵ_t. Consequently, ϵ_t seems to assume a higher value, which means that, under the ARCH framework, large shocks are followed by another large shock.

ARCH (Engle, 1982) frequently yield negative estimates of the alpha due to the over-parameterized model (Virginia et al., 2018). **ARCH**(q) a variance equation of $\boldsymbol{\sigma_t^2 = \omega + \sum_{t=i}^{q} \alpha_1\epsilon_{t-1}^2}$; where σ^2 is the conditional variance of returns at time t, ω accounts for the long-term volatility, ε_{t-i}^2 is the past shock and α_1 is the effect of past shocks on the volatility today or in other words, short-run shocks. In ARCH, large lagged values reduces the accuracy of the estimation but GARCH uses few parameters to capture long lagged effects and it improves the efficiency of the estimation (Lim & Sek, 2013). To achieve this, the arch fits models by using the conditional mean equation and conditional variance equation. Concerning the regression equation, the model may also have its ARCH in ARMA terms. To resolve the problem of negative estimates, Bollerslev, (1986) developed the Generalized Arch (**GARCH**) model. Whiles **GARCH** includes the lagged conditional variance terms as AR terms and hence, its conditional variance is considered a GARCH process if the following conditions are fulfilled;

(a) $\mathrm{E}(\epsilon_t|\epsilon_{t+h},) = 0,\ t \in \mathbb{Z}$ for all lags $h \neq 0$ and the innovations are uncorrelated

(b) The existence of a constant $\boldsymbol{\omega, \alpha_i, i = 1, \dots, q\ and\ \beta_j, j = 1, \dots, p}$ such that**;**

$$\sigma_t^2 = Var(\epsilon_t|\epsilon_u, u < 1) = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2 , t \in \mathbb{Z}$$

This can be compactly written as:

$$\sigma_t^2 = \omega + \alpha(A)\epsilon_t^2 + \beta(A)\sigma_t^2, t \in \mathbb{Z}$$

Where (A) is the standard past operator $\left[A^i \epsilon_t^2 = \epsilon_{t-i}^2 \; and \; A^i \sigma_t^2 = \sigma_{t-i}^2 \; for \; each \; integer \; i\right]$, and α and β are polynomials of degree p and q, respectively;

$$\alpha(A) = \sum_{i=1}^{q} \alpha_i A^i , \qquad \beta(A) = \sum_{j=1}^{p} \beta_j A^j$$

If $\beta(z) = 0$ in any case, the model becomes an ARCH model, thus that's the main difference between an ARCH(q) model and a GARCH (q, p) model. As such, a GARCH (q, p) process is identified as;

Where q= order of Garch and p= order of Arch or moving average. The conditions that must hold for the conditional variance to satisfy the stability condition or the non-negativity constraint are; $\boldsymbol{\alpha_1 \geq 0 \; and \; \alpha_0 > 0}$. An ARCH model does not capture leverage effects but **Garch** have several extensions that capture leverage and asymmetric effects of good and bad news and this study focused on one of them which is the GJR or Threshold Garch which we have used to check for the influence of Ripple company on XRP in the market. The Threshold Garch was developed by Glosten et al. (1993) to allow conditional volatility to possess different reactions to past shocks or innovations based on the news about a particular market or asset. This model can be econometrically written as GJR GARCH or TGarch (1,1) and is written as;

$$\sigma_t^2 = \alpha_0 + \sum_{i}^{q} \alpha_i \epsilon_{t-i}^2 + \gamma_i \epsilon_{t-i}^2 I_{t-i} + \sum_{j}^{p} \beta_i \sigma_{t-j}^2 + \varepsilon_t$$

Factoring out ϵ_{t-i}^2 from the equation, GJR GARCH (q, p) is rewritten as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha_i - \gamma_i I_{t-i})\epsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2$$

$$\begin{Bmatrix} I_{t-1} = 1\ if\ \epsilon_{t-1}^2 < 0\ (bad\ news) \\ I_{t-1} = 0 \qquad\qquad\qquad Otherwise \end{Bmatrix}$$

When ($\epsilon_{t-1}^2 > 0$) good news; has an impact on α_1, and bad news has different effects on the volatility; (i) impact on $\alpha_i + \gamma_i$ (Bad news). If $\gamma_i > 0$ bad news increases volatility which shows here is a leverage effect for the i-th order, if $\gamma_i \neq 0$ therefore the news impact is asymmetric.

CHAPTER IV

RESULTS DISCUSSION

4.1 Descriptive Statistics

The summary of price returns of Bitcoin and XRP are given in **Error! Reference source not found.**. below. Prices rose to a high point and peaked in 2017 due to market manipulation (Rooney, 2018). The standard deviations of the prices of Bitcoin and XRP are 6437.616 and 0.302885 respectively which further translates that, Bitcoin is highly volatile since standard deviation is a proxy for measuring the volatility of an asset (Chen, 2020). The mean prices of both currencies are close at 5,074.166 and 0.2115 whilst the trading volumes are 9,446,621,557.4 and 961,319,003.2. The descriptive statistics are tabulated in Table 4.1.

Table 4.1 Descriptive Analysis for the Returns of Bitcoin and XRP's Prices and Volumes

Cryptocurrencies	Bitcoin Prices	XRP Prices	Bitcoin Volumes	XRP Volumes
Observations	2603	2603	2603	2603
Mean	5,074.166	0.2115	9,446,621,557.4	961,319,003.2
St. Dev	6,437.616	0.302885	15,266,529,014.5	2,429,464,646.3
Maximum	48,717.29	3.38	123,320,567,399	34,974,233,953
Minimum	178.1	0.00281	2,857,830	8,316

4.2 Graphs of the Original Series

The graphs below visualized the historical picture of both the original series of prices and volumes and their returns of Bitcoin and XRP dated from 1 January 2014 to 15 February 2021. **Figure 4.1** and **Figure 4.2** represents the daily prices of Bitcoin and XRP, and **Figure 4.5** and **Figure 4.6** are visualizations of their respective returns daily. The market experienced a drastic rise in the prices of cryptocurrencies in the year 2017 towards the beginning of 2018 which was due to manipulation of the market by a Bitcoin holder hailed as **whale** which saw a huge jump in the price of Bitcoin from $1 in January to around $19, 000 in the latter part of that same year (Orcutt, 2019). But has afterwards shown stability in the prices of XRP. This price stabilization could be because, unlike Bitcoin, XRP is controlled by a certain entity called Ripple; and also, XRP is not as decentralized as other cryptocurrencies were. This further proves to show that XRP prices are less sensitive to outside information as compared to Bitcoin. These results are in line with the expected outcome of this study.

The daily trading volumes have also been quite low in the early periods of cryptocurrencies but it can be seen in **Figure 4.3** and **Figure 4.4** that, after the breakthrough in the price in 2017, they have taken huge steps towards being known to the whole world. As such, the daily trading volume for both currencies began to surge as the market attracts more and more investors by the day. It can also be seen that Bitcoin trading volume has been increasing at an increasing rate whereas, XRP's trading volume fluctuates from periods of increment to slightly constant periods until late 2019 when Bitcoin's trading volumes made a really huge rise.

Return of prices on the other hand showed a leptokurtic nature of stationary data where periods of higher volatility follow periods of higher volatility and vice-versa. They also appeared to fluctuate around the constant level but showed volatility clustering. The 2017 price rise can be visualized in the graphs below as there has been a huge increase in the market in 2017, returns in the same year for both currencies has been huge but XRP has been settling down from that and has not been piling up as Bitcoin does.

The return series for trading volumes have been more intense in the early years of the cryptocurrency market due to its unfamiliarity to the world until they made a scene and attracted a lot of interest from people and investors. Looking at the graphical representation of the trading volumes and the daily returns of trading volumes in **Figure 4.7** and **Figure 4.8**, it can be seen that, from 2014 towards 2017, not much had been traded within the market which is why the trading volume has been seemingly zero down the stretch, but after a market manipulation by the whale (Orcutt, 2019), the market started booming with a huge increment in the prices and people starting to trust the currency afterwards until it became the most volatile market in financial history. The volume return graphs also exhibit a volatility clustering nature, where turbulent periods are followed by similar turbulent periods and periods of lower changes follow one another (Ayele et al., 2017).

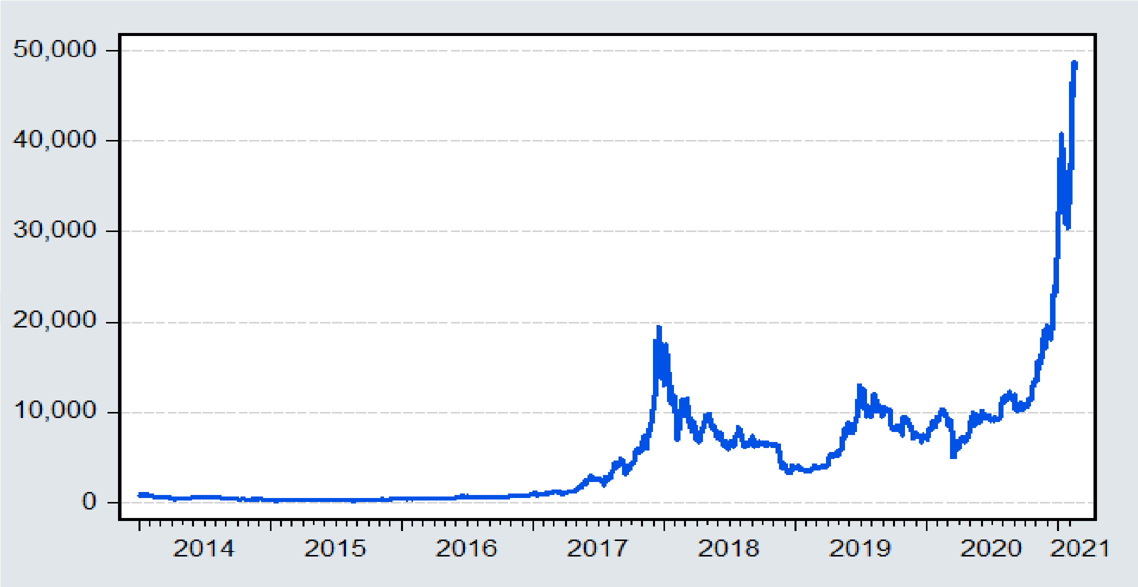

Figure 4.1 Bitcoin's Daily Prices

Figure 4.2. XRP's Daily Prices

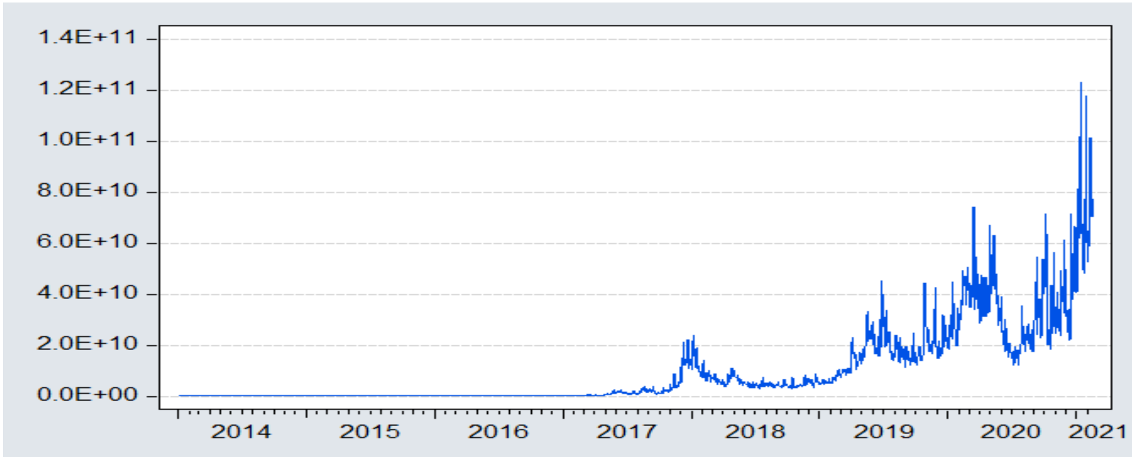

Figure 4.3. Bitcoin's Daily Trading Volume

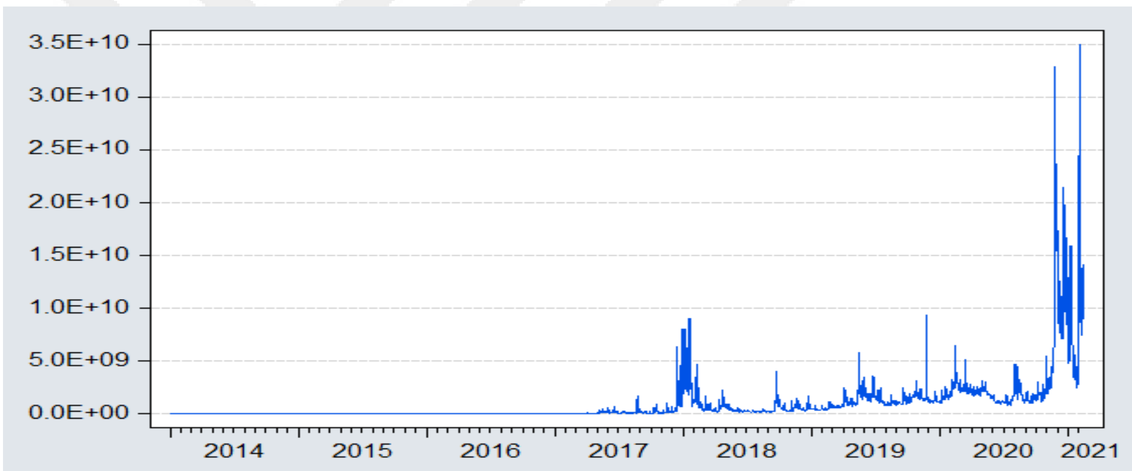

Figure 4.4. XRP's Daily Trading Volume

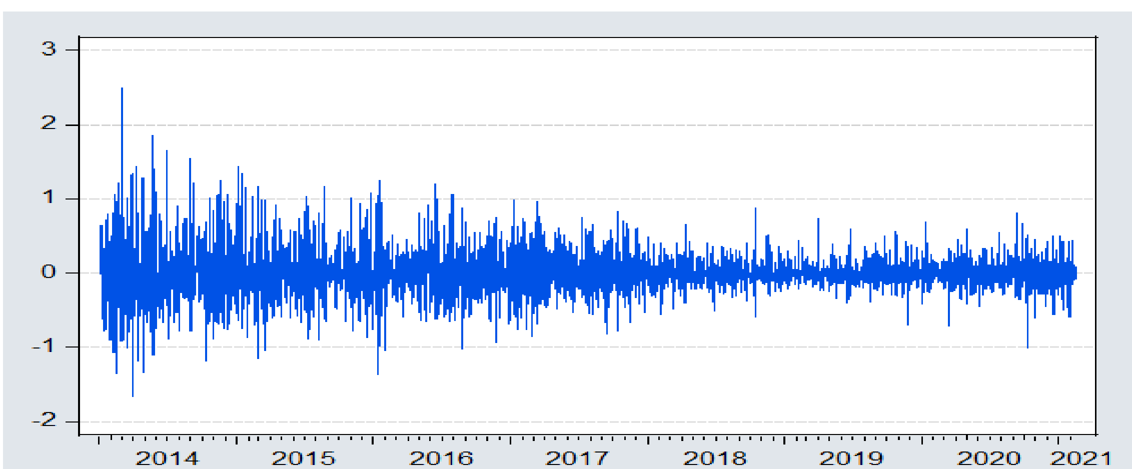

Figure 4.5. Bitcoin's Daily Price Returns

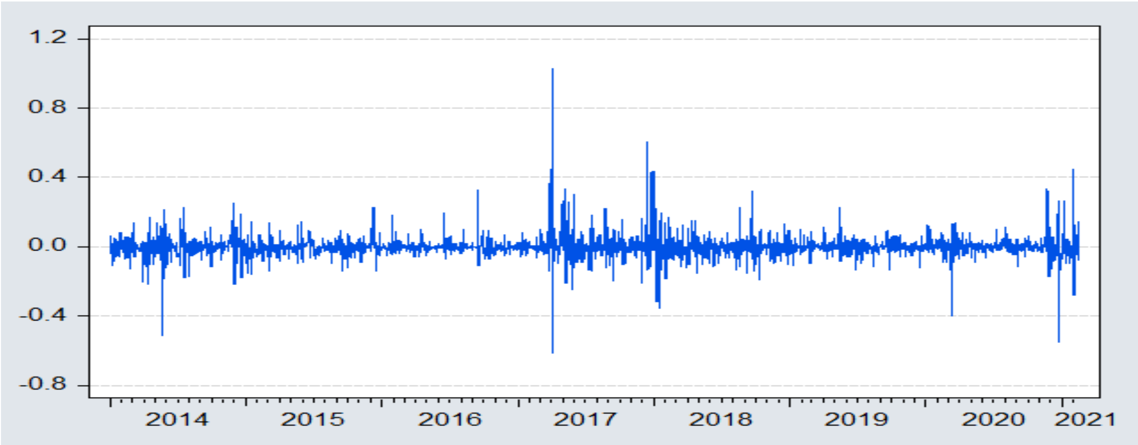

Figure 4.6. XRP's Daily Price Returns

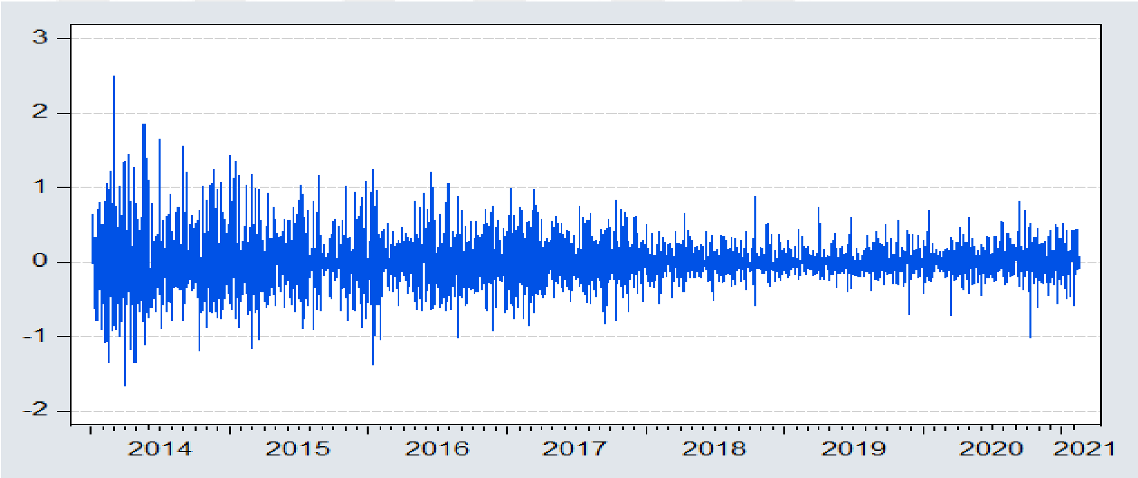

Figure 4.7. Bitcoin's Daily Volume Returns

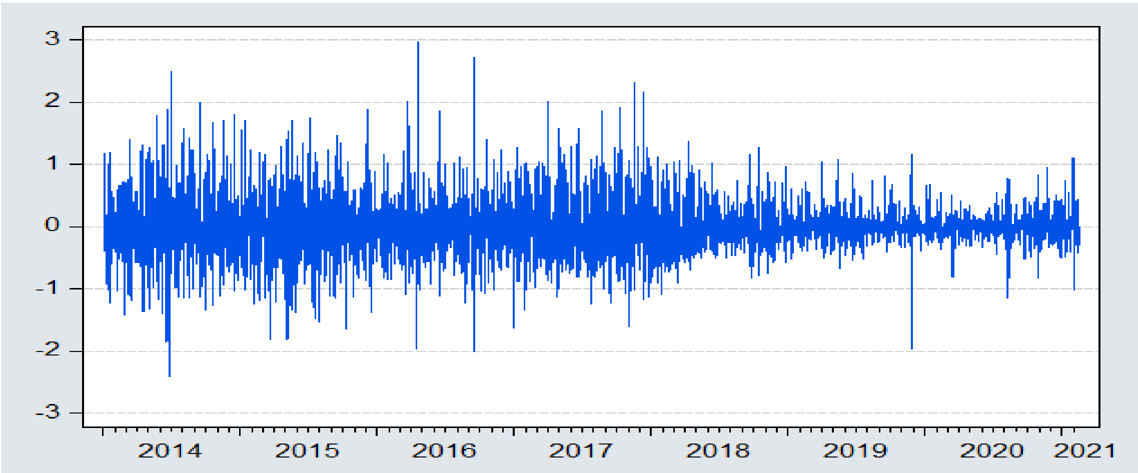

Figure 4.8. XRP's Daily Volume Returns

4.3 Unit Root Test Results

Data may come in different forms, depending on the kind of data you have and to avoid any misleading results from your regression, predictions or forecasting, it is wise to check for the stationarity of your data due to the simple fact that if the data isn't stationary, the ordinary least square principles may prove biased, and as such, we should always do the unit root testing to check for stationarity. Data can come in three forms based on the value of ɵ, namely; unit root, explosive and stationary. If δ=1, then the data is a unit root, and if δ>1 this means that, the data is explosive and if δ<1, therefore, the data is stationary. The most vital assumption is that of the stationarity of the data. The basic idea of stationarity is that, the probability laws that govern the behaviour of the process do not change over time in other words, the value doesn't increase with time. In a sense, the process is in statistical equilibrium (Degtyarev et al., 1983)**.**

A unit root process at levels may come in three (3) forms; with only constant, with constant and trend, and without constant and trend. And alternatively, when it is performed at the first difference, it takes some little changes in the coefficient of the previous values.

AR (1) processes at Levels

$y_t = \delta_0 + \phi_1 y_{t-1} + \varepsilon_t$,…………………. *With the intercept only*

$y_t = \delta_0 + \delta_1 t + \phi_1 y_{t-1} + \varepsilon_t$,…………………*With the Intercept and trend*

4.3.1 Augmented Dickey-Fuller Test:

The Augmented Dickey-Fuller test uses the basic Ordinary Least Square principle for testing the stationarity of data and if the data isn't stationary at levels. From the result table below, returns series all the variables (Prices and Volumes) for both Bitcoin and XRP are stationary at levels whilst prices on the other hand showed stationarity in only XRP prices and not Bitcoin prices. All the series are exhibiting stationarity with their series at all significant levels.

4.3.2 Phillips-Perron:

This is also another device for testing the stationarity of data and it has the same hypothesis as the first test, the Augmented Dickey-Fuller test. It has the same results as that of ADF with returns being a stationary series and Bitcoin prices showing stationarity in their series; this is common for Bitcoin Volume return series too. Similarly, the return for volume and prices of the XRP series are stationary at all levels as exhibited in **Table 4.2**

The following unit root test has a different hypothesis from that of the first two unit root tests. Kwiatkowski, Phillips, Schmidt and Shin, (1992) test has stationarity as its null hypothesis.

4.3.3 Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The KPSS on the other hand, has stationarity as the null hypothesis. Hence, its decision will be directly opposite to the ADF and PP tests but will all mean the same thing, either a unit root or stationarity. As stated above, this further confirms the results of the previous unit roots test for stationarity.

The stationarity of the series used all three scenarios to see if there are significant driving forces that determine the prices of both currencies as shown in **Table 4.2**, all the return series exhibited stationarity at all levels.

Table 4.2. Unit Root Tests for the Return Series of Bitcoin and XRP Prices and Volumes

Variables	ADF Test for Price Returns		ADF Test for Volume Returns	
	Constant	Constant & Trend	Constant	Constant & Trend
Bitcoin	-51.995***	-52.059***	-14.086***	-14.089***
XRP	-50.01***	-50.012***	-32.380***	-32.374***
	PP Test for Price Returns		PP Test for Volume Returns	
Bitcoin	-51.988***	-52.048***	-92.707***	-92.7155***
XRP	-51.327***	-51.316***	-79.477***	-79.4545***
	KPSS Test for Price Returns		KPSS Test for Volume Returns	
Bitcoin	0.394	0.151	0.0297	0.0247
XRP	0.128	0.110	0.0164	0.0162
Note: *** indicates significance at all levels, ** at 5% and * at 10% level of significance respectively				

4.4 Specifying the Conditional Mean Equation

By comparing the various Autoregressive (AR) and Moving Average (MA) orders of the ARMA models, the information criteria with the minimum values were selected as the mean equation for the GARCH model. In most cases, fewer order ARMA tentative models are used (Ayele et al., 2017) since parsimony is the main idea of tentative models. The econometric analysis of this thesis used the combination of forty-nine (49) ARMA models; AR (0—6) and MA (0—4) for Bitcoin's price return series, fifty-six (56) for volume return series; AR (1—6) and MA (1—7) and nine (9) combinations; AR (0—2) and MA (0—2) for price returns, fifty-six (56) for volume return series; AR (1—6) and MA (1—7) of tentative models for XRP. This is because the correlogram of the return series exhibited insignificant spikes for most lags, thus an ARMA Criteria Table was used to visualize the information criteria values of the possible ARMA models. Hence, the results from the top models with the least criteria values are tabulated in **Table 4.3** and **Table 4.4**.

Table 4.3. Model Selection Criteria Table for Daily Price Returns

Sample: January 01, 2014–February 15, 2021					
Observations: 2602					
Number of Estimated Tentative Models: Bitcoin (10/49) and XRP (9)					
Daily Volume Returns of Bitcoin			***Daily Volume Returns of XRP***		
Selected Model: ARMA (4,6)			*Selected Model: ARMA (2,1)*		
Akaike Information Criteria: -3.63026			*Akaike Information Criteria: -2.58717*		
ARMA (p, q) Models	***AIC***	***BIC***	***ARMA (p, q) Models***	***AIC***	***BIC***
(5,4)	***-3.63026***	*-3.605473*	***(2,1)***	***-2.58717***	*-2.575906*
(6,5)	*-3.63011*	*-3.60081*	*(1,2)*	*-2.58716*	*-2.575888*
(5,6)	*-3.63002*	*-3.600726*	*(1,1)*	*-2.58704*	***-2.578029***
(4,6)	*-3.6295*	*-3.602457*	*(2,2)*	*-2.58656*	*-2.57304*
(5,5)	*-3.6295*	*-3.602453*	*(2,0)*	*-2.58281*	*-2.573795*
(6,4)	*-3.62942*	*-3.602374*	*(0,2)*	*-2.58261*	*-2.573596*
(4,3)	*-3.62918*	*-3.608901*	*(0,0)*	*-2.58092*	*-2.576415*
(3,4)	*-3.62917*	*-3.608884*	*(1,0)*	*-2.58052*	*-2.573758*
(4,5)	*-3.62866*	*-3.603872*	*(0,1)*	*-2.58048*	*-2.573722*
(0,0)	*-3.62624*	***-3.621732***			
Note: Model Selection was based on Akaike Information Criteria					

With reference to **Table 4.*3*** AMRA (5,4) and ARMA (2,1) were selected as the mean equations for Bitcoin and XRP prices returns respectively. The best models for the return series of volumes are ARMA (4,6) for Bitcoin and ARMA (6,7) for the XRP volume return series as tabulated in **Table 4.4**. This is because, they have the lowest Akaike Information Criteria (AIC) values. It should be noted that, AIC also tends to favour over-parameterized models compared to Bayesian Information Criteria (BIC) (Ayele et al., 2017). If this concept is to be followed, our selection would have been based on BIC criteria, but it would mean that; ARMA (0,0) and ARMA (1,1) should have been the chosen models, and it will not make sense to say that, Bitcoin's past returns don't have any impact on today's Bitcoin return. Thus, we opted for Akaike Information Criteria (AIC) as our basis for model selection.

Table 4.4. Model Selection Criteria Table for Daily Volume Returns

Sample: January 01, 2014–February 15, 2021					
Observations: 2602					
Number of Estimated Tentative Models: Top 20 out of 56					
Daily Volume Returns of Bitcoin			***Daily Volume Returns of XRP***		
Selected Model: ARMA (4,6)			*Selected Model: ARMA (6,7)*		
Akaike Information Criteria: 0.4222			*Akaike Information Criteria: 1.3555*		
ARMA (p, q) Model	***AIC***	***BIC***	***ARMA (p, q) Model***	***AIC***	***BIC***
(4,6)	***0.4222***	*0.4493*	***(6,7)***	***1.3555***	*1.3893*
(5,7)	*0.4319*	*0.4635*	*(4,4)*	*1.3576*	*1.3802*
(4,5)	*0.4596*	*0.4844*	*(4,5)*	*1.3583*	*1.3831*
(6,7)	*0.4622*	*0.4960*	*(5,4)*	*1.3583*	*1.3831*
(6,4)	*0.4628*	*0.4898*	*(6,5)*	*1.3584*	*1.3877*
(3,6)	*0.4645*	*0.4893*	*(6,4)*	*1.3586*	*1.3857*
(3,7)	*0.4651*	*0.4921*	*(5,7)*	*1.3587*	*1.3903*
(5,3)	*0.4654*	*0.4879*	*(3,3)*	*1.3589*	*1.3770*
(2,4)	*0.4655*	*0.4835*	*(3,4)*	*1.3592*	*1.3795*
(6,3)	*0.4659*	*0.4907*	*(4,3)*	*1.3593*	*1.3796*
(2,6)	*0.4659*	*0.4884*	*(5,5)*	*1.3603*	*1.3874*
(5,4)	*0.4660*	*0.4908*	*(5,6)*	*1.3612*	*1.3905*
(2,5)	*0.4661*	*0.4864*	*(3,6)*	*1.3612*	*1.3860*
(3,5)	*0.4661*	*0.4887*	*(2,6)*	*1.3616*	*1.3841*
(2,7)	*0.4666*	*0.4914*	*(3,7)*	*1.3622*	*1.3893*
(6,5)	*0.4666*	*0.4959*	*(2,5)*	*1.3623*	*1.3826*
(4,3)	*0.4667*	*0.4870*	*(4,7)*	*1.3628*	*1.3921*
(3,4)	*0.4670*	*0.4872*	*(4,6)*	*1.3657*	*1.3928*
(3,3)	*0.4672*	*0.4852*	*(2,4)*	*1.3683*	*1.3863*
(5,6)	*0.4672*	*0.4965*	*(3,5)*	*1.3687*	*1.3912*
Note: Model Selection was based on Akaike Information Criteria					

4.5 ARCH-LM Test Results

This test was proposed by Engle, (1982) and it tests for heteroskedasticity in the data. This is to say, it checks for the ARCH effects using the squared residuals of the return series (Ayele et al., 2017). The null hypothesis of this test is that the series has no arch effects in it with the alternative being that, there's an arch effect or heteroskedasticity. So, early results before the GARCH regressions showed that, there's an arch effect in all the series for price returns and volume returns since the null hypothesis is rejected for all the variables under study. This confirms that, no information is left uncaptured and that is good enough to use as defence for the appropriate models as is tabulated in **Table** ***4.5***.

Table 4.5. ARCH-LM test to check for ARCH Effects using the Squared Residuals of the Fitted ARMA (p, q) Models: H_0: No ARCH Effects

	F-statistics			**Chi-Squared (X^2)**		
Statistical Lag	**1**	**2**	**3**	**1**	**2**	**3**
Bitcoin Price Returns	36.5876 (0.0000)	19.1676 (0.0000)	13.2960 (0.0000)	39.3448 (0.0000)	36.1075 (0.0000)	37.8211 (0.0000)
XRP Price Returns	259.288 (0.0000)	141.018 (0.0000)	94.8959 (0.0000)	235.949 (0.0000)	254.701 (0.0000)	256.939 (0.0000)
Bitcoin Volume Returns	67.6135 (0.0000)	59.4712 (0.0000)	52.3497 (0.0000)	92.6827 (0.0000)	113.865 (0.0000)	148.315 (0.0000)
XRP Volume Returns	45.3172 (0.0000)	41.3516 (0.0000)	31.6671 (0.0000)	44.5748 (0.0000)	80.2434 (0.0000)	91.7594 (0.0000)

Source: Author
Note: Values enclosed in the parenthesis are p-values

4.6 Estimation Results

Together, these results provide important insights into the Threshold GARCH model for both Bitcoin and XRP respectively. From the descriptive analysis to pre-estimation tests and Threshold GARCH or GJR-GARCH regression with the main aim of checking the impact of leverage on return volatilities of both currencies. To recap, the return series for both prices and volumes were all stationary at levels, with arch effects within them and the ARMA models for Bitcoin and XRP price returns series being (5,4) and (2,1) respectively. The best of models amongst the tried tentative ARMA (p, q) models for Bitcoin and XRP trading volume returns are ARMA (4,6) and ARMA (6,5) for Bitcoin and XRP. This is because, among Bitcoin's tentative models, ARMA (5,4) and ARMA (4,6) have the lowest information criteria values and ARMA (2,1) and ARMA (6,7) are the tentative models with the lowest information criteria values for the XRP return series for both the prices and trading volumes. The TGARCH or GJR-GARCH results for both currencies can be visualized below in **Table 4.6**.

Table 4.6. Results of Threshold or GJR-GARCH (q, p) for Bitcoin and XRP Conditional Returns and Variance

Models	**Parameters**	**Bitcoin Returns**		**XRP Returns**	
		Price	**Volume**	**Price**	**Volume**
Mean Equation	**Constant (μ)**	0.001586**	-0.0035**	-0.00217	-0.0041***
	AR (1)	-0.033465	0.4375***	0.853***	1.0566***
	AR (2)	1.23898***	-0.5335***	-0.034465*	-0.6525***
	AR (3)	-0.1119***	-0.1315**	-	0.3666
	AR (4)	-0.8669***	-0.5421***	-	-0.7432***
	AR (5)	-0.0520***	-	-	0.6805***
	MA (1)	0.015325	-0.8278***	-0.8429***	-1.3674***
	MA (2)	-1.2633***	0.4883***	-	0.7551**
	MA (3)	0.15859***	-0.0113	-	-0.4005
	MA (4)	0.90361***	0.4427***	-	0.772***
	MA (5)	-	-0.2429***		-0.8727***
	MA (6)	-	-0.2040***		0.0301
	MA (7)				0.1527***
Variance Equation	**Constant ω**	2.16E-05**	5.40E-05	0.00038***	6.79E-05
	ARCH (-1) α_1	0.35315***	0.0288***	0.901**	0.0304***
	Leverage Effects (γ)	-0.08454*	**0.02099**	**-0.02386**	0.0236*
	GARCH (-1) β_1	0.86908***	0.9647***	0.6705***	0.9636***

Note: * indicates significance at all levels, ** at 5% and * at 10% level of significance respectively.**

4.6.1 Price Returns

Comparing the two results, it can be seen that Bitcoin reacts very quickly to outside news whereas, XRP doesn't react to it at all. As per the GJR-GARCH results in **Table 4.6**, the long-term volatility for price returns is relatively different and significant in predicting today's volatility, but their impacts are very low compared to short term volatilities such as volatilities arising from past volatility shocks and past market shocks. The threshold term, *(γ)* is low and this entails that, news or outside information regarding the market, negatively impact Bitcoin price returns at (-0.08454), the negative sign of the threshold term, *(γ)* means that, the relationship between Bitcoin price return volatility and news is asymmetric, meaning the impact varies which also means that depending on whether the ϵ_t is less than zero or not. The past shock for Bitcoin price returns constitutes about 0.35315 compared to past volatility shock which is about 0.86908, this also entails that, past volatilities have more impact on today's return volatility than past shocks in the market in the cryptocurrency market. This characteristic is common for both currencies as XRP also have a lower resulting impact of past market shocks (0.0304) on today's volatility than the past volatility shock (0.9636). This could mean that, investors of Bitcoin are very sensitive to the surrounding news and they react based on their expectations of what's to come. That being said, XRP doesn't react to these kinds of shocks within the market. This is because XRP is different from Bitcoin when it comes to the manner in which they are been controlled. Even with that, the outside news or leverage doesn't significantly impact XRP prices which could be due to the fact that it is most common among banks (Reiff, 2020) and as such, only informed judgements or decisions can be made in order to impact the prices. This can confirm that, Ripple Company does interfere in the cryptocurrency market to control the price of XRP which is why it has never been as expensive as Bitcoin and other top cryptocurrencies with high market capitalization. Interestingly, XRP has a negative long-term volatility while Bitcoin has a positive value which actually translates correctly to how its price behaves in real life.

Furthermore, the one characteristic that, both Bitcoin and XRP share in common is that the past shocks are less persistent than the past volatility shocks in price returns. This is because the GARCH terms are greater than the ARCH terms for both currencies, if this happens as aforementioned, then the volatility effect, therefore, has greater persistence than the effects of past shocks (Chen, 2020).

4.6.2 Volume Returns

Turning now to the evidence on the trading volume of the studied cryptocurrencies and striving to further prove the authenticity of the study by looking at the volatility from the daily returns of volumes standpoint using the same model as the price return volatility, the volume returns volatility further support the study's findings. The results obtained from the Threshold GARCH analysis of the volume returns for both cryptocurrencies are summarised in **Table 4.6** above. It is found that the threshold term (γ) has a positive significant relationship with the volatility of the returns of XRP's trading volume; whereas, it has no significant relationship with the volatility of the returns of Bitcoin's trading volume. From the table, it can be seen that, the relationship between news and XRP trading volume is positive, which means that, good news has more impact on the volume returns than bad news. News is something that cannot be calculated in numeric terms, but its impacts can be measured using the threshold term (γ) of the GJR-GARCH model and in the case of XRP volume returns, it has an impact of 0.0236 at a 10% significance level at 0.0768. The positive coefficient shows that the news impact increases volatility and the impact indicates a leverage effect. This also means that the good news will have an impact on only the past shock because the dummy variable (I_{t-1}) will be zero. Shocks from the past return volatility for both XRP and Bitcoin are 0.9636 and 0.8691 respectively while past shocks are 0.0304 and 0.35135, both of which are significant at all levels.

No evidence was found for associations between Bitcoin volume returns and outside news. Since investors know that there is no central body that owns or controls the activities of Bitcoin within the market, and also, they trust Bitcoin so much that they won't care how much the price rises or fall because they believe it will always recover itself. And what makes this interesting is that, once the news breaks out, it will either increase or reduce the price of Bitcoin and once this happens; investors have nothing much to lose. This is because, most investors sell their coins once the prices rise, and they buy when the prices fall below because they always knew they can hold on to it and wait for the prices to rise again so that they can sell it again. This is why news, whether good one or bad, does not affect the trading volume of Bitcoin because there is always going to be someone to either buy when prices fall and sell his coins off when the prices rise. This is what we call the cryptocurrency market phenomena.

This makes more sense because there have been notions that Ripple controls the prices of XRP by reducing the trading volume of XRP within the market since they still own most of the coin. Even though the CEO of Ripple Company, Bradley Garlinghouse, denies the claim (Suberg, 2020) but he further claimed that they are taking steps to keep most of their XRP tokens in escrows so they won't be touching it. Since the number of coins sold and bought within a day is the trading volume, and the more cryptocurrencies are traded, the more they gain attention and hence increase in value, it is safe to say that, to control the price of any cryptocurrency, one has to keep a significant part of the coins off the market in order to stabilize the price. This makes much sense for XRP simply because most of it is owned by its creator, and they have some degree of control over it; it will be easy for them to hoard it for some time in order to make sure its price doesn't surge like Bitcoin, Ethereum and other cryptocurrencies do. These results can be supported by a 2019 article by Max Boddy which revealed that Ripple has sold a whopping $250 million worth of XRP during the second quarter of 2019 which shows an increase in XRP sales to about 48% from the first quarter (Boddy, 2019). Subsequently, this increase prompted Ripple to decrease future coin sales substantially. This is one of the mechanisms used by the company to control the prices of XRP.

Finally, the post-estimations tests were conducted for the tests, and they all can confirm the validity of the models as well as the normality of the residuals. The two basic tests conducted were the ARCH-LM test which was proposed by Engle (1982) and the correlogram test using the squared residuals. The result of the Squared Residuals test of correlogram will be found in the appendix for all the series under study. ARCH-LM test checks for the arch effects or, in other words, serial correlation in the squared residual series while the correlogram checks for the autocorrelation in the residuals. The null hypothesis for the ARCH-LM is that there are no arch effects and the result of the diagnostics showed that the null hypothesis can't be rejected since the P-values of the *F-statistics* and *Chi-squared (X^2)* for both currencies are for Bitcoin and XRP respectively. This means that there is no statistical evidence that there is autocorrelation in the squared residuals. The results of these tests can be found in **Table** ***4.7***.

Table 4.7. ARCH-LM test to check for ARCH Effects using the Squared Residuals of the Fitted Volatility Models: H_0: No ARCH Effects

	F-statistics			**Chi-Squared (X^2)**		
Statistical Lag	**1**	**2**	**3**	**1**	**2**	**3**
Bitcoin Price Returns	0.0064 (0.9365)	0.2191 (0.8032)	0.4053 (0.7492)	0.00636 (0.9364)	0.4387 (0.8032)	1.2171 (0.7489)
XRP Price Returns	0.1023 (0.7491)	0.3094 (0.7339)	0.4793 (0.6967)	0.1024 (0.7490)	0.6194 (0.7337)	1.4394 (0.6963)
Bitcoin Volume Returns	0.00669 (0.9348)	0.22816 (0.796)	0.41695 (0.7409)	0.00669 (0.9348)	0.45677 (0.7958)	1.25216 (0.7405)
XRP Volume Returns	0.22961 (0.6319)	0.38835 (0.6782)	0.53305 (0.6596)	0.2298 (0.6317)	0.7774 (0.6779)	1.6006 (0.6592)

Source: Author
Note: Values enclosed in the parenthesis are p-values

CHAPTER V

CONCLUSION

In summary, these results conclude that both GARCH, ARCH and news shocks emerged as reliable predictors of the next day price return of Bitcoin and volume return of XRP. XRP price returns, on the other hand, do not react to asymmetric shocks in the market. XRP price returns only react to the volatility shocks. This study has found that generally, it takes a while for market shocks to affect XRP prices, and outside news does not affect any change in the price of XRP. The findings regarding the returns of trading volumes proved directly opposite when the impact of news is compared. News or threshold term isn't significant for Bitcoin's trading volume return volatility but on the contrary, it has a significant relationship with XRP. The relationship is positive which means that good news has more impact on the volatility of XRP volume returns than bad news. This means that the volatility increases with good news for XRP, but investors of Bitcoin do not care much because, with good news, prices increase and once it does, they sell more coin to earn more profit, and with bad news, on the other hand, prices are expected to fall and once that happens, they buy more coins to sell more again once the prices increase and vice-versa.

These findings answered our research question because, the good news is expected to put trust in investors and they would want to buy more of the currency. Like the stock exchange, the more a currency that is traded in the crypto market, the more it gains values. Since Ripple's plan is contrary to the inflationary nature of the cryptocurrency market, they'd **hold** the currency for a significant period of time so that the price will not surge up as much as Bitcoin and other currencies. This is why XRP's price return has an opposite reaction to news compared to trading volumes. This is how Ripple controls the price of XRP.

Furthermore, the investigation of the volatility phenomena between the two currencies has shown that Bitcoin is more volatile than XRP and as such, for a rational investor, XRP will be much preferred to Bitcoin (Chen, 2020). But Bitcoin is way more expensive and has been on the market much longer than XRP. XRP has unstable volatility compared to Bitcoin. for this reason, investors tend to be more interested in Bitcoin than XRP since its volatility yields higher returns than XRP whose price has been historically stable since 2018.

The GJR or Threshold GARCH model has proven to be a good predictor of the volatility of return series of both prices and volumes of both currencies because, from the post-estimation tests, we can confirm the validity of the models and stability conditions for the model using both currencies were met.

CHAPTER VI

RECOMMENDATION

In a nutshell, to answer the research question of whether there really exist threats of intervention in the crypto market, these results can vividly confirm that, Ripple Company actually intervenes in the cryptocurrency market to control or stabilize the price of XRP so that it won't be as inflated as other cryptocurrencies. Since this approach will prove useful in expanding our understanding of how Ripple controls the price of XRP, further studies can be made to find out about alternative ways and mechanisms they used when controlling it besides controlling the supply of XRP.

CHAPTER VII

DIRECTIONS FOR FUTURE RESEARCH

There are potentials for future research in the topic to further broaden the area of study. Possible future researches can be made on checking the effects of crisis such as the COVID-19 Pandemic on the volatility of cryptocurrencies. Another gap that could be found in this area could be examining the long-run relationship between BTC and XRP etc. Basically, these are the gaps found in the study.

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