Universidade de Aveiro
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GONÇALO PEREIRA DE ALMEIDA

MODELOS DE VOLATILIDADE NO MERCADO DAS CRIPTOMOEDAS: EFEITOS SOBRE RETORNOS

VOLATILITY MODELING IN CRYPTOCURRENCY MARKETS: EFFECTS OVER RETURNS

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Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Economia, realizada sob a orientação científica da Doutora Mara Teresa da Silva Madaleno, Professora Auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro.

" You never know. You hope for the best and make do with what you get."

- Samuel L. Jackson

o júri

presidente

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agradecimentos

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palavras-chave

Criptomoedas, modelo generalizado autoregressivo condicional heteroscedástico (GARCH), retornos, volatilidade

resumo

O trabalho que se propõe desenvolver pretende estudar a influência da volatilidade da Bitcoin no retorno de um conjunto de moedas, conjunto esse definido pela Ethereum (ETH), Cardano (ADA), Binance coin (BNB) e Ripple (XRP). Com o intuito de atingir os resultados pretendidos, conduziu-se, numa primeira fase, um modelo univariado GARCH e, numa segunda fase, um modelo multivariado GARCH. Estes modelos tinham como base de dados os preços diários das cinco moedas, recolhidos no Yahoo Finance, num período compreendido entre outubro de 2017 e agosto de 2021. Os resultados obtidos através do primeiro modelo levam à conclusão de que, principalmente na Bitcoin, os retornos passados não são um bom indicador de retornos presentes e futuros. No segundo modelo, foi testado se as volatilidades deste conjunto de moedas impactavam, e se sim como, os retornos das mesmas. Deste modelo pode-se concluir que todas as moedas prosperam com a sua própria volatilidade e que a volatilidade nas outras moedas tem um impacto negativo no retorno das próprias. Em suma, sendo este um mercado bastante volátil, esta volatilidade revela-se como sendo de influência positiva para os retornos. Assumindo esta premissa, existe uma grande oportunidade para "day-to-day trading", sendo que os investidores podem estar atentos às quebras do mercado e capitalizar na expectável subida.

keywords

Cryptocurrencies, generalized autoregressive conditional heteroskedasticity (GARCH) model, returns, volatility

abstract

The proposed work aims to study the influence of Bitcoin's volatility on the return of a set of currencies, defined by Ethereum (ETH), Cardano (ADA), Binance coin (BNB), and Ripple (XRP). To achieve the desired results, a univariate GARCH model was conducted in the first stage and a multivariate GARCH model in the second stage. These models were based on the daily prices of the five currencies, collected from Yahoo Finance, for a period between October 2017 and August 2021. The results obtained from the first model led to the conclusion that, especially in Bitcoin, past returns are not a good indicator of present and future returns. In the second model, it was tested whether the volatilities of this set of coins impacted, and if so, how, their returns were affected. From this model, it can be concluded that all currencies thrive on their volatility and that volatility in the other currencies presents a negative effect on their returns. In short, since this is a very volatile market, this volatility turns out to be positive for returns. Assuming this assumption, there is a great opportunity for day-to-day trading, and investors can watch for market dips and capitalize on the expected upside.

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1. Introduction

The times when fiat money dominated the entire financial and exchange market are far behind us. With the fast-changing times are emerging innovative and groundbreaking concepts, that have arrived and vowed to transform the world and the way we engage with money. Cryptocurrencies have been on the rise since their creation and gathered a lot of attention around them. From investors to analysts, through the past decade, a lot of curious and experts have dedicated their time to understanding and mastering this new field of knowledge. A cryptocurrency is a digital asset that works as a medium of exchange. This “new” asset uses cryptography to secure financial transactions, control the creation of additional units and keep track of every transaction. This pioneer asset comprises a brand-new alternative shape of currency, focusing on the digital dimension, to the detriment of the commonly used non-virtual fiat currency. It enables immediate payment from one part of the world to another, dismissing intermediaries and hastening the existing process.

Even though it is a fairly recent market, the cryptocurrencies world developed at a staggering rate, going from one to thousands in twelve years. The first-ever cryptocurrency was named Bitcoin and it was based on the work of Satoshi Nakamoto, back in 2009, as a response to the financial crisis it quickly attracted the attention of the world (Davis, 2011). The technology adjacent to this creation is called blockchain, which is *“based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party”* (Nakamoto, 2008, p.1). Also, the blockchain assures transparency to all the involved parts, since the information is available to all nodes, and grants anonymity to the actors involved in the transaction, thereby conferring an additional dimension of security (Yli-Huumo et al., 2016). The crucial trait that differentiates Bitcoin, and subsequently cryptocurrencies, from the remaining currencies’ types, is the lack of dependability on third parties to control the currency value (Yli-Huumo et al., 2016), which created a distinctive factor and a focus of interest for many. Since then, the world has witnessed the creation of many other cryptocurrencies that mimic the original blockchain and payment system (Elbahrawy et al., 2017).

Bitcoin is, currently, the crypto market's greatest asset followed by a well-established Ethereum in second place. In January 2016, the total market capitalization of all cryptocurrencies was, approximately, $7 billion and in May 2021 recorded over $2.4 trillion.

Since cryptocurrencies emerged as a new concept in the financial world, the doubt on how to measure and evaluate them arose. Many academics and economists assess them, largely bitcoin alongside gold, since both have constrained supply, are tough to find, and are both able to act as safe-haven assets. Nonetheless, assets diverge on some points, mainly the security coupled with cryptocurrencies, low transaction fees associated with the before mentioned, and the decentralization, that can cause fear among today's rulers and banks.

A great deal of attention around this type of asset is primarily due to its rapid and massive growth in market capitalization. The cryptocurrencies market is primarily dominated by day-to-day traders and speculators. Throughout this investigation, the emphasis will be on the benefits of holding cryptocurrencies in a personal portfolio, making a distinction amongst the existent assets, and usually used for diversification purposes inside a portfolio. The main aim is to understand whether a long-term position is better than a short-term one, or vice versa. The primary purpose of the present dissertation is, thus, to analyze cryptocurrencies returns, which are highly volatile (Liu & Serletis, 2019), and evaluate the impacts it may pose in terms of risk hedging inside a portfolio (Brauneis & Mestel, 2019) since returns and volatility play a key factor when discussing the weight of assets in a portfolio (Kyriazis et al., 2019). It becomes important to study this phenomenon since *"the cryptocurrency market is rather young (Bitcoin was created in 2009, but active trade only started in 2013) and therefore is still mostly unexplored*" (Liu & Serletis, 2019, p. 780). The methodology employed mirrors the work of Jinan Liu and Apostolos Serletis, from 2019, resorting to the Univariate GARCH-in-mean models, introduced by Bollerslev (1986), updating the database to the top currencies in 2021. This study includes a wider database when compared to other works. This specific set of coins has never been studied as a whole in the literature, therefore the present Master's thesis provides new insight and innovation to the field. The period under analysis comprehends the period between 2017 and the referred year since the first marks the creation of the newest coin analyzed. Since 2020 is a year marked by the breakout of the COVID-19 pandemic, this will also be an element of study, understanding how it impacted the cryptocurrencies market.

The present master thesis will be structured as follows. The Literature Review chapter focus on the studies carried out so far on the cryptocurrency arena, mainly on some models that have been developed and the COVID-19 pandemic effects. The following chapter concerns the methodology – GARCH models - and presents the data used, with some tests to determine the relevance of the same. The fourth chapter, Main Results, and Discussion illustrate the results achieved with the implementation of the previously mentioned models. Furthermore, it is carried a discussion bearing in mind the results and the existing literature. The final chapter of this work, the Conclusion, gives an overall view of the work and discussion, as well as the main limitations faced and some suggestions for further work.

2. Literature review

2.1. The emergence and rise of cryptocurrencies

After the global crisis of 2008, public trust in conventional banking systems was a concern, which all started when in March 2008 Bear Sterns and Lehman Brothers declared bankruptcy (Wilson, 2019). The shock's ramification did not stop at these institutions; instead, the debt contagion continued to spread and hit other financial powerhouses such as AIG – American International Group -, the Bank of America, Citigroup, JPMorgan Chase, Goldman Sachs, and Morgan Stanley. Beyond the United States, the global financial crisis also spread to Europe and Asia (Rejeb et al., 2021). At a global level, the bank's reputation and trust among the public eye were as fragile as ever.

In the aftermath of the 2008 global financial crisis, an unknown person, group, or organization operating under the pseudonym 'Satoshi Nakamoto' introduced an electronic peer-to-peer system based on the cryptocurrency bitcoin. Bitcoin is a decentralized digital currency introduced in 2008 and deployed at the beginning of 2009. It came as a response to the financial institutions that often privatized profits and socialized losses (Lerer & McGarrigle, 2018).

Ever since the release of the first cryptocurrency whitepaper in 2008, a whole new asset class has been introduced to the world. What originally was an idea to replace fiat currency, cryptocurrencies have become an innovative tool with endless usage possibilities. On one hand, there is the possibility of faster, more secure, and peer-to-peer – no need for an intermediary – transactions. On the other hand, there is the possibility of a store of value and even a short-term investment opportunity.

Cryptocurrencies constitute an alternative way of payment, allowing payments from one part of the world to another without the need of any intermediary – many authors make the comparison of cryptocurrencies and gold – "Cryptocurrencies, in particular Bitcoin, have been labeled the New Gold by some media, banks, and also data providers throughout the last years" (Klein et al., 2018, p. 105). In the same way, "The Commodity Futures Trading

Commission (CFTC) has officially declared virtual money a commodity, just like crude oil or Gold. The Commission states that Bitcoin as a virtual currency is a digital representation of value that functions as a medium of exchange, a unit of account, and/or a store of value, but does not have legal tender status in any jurisdiction." (Klein et al., 2018, p. 106). This argument is now obsolete, as, since September 2021, El Salvador has officially made Bitcoin legal tender.

One of these differentiating characteristics is the fact that cryptocurrencies are based on an algorithm that provides great security, detects all transactions on the network, and has low transaction costs. Also, they are not issued by a central bank or government resulting in detachment from the real economy (Kyriazis et al., 2019, p. 1).

2.2. Cryptocurrencies take the world: what about now?

Although this rapid growth has gathered the attention of investors as a new asset that can improve portfolios, it has also raised some red flags to scholars debating that the crypto market is a bubble (Peetz & Mall, 2018). Cryptocurrencies tend to show high volatility since there is no central authority assuring their value's stability. This volatility can be leveraged and intensified if financial institutions engage in speculative investments, resulting in chain reactions and financial crises (Rejeb et al., 2021).

Since September 2015, the crypto market has been in a long-term uptrend with momentum accelerating since mid-2017, although historically these price increases seem unsustainable in the long-term, there are arguments for a continuation of this trend in the short to medium term. In a study conducted by Benjamin M. Blau in 2018, empirical evidence was shown proving the opposite, that is, no sufficient positive relation was observed between Bitcoin's volatility and speculative trading to prove the existence of a bubble (Blau, 2018).

Cryptocurrencies, mainly Bitcoin, tend to be associated with illegal activity on the dark web. As stated by Baldimtsi et al. (2021), the advent of Bitcoin has already revived black markets and provided opportunities due to their quasi-anonymity, which makes it difficult to trace and identify the operators and users. Cryptocurrencies are, as such, considered the largest unregulated market in the world. The decentralized nature of crypto transactions makes it hard and may help disguise criminal activity. Still, once cryptocurrencies are exchanged for fiat currencies, it is easier to detect and trace the source of the money (Rejeb et al., 2021). On the other hand, Manimuthu et al. (2019) believe that Bitcoin, contrary to what most believe, is not anonymous and was not built for bad actors, though bad actors have, at times, brought it into the headlines.

2.3. A new branch of study: cryptocurrencies

Financial markets are constantly developing, due to higher globalization. There is common knowledge that changes in one market might have repercussions on another, and so the stock market, currency market, commodity market, and equity have been targeted by a lot of different scholars. However, since the crypto market is fairly recent, there are not those many studies on the topic.

Cryptocurrencies have, in the past decade, received a lot of attention and are now being compared to fiat currencies – euro, dollar. Wi (2016) presents the case that Bitcoin can and should be considered money. Peetz and Mall (2018) argue that Bitcoin cannot be labeled as a currency, this can be defined as a facilitator of transactions between two parties; it is a medium of exchange that helps buyers and sellers set a price for a transaction to take place, however, when a currency cannot be correctly evaluated this definition of price becomes impossible.

The realm of cryptocurrencies can be perceived in different ways. Individuals may be interested in the investment's perspective, for academic purposes, even from a scientific point of view – being an innovative technological breakthrough attracts many enthusiasts.

Looking at them as an investment and, consequently, a part of portfolios, the need to investigate and understand volatility and the optimal time to own cryptocurrencies arose. "The market in which the cryptocurrencies are traded is dominated by short-term investors as well as speculators" (Kyriazis et al., 2019, p. 1). This is a very frequent topic among researchers. However, there is still space to grow and work on the assessment of its advantages. The present research proposes to emphasize this same topic, as a valuable addition to the existent literature.

The analysis of cryptocurrencies as a financial asset, in a much complex perspective, is another recurring issue when studying the already published work. An early study by Ciaian et al. (2015) evaluates how people's perception and opinion toward bitcoin would affect its price. To do so, the authors used a forum as a database and proved that an increase in the variable number of posts would be positively correlated with an upsurge in bitcoin's price. Being this a pioneer study in the field, it revolutionized the way researchers and investors were looking to bitcoin, as well as perceiving cryptocurrencies in general.

The work done by Aloosh and Ouzan (2020) concludes that cryptocurrency investors' behavior appears to be biased and largely driven by price level and its impact on their beliefs. Also, that low priced cryptocurrencies are more volatile but have lower past monthly returns. This leads to the belief that cryptocurrencies can be grouped up "financially", meaning that some cryptos might perform better in the long term, while others perform better in the short term.

Authors such as Kyriazis et al. (2019) in their study refer that most digital currencies are complementary to the top three coins – Bitcoin, Ethereum and Ripple -, suggesting that these may be the best ones to hold in the long run, using the rest of the cryptocurrencies to day to day trade and profit from its high volatility.

One other factor that keeps getting more and more attention from researchers is cryptocurrencies' capability of being a safe haven to the financial market. Taking as an example the work of Bouri and Azzi (2017), which studies bitcoin's behavior before and after a crash in price, they state that bitcoin had a safe-haven property before the crash, but after the crash, however, the safe-haven property disappears. Going even beyond saying that adding Bitcoin to US equity portfolios leads to an effective risk reduction, in particular before the price crash of 2013. Leaving us to wonder if the fact that cryptocurrencies may experience significant price crashes leads investors to slowly start losing faith in the asset.

As described so far it is possible to affirm even though the cryptocurrency market is fairly recent, the academic world is already riddled with studies and models that try to understand a little better how this technological phenomenon acts and interferes with the surrounding environment and markets. Table 1 does a summary of some of these models and their main findings, that took place in the last couple of years. Cross et al. (2021) used a time-varying parameter model to study the risk premium on Bitcoin, Ethereum, Ripple, and Litecoin during the 2017's boom, discovering that Bitcoin and Ethereum did not show any evidence of risk premium, maybe due to their already acquired trustworthiness in the eyes of investors. Bouri et al. (2021) used a GARCH model, studying the same coins as the previous authors, to see if there was any relationship between investor sentiment hedging capabilities in the crypto market. This relationship was found to be true when investor sentiment is weak. Uzonwanne (2021) studied the presence of spillover shocks between the crypto market and the stock market, with the use of a GARCH model. Bi-directional shocks were found between both markets. A similar study was performed for the crypto market within itself, instead of the previous methodology that compared the crypto market and stock market. Bi-directional shocks were found between Bitcoin and Ethereum, in the long term, but only uni-directional shocks from Bitcoin to Ethereum, in the short term. Bitcoin also acts as a shock transmitter to all major cryptocurrencies (Moratis, 2021). Leirvik (2021) studied the correlation between liquidity volatility and returns, concluding that investors demand a premium for a high variation in liquidity variation. Finally, with the use of a stochastic volatility model, Yen and Cheng (2021), found a relationship between China's EPU – economic policy uncertainty - and cryptocurrencies' volatility.

Table 1 Review of the current literature

Model	***Coins***	***Main findings***	***Reference***
Time-varying parameter model	BTC, ETH, XRP, LTC	(i) Volatility of Litecoin and Ripple incurred a risk premium by investors during the boom of 2017 (ii) no such relationship was found in either Bitcoin or Ethereum during this period (iii) possible explanation for this is that Bitcoin and Ethereum are the two largest cryptocurrencies in terms of market capitalization thereby making them more trustworthy in the eyes of investors	(Cross et al., 2021)
DCC-GARCH	BTC, ETH, XRP, LTC	(i) lower quantiles of investor happiness, built on Twitter feed data as a proxy for investor sentiment, is positively associated with the entire conditional distribution of connectedness, but the opposite is observed at higher values of investor happiness (ii) cryptocurrencies are used for hedging when investor sentiment is weak	(Bouri et al., 2021)
VARMA-AGARCH	Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Monero, Dash, NEM, Dogecoin, etc	(i) bi-directional presence of returns and shock spillovers across the bitcoin market and the stock market (ii) rational investors move across markets in search of alternative assets to avoid the crystallization of shocks to their returns in the stock market or simply exit these markets when they anticipate future shocks	(Uzonwanne, 2021)
Spread estimator	BTC, ETH, LTC, BCH, XRP	(i) the correlation between liquidity volatility and returns is overall significantly positive (ii) investors demand a premium for a high variation in liquidity volatility (iii) when liquidity is low, expected returns are high	(Leirvik, 2021)
DCC-MGARCH	BTC, ETH, USDT	(i) bi-directional relationship for returns and long-term spillovers between BTC and ETH (ii) unidirectional short-term spillover effect from BTC to ETH	(Smales, 2021)
Stochastic volatility model	BTC, LTC, XRP	(i) a change in EPU of China predicts cryptocurrency volatility (ii) a change in the EPU of the U.S., Japan, or Korea has no such effect (iii) changes in the China EPU are negatively associated with Bitcoin and Litecoin future volatility, which may imply that Bitcoin and Litecoin are hedging tools against the EPU risk	(Yen & Cheng, 2021)
rolling-window Bayesian Vector Autoregressive Model	BTC, ETH, XRP, LTC, XLM, USDT…	(i) Bitcoin acts as a shock transmitter to all major cryptocurrencies, therefore being a dominator in market spillover	(Moratis, 2021)

2.4. COVID-19 pandemic and its impacts on the cryptocurrencies arena

Undoubtedly, the most recent branch of literature focuses on the COVID-19 pandemic. Ali et al. (2020) analyze the responses, in terms of volatility, of financial markets as COVID-19 spread from China to Europe and the US and find that global markets went into a freefall in March 2020 and that even safer commodities suffered due to the arrival of the pandemic in the US. Corbet et al. (2020) examined the potential contagion effects of the COVID-19 pandemic on gold and cryptocurrencies and consider that cryptocurrencies may play a role similar to that of precious metals during economic crises. Rizwan et al. (2020) examine how COVID-19 influenced the banking sector of the eight countries most affected by SARS-CoV-2.

There is also a branch of recent literature that studies the interdependences among cryptocurrencies following different methodologies, for example, Corbet et al. (2020) using GARCH models or Symitsi and Chalvatzis (2019) who use VAR-GARCH models.

In the first quarter of 2021, the COVID-19 pandemic started to ripple its effect on the financial markets. Bitcoin, for instance, declined 19% from January 1st to March 23rd, where there was the biggest crash day observed in Bitcoin's history, a drop of 36% on March 13th. Since this recent pandemic had such a huge impact on the financial markets, the study comparing pre-covid and covid periods emerged as an interesting case study. Studies as the one published in 2020 by Imran Yousaf and Shoaib Ali revealed that the returns of Bitcoin could be used to predict returns on cryptos, such as Ethereum and Litecoin, in the periods pre-covid. However, when analyzing covid periods the same could be not proven, provided returns on the crypto market started to diverge from Bitcoin's returns. In a study carried by Umar et al. (2021), analyzing the impact of pandemic-related news in the crypto market and the fiat currencies, the conclusion was that cryptocurrencies acted as a transmitter of shocks while fiat currencies acted as receivers.

3. Methodology and Data Description

3.1 Variables description

The cryptocurrencies under analysis for this study will be Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), Binance Coin (BNB), and Ripple (XRP). These cryptos have different use cases, for example, payment method, a reserve of value, or token platforms, and they can also be decentralized or centralized – depending on whether there is a central authority or not.

Bitcoin was developed as a decentralized, peer to peer, payment method, which means that it completely removes the need for an intermediary on transactions. The creation of new Bitcoins works based on a proof of work system, meaning that anyone who provides computational power to the blockchain gets rewarded with Bitcoin. Since Bitcoin is open source, no single entity owns it, and everyone has a say in the future.

Ethereum is a decentralized platform capable of performing smart contracts – applications that work exactly as they were programmed to, bringing to participating parties more transparency and no possibility for fraud - using blockchain technology. Currently, hundreds of different tokens use Ethereum's blockchain.

Cardano is a proof of stake - a person can mine or validate block transactions according to how many coins they hold, meaning that the more coins owned by a miner, the more mining power they have - blockchain platform, directly competing with Ethereum it is designed to be more efficient, scalable, and sustainable.

Binance coin is an exchange coin from the largest exchange – Binance. It aims to boost the operations performed on the exchange and its ecosystem. It supports multiple utilities such as trading fees, exchange fees, listing fees, etc. As is the case for Ethereum and Cardano, Binance coin also is built on a blockchain that allows for the creation of new cryptocurrencies.

Finally, Ripple is a technology that acts as both a cryptocurrency and a digital payment network for financial transactions. Ripple's main process is a payment settlement asset exchange and remittance system, similar to the SWIFT system for international money and security transfers, which is used by banks and financial middlemen dealing across currencies.

3.2. Methodology

This work will be divided into two main methodologies. The first one will be a Univariate GARCH Model, which will analyze each coin individually. The second part will be the multivariate GARCH model, which will analyze Bitcoin's effect in each of the other cryptocurrency' returns.

Cryptocurrency returns are calculated based on the crypto market price at p_t. The cryptocurrency return is then calculated, at period *t*, as in equation (1).

$$r_t = \log p_t - \log p_{t-1} \tag{1}$$

3.2.1 **Univariate GARCH Model**

The Univariate GARCH Model was first introduced by Bollerslev (1986), with the aim to mode/forecast the volatility on one, or several, time series at once. This model allows the simultaneous modeling of both the first and second moments of the return series. As previously analyzed, the degree of uncertainty in cryptocurrency returns varies dramatically over time, suggesting that the compensation required by risk-averse economic agents for holding these assets also varies accordingly (Liu & Serletis, 2019). For this effect, the GARCH-in-mean model will be the tool used to explore the possibility of risk being the explanation for the higher returns in the crypto market.

One of the key postulates is that varying risk premia on different cryptocurrencies can be well modeled as unanticipated shocks and are measured by the conditional variances of the one-period holding yields. The ARCH model – Autoregressive conditional heteroscedasticity, introduced by Engle (2001), explicitly models time-varying conditional variances by relating them to variables known from previous periods. In its standard form, the ARCH model expresses the conditional variance as a linear function of past squared innovations; in markets where prices follow a martingale, price changes reflect innovations. The ARCH model is used to provide a rich class of possible parameterizations of heteroscedasticity. This paper first introduces the GARCH-in-mean model to allow the conditional variance of cryptocurrency to affect the mean cryptocurrency return. In this way changing conditional variances directly affect the expected return on a portfolio.

As it is standard in the GARCH literature, the conditional variance (covariance under the bivariate setting) is the proxy for the market risk. If the market risk is priced, the conditional variance (covariance) will be positively correlated with the market (portfolio) return. The slope of the return-variance relationship is the proxy for the risk premium. The time-series approach links daily return with daily volatility over a long sample period (1430 observations in our study) which involves a long series of return-volatility data pairs to generate the return-risk regression slope. It should hence have stronger statistical power to track down the true relationship.

The Akaike Information Criterion (AIC) was used to select the best-fitted model, this led to the finding that an ARMA (1,2) with a GARCH (1,2) yields the lowest AIC value for all cryptocurrencies. The Univariate GARCH-in-mean model for each cryptocurrency is specified as in equations (2) and (3).

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \alpha_2 r_{t-2} + \alpha_3 \epsilon_{t-1} + \alpha_4 \epsilon_{t-2} + \alpha_5 h_t + \epsilon_t \qquad (2)$$

$$\epsilon_t | \Phi_{t-1} \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \epsilon^2_{t-1} + \beta_2 \epsilon^2_{t-2} + \beta_3 h_{t-1} + \beta_4 h_{t-2} + \beta_5 \epsilon^2_{t-1} I_{t-1} + \beta_6 \epsilon^2_{t-2} I_{t-2} \qquad (3)$$

Where r_t is the cryptocurrency rate of return, h_t is the variance of ϵ_t conditional upon the information set Φ_{t-1}. The conditional variance is used here as a proxy for the market risk anticipated by investors. To capture the leverage effects in cryptocurrency return volatility, the Glosten-Jagannathan-Runkle (GJR) asymmetry coefficient of Glosten et al. (1993), $\epsilon^2_{t-1} I_{t-1}$, was included. This represents the disproportionate response of the variance of unexpected price decreases.

Since standardized residuals are usually not normally distributed (Diebold & Nerlove, 1989), a quasi-maximum likelihood estimation is used. All the estimations are performed in Stata 16.1.

3.2.2 Multivariate GARCH Model

This model estimates the parameters of dynamic conditional correlation (DCC) multivariate generalized autoregressive conditionally heteroskedastic (MGARCH) models in which the conditional variances are modeled as univariate generalized autoregressive conditionally heteroskedastic (GARCH) models and the conditional covariances are modeled as nonlinear functions of the conditional variances. The conditional quasi-correlation parameters that weigh the nonlinear combinations of the conditional variances follow the GARCH-like process specified by Engle (2002).

This model can be written as:

$$y_t = Cx_t + e_t \quad (4)$$

$$e_t = H_t^{1/2}v_t \quad (5)$$

$$H_t = D_t^{1/2}R_tD_t^{1/2} \quad (6)$$

$$R_t = \text{diag}(Q_t)^{-1/2}Q_t\text{diag}(Q_t)^{-1/2}$$

(7)

$$Q_t = (1 - \lambda_1 - \lambda_2)R + \lambda_1\hat{e}_{t-1}\hat{e}'_{t-1} + \lambda_2Q_{t-1} \quad (8)$$

where,

y_t is an m x 1 vector of dependent variables;

C is an m x k matrix of parameters;

x_t is a k x 1 vector of independent variables;

$H_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix H_t;

V_t is an m x 1 vector of normal, independent, and identically distributed innovations;

D_t is a diagonal matrix of conditional variances.

Once again, all the estimations were performed using STATA 16.1.

3.3. The Data

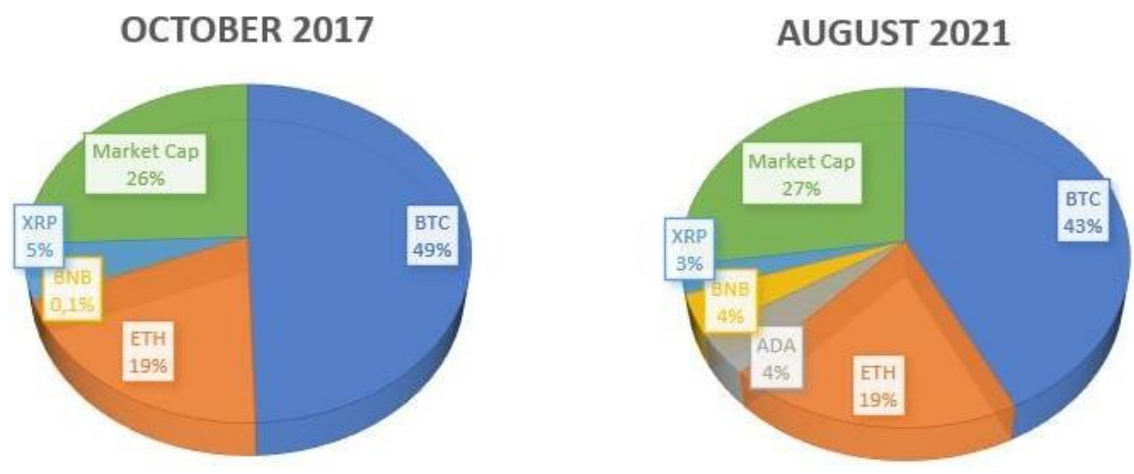
To investigate the price evolution and Bitcoin's return effects on other cryptocurrencies, daily time series from October 1st, 2017, to August 31st, 2021, were used – a total of 1431 observations. This dataset was retrieved from Yahoo Finance. The data starts on the 1st of October since Cardano ADA started trading that day. As shown in Figure 1, the 5 together capture more than 70% of the market.

Crypto's market cap saw an increase of over 1400% in these 4 years, it went from around $147B to over $2T. As seen in Figure 1, Bitcoin has always been a dominant force in the cryptocurrency market, decreasing from 49% to 43%. Ethereum has always been the number two, holding the same market capitalization. However, as we go further down the list, the cryptocurrencies fight for their place on the upper list, through the years the top 5 cryptocurrencies varied from the current ADA, BNB, and XRP, coins like DOGE and LTC have once been members of the top 5.

Detailed time series plots of cryptocurrencies used in this dissertation are presented in the appendix (both prices and returns, individually).

Source: Own elaboration based on collected data.

Figure 1 Market Share of Top 5 cryptocurrencies



4. Main Results and Discussion

4.1. General results

Table 2 presents the descriptive statistics for the logarithmic prices as well as for the returns of cryptocurrencies. The mean returns range from 0.001 to 0.004, whereas Ripple shows the lowest mean return and Binance the highest. In terms of standard deviation, the conclusion can be made that Bitcoin is the least volatile of the set, with 0.042, followed by Ethereum (0.053) and Cardano as the most volatile (0.073). These results are following previous studies carried that conclude that the high return and low risk of Bitcoin predetermine its dominance in the cryptocurrency portfolio (Hrytsiuk et al., 2019).

Table 2 Summary Statistics of top 5 cryptocurrencies

	Mean	Standard Deviation	Skewness	Kurtosis
Logarithmic prices				
Bitcoin	9.280	0.736	0.904	3.021
Ethereum	5.961	0.945	0.766	2.546
Cardano	-2.063	1.232	0.864	2.668
Binance	3.096	1.317	0.828	3.868
Ripple	-0.944	0.583	0.904	3.322
Returns				
Bitcoin	0.002	0.042	-0.816	14.926
Ethereum	0.002	0.053	-1.020	13.559
Cardano	0.003	0.073	1.794	23.163
Binance	0.004	0.065	0.392	16.190
Ripple	0.001	0.068	0.831	18.208

Based on the Skewness estimation, the Bitcoin and Ethereum series are skewed to the left – with Bitcoin being moderately skewed and Ethereum highly skewed -, while the other three are skewed to the right – where Cardano is highly skewed, Ripple moderately skewed and Binance's distribution is approximately symmetric. As for the Kurtosis statistic, all five cryptocurrencies are shown to be leptokurtic, since the statistic is greater than 1, meaning that the distributions have a flatter shape with fatter tails resulting in a greater chance of extreme positive or negative events. Considering this, Cardano achieved the higher kurtosis, also being the most volatile and the smallest kurtosis presents itself in Ethereum and not on Bitcoin. So, one can assume that although Bitcoin is less volatile, it presents a higher probability to peak, both high and low.

Figures A.1 to A.4 of the appendix show the volatility of the returns series over the analysis period. As shown in Figure 2, as Bitcoin's price peaks, so do its volatility since high peaks are followed by low peaks. From March 2021 to July 2021 Bitcoin's price rose more than 20 times, and in August 2021 had dropped close to 50% from its all-time high. These huge swings can be observed in every cryptocurrency, not just in Bitcoin.

In the graphs, the covid-19 effect can be seen around March 2021, when every cryptocurrency's return reached its lowest point, meaning their daily variation was significantly negative. This effect will be analyzed in the next chapters.

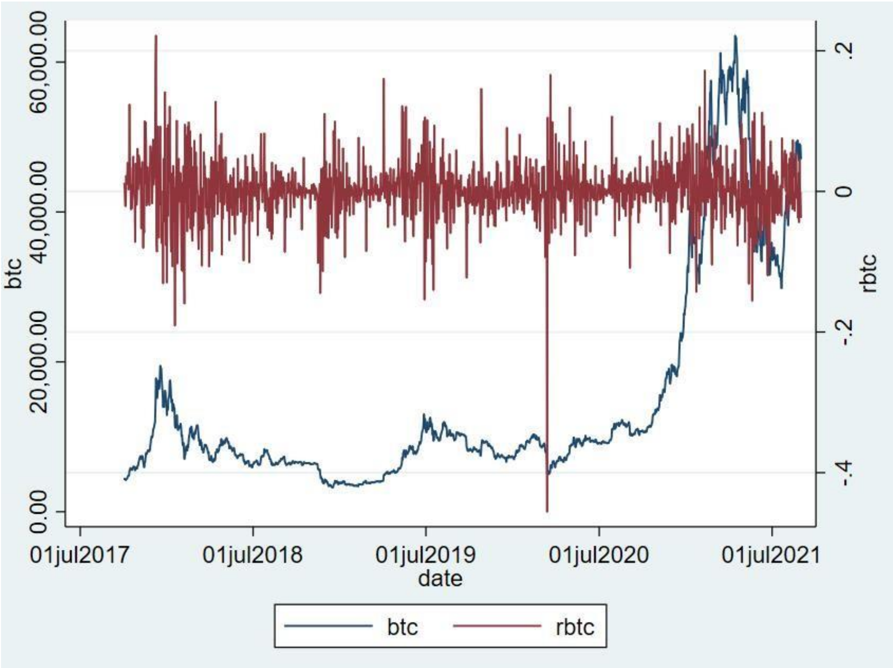


Figure 2 Bitcoin price and returns

The correlations of logarithmic prices and returns of the top five cryptocurrencies are shown in Table 3. Every cryptocurrency, apart from Ripple, are highly correlated. Bitcoin's most correlated crypto is Ethereum (88%), but the most correlated cryptos are Ethereum and Cardano (95%). Ripple demonstrates to be the least correlated with Binance (45%). Ripple is also the least correlated with Bitcoin, at 48%.

Table 3 Correlations of top 5 cryptocurrencies

	Logarithmic prices					**Returns**				
	Bitcoin	Ethereum	Cardano	Binance	Ripple	Bitcoin	Ethereum	Cardano	Binance	Ripple
Bitcoin	1	0.88	0.83	0.84	0.48	1	0.76	0.58	0.62	0.52
Ethereum	0.88	1	0.95	0.71	0.72	0.76	1	0.66	0.62	0.63
Cardano	0.83	0.95	1	0.77	0.80	0.58	0.66	1	0.50	0.60
Binance	0.84	0.71	0.77	1	0.45	0.62	0.62	0.50	1	0.45
Ripple	0.48	0.72	0.80	0.45	1	0.52	0.63	0.60	0.45	1

The returns of the cryptocurrencies are also positively correlated, with the highest being Bitcoin and Ethereum (76%) and the lowest Ripple and Binance (45%). As is the case for the logarithmic prices, the least correlated with Bitcoin is Ripple (52%). Figure 3 can be used to confirm this since the prices can be seen moving up and down together.

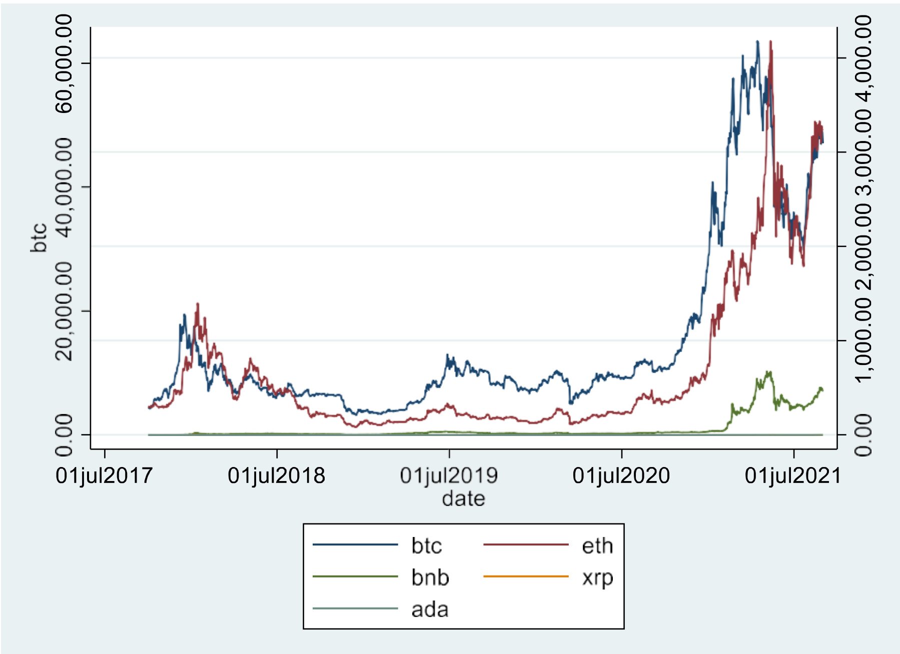


Figure 3 Prices of Bitcoin, Ethereum, Cardano, Binance, and Ripple

Based on the work of Pindyck and Rotemberg (1993), these correlations can be determined to be statistically significant, or not, by performing a likelihood ratio test of the hypothesis that the correlation matrix is equal to the identity matrix. This hypothesis gets rejected because as seen in Table 3 the correlation matrix is not an identity matrix.

The first step in volatility modeling is to test for the presence of a stochastic trend - a unit root - in the autoregressive representation of each series. Thus, a set of unit root and stationary tests of the logarithmic prices of each cryptocurrency was performed. Both the Augmented Dickey-Fuller (ADF) and the Phillips–Perron (PP) cannot reject the null hypothesis of the presence of a unit root as shown in Table 4, suggesting that all logarithmic price series are nonstationary. Lastly, for the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) the null hypothesis is rejected, concluding that each of the five cryptocurrencies logarithmic prices series is nonstationary. The same tests were performed for the returns, the null hypothesis of the ADF and PP are rejected, and the KPSS cannot be rejected, for Bitcoin, Ethereum, and Ripple, suggesting that for these three the returns are stationary.

Table 4 Unit root and stationary tests

	ADF	PP	KPSS
Logarithmic prices			
Bitcoin	-1.224	-1.361	2.57
Ethereum	-0.482	-0.66	3.33
Cardano	-0.549	-0.826	2.78
Binance	-1.385	-1.527	1.51
Ripple	-2.018	-2.262	1.96
Returns			
Bitcoin	-25.701	-39.137	0.0822
Ethereum	-25.433	-39.998	0.0872
Cardano	-23.499	-38.028	0.167
Binance	-25.347	-38.022	0.154
Ripple	-25.128	-37.374	0.0681

4.2. Impacts of the COVID-19 pandemic

The COVID-19 pandemic outbreak started in 2019 in China, and it affected the rest of the world during the year 2020. As a way to prevent the spread of the virus, people were confined in their homes and the world shut down, which brought catastrophic consequences to the modern society that are felt up to this date. The effects of this pandemic are evident in all areas and sectors and no world economy has escaped unscathed. The cryptocurrency market is no exception, and therefore it then becomes relevant to understand what damage has been left behind by this pandemic. To prove the importance of the covid in the crypto market, a Supremum Wald test for a structural break was performed in every currency. The results for this test are as presented in Table 5.

Table 5 Results from the Supremum Wald structural test

Currency	Break date
Bitcoin	18/03/2020
Ethereum	18/03/2020
Cardano	18/03/2020
Binance	13/12/2020
Ripple	01/01/2021

For Bitcoin, Ethereum and Cardano, the break date is March 2020, which is the month that Covid shuts every economy in the world into quarantine. For Binance and Ripple, although Covid's impact was still felt, bigger events were happening for each, for Binance there was an innovation revolution happening in the platform making its price jump to new all-time highs overnight, for Ripple was the lawsuit pressed by USA's Securities and Exchange Commission (SEC) announced in late December of 2020.

As done previously, the returns were calculated, separating the data in two – from 1st of October 2017 to 28th of February 2021 and from 1st of March to the 31st of August 2021. The results are shown in Table 6.

Right away, it is visible that the pre-Covid period has slightly no variances from the entire data, which might be justified for the short amount of data on the Covid period. However, the 184 samples in analysis for the covid period allow some interesting conclusions.

Table 6 Summary Statistics of top 5 cryptocurrencies - Covid period comparison

	Mean	Standard Deviation	Skewness	Kurtosis
Pre-covid				
Logarithmic prices				
Bitcoin	9.070	0.519	0.954	4.916
Ethereum	5.694	0.678	0.652	2.738
Cardano	-2.422	0.857	0.813	3.239
Binance	2.681	0.802	-0.646	5.654
Ripple	-1.058	0.516	1.282	5.019
Returns				
Bitcoin	0.002	0.042	-0.909	16.571
Ethereum	0.001	0.052	-1.091	14.721
Cardano	0.003	0.074	2.009	24.997
Binance	0.004	0.064	0.633	17.579
Ripple	0.001	0.065	1.025	21.812
Covid				
Logarithmic prices				
Bitcoin	10.708	0.218	-0.109	1.576
Ethereum	7.774	0.239	0.232	2.316
Cardano	0.365	0.237	1.283	4.161
Binance	5.903	0.287	0.460	2.203
Ripple	-0.174	0.396	0.099	1.863
Returns				
Bitcoin	0.0002	0.042	-0.204	4.185
Ethereum	0.004	0.060	-0.723	8.351
Cardano	0.004	0.069	-0.070	5.566
Binance	0.004	0.073	-0.772	9.749
Ripple	0.005	0.086	0.138	7.365

The mean daily return of Bitcoin is close to 0, so although this crisis had huge highs and lows, the currency was able to maintain its value. As for the other coins, there is a significant increase in the mean daily returns of all of them but mainly Ripple, which increased 500%, from 0.001 to 0.005.

Despite the fact that March was a very negative month, in terms of returns, there was a very fast recovery, as seen in figures 2 and A1 to A4. It was such a recovery, that every currency reached its all-time high during the covid period.

Table 7 Mean daily volatility - pre-COVID vs COVID

	BTC	ETH	ADA	BNB	XRP
Pre-COVID	0.002	0.003	0.003	0.003	0.003
COVID	0.002	0.004	0.004	0.004	0.004

During the COVID period, the crypto market has also seen a general increase in the mean daily volatility. As seen in Table 7, apart from Bitcoin that has seen pretty much the same volatility in pandemic time compared to its normal values, all the other four cryptocurrencies have seen an increase of close to 33% in the daily volatility.

4.3. Univariate GARCH Modeling

Following the study previously done by Liu and Serletis (2019), a univariate GARCH model was performed for every cryptocurrency. The conditional variance enters into the conditional mean equation as well as the error. The results are presented in Table 8.

For Bitcoin, there are not any statistically significant GARCH-in-mean effects. This result is following previous studies, like Liu and Serletis (2019), where they argued Bitcoin could be integrated with other cryptocurrencies and financial markets, and so exposed to the market innovations and macroeconomic shocks. These results might also indicate the weak relation between Bitcoin's volatility and its price. These results are under the current literature's findings that Bitcoin is losing its safe-haven characteristics and so is getting more and more susceptible to shocks of financial markets (Hussain Shahzad et al., 2020).

Although it is not statistically significant, the negative might indicate that the mean returns decrease when there is a greater risk. The assumption that the mean return of Bitcoin is dependent on risk is not achievable with this

GARCH-in-mean model. The empirical estimates of the price evolution of Ethereum are reported in Table 8 and close to all the coefficients in the mean equation are statistically significant.

Table 8 Univariate GARCH-in-mean models

Coefficient	Bitcoin	Ethereum	Cardano	Binance	Ripple
A. Conditional mean equation					
Constant	-0.002 (0.631)	-0.004 (0.248)	0.007 (0.048)	0.002 (0.246)	0.000 (0.826)
r_{t-1}	0.469 (0.318)	0.003 (0.980)	0.210 (0.660)	0.140 (0.406)	-0.296 (0.000)
r_{t-2}	0.495 (0.290)	-0.661 (0.000)	0.200 (0.613)	0.832 (0.000)	-0.950 (0.000)
$\in_{t-1}$	-0.499 (0.301)	-0.024 (0.835)	-0.251 (0.601)	-0.163 (0.378)	0.318 (0.000)
$\in_{t-2}$	-0.445 (0.352)	0.741 (0.000)	-0.130 (0.745)	-0.805 (0.000)	0.981 (0.000)
Dummy	0.005 (0.141)	0.007 (0.012)	0.010 (0.010)	0.007 (0.061)	-0.006 (0.122)
h_t	2.698 (0.207)	2.710 (0.127)	1.293 (0.114)	0.659 (0.311)	0.547 (0.201)
B. Conditional variance equation					
Constant	0.001 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.003 (0.000)
$\in_{t-1}$	0.110 (0.011)	0.137 (0.000)	0.105 (0.000)	0.184 (0.000)	0.247 (0.000)
$\in_{t-2}$	-0.034 (0.480)	-0.041 (0.321)	0.092 (0.000)	0.130 (0.000)	-0.218 (0.000)
h_{t-1}	0.810 (0.010)	0.423 (0.024)	-0.089 (0.004)	-0.056 (0.008)	1.159 (0.000)
h_{t-2}	0.098 (0.726)	0.424 (0.008)	0.766 (0.000)	0.684 (0.000)	-0.204 (0.000)
$\in^2_{t-1} I_{t-1}$	-0.021 (0.630)	0.012 (0.772)	0.006 (0.845)	-0.73 (0.016)	0.428 (0.000)
$\in^2_{t-2} I_{t-2}$	-0.015 (0.730)	-0.031 (0.399)	0.065 (0.037)	0.125 (0.002)	-0.393 (0.000)
Dummy	-0.191 (0.048)	0.007 (0.012)	0.009 (0.010)	0.007 (0.061)	-0.006 (0.122)
Log likelihood	2636.378	2305.98	1915.268	2150.651	2151.698

Note: Values in (.) stand for p-values.

The constant term is −0.004 and statistically significant. Bollerslev et al. (1986) argue that the negative expected excess return on the market portfolio may be attributed to the preferential tax treatment on capital gains. Because of a lower tax on capital gains of the cryptocurrency, investors have the incentive to hold the market portfolio even when its gross expected excess return is negative. The negative intercept could also be an artifact of approximating a nonlinear relation with a linear function. Trend-wise, there seems to be a close relationship between the results of Ethereum and Bitcoin. Their results show that, although external shocks might also affect Ethereum's returns and price, there is a strong effect of past returns on current returns. The dummy variable shows that the mean returns are higher in the pre-covid period when compared to the later samples. For Cardano's equation, the constant proves to be statistically significant, which might suggest that the mean returns are dependent on risk. The Dummy is also statistically significant and positive, this result indicates that the mean return before the break - in Cardano's case represented by COVID-19 – is 0.1% higher than the daily return over the whole sample period. Binance's conditional mean equation's variables are all statistically significant. When comparing the ARCH and GARCH effects, the conclusion can be made that the impact of old news is higher than the impact of recent news on the volatility.

In the case of Ripple, the Dummy variable is negative, suggesting that the mean return before the break is 0.6% smaller than the daily return over the whole sample period. This might be explained because of the type of break in the Ripple since this was due to negative news concerning Ripple, which was then involved in a lawsuit. Once the lawsuit was over and Ripple seemed to have come on top of it, there was an explosion in price. In this case, the conditional mean equation's variables are all statistically significant, which might indicate that the mean returns are positively dependent on risk.

The results from the univariate GARCH model allow for the conclusion that for the set of five cryptocurrencies being studied, past returns, the impact of news and innovation do not account for good and reliable indicators of their returns. Since this is the case, a multivariate GARCH model will be designed in the next subsection to, mainly, see the impact of each crypto's volatility and returns in the other cryptocurrencies' returns.

4.4 Multivariate GARCH Model

Already set as a well-established model in current literature, the multivariate GARCH model is used to analyze how different cryptocurrencies behave with one another in volatility. The model was used with Bitcoin as the basis, meaning the results obtained will allow concluding whether the rest of the cryptocurrencies' volatility is influenced by Bitcoin's. The results are shown in Table 9.

In Table 9 the effects of volatility on returns can be seen for each currency. When analyzing each cryptocurrency with itself the conclusion can be made that the higher the volatility the higher the returns. This conclusion, however, cannot be made for Ethereum since it has achieved a not statistically significant negative value throughout estimations.

Table 9 Cryptocurrencies' volatilities effect on returns

	BTC returns	ETH returns	ADA returns	BNB returns	XRP returns
BTC variance	0.839 (0.004)	-1.349 (0.000)	-0.562 (0.000)	-0.522 (0.000)	-0.048 (0.000)
ETH variance	-1.663 (0.000)	-0.187 (0.439)	-1.943 (0.000)	-2.264 (0.000)	-1.522 (0.000)
ADA variance	0.248 (0.000)	0.227 (0.000)	1.820 (0.000)	0.220 (0.000)	0.351 (0.000)
BNB variance	-0.408 (0.000)	-0.759 (0.000)	-0.765 (0.000)	0.693 (0.000)	-0.942 (0.000)
XRP variance	0.059 (0.346)	-0.073 (0.972)	-0.058 (0.449)	-0.082 (0.318)	1.581 (0.000)
Arch	0.136 (0.000)	0.122 (0.000)	0.233 (0.000)	0.192 (0.000)	0.370 (0.000)
Garch	0.847 (0.000)	0.850 (0.000)	0.752 (0.000)	0.823 (0.000)	0.680 (0.000)
Constant	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)

Note: Values in (.) stand for p-values.

Bitcoin's variance impacts all the other cryptocurrencies negatively, meaning that the higher the volatility the lower returns the other cryptocurrencies present. These results are following previous literature that, also, proves Bitcoin's great influence on other coins, acting as a shock transmitter to all other cryptocurrencies (Moratis, 2021). This effect is greater for Ethereum (-1.349) and smaller in Ripple (-0.048), which can be seen in Table 10 where the returns of Bitcoin and Ethereum are the most correlated and Bitcoin and Ripple the least. Ethereum variance reveals the same, however on a much greater scale, more impact of the volatility, which is more visible on Cardano and Binance cryptos. The relation between Ethereum, Cardano, and Binance is, in itself, an interesting case study, since all serve the same purpose of being an incubator to new and fresh crypto projects. This makes them "direct competitors" and so it makes that there is a great impact of the volatility, as well as high values of correlation between its returns, presenting the higher correlation of the whole set of cryptocurrencies in Ethereum with Cardano of 0.913.

Cardano’s variance impacts positively and statistically significantly the other four cryptocurrencies, making their returns thrive off of Cardano's volatility. The impact, despite being positive, is small for every cryptocurrency with the highest being Ripple with 0.651. Binance’s variance follows the same pattern as Ethereum’s but on a smaller scale, the most relevant impact is on Ripple with -0.942.

Table 10 Correlation matrix of returns – MGARCH DCC (Dynamic conditional correlation multivariate GARCH model)

	rBTC	rETH	rADA	rBNB	rXRP
rBTC	1	0.905	0.858	0.855	0.825
rETH	0.905	1	0.913	0.890	0.890
rADA	0.858	0.913	1	0.857	0.879
rBNB	0.855	0.890	0.857	1	0.845
rXRP	0.825	0.890	0.879	0.845	1

As previously stated, Binance’s correlation of returns is greater for Ethereum and Cardano. Finally, Ripple’s variance proves to be not statistically significant, not allowing for any relevant conclusion. The return correlation between these two is also the lowest value achieved of 0.825. Regarding the other cryptocurrencies, Ripple also proves to not be statistically significant with either of them.

As seen in Table 7, COVID-19 caused an increase in market volatility. As in this chapter was proved that the higher the volatility, the higher the returns, the COVID-19 can serve as a small sample to analyze this. With the help of Table 6, Ethereum, Cardano, and Ripple have increased their mean daily returns, Cardano has maintained them, and Bitcoin has decreased the returns, keeping them positive, nonetheless.

5. Conclusion

The price of cryptocurrencies and their returns have become of great concern to investors and policymakers. What started as an idea to revolutionize the way payments were made, has now become one of the most valuable asset categories. Bitcoin alone has a greater market cap than the GDP – Gross Domestic Product - of 96 countries. With this exponential growth over the last decade, world rulers have started to look at this non-taxed asset as an unstoppable enemy to their fiat currencies. Attempts to "kill" cryptocurrencies have completely backfired, for example, China has already banned cryptocurrencies 18 times and it has only made cryptos even stronger.

This work aims to shed some light on the way how cryptocurrencies behave and correlate with each other. It is divided into two major econometric models: (i) a univariate GARCH model where each cryptocurrency's returns were analyzed concerning past returns, impact of news, and innovation; and (ii) a multivariate GARCH model that uses the variances of each cryptocurrency to see if and how it impacts their returns. This last model also provided the correlation matrix for every pair of returns, allowing for a deeper analysis of returns impacts.

The first model had almost every variable not statistically significant, which considering the current literature made sense, in the way that Bitcoin's past returns do not justify or are a good tool to predict future returns. Using data from the stocks markets, the forex market, or the commodities market, better results are expected. For Ethereum, Binance, and Cardano the results were very similar to Bitcoin's, again as is well documented in the literature, most cryptos follow the same trend as Bitcoin and so basing predictions of returns on past returns should not be effective. Finally, for Ripple, the situation is different, since most of the variables found are statistically significant, which might indicate an "abnormality" in the crypto market – crypto that might not follow Bitcoin's trend as well as the others. This can be justified by the difference in the nature of this coin, as it is the most centralized of the set and since it is associated with a private company, Ripple can easily be manipulated and controlled, as well as sued, which was the case in December of 2020.

The second model builds upon bridging the gaps and correcting the malfunctions of the first model. In this equation, the returns of each crypto are related to the volatility of all the others. The main conclusion this model should show is the great impact of Bitcoin’s variance in the other cryptocurrencies, a hypothesis that was proved valid. Another interesting interaction is Ethereum’s variance impact on Cardano and Binance’s returns and vice versa. Cardano came out as the only one whose variance positively impacts the rest. Once again, XRP’s results vary from the bunch, results showing close to no impact of crypto’s variance on its returns. Globally, this speculative market thrives with high volatility since all currency’s returns are greatly and positively impacted by their volatility. In terms of returns correlations, a highlight to every pair of Ethereum, Cardano, and Binance, that present high correlation and also Bitcoin and Ethereum.

The analysis for the COVID-19 period revealed to be a necessity because Bitcoin, Ethereum, and Cardano had a structural break in March of 2020. In the early stages of lockdown and as FUD – Fear, Uncertainty, and Doubt – started spreading through every market, cryptocurrencies witnessed massive crashes and fast recoveries. This phenomenon increased volatility, however, only allowed for the thriving of the market and new all-time highs recorded not long after.

As with any other research work, this investigation has also encountered some limitations. The main one was the lack of literature regarding this specific set of coins and very limited daily data to retrieve. When testing the modules and noticing the results, these were all non-significant for the univariate GARCH model, the scarce literature presented a huge obstacle since it was not clear how it would be feasible to justify the results achieved.

Bearing in mind the results and discussion presented throughout this research, and the limitations previously pointed, future work may encompass a broader scope of work on Bitcoin’s external factors impacting its price and returns. Furthermore, it suggested to study also, the “outsider” crypto of this study – Ripple – that achieved quite different results from the others, and can be more thoroughly investigated.

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Appendix

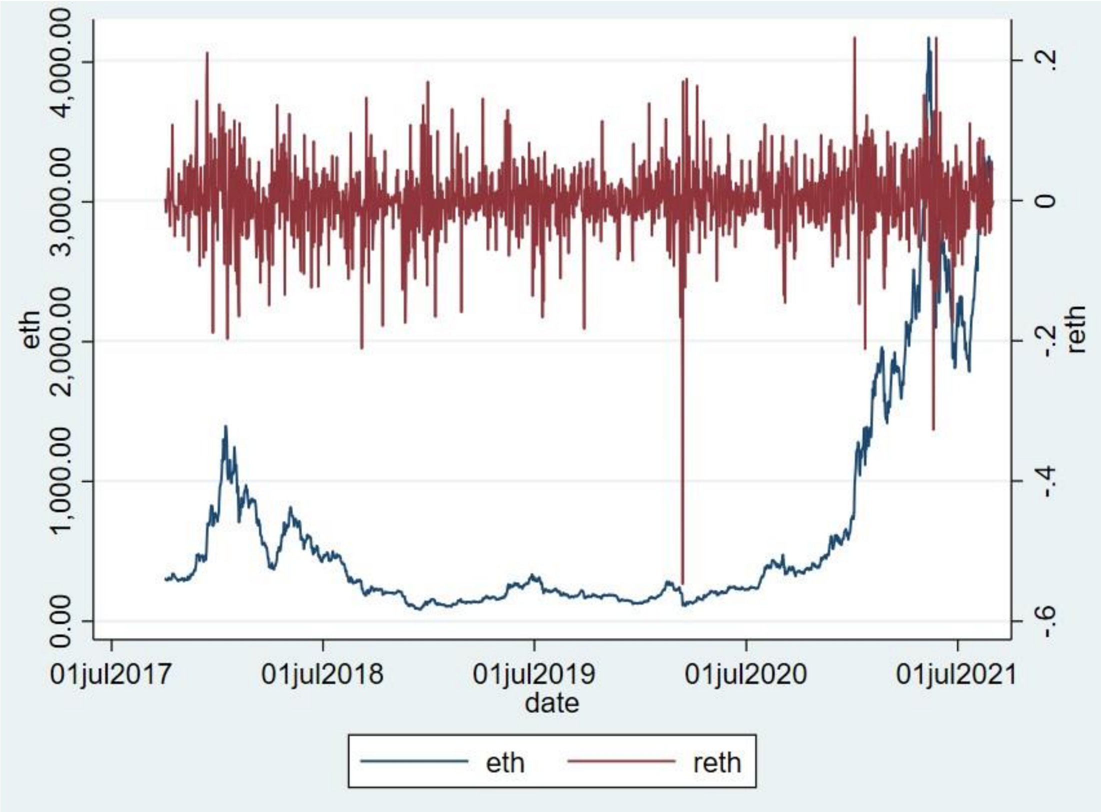

Figure A.1 Ethereum price and returns

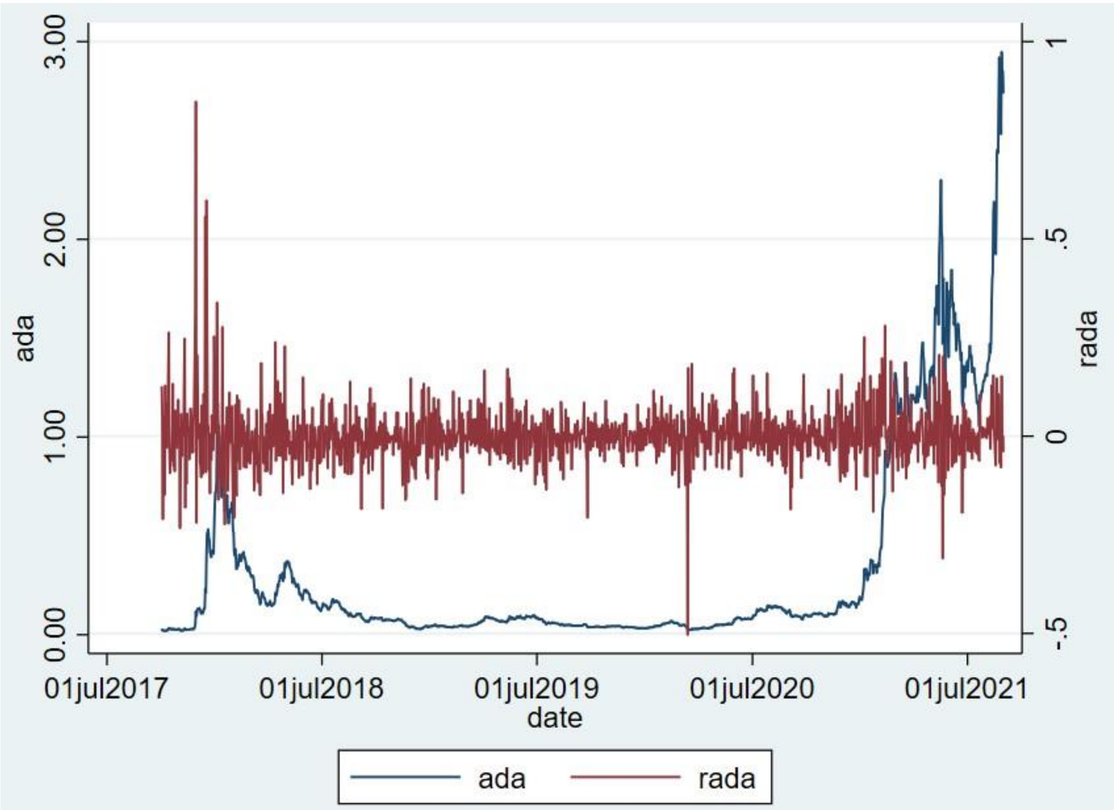

Figure A.2 Cardano price and returns

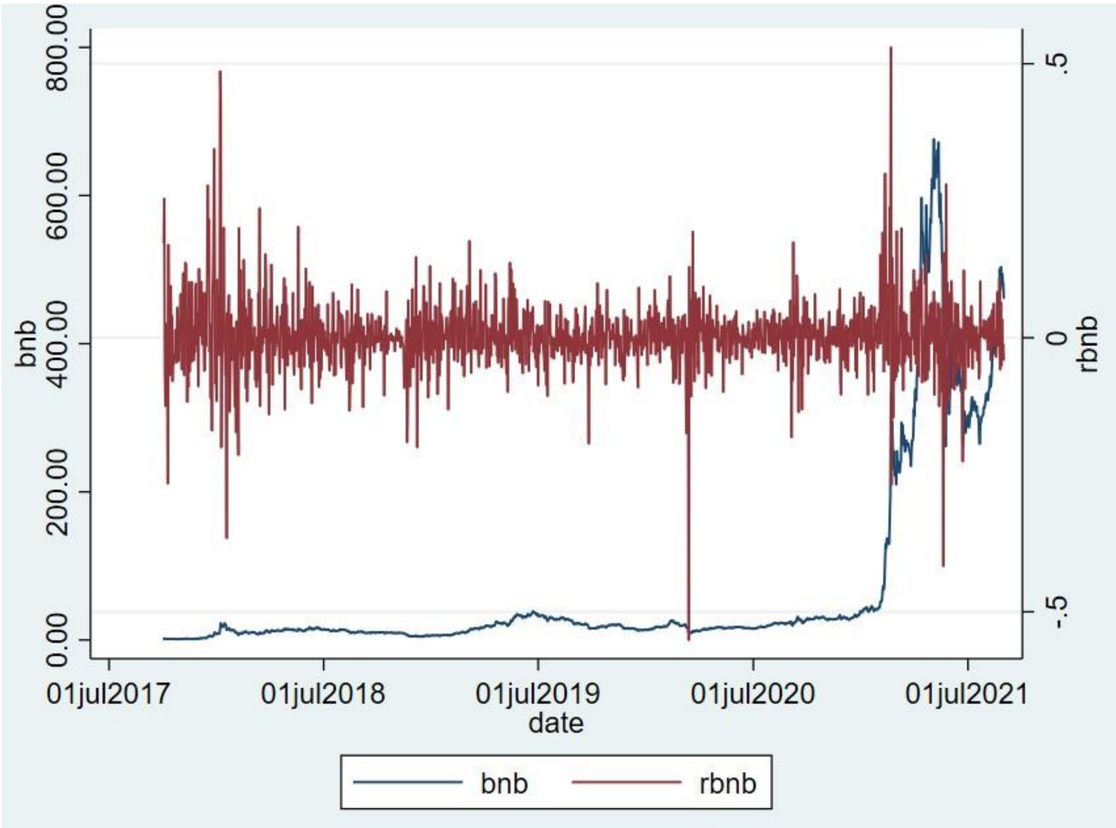

Figure A.3 Binance price and returns

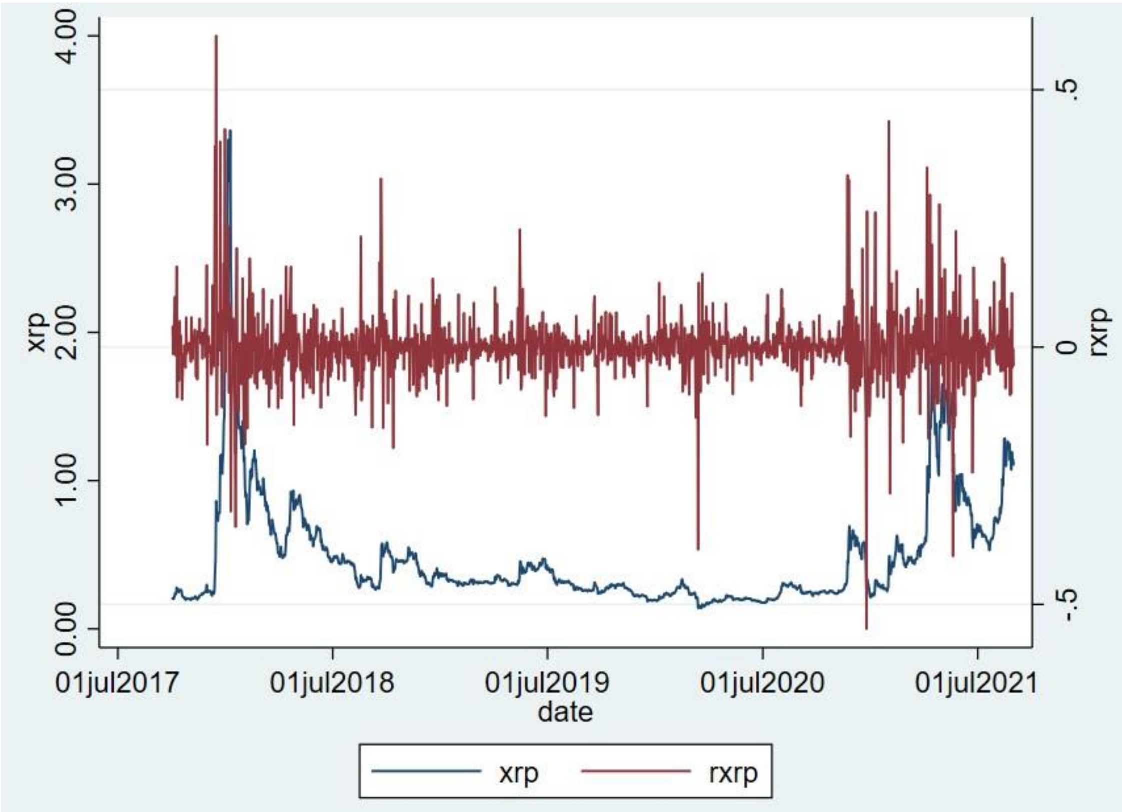

Figure A.4 Ripple price and returns