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MARCO JOSÉ COSTA DOS SANTOS

CRIPTOMOEDAS: RETORNO, RISCO, PERFOMANCE, RELAÇÃO COM OUTROS ATIVOS E COMPOSIÇÃO DE CARTEIRAS DE INVESTIMENTO – DESAFIOS COVID

CRYPTOCURRENCIES: RETURN, RISK, PERFOMANCE, RELATIONSHIP WITH OTHER ASSETS AND COMPOSITION OF INVESTMENT PORTFOLIOS – COVID CHALLENGES

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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 Silva Madaleno, Professora Auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro, e sob a coorientação científica do Doutor Júlio Fernando Seara Sequeira da Mota Lobão, Professor Auxiliar da Faculdade de Economia da Universidade do Porto.

Para os/as cripto-entusiastas.

o júri

presidente

Prof. Doutora Marta Ferreira Dias
professora auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro

Prof. Doutor Vasco Jorge Salazar Soares
professor auxiliar da Universidade Portucalense

Prof. Doutora Mara Teresa da Silva Madaleno
professora auxiliar do Departamento de Economia, Gestão, Engenharia Industrial e Turismo da Universidade de Aveiro

agradecimentos

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Palavras-chave

Efeitos de contágio; Criptomoedas, Forex, Índices de Mercado; Carteiras ótimas, Correlação de Pearson, MGARCH, Função Resposta Impulso

Resumo

As criptomoedas têm vindo a ganhar cada vez mais espaço na vida académica e, especialmente, dos investidores. Este mercado ainda está pouco maturado, uma vez que atingiu agora uma década de existência apenas. No geral, as cryptomoedas tiveram uma performance impressionante ao nível dos retornos, apesar de apresentarem ainda uma enorme volatilidade. Sendo um ativo interessante em termos de investimento, importa perceber a sua performance risco-retorno, a relação com outros ativos financeiros (e.g.: mercado cambial e índices bolsistas), e o impacto da sua inclusão em portfolios de investimento.
Nesse sentido usamos a correlação de Pearson para testar a relação entre as variáveis da mesma classe de ativos e para perceber os que são mais semelhantes, estudamos a *Impulse Response Function* (IRF) para perceber o impacto que um choque num ativo gera no outro, e por fim aplicamos o modelo multivariado GARCH para perceber as conexões existentes em termos de volatilidade. Para estimar as carteiras de investimento ótimas recorremos ao modelo de Markovitz e ao Índice de Sharpe. Todas estas aplicações consideraram o período de 2015 a 2021, sendo que o período do COVID-19 foi também analisado separadamente. As criptomoedas em estudo são: Bitcoin, Ethereum, Ripple, Litecoin, Dash, Stellar, Monero, Dogecoin, Verge, NXT. As moedas fiduciárias analisadas são: dólar americano, euro, libra esterlina, yen japonês, dólar australiano, franco suíço, dólar canadiano e o dólar neozelandês. Em termos de índices bolsistas incluímos o S&P500, STOXX 50, FTSE 100, NIKKEI 225, ASX 200, SMI, TSX e NZX 50.
Durante as etapas desta investigação concluímos que o mercado forex e dos índices bolsistas ainda não têm grande relevância na tendência do preço das criptomoedas, e vice versa. Verificou-se também que o mercado das criptomoedas é mais interligado do que o das outras classes de ativos, sendo que os impactos dos choques ocorridos nos ativos digitais são mais acentuados do que em todos os outros. Ao nível da volatilidade acontece o mesmo. Relativamente ao portfolio ótimo podemos notar que, incluindo o índice americano S&P500 e ouro numa carteira, a melhor solução é deter 20% de Bitcoin e 7% de Ethereum simultaneamente. Com a chegada da pandemia, todos os pontos anteriores ficaram ainda mais salientes e a recomendação para a presença de criptomoedas nas carteiras ótimas é também superior em termos percentuais.
Este estudo permitirá aos investidores terem mais informação no processo de tomada de decisão dos seus investimentos e permite ainda aos decisores políticos perceber um pouco melhor as tendências evolutivas das criptomoedas, tendo em vista a sua futura regulação e eventual adoção para o sistema monetário.

Keywords

Contagion effects, Cryptocurrencies, Forex, Stock Indexes, Optimal portfolios, Pearson correlation, MGARCH, Impulse Response Function.

Abstract

Cryptocurrencies have been increasing their relevance in academic life and, especially, among investors. This market is still not mature, as it has now only reached a decade of existence. However, cryptos performed impressively in terms of returns, despite having strong volatility. As an interesting asset in terms of investment, it is important to understand its risk-return performance, the relationship with other financial assets (e.g.: forex and stocks), and the impact of its inclusion in investment portfolios.

Therefore, we use Pearson's correlation to test the relationship between variables of the same asset class, and to see those that are more similar, we study the Impulse Response Function (IRF) to understand the impact that a shock on one asset generates on the other, and finally, we apply the multivariate GARCH to evaluate the existing connections in terms of volatility. To estimate the optimal investment portfolios we use the Markovitz model and the Sharpe Ratio. All these phases were carried out for the period from 2015 to 2021, and the period of COVID-19 was also analyzed separately. The cryptocurrencies that will be studied are Bitcoin, Ethereum, Ripple, Litecoin, Dash, Stellar, Monero, Dogecoin, Verge, NXT. The fiat currencies in the analysis are the American dollar, euro, British pound, Japanese yen, Australian dollar, swiss-franc, Canadian dollar, and New Zealand dollar. In terms of stock indexes we use S&P500, STOXX 50, FTSE 100, NIKKEI 225, ASX 200, SMI, TSX e NZX 50

During the phases of this research work, we concluded that the forex market and stock indexes still do not have great relevance in the cryptocurrency price trend and vice versa. It was also found that the cryptocurrency market is more interconnected than other asset classes, with the impacts of shocks occurring in digital assets is more accentuated than in all others. The same happens for volatility. Regarding the optimal portfolio, we can note that, including the American S&P500 index and gold in a portfolio, the best solution is to hold 20% of Bitcoin and 7% of Ethereum as well. With the arrival of the pandemic, all the previous points became even more salient and the presence of cryptocurrencies in the optimal portfolio is also greater.

This study will allow investors to have more information in the decision-making process for their investments and will also allow policy makers to better understand the evolutionary trends of cryptocurrencies, considering its future regulation and eventual adoption for the monetary system.

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1. Introduction

Following recent news, amid global health and economic crisis caused by the spread of COVID-19, the forex market is experiencing heightened levels of volatility and thinner liquidity, thus turning interesting the analysis of this effect (Huang, 2021). As well, digital currencies have also been affected, falling in value, and therefore moving in the same direction as more traditional assets. Many market analysts portrayed Bitcoin as a safe haven during times of geopolitical uncertainty and during the pandemic we observe digital currency's price moving in the same direction as other stocks. However, Bitcoin does not correlate exactly with other assets in the financial market and this price drop in the same direction as with other stocks might have been simply a temporary occurrence.

Our object of study will be more specifically the forex market and the cryptocurrency market. In this dissertation, we will analyze the period between 2015 and 2021 because it is difficult to obtain historical data of cryptocurrencies before that year once these are recent assets. With this period of analysis in mind, we will also be able to insert the recent COVID-19 effects into the analysis to see if these impacts imposed changes considering or the forex market or the cryptocurrency market as well.

The beginning of 2017 coincided with the Bull Run period of cryptocurrencies, which were valued quite daily and were captivated by investors. However, these first periods coincided with the creation of hundreds of new projects and currencies, which made this market very dispersed and ambiguous (Kyriazis, 2021; Wang, 2021).

The money market is the most liquid in the world (Sornmayura, 2019). It is a market that covers almost all countries of the globe, while cryptocurrencies are not adopted worldwide, although they continue to grow. In this sense, it is important to understand the evolutionary process of currencies, which are moving more and more from physical to digital (Biagio, 2021).

The latest empirical studies of cryptocurrencies demonstrate that these virtual currencies are still very volatile and not very stable, which is important for reserving value and maintaining the trust of its users. Even so, we believe that with the consolidation of crypto markets, these could be alternatives to fiat currencies. With this work, we intend to reach new conclusions given the greater maturity of the emerging markets and to update or complement the existing literature, in the sense of being able to help the political and governmental decision-makers, because up to the moment there is no great regulation on a worldwide scale (Nabilou, 2019).

If investors want to invest/speculate on this new asset class, it is important that they also choose diversity. Thus, the central questions and the main motivation of this work are the following: should investors diversify only within the forex using currencies or only within the cryptocurrency class? Is it worth diversifying between these two currency groups? Empirical studies to date have suggested that Bitcoin has only a limited correlation with other assets, although the data used ends in approximately 2015. This limited correlation is true for other cryptocurrencies as well? Our main contribution to the already existent literature relates as well to diversify our analysis, in both the period analyzed and in the number of cryptocurrencies and FX currencies included in the analysis.

The existing literature suggests that cryptocurrencies despite having high returns are also associated with high volatilities in their price (Dyhrberg, 2016a; Koutmos, 2018; Kurka, 2019; Urquhart & Zhang, 2019; Rognone et al., 2020a), which is not beneficial for incorporating them in investment portfolios. Some analysts referred to the divergence of stocks and Bitcoin as the "decoupling" (Drozdz et al., 2019; Sifat, 2021). If an investor who holds bonds and equities swapped a percentage of their prior holdings into Bitcoin, because of Bitcoin's low correlation and superior absolute performance, they could have decreased the volatility of the portfolio while simultaneously increasing absolute returns. At this point of view, it is better and safer to have forex currencies in our portfolios. One of our goals is to examine empirically if cryptocurrencies have stabilized their performance.

Another evidence that is intended to be checked is the existence of some contagion effect between crypto and fiat currencies, especially with those whose main function is the payment method and/or value reserves like Bitcoin, Dash, and Litecoin for example. One of the objectives of this investigation is also to contextualize the performance of the two types of assets with the macroeconomic state during the analysis period. It will also be desirable that public policy recommendations emerge at the end of the work.

To sum up, this work's main goal is to study the contagion and correlation effects between crypto and forex. For that, an empirical analysis about diversification and volatility between the two asset classes will be performed, and given the period under analysis, we will also be able to include recent macroeconomic scenario impacts into analysis, namely the recent pandemic.

The rest of the work develops as follows. Chapter 2 provides a brief literature review to justify the research questions and objectives of this work. Chapter 3 presents both the Methodology and Data used, while chapter 4 exposes all the results and discusses them. Finally, chapter 5 concludes this work pointing policy directions, limitations, and future research directions.

2. Literature Review

Cryptocurrencies have attracted significant attention from the general public, investors, and policymakers in past years, mostly in the latter 2019. Some people focus on the new technology, while others focus on huge returns, and that explains the need for new studies that include other types of crypto to identify whether cryptocurrencies, in general, assume similar trends as compared to other financial assets. Nonetheless, previous studies report that Bitcoin is very weakly correlated with other instruments and assets (Dyhrberg, 2016a; Ji et al., 2018).

2.1. Digital vs. Physical money

Currency has a set of properties to be considered valid, whatever the format they are - physical, electronic, virtual. McLeay et al. (2014) listed the 3 functions of money: unit of account, medium of exchange, and value storage. In general, all cryptocurrencies have these properties and can, therefore, be considered in the currency category. However, each cryptocurrency has its focus on one or more features. Bitcoin has special utility as a medium of exchange and reserve of value for example. If a coin combines the 3 properties well it will tend to be more valuable (Borgonovo et al., 2018), as it will serve for more things. This justifies the constant technological updates in the cryptocurrency network of cryptocurrencies and the different valuations.

Before going deeper into the subject of cryptocurrencies, it is important to mention that there are still some ideological factions around the theme (Koutmos, 2018). On the one hand, there are plenty of crypto-enthusiasts who believe that this will be the future and it will revolutionize the monetary system as we know it, and these people have an enormous fear of missing out – FOMO (Wong et al., 2018). On the other hand, many skeptics and conservatives, who do not trust in blockchain and digital currencies (especially policymakers), believe that there is no way to change the conventional form of physical money to give a turn to speculative and insecure assets with a high probability of cyberattacks (Cheah & Fry, 2015). In fact, after six years of its creation, Bitcoin was worth $ 19,000 at the end of 2017 (Molloy, 2019), in contrast to the April 2011 values it was worth $ 1 - tremendous returns.

There are many differences between the fiat currencies of the FX Market and cryptocurrencies or digital currencies. The first has to do with their ownership. While cryptos are mostly anonymous and only controlled by their creators (Low & Teo, 2017), fiat currencies are managed by governments or central banks (Dang, 2019). The sample of this work has the presence of only two centralized cryptocurrency exceptions: Ripple and Stellar. It is also important to note that in July 2019, Bitcoin was the dominant digital currency compared with other cryptocurrencies, with a market capitalization of around $217 billion and covering 63.4% of the entire cryptocurrency market (Rognone et al., 2020b), which justifies why most of the time we focus on the BTC and generalize the comments to the other cryptos.

2.2. Cryptocurrencies and the future of the monetary system

Cryptocurrencies are changing the financial and banking paradigm (Böhme et al., 2015). Their increased use as a payment method and as a reserve of value gives it the status of a currency. Besides that, they have some characteristics that fill the failures of the current monetary system, such as the inability of manipulating currency prices by “money printing” (Hussain Shahzad et al., 2020) or control the money supply. While in fiat currencies the government can define the interest rate, liquidity, money supply, and the velocity of money (Dang, 2019), in decentralized cryptocurrencies this does not happen. Roubini (2018) is one of the biggest critics because he considers cryptos a utopia and will be an economic hell, calling Bitcoin the "mother of bubbles".

Therefore, there is already econometric evidence that economic conditions do not directly affect the ability to control speculative behavior or bubbles in crypto markets, and the Economic Policy Uncertainty Index has not influenced the high levels of volatility either (Papadamou et al., 2021). These conclusions are in line with the highlight of this study, which reinforces the idea of non-linear dependence between cryptos, gold, and financial markets (Lahiani et al., 2021).

A recent study by Othman et al. (2021) concludes that it is especially during crises that makes sense to include Bitcoin and Gold in an investment portfolio and withdraw fiat money. This finding allowed him to state that, if our monetary system starts being based on Bitcoin and Gold, we would have more stability during periods of crisis but would be more unstable in non-crisis periods because banks will not have the capacity to create money when needed to make everyday life easier. This same work states that Bitcoin presents a good correlation with the USD evolutionary line during non-crisis periods and in periods of crisis it has a higher correlation with gold.

2.3. Regulation and bubbles

In addition to being difficult to control the evolution of digital currencies, the regulation does not exist in most countries, and here we enter the dark side of anonymous cryptos (Guesmi et al., 2019) considered as well illegal crypto (in the group of illegal activities such as prostitution, arms and drugs trafficking (Foley et al., 2018; Hendrickson & Luther, 2019)). Vulnerability to hackings, poor protection for investors, and risk of bankruptcy of exchanges are also some controversial aspects. Actually, in most countries, cryptocurrencies exist in a legal grey area because there are no effective enforcement mechanisms and regulatory agencies (Molloy, 2019). However, some countries like China banned cryptos and ICO's (Nabilou, 2019). Overall, the growth of enthusiasm about cryptocurrencies is undeniable, which leads to the consecutive increase in its transactions – and price (Elendner et al., 2016).

In 2014, several authorities claimed that cryptocurrencies did not pose a serious risk to financial stability (Ali et al., 2014). Three years later, at the end of 2017, the price of Bitcoin was approximately 20,000 USD, followed by a big drop in early 2018. However, these years were considered moments of affirmation and consolidation of cryptographic projects (Bouri et al., 2020; Hussain Shahzad et al., 2020). According to Bariviera (2017), from 2011 until 2014 the returns' time series was persistent but after that, the behavior seems to be like white noise, and it's one of the Bitcoin inefficiencies.

2.4. The impact of news

Recent times have been marked by major influences on the cryptocurrency market caused by external noise. One of the main, most influential, and most active players was Elon Musk (CEO of TESLA), who essentially manipulated the price of Dogecoin - present in this study - and who ended up influencing the entire market in general (Ante, 2021). He, and many other investors or crypto-followers, use the social network Twitter to provide daily and real-time feedback on developments in this unregulated market. Wu et al. (2021) demonstrated that Twitter is positively correlated with the returns observed in cryptocurrencies and these extraordinary returns during COVID-19 make Bitcoin, Ethereum, and Ripple interesting case studies. These should be considered as a diversification portfolio according to this same work. Kozinets (2021) concluded that this impact of clicktivism[1] has been growing, mainly from social networks or platforms such as Youtube, and has increasingly come to be associated with capitalism.

Outside the period of bubbles like the one we have seen recently, it's the fiat currencies that react immediately to economic news, especially bad ones (Rognone et al., 2020a). These authors also studied the impact of news on Bitcoin and concluded that it does not have an immediate effect and that only good news tends to affect the market,

[1] According to Cambridge Dictionary, it means the impact of digital activism for a specific topic. In this case, the interest in news or web information about cryptocurrencies.

that is, there is a feeling of "crypto enthusiasm". BTC's volatility is independent of the news and only cyber-attacks or fraud are truly negatively affecting the market.

Corbet et al. (2020) present a sentiment index. This is based on news stories that follow the announcements of the macroeconomic indicators GDP, unemployment, Consumer Price Index (CPI), and durable goods. Afterward, determine whether each of the series' has a significant impact on Bitcoin returns. Opposed to equity returns, the authors found that an increase in positive news surrounding unemployment rates and durable goods leads to decreases in Bitcoin returns, and the opposite with negative news is found. No significant impact is denoted concerning news relating to GDP and CPI. Results allow inferring that this developing cryptocurrency market is getting mature through interactions with macroeconomic news. The literature also points that the volatility of bitcoin reacts most strongly to news (Google searches) on bitcoin regulation (Lyócsa et al., 2020). Hacking attacks have a particularly strong impact on bitcoin volatility. Similar to previous authors, they found that the volatility of bitcoin is not influenced by most scheduled US macroeconomic news announcements (government budget deficits, inflation, or even monetary policy announcements). By opposition, bitcoin volatility increases with announcements of forward-looking indicators (e.g., consumer confidence index (Lyócsa et al., 2020).

2.5. Empirical results from the literature

In terms of performance, the existing literature comparing cryptocurrencies with the forex market and commodities proves that cryptocurrencies are commonly good portfolio diversifiers and have hedge properties if they have an optimal allocation (Kang et al., 2019). Withal, cryptos have high volatility and risk despite being attractive returns (Feng et al., 2018; Koutmos, 2018; Baumöhl, 2019). As a way of defending portfolios when the bitcoin price falls, investors tend to move towards NASDAQ and NIKKEI225 assets, respectively (Matkovskyy & Jalan, 2019).

In terms of contagion effects, we can say that Bitcoin's returns infect the returns of most other cryptocurrencies, except for Tether - which is a stable coin (Ferreira & Pereira, 2019). According to the work of Baumöhl (2019), it is beneficial to diversify between forex and cryptos because in times of distress the low returns are negatively related. In the same work, it was proved that Bitcoin and Ethereum do not have the same adjacent assets, so they should not behave completely the same. Baumöhl (2019) found that Bitcoin is not the cryptocurrency with the best risk-return portfolio features (only if in small proportion).

Many studies have found financial contagion among assets (King & Wadhwani, 1990; Eichengreen et al., 1994). The present work will use all pairs indexed to the US Dollar because there is a stronger effect from US Dollar to mutual markets than in reverse case and currencies with higher values for Kurtosis reveal higher VaR (value at risk) volatility (Kilic, 2017). Trucíos et al. (2020) designed an estimation that allows measuring how cryptocurrencies are useful for investors, hedge funds, traders, and market makers and, subsequently, quantifying as better investment decisions. Despite the liquidity and dominance of forex currencies (Karnaukh et al., 2015), there is currently a challenge for them to become more competitive than the anonymity and low cost of transaction and maintenance of cryptocurrencies. A study by Kočenda and Moravcová (2019) showed that during the global financial crisis and the EU debt crisis those who had the new EU fiat currencies had benefits in diversifying and hedging their portfolios.

If digital currencies want to take precedence over international monetary policies, they will have to immediately correct the volatility and problematic combination of exchange rate targeting and using, avoiding speculative attacks (Urquhart, 2016). Bitcoin has been very susceptible to bubbles and has a speculative component, making its fundamental value to be zero (Cheah & Fry, 2015). These situations increase resilience to self-tokenizing[2] techniques (Pernice et al., 2019). Furthermore, if central banks take too long to make decisions to adopt these new technologies, large tech companies will likely anticipate and create currencies that are widely adopted (such as the Libra project (Libra Association, 2020)) and that destabilize the dominance of fiat currencies (Lee & Teo, 2020). Regarding the central banks' value reserve, the case of Barbados introduced a small proportion of Bitcoin in its reserves (did not exceed 10%) and verified empirically that the volatility of the reserve portfolio did not increase significantly and BTC's returns had a positive impact on the valuation of reserved wealth. An example of a banking application is that large banks like Citibank are developing their cryptocurrencies and digital protocols. Facebook credits, Microsoft points, and Amazon coins are other practical applications of large corporations (Moore & Stephen, 2016).

The crypto market is also considered a self-gravitational process according to Ballis and Drakos (2021), as the increase in the number of cryptocurrencies in the market year after year has also increased the overall market cap of the sector. Then, as the market grew and gained more influence because of the processes mentioned above, more cryptocurrencies will continually be created in the following periods and, in turn, more money enters the market - creating a continuous cycle of growth.

[2] A way to create new tokens underlying some project, which generally holds value. Sometimes it has speculative interests.

The existing literature has shown that although cryptocurrencies have some properties of diversification and hedging, they are not the best in this function. When compared to traditional safe assets, they performed less effectively (Bouri, Molnár, et al., 2017; Hussain Shahzad et al., 2020). Dyhrberg (2016b) demonstrated that Bitcoin has many similarities to both the US dollar and gold. The same author but in another article, Dyhrberg (2016a), shows that BTC is a good hedging tool against the U.S. dollar in the short run. After the crash in December 2013, Bitcoin could be considered only as a diversifier (Bouri et al., 2017). However, Kurka (2019) found a very low connectedness between BTC and other forex pairs, including EUR/USD and JPY/USD, until December 2015. Virk (2021) also concluded in the same direction, having studied the relationship between Bitcoin and the 5 most liquid forex pairs between 2010 and 2018, and note that changes in Bitcoin price are uncorrelated with changes in fiat currencies log returns. Also, for this reason, the inclusion of Bitcoin in portfolios presupposes the adoption of new risks. A possible justification for the last empirical results is the fact that they are only a few years old and are still consolidating their evolution. A real test of its stability and growth will now be the Covid 19 period.

Bondar et al. (2020) carried out a study that analyzed the composition of portfolios between 2016 and 2019, with the possibility of including forex currencies, American and European stocks, European and Ukrainian real state, government bonds, and Brent Oil. The authors conclude that, according to the Sharpe Ratio and the Return on Investment ratio, the most efficient portfolio in terms of risk-return should include 2.31% Bitcoin, 1% Ripple, and 1% Litecoin.

2.6. Covid-19 period

During this pandemic period, several socio-economic problems arose and we saw a drop in sales, production, and employment. The first days of the lockdown coincided with Bitcoin's halving (Johnson, 2020), which caused strong speculative pressure, raising the price (Lahmiri & Bekiros, 2020). Even so, the increase in the number of trading platforms and the easy access to them generated more capital inflow into cryptocurrencies, increasing their prices (Wątorek et al., 2021), because before it was only possible on specific exchanges with fewer facilities to convert crypto money into fiat currencies.

This period of confinement also increased the level of digitalization of societies and accelerated the use of technological and virtual products and services. Inherent in the health care added at the time, researchers were concerned about the risks of transmission through fiat cash (eg: coins, notes) and this increased the use of digital payment and transaction solutions, including cryptographic solutions (Pal & Bhadada, 2020). Large injections of liquidity in the forex market are anticipated, manipulating the currency in circulation. This will alter the correlation between fiat currencies and cryptocurrencies, because cryptos will remain faithful to the law of supply and demand, knowing in advance that interest will grow for the reserve of value and as a safer payment method (Wójcik & Ioannou, 2020).

Without counting the pandemic, we could say that in 10 years of existence of cryptocurrencies, their variances are more similar than their returns, due to the homogeneity in structural breaks. On the contrary, this did not happen during coronavirus (James et al., 2021). An investigation by Vidal-Tomás (2021) also analyzed a set of 69 cryptocurrencies and concluded that they did not react to the onset of the pandemic (31 December 2019), nor to the WHO announcement that declared the state of a worldwide pandemic; however, between March 12 and the end of that month, there was a panic effect that stock indexes also suffered, leading to synchronization with the market in general - this approximation between cryptos and stocks rarely was observable in the past. Compared to some forex pairs, the Euro and British Pound also followed this general market trend (Umar & Gubareva, 2020).

A discussion that arose in the moment of panic was also some possible speculative bubbles that occurred in cryptocurrencies, where Bitcoin was the most efficient and resistant currency during these situations in pré-Covid moments, but in post-Covid it changed to Ethereum (Mnif et al., 2020). Looking at the herd effects, the period of market turmoil had not amplified the interconnection between the cryptocurrencies, remaining practically at the same level (Yarovaya et al., 2021). The same study indicates that the herding of cryptos is cyclical like most assets and is decreasing more recently in pairs traded in Euros and Dollars, because of the expansive monetary policy of these central banks (Vidal-Tomás, 2021; Yarovaya et al., 2021).

One of the first studies about Bitcoin's ability to act as a safe haven during the pandemic concludes that cryptocurrency has not demonstrated its ability to defend the value of investments (Conlon & McGee, 2020). Though, this study only used short data between 21st March 2019 and 20th March 2020. Another investigation by Conlon et al. (2020), one month later, recognizes Bitcoin and Ethereum as a *safe haven* even during coronavirus, concluding that if we allocate up to 16% of our portfolio to BTC or up to 14% to ETH, it will be useful to reduce its risk. The work of Othman et al. (2021) says that in the pandemic crisis it was essential to reduce fiat money (USD) and replace it with Bitcoin and gold directly. These conclusions are complemented by the fact that Bitcoin and Ethereum (the two main ones) are suitable for short-term safe haven, despite the volatility being higher than S&P500 and gold (Mariana et al., 2021).

If we apply a wavelet coherence approach to cryptocurrencies and American and European stock indexes, it will be possible to notice that the frequencies are low, except for March 2020 for the reasons mentioned above (Caferra & Vidal-Tomás, 2021). The same author applied the Markov switching autoregressive model to highlight the rapid recovery of cryptos in the period of international instability, which means that the coronavirus only had a short-term impact.

Another type of analysis was carried out, such as the relation of cryptos price and the number of deaths of covid-19. A simple analysis of the first month of a pandemic with a worldwide presence was done for April 2020, showing that the increase in daily cases of the virus was increasing the price of Bitcoin as well (Goodell & Goutte, 2021). Other authors have also demonstrated that there was not a proper relationship between the number of infections and the performance of cryptocurrencies through the application of a Quantile-on-Quantile-Regression (Iqbal et al., 2021); even so, they concluded that cryptos were good diversifiers, especially Bitcoin, Ethereum, Cardano and Crypto.com Coin. The same authors demonstrate that these assets usually absorb a good part of the external shocks and act as a hedge in unstable moments in general markets.

3. Methodology and Data

3.1. Data description

To carry out this study, it was necessary to create a database referring to the past five and a half years, namely between 18th August 2015 and 12th March 2021. The year 2015 was chosen because it was the beginning of many cryptographic projects. Before that, only existed one or two digital currencies that still exist today. Since one of the problems in the existing literature is that there are no researches with a variety of active cryptography, in this work, it was proposed to extend the observations to 10 cryptocurrencies.

One of the jobs that had to be done in the construction of the database was the standardization of the dates observed. While the cryptocurrency market is traded 24/7 without limitations, stock markets are only open on weekdays generally, and at a specific time. The same happens with the gold spot market and forex pairs. Not only do the weekends had to be taken out, but also holidays of different countries were forced to be removed from the observations of all assets. This caused a significant decrease in the number of cryptocurrency observations, which under normal conditions would be 365 per year. Therefore, the average number of annual observations in the sample of this work was set at 225.

The cryptocurrencies that will be analyzed are Bitcoin, Ethereum, Litecoin, Dogecoin, Ripple, Dash, Monero, Verge, NXT, and Stellar. These 10 assets operate in different areas of the strategy of cryptocurrencies: payment method, value reserve, private token or platform, etc. Ripple and Stellar are examples of decentralized currencies, a property not common to most of these assets. The developers have a special objective in creating useful solutions for the banking system, in the hope that they will effectively have widespread adoption by institutions in this sector.

Unlike these currencies, which are intended to be adopted by banking institutions, other projects such as Bitcoin, Litecoin, and Dogecoin precisely aim to eliminate banking intermediaries by creating peer-to-peer solutions. These initiatives try to facilitate the forms of payments and money transfers, in terms of costs and time required per transaction. Furthermore, some international payment companies do not have operations in certain countries, but cryptocurrencies are universal and can be used everywhere.

Ethereum and NXT are platforms that created their blockchain, which allows other people to create private projects for their purposes, like DAPPS (decentralized applications). These two ecosystems support many other projects of tokenization. So, the more projects the network can attract, the greater the demand for cryptocurrency will tend to be, and the price increases. If demand decrease, price follows the tendency too.

Private currencies guarantee another of the main ambitions of this new market, namely, the anonymity of those who send and those who receive. DASH and Monero are currencies that share this goal and pretend to facilitate personal transactions. In terms of programming and features, Monero is more focused on not being detectable, even though Dash ends up being faster and cheaper to complete as transactions. A summary of the description of all these cryptos and categories is presented in *Table 1*.

Table 1. Description of cryptocurrencies in the sample (Source: website of each crypto)

Name	Category	Description	Source
Bitcoin (BTC)	Method of Payment	Bitcoin uses peer-to-peer technology to operate with no central authority or banks; managing transactions and the issuing of bitcoins is carried out collectively by the network. Bitcoin is open-source; its design is public, nobody owns or controls Bitcoin and everyone can take part. Through many of its unique properties, Bitcoin allows exciting uses that could not be covered by any previous payment system.	https://bitcoin.org/en/
Ethereum (ETH)	Platform	Ethereum is the community-run technology powering the cryptocurrency, ether (ETH), and thousands of decentralized applications.	https://ethereum.org/en/
Ripple (XRP)	Centralized Currency	XRP is a digital asset built for payments. It is the native digital asset on the XRP Ledger — an open-source, permissionless, and decentralized blockchain technology that can settle transactions in 3-5 seconds.	https://ripple.com/xrp/
Litecoin (LTC)	Method of Payment	Litecoin is a peer-to-peer Internet currency that enables instant, near-zero cost payments to anyone in the world. Litecoin is an open-source, global payment network that is fully decentralized without any central authorities.	https://litecoin.org/
Dash (DASH)	Private currency	Instant transactions and micro-fees. Any amount, anytime, anywhere.	https://www.dash.org/

Stellar (XLM)	Centralized Currency	Stellar makes it possible to create, send, and trade digital representations of all forms of money: dollars, pesos, bitcoin, pretty much anything. It's designed so all the world's financial systems can work together on a single network.	https://www.stellar.org/
Monero (XMR)	Private currency	Monero is cash for a connected world. It's fast, private, and secure. With Monero, you are your bank. You can spend safely, knowing that others cannot see your balances or track your activity.	https://www.getmonero.org/
Dogecoin (DOGE)	Method of payment	Dogecoin is an open-source peer-to-peer digital currency, favored by Shiba Inus worldwide.	https://dogecoin.com/
Verge (XVG)	Private currency	Verge provides the security of blockchain-based payments to everyday users with easy-to-use software tailored to real-life needs and applications.	https://vergecurrency.com/
NXT (NXT)	Platform	Nxt is an open-source blockchain platform and the first to rely entirely on a proof-of-stake consensus protocol.	https://www.jelurida.com/nxt

On the side of fiat currencies, we have the 8 most liquid currencies in the forex markets worldwide, which are the US dollar, Euro, British pound, Australian dollar, Japanese yen, Swiss franc, New Zealand dollar, and Canadian dollar. All pairs will be indexed to the US dollar as it is the dominant currency in the money market world (Siddiqui, 2020).

To also understand the hedging capabilities that cryptos have concerning stock markets in different countries, we collected data from the respective markets for each forex pair. The market index information, countries, and Forex (FX) pair associated are presented in *Table 2*.

Additionally, gold was selected as a refuge commodity, to compare the hedging capacity of cryptocurrencies with it. Several studies try to determine the capacity of gold to be an asset as a refuge and, more recently, there has been a lot of discussion between the capacity of BTC and gold to reduce risks when they are in investment portfolios.

This database was created based on various data collection software/platforms: for cryptocurrencies, *CoinMarketCap* and *Investing* were used; for the forex market, all data were available at *Yahoo Finance* and for stock indexes, we used *Investing* and *Refinitiv Eikon*.

Table 2. Description of stock exchange indexes and forex pairs in the sample

Stock name	Country	Forex pair associated
S&P500	United States of America	USD
EURO STOXX 50	European Union	EUR (Euro)
FTSE 100	United Kingdom	GBP (British pound)
NIKKEI 225	Japan	JPY (Japanese Yen)
ASX 200	Australia	AUD
SMI	Swiss	CHF
TSX	Canada	CAD
NZX 50	New Zealand	NZD

3.2. Methodology

This work is essentially divided into two methodological approaches.

Firstly, the empirical analysis to be carried out in this study will aim to ascertain the rates of return, volatility, and the effects of contagion existing between the various assets. Traditional contagion and correlation models will be used. These include Dynamic Multivariate GARCH models, which are appropriate for measuring time-varying conditional correlations and allow to address the heteroscedasticity problem while accounting for volatility modeling. As such, and through the use of this type of model, this insight will be informative for global investors, helping them to make better decisions concerning asset and risk management, including asset allocation, portfolio diversification, and hedging strategy.

And it is precisely to assess the practical implications of the performance of financial assets, especially cryptocurrencies, that at a final stage of the analysis we will apply the Markowitz method to understand what choices should be made to create an optimal investment portfolio in terms of risk-return.

3.2.1. Contagion effects

The first stage of data preparation consists of computing the natural logarithm of daily prices and, right after that, daily returns were created for each day of the sample, losing an observation concerning the total number before this action. To calculate the daily log-return we have used equation (1).

$$r_{i,t} = log\left[\frac{P_{i,t}}{P_{i,t-1}}\right] \quad (1)$$

Where P_t is the price of the i^{th} asset on day *t* and $P_{i,t-1}$ corresponds to the price of this asset in period t-1, that is, the previous day. R_t is the daily return of asset *i* in period *t*. By using returns we ensure the stationarity of our data. However, we have as well tested for the presence of unit roots in levels and first differences of prices, and with returns, where ADF (Augmented Dickey-Fuller), PP (Philips Perron), and KPSS (Kwiatkowski–Phillips–Schmidt–Shin) tests indicated to us that returns are stationary at levels. We then proceed to calculate the expected return of each variable and its standard deviation following the formulas presented in equations (2) and (3):

$$\mu_i = E(r_i) = \frac{\sum_{t=1}^{n} r_{i,t}}{n} \quad (2)$$

$$\sigma_i = \sqrt{\frac{\sum_{t-1}^{n}(r_{i,t}-\mu_i)^2}{n-1}} \quad (3)$$

Where *t* refers to the observation of asset *i* on day *t*.

Having the returns of each asset as a variable, and being these stationary, we begin to deal with the relationships that exist between different assets. Then, it starts the replication of some steps used in the article of Huynh (2019) and Mendes & Carneiro (2020) relating to the effects of contagion between different assets. For this purpose, Pearson Correlation (Galton, 1889) was used to understand the statistical relationship between different variables. This is described in equations (4) and (5).

$$\widehat{\rho} = \frac{\sum_{i=1}^{n} w_i(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n} w_i(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n} w_i(y_i-\bar{y})^2}} \quad (4)$$

Where w_i represents the weight of the asset and *x* and *y* refers to specific crypto, forex, or stock variable and x̄ and ȳ are their means, respectively. The next step is to calculate the unadjusted significance level for testing the significance level.

$$\rho = 2 * ttail\left(n-2, |\bar{\rho}|\frac{\sqrt{n-2}}{1-\widehat{\rho}^2}\right) \quad (5)$$

Then, we proceed to the application of the VAR (Vector Autoregressive Model), a stochastic model that is widely used in the economic field and we follow the methodology of Lütkepohl (2005). It allows us to evaluate the impact of stochastic shocks in different variables of the study. This model is written as VAR(p), where (p) corresponds to the number of lags of the variable as provided in equation (6).

$$y_t = A\Upsilon_{t-1} + B_{0Xt} + u_t \tag{6}$$

Where y_t corresponds to the matrix of a temporal multivariate series of endogenous variables with *(K x 1)*; *A* is a matrix with the dimension *(K x K_p)* of coefficients of lagged values of Υ *(Υ_{t-1})*; Υ_t is the matrix *(K_p x 1)*; B_o contains coefficients of matrix χ, and this matrix *(M x 1)* has all exogenous variables and includes intercept terms in VAR model; u_t represents the matrix *(K x 1)* of white noises.

Through this process, it will be possible to ascertain the optimal number of lags and check if there are exogenous variables.

The optimal number of lags to be included was tested and selected through the AIC (Akaike Information) criteria as commonly used in the literature (Guesmi et al., 2019; Mighri & Alsaggaf, 2019; Mokni & Ajmi, 2021; Trucíos et al., 2020; Yousaf & Ali, 2020). The tests revealed an optimal number of lags to be included: 4 for the 2015-2021 analysis and 1 for the COVID-19 period. Furthermore, and provided the nature of our time-series data, we have tested for possible cointegrating relationships using the Johansen cointegration test. Results revealed the existence of cointegrating relationships, and for the rest of the analysis, we had to resort to the application of the VEC model.

Thus, we advance to the VECM (Vector Error Correlation Model) by Engle and Granger (1987) to analyze and capture the cointegrating elements of assets. The model used is presented in equation (7) (Keilbar & Zhang, 2021).

$$\Delta X_t = \prod X_{t-1} + \sum_{i=1}^{k} \Gamma_i \, \Delta X_{t-1} + \Phi D_t + \varepsilon_t \tag{7}$$

In equation (7), D_t corresponds to deterministic variables and ε_t are the independent error terms. The parameter Γ_i represents the matrices affected by lagged values of ΔX_t. If we have cointegration results, a stationary linear combination will exist, and it is observed in equation (8).

$$\Delta X_t = \alpha\beta^T X_{t-1} + \sum_{i=1}^{k} \Gamma_i \, \Delta X_{t-1} + \Phi D_t + \varepsilon_t \tag{8}$$

In which α is the loading matrix and β is a matrix with cointegration vectors.

That said, and because it will be difficult for this sample to qualitatively analyze the coefficients obtained in the VAR and VECM tests, we move on to the assessment of how the shocks occurring in each period influence other variables, in terms of time and terms of the magnitude of the same impact. Then we compute the Impulse Response Function – IRF model (Caporale et al., 2019; Nasir et al., 2019).

Finally, the multivariate GARCH (MGARCH) was performed to understand how the past of a variable affects its structure (Bauwens et al., 2006). Thus, and according to Kearney and Patton (2000), we write equations (9) and (10).

$$y_t = \mu_t(\theta) + \varepsilon_t \tag{9}$$

$$\varepsilon_t = H_t^{\frac{1}{2}}(\theta) z_t \tag{10}$$

Where $\mu_t(\theta)$ refers to the conditional mean vector (*m x 1*), and H_t is the conditional variance matrix of y_t that can be obtained by using equations (11) and (12).

$$H_t = H_t^{1/2} Var_{t-1}(z_t) \left(H_t^{1/2}\right)' = Var_{t-1}(\varepsilon_t) \tag{11}$$

$$Var_{t-1}(\varepsilon_t) = Var_{t-1}(y_t) = Var\,(y_t \mid I_{t-1}) \tag{12}$$

Where H_t is a N x N matrix. We also have a random vector z_t that is expected to be zero, with a dimension of N x 1, and its variance is calculated following equation (13).

$$Var(z_t) = I_N \tag{13}$$

This parameter I_N represents the identity matrix of order N.

3.2.2. Portfolio Optimization

To implement the portfolio optimization process, we start by annualizing the average returns and standard deviations of the various assets. Next, we will carry out a Markowitz Mean-Variance analysis to understand the optimal weight of assets when deciding on the composition of the portfolio, as well as the Sharpe Ratio to analyze the risk-return of each of the assets. Markowitz portfolio (Markowitz, 1952) allows us to understand which combination maximizes the expected return for a given level of risk to be assumed by the investor. This optimization methodology is based on two articles

(Bondar et al., 2020; Ma et al., 2020) and will be performed for the general period (2015-2021) and the COVID-19 period.

To calculate the return and variance on portfolios, E(r), we use the following equations (14) and (15).

$$E(R) = \sum_{j=1}^{m} w_j \mu_j \tag{14}$$

$$Variance = w^T \sum w \tag{15}$$

The expected return of asset j is obtained by multiplying the weight of assets with their return. In terms of variance, we must multiply the weight vector by the sum of the variance-covariance matrix of the assets in the portfolio.

The next step is to maximize the portfolio's return, given the weights of the assets in question (the model in equation (16)).

$$\textbf{Max E}(\boldsymbol{R}) \tag{16}$$

$$\text{s.t. } w^T \sum w = \alpha \tag{16.1}$$

$$\sum_{i=1}^{m} w_i = 1 \tag{16.2}$$

$$w_i \geq 0, \ for \ all \ i \tag{16.3}$$

And α represents the level of risk according to the variance obtained.

With the support of Excel's Solve tool, we proceeded to estimate the optimal portfolios for the two time periods under analysis and considering the main assets of each investment class.

Another analysis that was carried out was by the Sharpe Ratio, which allows for an understanding of the additional return compared to the risk-free rate and compares it with the risk assumed by that same portfolio or individual asset. We used equation (17).

$$Sharpe\ Ratio = \frac{E(R) - R_f}{Stand.Deviation} \tag{17}$$

where R_f corresponds to the annualized risk-free rate.

This concept was created by Sharpe (1966), whose coefficient the higher the better it will be – it will have a higher return per unit of inherent risk, considering that the risk-free is discounted. The risk-free rate used was 0.1% as it was impossible to find a more realistic and consensual world interest rate than the U.S. yield on March 12, 2021 (end of the sample period). This decision was made after reading the article by Ma et al. (2020) for this methodological part, whose authors implemented the same strategy. The fact that cryptocurrencies do not have a directly associated risk-free is a big problem for this type of analysis, so the one that is globally most accepted was used.

In the portfolio optimization process based on the maximization of the Sharpe Ratio, we gave rise to the efficient portfolio frontier with the following step (18).

$$Max \ \frac{E(R) - R_f}{Standard\ Deviation} \tag{18}$$

$$\text{s.t. } \sum_{i=1}^{m} w_i = 1 \tag{18.1}$$

So, the sum of all assets weights should be 1, not allowing for short-selling.

4. Results and discussion

4.1. Contagion effects

4.1.1. Total sample (2015-2021)

Our research collected 1239 observations that resulted in 1238 return observations. In a general view, it's possible to conclude that cryptos' returns and standard deviation are the higher ones. Stocks are the second biggest variables in terms of gains and volatility. The most stable variables are pairs of forex, which have residual returns and a modest deviation.

Table 3. Descriptive statistics by category of the asset (2015-2021)

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis
Cryptos	12380	0.4092	0.0917	2.1310	32.6109
Forex	9904	0.0030	0.0057	-0.0455	8.1430
Stocks	9904	0.0247	0.0120	-1.0312	18.1166
Gold	1238	0.0347	0.0100	0.0042	7.9734

Looking into the descriptive statistics of the assets *(Table 3)* that compose our sample, we can observe that the average daily returns of the cryptographic sample are 0.409%, an extremely high value when compared to the 0.035% of the average daily growth in the price of gold, or 0.025% of stock indexes. Forex pairs grew, on average, only 0.003% per day, a weak percentage. If we convert these daily sample growths into

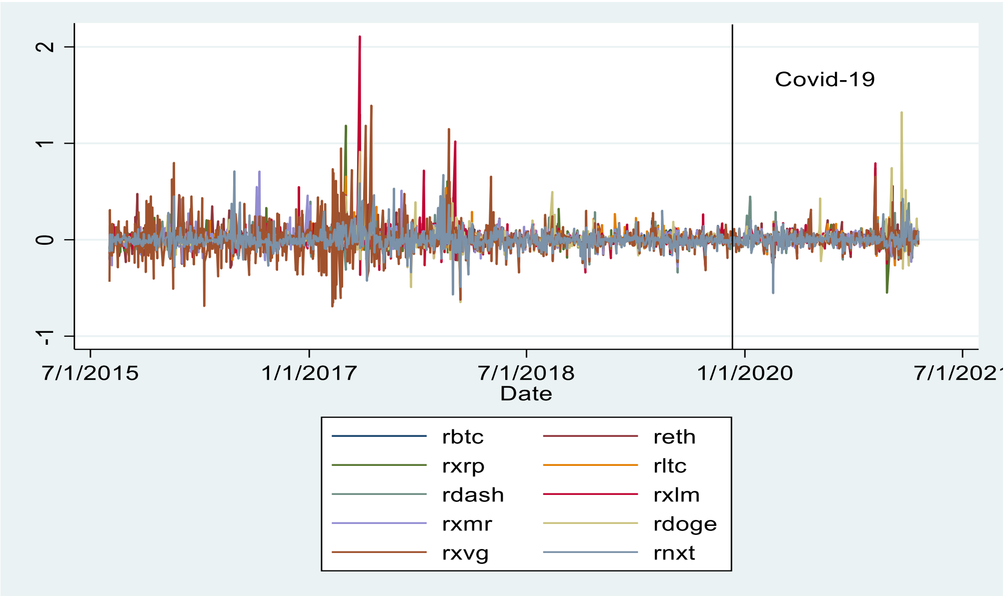

Figure 1. Evolution of cryptocurrency returns (2015-2021)

annual rates of return for each asset category, we have cryptos (+92.02%), gold (+7.81%), stock indexes (+5.56%), and forex pair (+0.68%).

Despite the high rates of return of digital currencies, they also have much higher volatility as expressed in the standard deviation column. This finding underlines the need to evaluate the composition of portfolios considering the return per risk unit through the Sharpe Ratio and the Markowitz model - which will be studied further on.

Ethereum is the cryptocurrency with the highest daily return (about +0.589%), followed by Verge (+0.587%) – *Table 4*. The latter was strongly influenced by the speculative factor, as in several observations the daily return is null, but considering the low liquidity (compared to the other currencies) allowed it for some abnormal returns on other days that bias the average compared to reality.

The main cryptocurrency – Bitcoin – has an outstanding average daily return (+0.436%) and, at the same time, it has the smallest standard deviation between cryptos, that is, lower exposure and risk to volatility. That's why we should, as a general rule, in times of greater volatility in the cryptocurrency market, convert the cryptos we have into Bitcoin to reduce the risk of these price fluctuations and thus be hedging our digital currency portfolio.

Table 4. Descriptive statistics of cryptocurrencies (2015-2021)

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis
BTC	1238	0.4365	0.0510	-0.6957	11.8645
ETH	1238	0.5892	0.0809	0.6299	10.2414
XRP	1238	0.3209	0.0928	4.5800	62.5139
LTC	1238	0.3243	0.0730	1.3079	18.3814
DASH	1238	0.3513	0.0747	0.5047	10.1169
XLM	1238	0.4189	0.1108	6.8635	118.0116
XMR	1238	0.4768	0.0827	1.2511	14.3166
DOGE	1238	0.4775	0.0987	4.0681	48.6032
XVG	1238	0.5874	0.1609	1.5782	15.7348
NXT	1238	0.1089	0.0919	1.2223	16.3244
Cryptos*	12380	0.4092	0.0917	2.1310	32.6109

Following the analysis of assets with less variance, we can find that currencies related to methods of payment or to facilitate peer-to-peer transactions and be a private tradable asset (like Litecoin, Dash, Monero) are also less unstable currencies when compared to the remaining market. This stability is intended to introduce some confidence into the process and ensure that the framework does not lose credibility (e.g.:

avoid currency price devaluations too quickly). Furthermore, when coins that have these purposes do not have so much speculative ambition, quite the contrary.

In terms of the descriptive analysis of cryptocurrencies, NXT is the currency that deviates somewhat from the general trends in terms of average daily returns – just have +0.109%. Although this coin was created in 2013 and had some prominence in this first stage of the project, the truth is that over time it lost influence to other projects that performed better and had more potential. Therefore, and looking at the graph of crypto returns, we can note that in recent years the currency has lost some relevance, so the following results on this asset should be read with some reserve and weighting.

Table 5. Descriptive statistics of forex pairs (2015-2021)

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis
USD	1238	-0.0047	0.0044	-0.0594	5.5399
EUR	1238	0.0063	0.0051	-0.0035	6.4114
GBP	1238	-0.0091	0.0067	-1.2694	21.8125
JPY	1238	0.0110	0.0059	0.6840	9.6560
AUD	1238	0.0045	0.0067	-0.0585	5.8851
CHF	1238	0.0045	0.0049	0.4324	6.1610
CAD	1238	0.0036	0.0050	-0.0087	4.7159
NZD	1238	0.0080	0.0070	-0.0808	4.9622
Forex*	9904	0.0030	0.0057	-0.0455	8.1430

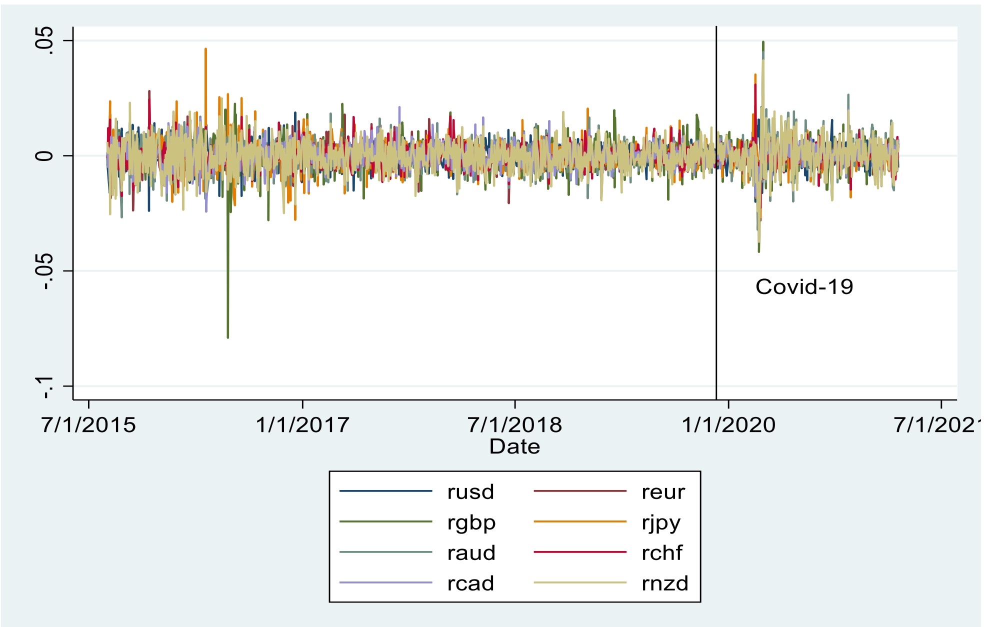

Figure 2. Evolution of forex returns (2015-2021)

Regarding the forex pairs *(Table 5)*, both currencies have positive returns (although not very expressive), except the USD dollar and the British Pound, which had a negative performance during the years analyzed. The exchange devaluation of these currencies, together with the inflation that occurred in their national economies, proves that keeping money in cash is not a rational option, since a certain amount of money has a lower purchasing power as the years go by.

Table 6. Descriptive statistics of stock indexes (2015-2021)

	Obs	Mean	Std. Dev.	Skewness	Kurtosis
S&P500	1238	0.0447	0.0140	-1.0426	18.8190
STOXX	1238	0.0074	0.0137	-1.2286	16.0256
FTSE	1238	0.0026	0.0119	-0.9273	15.2414
NIKKEI	1238	0.0295	0.0138	-0.0731	8.2830
SMI	1238	0.0097	0.0110	-1.0661	13.8268
TSX	1238	0.0226	0.0116	-1.9689	41.2794
ASX	1238	0.0187	0.0115	-1.0918	15.0548
NZX	1238	0.0626	0.0085	-0.8513	16.4029
Stocks*	9904	0.0247	0.0120	-1.0312	18.1166
Gold	1238	0.0347	0.0100	0.0042	7.9734

Note that the GBP had a huge drop in its value on the precise day of the Brexit referendum (June 23, 2016), which certainly influenced and marked the history of this currency. This was also the highest abnormal return in our sample of fiat currencies.

The biggest daily returns of the forex market are the JPY ones, which in the years observed has an average return of +0.011%, followed by the NZD with an average daily return of +0.008%. The standard deviation values of fiat currencies are also manifestly low. It is important to know that these forex values are incomparable to other asset classes, which makes it difficult to conclude.

In terms of stock indexes *(Table 6)*, it is worth noting the average daily return of the S&P500, which is +0.045%, that is, around 10% per year, on average. This amount is in line with the historical performance of the American market and with literature studies. On the other hand, it is important to highlight the residual growth of the main European stock market (+0.007), which allows us to state that the STOXX 50 has stagnated compared to the other markets. The same can be said concerning London markets, where the FTSE had an average performance even closer to a nullity in terms of returns (+0.003). The Swiss stock exchange also did not have extraordinary results in comparative terms, but the SMI set a daily growth rate at 0.01%. So, the European financial markets had an insignificant evolution, and it is interesting to check this geographical trend.

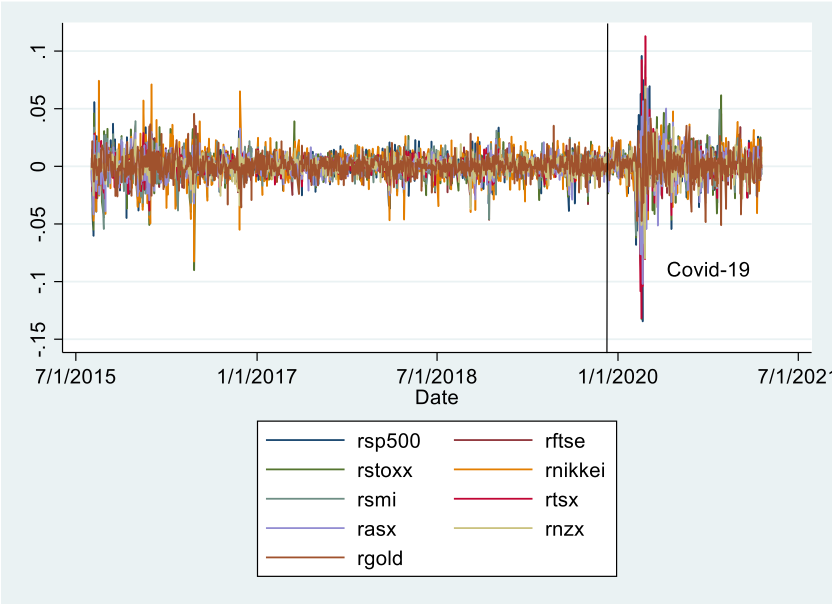

Figure 3. Evolution of stock indexes returns (2015-2021)

The most impressive result within the observed stocks is that of the New Zealand market. NZX accumulated, on average, about +0.063% per day, which indicates that per year it grew by an average of more than 14%. In addition, its standard deviation was also the lowest in its asset class. However, it is important to note that in general, the standard deviations of all indices are acceptable and by the standards.

Making a superficial comparison between the stock markets and the cryptographic market *(Table 3),* we can verify that the returns of cryptos are 16.56 times over the stock indexes. In terms of price fluctuations, we can mention that the average standard deviation of cryptocurrencies exceeded approximately 7.65 times that of stocks. Here is the first inference between these two markets.

By adding the Gold variable to the analysis, it is also possible to have one more type of asset to be compared, as it is a safe haven asset according to some researchers and investors. The average daily return of +0.035% and the standard deviation of 0.01% allow us to affirm that it has a gains performance similar or even superior to most markets and with less volatility. Even so, the NZX managed to have much higher profitability and lower risk, so in this case, there was no refuge capacity of gold. Therefore, this is the first indication that Gold will be relevant for the exercise of efficient portfolio composition later on.

Pearson Correlation presents the coefficient that measures strength and direction between two variables. This analysis will be relevant to understand the relationship between different assets or inside the same category.

Cryptocurrencies have a positive correlation between each one and we note that some of them have the strongest relationship because of some of their properties. For example, Bitcoin has a stronger correlation with Ethereum, Litecoin, Monero, and Dash – and both are considered as a method of payment – and a weak association with Ripple and Stellar – because they are centralized currencies as opposed to BTC. All correlations between cryptos are statistically significant (*Table 7*).

If we study the connections between a cryptocurrency and a fiat currency it will not be possible due to any of the conjugations being statistically nonsignificant.

Table 7. Pearson correlation of cryptocurrencies and gold (2015-2021)

	BTC	ETH	XRP	LTC	DASH	XLM	XMR	DOGE	XVG	NXT	GOLD
BTC	1.0000 ***										
ETH	0.5572 ***	1.0000 ***									
XRP	0.4137 ***	0.3364 ***	1.0000 ***								
LTC	0.6801 ***	0.5114***	0.5320 ***	1.0000 ***							
DASH	0.5627 ***	0.5387 ***	0.3393 ***	0.5229 ***	1.0000 ***						
XLM	0.4267 ***	0.3809 ***	0.6901 ***	0.5045 ***	0.3636 ***	1.0000 ***					
XMR	0.5727 ***	0.4902 ***	0.3517 ***	0.4851 ***	0.5644 ***	0.3998 ***	1.0000 ***				
DOGE	0.4838 ***	0.4006 ***	0.4566 ***	0.5080 ***	0.3589 ***	0.5054 ***	0.3796 ***	1.0000 ***			
XVG	0.3502 ***	0.2788 ***	0.2252 ***	0.2855 ***	0.3419 ***	0.2786 ***	0.3505 ***	0.3673 ***	1.0000 ***		
NXT	0.4909 ***	0.3669 ***	0.3904 ***	0.4455 ***	0.4182 ***	0.4713 ***	0.3787 ***	0.4435 ***	0.3218 ***	1.0000 ***	
GOLD	0.0920 ***	0.1083 ***	0.0063	0.0376	0.0019	-0.021	0.0610 **	0.0429	0.0305	0.0278	1.0000 ***

Notes: * - significant at the 10% significance level; ** - significant at the 5% significance level; *** - significant at the 1% significance level.

Reconciling the different stocks with the different cryptos we can affirm that there is a small positive correlation in the same direction between the two asset classes *(Appendix 93)*. The Canadian index (TSX) is the most correlated stock with cryptos, followed by SP500, Stoxx, and FTSE. These shreds of evidence are sufficient to conclude that cryptocurrencies follow the general trends of the financial markets and the economy as a whole.

Another focus of our analysis is to understand the ability that cryptocurrencies have to work as a safe haven for other financial and investment assets. Looking at the correlations between gold and the main world indices, we can see that there is a movement in the opposite direction to the indices, except for the ASX and NZX stocks that do not have statistical significance to allow us to confirm anything *(Appendix 2)*. This gold trend is contrary to the behavior of all cryptos, which may call into question their ability to be better hedging in portfolios. On the other hand, gold has a positive correlation with all cryptos, and especially with Bitcoin and Ethereum *(Table 7)*.

After realizing the correlation between variables, the study on the impulse exerted between each of the currency pairs (digital or physical) follows. Finally, the MGARCH test is performed to understand the influence of the volatilities of the variables on the variations of the others.

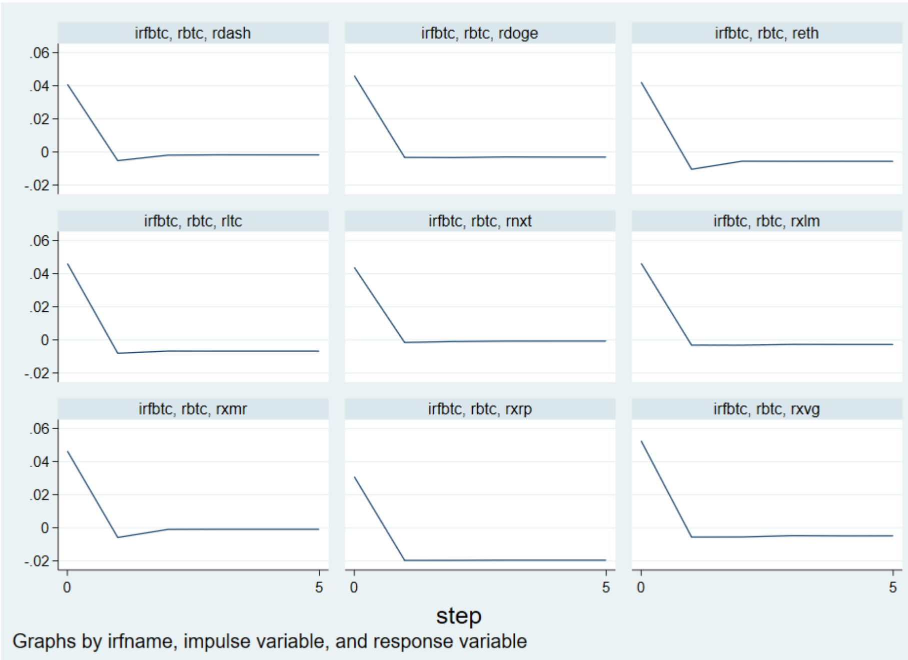

Figure 4. Impulse Response Function from Bitcoin to other cryptocurrencies (2015-2021)

First, we will analyze the interactions between cryptocurrencies individually. Starting with Bitcoin *(Figure 4)*, we can conclude that an impulse in it exerts a response effect in other cryptos on the first day, and then, that effect disappears in the following days. This process is very similar to the other currencies *(see Appendix 3, Appendix 5, Appendix 7, Appendix 9, Appendix 11, Appendix 13, Appendix 15, Appendix 17, Appendix 19)*.

Given the MGARCH outputs, we can see that a variation in BTC's prices causes strong volatility in Litecoin's price, in the same direction *(Table 8)*. However, a fluctuation in the main cryptocurrency also gives rise to interesting volatilities in ETH, XMR, DASH, and DOGE, always in the same direction. These 5 currencies that float in the same trend are precisely cryptocurrencies that have the same function in practice, that is, they are used as means of payment. Withal, Bitcoin has a negative coefficient of MGARCH with Stellar and a null value with Ripple, which demonstrates some distance in the performance with these last two currencies that are centralized.

Regarding the second digital currency with the largest market cap - Ethereum - we can see that it has a stronger momentum in Bitcoin *(Appendix 4)*. Furthermore, we can conclude that with less liquid and less expressive currencies (such as Doge, Verge, and NXT) the impulses that ETH produces are observed in two days, which leads to the conclusion that it has a longer impact than normal currencies. Observing the effects of ETH on the volatility of the other currencies, we can conclude that this impact is more positive and more relevant in Bitcoin, although it is also positive in other currencies such as Litecoin, XRP, and Dash.

Table 8. MGARCH model applied for Bitcoin and other cryptocurrencies (2015-2021)

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
rEth	0.09199	0.014	6.530	0.000	0.064369	0.119618
rXrp	0.00041	0.015	0.030	0.978	-0.02915	0.029966
rLtc	0.31780	0.020	15.740	0.000	0.278223	0.357375
rDash	0.07084	0.015	4.610	0.000	0.040731	0.100941
rXlm	-0.03002	0.014	-2.160	0.031	-0.05731	-0.00274
rXmr	0.09594	0.014	7.070	0.000	0.069337	0.122535
rDoge	0.04274	0.013	3.250	0.001	0.016961	0.068514
rXvg	0.01223	0.006	2.090	0.037	0.000758	0.023702
rNxt	0.11033	0.013	8.280	0.000	0.084231	0.136437
_cons	0.00166	0.001	2.400	0.016	0.000306	0.003013

By analyzing the impulse response functions (IRF), we can determine that a unitary variation in the XRP will cause a shock of 0.07 in its centralized counterpart XLM in period 1, being one of the main shocks in the sample of cryptocurrencies *(Appendix 5)*. The same stance can be seen in terms of the analysis of the MGARCH coefficients, where XRP continues impacting the XLM's volatility more strongly. A variation in the price of XRP also has some impact on the variations of BTC, LTC, XMR, DOGE, and ETH, which are to stand out *(Appendix 6)*.

Litecoin presents an interesting coefficient in the MGARCH test with Bitcoin because it is extremely high *(Appendix 8)*, which means that a fluctuation in the price of

LTC has a high impact on the volatility of BTC. This statement may indirectly question whether one of the main drivers of the cryptographic market could be Litecoin since its performance seems to be decisive for stabilizing Bitcoin's price trend - which is said to be the biggest driver of the entire market.

An interesting fact is to realize that Dash and Monero (coins with similar properties) have a great boost in XVG that is much less liquid than other currencies at least in this sample period. In terms of impact on volatility, a change in Monero's price has a strong impact on Bitcoin and Dash *(Appendix 12)*, as does the reverse that was previously mentioned. In case of variation in the DASH price, it is expected that Monero, Ethereum, Bitcoin, Litecoin, and Verge will also suffer some variations in their values *(Appendix 10)*.

When Stellar suffers a shock, this tends to be transmitted more intensely to XRP, but also Dogecoin *(Appendix 13)*. The values of MGARCH also confirm it. Variations in XLM generate variations in the same direction in XRP mainly *(Appendix 14)*. On the other hand, XLM's volatility generates a change in the opposite direction in BTC, so there are hedging opportunities here.

The last three cryptocurrencies analyzed (DOGE, XVG, and NXT) have less expressive characteristics in terms of correlation, since they are currencies with a lower market cap and greater demand, with no relevant and consistent trends *(Appendix 16, Appendix 18, Appendix 20)*.

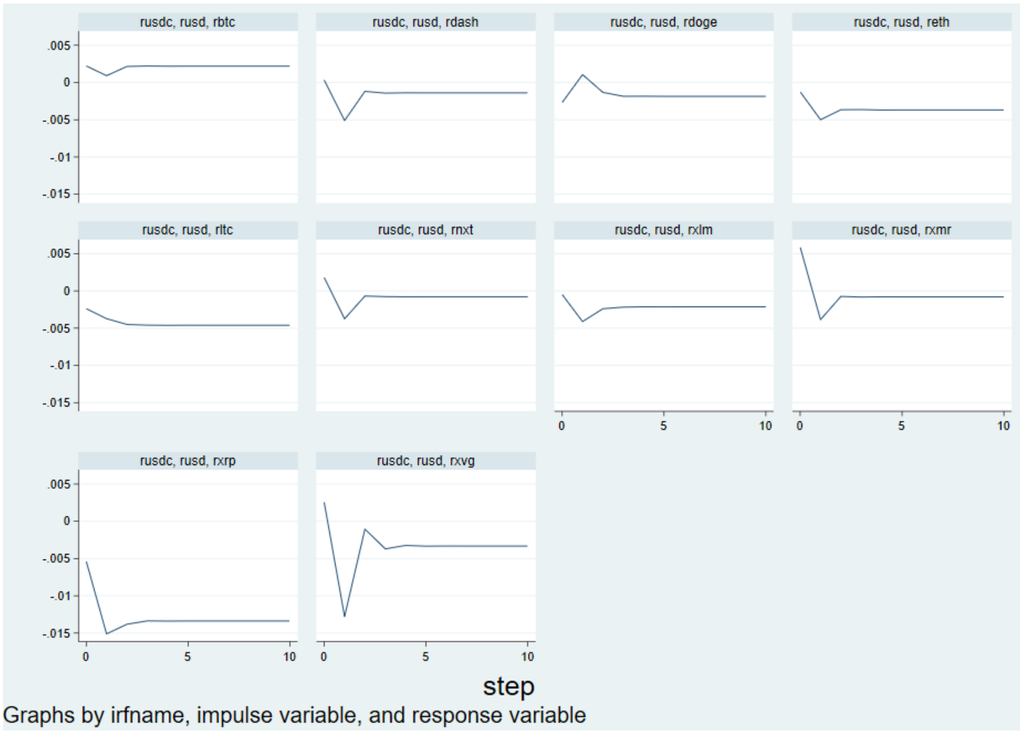

Figure 5. Impulse Response Function from USD to cryptocurrencies (2015-2021)

After that, we intend to analyze the impacts of fluctuations in the exchange rate of fiat currencies and understand the impact of these variations on the price of digital currencies. Because they are completely different realities in terms of dimension and performance, sometimes it's difficult to draw statistically relevant conclusions from the applied methods. However, there are some notes to highlight.

Therefore, the IRF will have a percentage impact much lower than what we saw in the previous analysis of crypto vs. crypto. In the case of the USD, the momentum is only positive with the BTC – and with an insignificant coefficient of less than 0.003 *(Figure 5)*. A shock to the US dollar has a slight negative impact on the remaining cryptocurrencies. The most relevant shock is reflected in XRP. In terms of the MGARCH analysis, we can see that it is only possible to draw statistical conclusions regarding Monero, even though its coefficient is almost null, that is, a variation in the USD price practically does not generate a variation in the XMR price *(Appendix 21)*.

Observing the main currency of the European continent (EUR), this one also only presents a positive impulse at the precise moment of the shock occurrence (moment 0), but the effects caused in the cryptocurrencies vanish soon afterward. The main thrust to be highlighted is at XVG *(Appendix 22)*. On the other hand, a variation in the price of the EUR/USD pair has a positive impact on XRP and a negative impact on DOGE, despite the impacts being manifestly low *(Appendix 23)*. A variation in the GBP price also causes very little volatility in Ethereum, for a 10% significance level *(Appendix 25)*.

Similar to the USD, a shock to the JPY or CHF sends a negative impulse to the XRP *(Appendix 26, Appendix 30)*, which tends to perpetuate over time (albeit very weak). The opposite finding is verified in the IRF of CAD, AUD, and NZD, which give a positive response in the main centralized cryptocurrency *(Appendix 28, Appendix 32, Appendix 34)*.

The remaining pairs have many individual conclusions at the MGARCH level, and which do not have a very similar relief in the sample. Just mention that volatility in the JPY generates fluctuations in the same direction in the ETH and the opposite direction in the DASH *(Appendix 27)*; a variation in AUD causes volatility in the same direction in ETH, XRP, and XVG, while in XMR the variation occurs in the opposite direction *(Appendix 29)*; the volatility observed in CHF also generates similar fluctuations in ETH and XRP *(Appendix 31)*.

If we change the typology of the analysis, looking now to verify the impulses generated by a shock in a cryptocurrency and the respective repercussions in the forex market, we find that the conclusions are not brilliant either. It should be noted that we are also comparing markets with completely different liquidity levels so that the capacity of cryptocurrencies to influence fiat currencies a priori was predictably null (Iqbal et al., 2021).

The first major conclusion to be drawn is that the impulses generated by crypto shocks have even less impact on forex volatility than the other way around.

Analyzing the implications of the price fluctuations of BTC, LTC, and DASH, there are no great relationships to affirm *(Appendix 37, Appendix 39, Appendix 41, Appendix 43, Appendix 45, Appendix 47, Appendix 49, Appendix 51, Appendix 53)* – perhaps because they are currencies that tend to have a smaller variance compared to the rest of the asset class in which they belong. Furthermore, looking into the impulses of cryptocurrencies with a smaller market cap these impulses tend to be weaker, so they are residual and have no interpretation.

However, in the case of ETH, there is a strong relationship between the level of volatility and the Euro, with a variation in Ethereum generating a variation in the opposite direction in this fiat currency, for a significance level of 10% *(Appendix 37)*. At this same level of statistical significance, we can conclude that an oscillation in Monero's price also generates a movement in the same direction in Bitcoin's price *(Appendix 47)*.

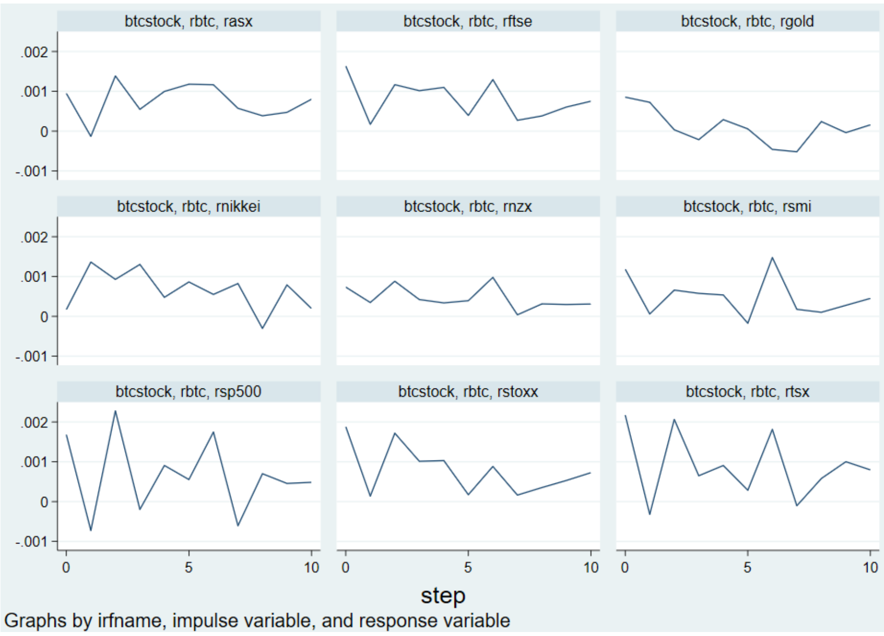

Figure 6. Impulse Response Functions from Bitcoin to Stock Indexes (2015-2021)

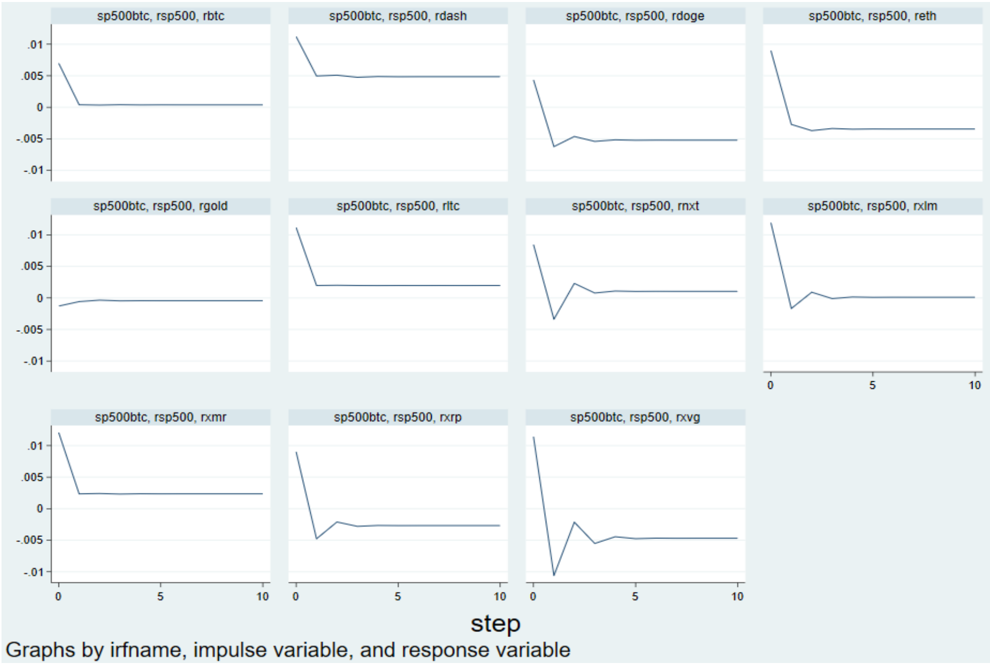

Figure 7. Impulse Response Function from S&P500 to cryptocurrencies (2015-2021)

Regarding the BTC influences on stock indexes, we can see that the impulses generated by the cryptocurrency are also very low and insignificant. Even so, for a period of 10 moments under analysis, we found that the incidence of the impulse fluctuates *(Figure 6)*. About the volatility of these two classes, we can state that a Bitcoin price fluctuation generates a remarkable variation in the Canadian index for a significance level of 1%. If we analyze for a level of 10% we can say that the ASX is also positively correlated in terms of volatility with Bitcoin *(Figure 7)*.

Making an inverse analysis exercise, we can notice that the main world index – S&P500 – when it suffers a shock in its standard deviation, it generates a positive impulse in all cryptocurrencies *(Figure 7)*, but practically only at the precise moment of the shock, as the effect tends to dissipate afterward. A unitary change in the American index also causes a very small positive change in Monero's volatility *(Appendix 54)*. The relationship with the remaining cryptocurrencies is not statistically significant.

4.1.2. Covid-19 Period

The period of COVID-19 was marked by major shocks and movements in the financial markets, as a result of the enormous expectations and anxiety of investors. These moments of greater turbulence are interesting to understand, namely, the capacity of some assets to respond as a store of value and risk diversification. In this sense, it is particularly important to create a temporal macro to repeat the same processes of the original study and compare the results obtained, as well as drawing other specific conclusions from this period. Therefore, we decided to analyze the data for the period between December 3, 2019, and March 12, 2021 (end of the overall sample). December 3rd corresponds to the first day of the sample after the diagnosis of the first coronavirus case worldwide, in China (*back to Figures 1, 2, 3*).

In general terms, we can note that the broad trends remain in this sample. Cryptos continue to be the most profitable and volatile, followed by stock indices and, finally, the forex market *(Table 9)*.

Table 9. Descriptive statistics by category of the asset (Covid-19 period)

	Obs.	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**
Cryptos	2810	0.6327	0.0815	0.4544	22.6708
Forex	2248	0.0218	0.0062	0.2196	8.5643
Stocks	2248	0.0264	0.0180	-0.9321	11.7523
Gold	281	0.0577	0.0142	-0.1652	6.3485

The average daily return of cryptocurrencies in this study rose by more than 50% compared to the initial sample period, standing at +0.633% in the COVID period *(Table 9)*. Furthermore, contrary to what happened in the other asset classes, its standard deviation decreased in this pandemic period. The pandemic coincided with a period of a bonanza for digital currencies, especially in the year 2021, when a real bull run was confirmed *(Figure 1)*. These assets are also reaching higher maturity levels, so their price tends to slowly stabilize.

Forex pairs, as a rule, also had positive daily average returns and were higher than those observed in the large sample. This case was due to the major monetary policy decisions taken around the world, namely by the United States, which made large injections of capital into the economy and because it was the USD dollar, as it was the FED that took the most aggressive measures. The standard deviation of this asset class was slightly higher, because of this instability in the markets.

At the end of February 2020, there was an aggressive market crash in the stock markets, together with a bear market until April of the same year. It was the fastest fall ever in the history of financial markets. However, not only was the biggest drop ever in the markets in this covid period, but these stocks also recovered and even some continue to hit historic highs such as the S&P500. From what we have just mentioned, it is evident that the standard deviation of stock indices has increased significantly compared to the values of the total sample in this study. In the case of Gold, we can see the same trends: an average return higher than in the total sample, as well as a fluctuation in its daily price.

Table 10. Descriptive statistics of cryptocurrencies (Covid-19 period)

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis
BTC	281	0.7324	0.0536	-2.3304	25.0124
ETH	281	0.8810	0.0728	-1.2026	16.5890
XRP	281	0.2483	0.0852	1.2193	30.5190
LTC	281	0.5597	0.0698	-1.0458	10.7295
DASH	281	0.5235	0.0849	0.8533	12.0151
XLM	281	0.6882	0.0885	3.0236	30.9545
XMR	281	0.5051	0.0630	-2.0492	17.3584
DOGE	281	1.1421	0.1248	5.4209	51.6422
XVG	281	0.6440	0.0978	0.9544	14.0098
NXT	281	0.4027	0.0747	-0.2996	17.8783

Within the universe of digital coins, there is a case that stands out which is the Dogecoin, a coin that was strongly influenced by personal opinions and direct association to the project uttered by Elon Musk – CEO of Tesla – and one of the most influential and futuristic men in the world. The fact that cryptocurrencies are not a regulated market allows any individual to exercise their power of influence to manipulate the market, in a positive or negative sense. The interconnection of Tesla and its CEO to DOGE (Ante, 2021) has resulted in it having an impressive average daily return of +1.14% in this period, equivalent to approximately 257% per year *(Table 10)*.

Moreover, it wasn't just this crypto that had fantastic returns. The cryptocurrency market, in general, had an extremely positive performance, suffering high valuations in many currencies *(Table 10)*. Due to the entry of new investors in the market (namely some giant players), the increasing dissemination and advertising of the cryptographic market in social media and social networks, the continuous emergence of new projects and currencies, among other reasons, made the market enter on a bull run. Bitcoin itself, due to being the best-known currency, turned out to be naturally the most sought after, achieving an average daily return of 0.73% which means that it grew on average 164% for 1 year. The most curious thing about this analysis is to verify that, despite this exceptional upward movement, the standard deviation barely increased (from 0.051 in the general period to 0.054 in covid time). The second-largest cryptocurrency – Ethereum – was also a success story and outperformed the BTC. It had an average daily return higher than the overall sample (about +0.88% in Covid period, compared to +0.59% in daily growth in the total sample) and was able to see its volatility decrease in this short period, which demonstrates that it may have improved its capacity to act as hedging to the markets and be useful when building an investment portfolio.

The centralized Ripple (XRP) was the only currency that did not have an average daily return higher than the initial sample *(Table 10)*. At the origin of this situation are some judicial details, between the entity issuing the digital currency and some regulatory bodies in the USA, which came to prohibit the currency. These advances and setbacks in the American courts caused successive valuations and corrections to this asset.

Looking at Litecoin, we can see some similarities with Bitcoin's behavior: the increase in daily returns in this period and continues to be one of the currencies with less volatility, according to what is desirable for a currency focused on being a medium of exchange. Monero was one of the currencies that did not have daily growths that were very different from the general sample but saw its volatility decrease during the pandemic period, such as XLM, XVG, and NXT *(Table 10)*.

Table 11. Descriptive statistics of forex pairs (Covid-19 period)

	Obs.	Mean	Std. Dev.	Skewness	Kurtosis
USD	281	-0.0257	0.0046	0.2046	5.4460
EUR	281	0.0301	0.0050	-0.1144	7.8447
GBP	281	0.0289	0.0075	0.1075	12.3728
JPY	281	0.0014	0.0056	0.8985	13.7494
AUD	281	0.0495	0.0085	0.1386	6.8201
CHF	281	0.0267	0.0051	0.6858	10.6506
CAD	281	0.0213	0.0051	-0.1838	4.8246
NZD	281	0.0424	0.0079	0.0201	6.8062

After all, paying attention to the forex pairs, the USD Dollar was the only currency to suffer a depreciation in the pandemic period *(Table 11)*, although the same was seen in the original sample, but with less strength. Also noteworthy is the British Pound, which in the initial sample had a negative average daily return and is now positive at around 0.029%. The Australian dollar was the currency that appreciated the most daily (about 0.05%), followed by the New Zealand dollar, which appreciated on average 0.042% per day during the pandemic period. The currencies EUR, CHF, and CAD appreciated between 0.02% and 0.03% per day. It should also be noted that the standard deviations of these assets remained essentially constant compared to the initial sample despite the higher returns.

A special point in this analysis concerns the Yen, as in the initial sample the JPY was the currency that registered the highest average daily return (remember that it was +0.011%) and in this pandemic analysis, it had almost a null appreciation (about 0.001%) - a daily variation close to zero. It is worth mentioning this since the Japanese stock index was the one that simultaneously grew the most during covid-19, totaling average daily gains of 0.083% *(Table 12)*.

Table 12. Descriptive statistics of stock indexes (Covid-19 Period)

	Obs	Mean	Std. Dev.	Skewness	Kurtosis
S&P500	281	0.0570	0.0221	-0.9857	12.1146
STOXX	281	0.0197	0.0199	-1.2204	12.5366
FTSE	281	-0.0266	0.0183	-0.9512	10.7802
NIKKEI	281	0.0831	0.0164	0.2350	6.7010
SMI	281	0.0122	0.0152	-1.3701	13.3856
TSX	281	0.0372	0.0206	-1.5134	18.4431
ASX	281	-0.0050	0.0185	-0.9707	9.0573
NZX	281	0.0338	0.0132	-0.6802	11.0002
Gold	281	0.0577	0.0142	-0.1652	6.3485

In addition to the devaluation of the English currency, its FTSE index also suffered a fall compared to the pre-covid period (on average it fell 0.027% per day), when its average return over the extended sample period was positive. The index that also had a negative performance in the pandemic period was the Australian one, despite being a residual value in comparative terms (it lost an average of 0.005% per day). Returning to the European continent, the STOXX grew 0.02% daily and the SMI only 0.012% - inferior values compared to the American competitor markets, clearly demonstrating that the American economic recovery happened in a more accentuated way than the European one.

Gold also had a positive daily return during this new time frame (around 0.058% per day), despite having seen a greater fluctuation in its daily price. Note that, during the Covid period, gold returns were above the average growth of the S&P500, with the commodity also reaching historical maximums at times in this analysis. The daily appreciation of the price of gold was more than double the average growth of stock indices and with less volatility in the process.

Moving on to the Pearson Correlation *(Table 13)* analysis to understand the performances in terms of direction and intensity between the various variables, we can first conclude that in this analysis of the COVID-19 sample there is a reinforcement of the existing correlations between the variables and the sample of this dissertation. The existence of a bull market in the crypto sector largely justifies this trend.

Starting with crypto assets, Bitcoin sees its correlation grow stronger with all other digital currencies, except DOGE and NXT *(Table 13)*. We highlight the strong correlation that exists with the second-largest digital currency (ETH) and the second-largest payment method currency (LTC), with XMR also strengthening their association.

Although centralized currencies continue to be the least correlated with the BTC in comparative terms (as in the total sample), the truth is that during the pandemic period they also reinforced their positive relationship with the crypto-mother. As might be expected, in general terms, Bitcoin continues to have special correlations with payment method currencies and with private currencies. Gold has also reinforced its correlation with the main cryptographic asset, which may mean that they have come closer in terms of performance and that they are moving together to be increasingly associated with hedging portfolios.

Table 13. Pearson correlation of cryptocurrencies and gold (Covid-19 period)

	BTC	ETH	XRP	LTC	DASH	XLM	XMR	DOGE	XVG	NXT	GOLD
BTC	1.0000 ***										
ETH	0.8359 ***	1.0000 ***									
XRP	0.5056 ***	0.6080 ***	1.0000 ***								
LTC	0.8649 ***	0.8475 ***	0.5589 ***	1.0000 ***							
DASH	0.5787 ***	0.5751 ***	0.5187 ***	0.6171 ***	1.0000 ***						
XLM	0.5606 ***	0.6589 ***	0.7545 ***	0.5794 ***	0.5322 ***	1.0000 ***					
XMR	0.7032 ***	0.6655 ***	0.5013 ***	0.6972 ***	0.7392 ***	0.5229 ***	1.0000 ***				
DOGE	0.4359 ***	0.4346 ***	0.3579 ***	0.3700 ***	0.1748 ***	0.4218 ***	0.2033 ***	1.0000 ***			
XVG	0.5973 ***	0.6248 ***	0.6819 ***	0.5807 ***	0.4763 ***	0.7095 ***	0.5219 ***	0.4677 ***	1.0000 ***		
NXT	0.5831 ***	0.5267 ***	0.4747 ***	0.5213 ***	0.4457 ***	0.4324 ***	0.4872 ***	0.2974 ***	0.4328 ***	1.0000 ***	
GOLD	0.2219 ***	0.1839 ***	0.0354	0.1736 ***	0.0728	0.0025	0.1472 **	0.0908	0.0223	0.1413 **	1.0000 ***

Notes: * - significant at the 10% significance level; ** - significant at the 5% significance level; *** - significant at the 1% significance level

On the part of Ethereum, we can immediately note that it continues to associate itself even more with the behavior of Gold, even though it is no longer the most correlated cryptocurrency with Gold as it was in the total sample. Although ETH also showed an even greater correlation with the remaining assets in this period, it is with Litecoin that there is a resounding correlation *(Table 13)*.

Paying attention to the third crypto asset by market cap, Ripple also follows the bull run of the crypto market and confirms the strengthening of the correlation with Stellar, its centralized partner. It should be noted that the correlation between XRP and XVG soared with the total sample, with the two variables being strongly positively correlated with each other. However, it is also curious to see that the same XVG saw its correlation grow significantly with Stellar, that is, Verge followed the trend of centralized currencies during COVID and not before *(Table 13)*.

Regarding Litecoin, this proved to be the third digital currency in the sample most correlated with gold in this period. Crypto also maintained the good correlation that it previously had with the privacy currencies DASH and XMR, since it has very similar purposes. It has a high correlation with Bitcoin and Ethereum, which are the highest values to highlight in its performance in terms of coronavirus *(Table 13)*.

Similar to Litecoin, DASH continued to show a strong correlation with the XMR homogeneous currency. It should be noted, for inverse reasons, that the DASH showed a very low correlation with the DOGE since we are comparing the sample currencies with the highest and lowest returns, respectively. In addition, due to the extraordinary evolution of Dogecoin's price and highlighted by the others *(Table 13)*, this led to a lower statistical correlation coefficient in most cases.

Finally, it should be remembered that Verge's improvement in correlational terms was not only with the centralized currencies as mentioned above, but with the remaining assets as well, which demonstrates that Verge has followed the general trend of market growth *(Table 13)*. NXT also experienced the same dynamics of improvement in terms of correlation with partners, although it continued to be slightly below average.

Taking into consideration the analysis of the intra-forex pairs correlation, we can see from the outset that the USD maintained its perspective of negative correlation against the other pairs, and even saw the intensity of the correlation increase *(Appendix 55)*. With the same trend, but in the opposite direction, the Euro increased its correlation with the other currencies, and it continues to show greater affinity with the geographically closer currencies: CHF and GBP. In addition to the GBP correlation with the European pairs, we can note that there is a notable correlation with the currencies related to the British descent countries: NZD and AUD. So, the importance of cultural heritage is also verified in monetary terms. The British pound reinforces its opposite relationship with the USD, as the coefficient became more negative than in the total sample.

Moving on to the Asian continent, it should be noted that the JPY was closely correlated with the CHF during the pandemic, but also with the most liquid pairs in Europe: EUR and GBP *(Appendix 55)*. It was, therefore, clear that there was a greater association with the European continent in monetary terms during this crisis – perhaps because of similar actions by its Central Banks.

Once again, the Australian dollar presents strong evidence of the importance of cultural heritage in the macroeconomic part, as it has a good correlation with the GBP, CAD, and NZD. New Zealand and Canadian dollars also have a strong positive relationship that it is important to reiterate *(Appendix 55)*.

Of the very few examples of statistically significant correlation with gold, the Canadian dollar is an example of who tends to follow the commodity's performance similarly.

Changing the asset class to the stock indexes *(Appendix 56)*, we can see that the same thing happened as in the previous analyses. The S&P500 index reinforced the correlation with all other stocks, highlighting here the very strong association with the performance of the TSX. The correlation with European markets was also more salient in this pandemic period. Also on European soil, there was a strong correlation between the STOXX and the FTSE, followed by a high relationship with the SMI – a trend that had already been verified in the period of the total sample. The FTSE, in addition to the European indices, also has some similarities in terms of performance with the TSX. Also, the only Asian index – the NIKKEI – showed a higher correlation with Europe in this pandemic period.

As seen in forex peers, the TSX also highlighted issues of cultural heritage among stock indexes. On the other hand, ASX and NZX have correlation coefficients quite balanced with all others.

Gold completely changed its behavior in the pandemic period compared to the period of five and a half years of the total sample. On the total sample, it had a negative correlation coefficient with all indices, but in this period of COVID-19, gold presented positive correlations with all of them, largely due to the general bull run of the financial markets and the prices of raw materials, associated with the inherent inflationary process generated by them. Gold turns out to have interesting correlations with STOXX, FTSE, NIKKEI, SMI, and TSX.

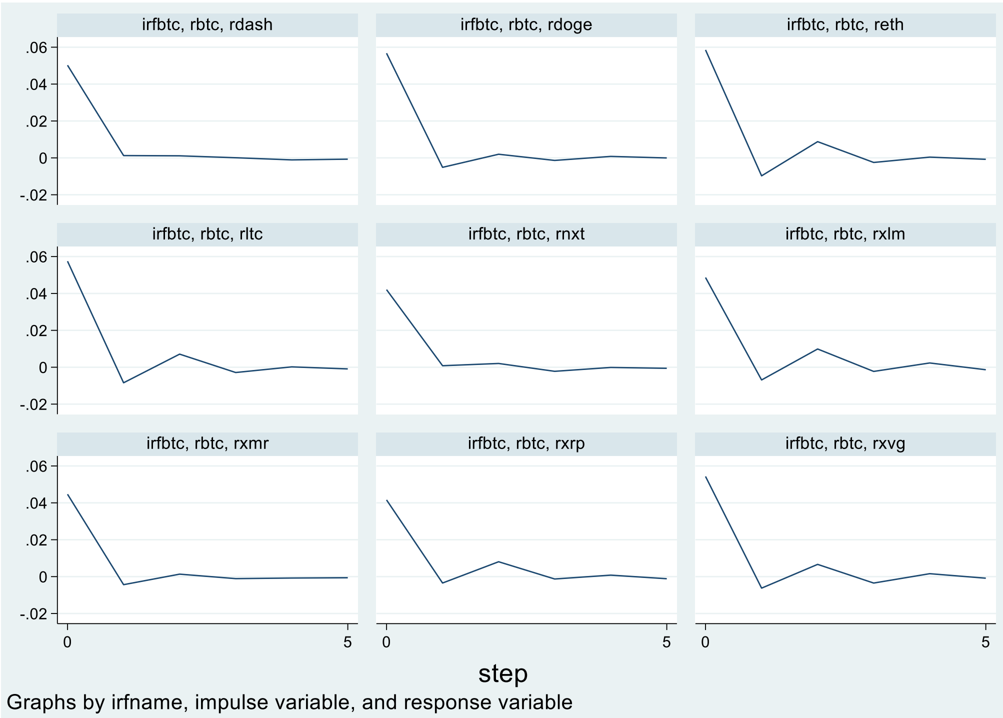

Figure 8. Impulse Response Function from Bitcoin to other cryptocurrencies (Covid-19 period)

Analyzing now the results of the Impulse Response Function and the Multivariate GARCH *(Figure 8 and Table 14)*, we can conclude that in terms of IRF, the same thing that has already been said here is verified. Greater involvement and incidence in the relationship between the various variables in the period of COVID-19. It was found at the level of impulses emitted during shocks in a variable that these were, in general, slightly more intense than in the periods of the broader initial analysis.

Starting from the beginning with Bitcoin, the impulses emitted to the remaining cryptocurrencies were only practically felt at the precise moment of the occurrence of the shock, and the IRF coefficient was higher than the average of 0.04 verified in the larger sample, therefore the impulses were more robust. About the MGARCH outputs (Table 14), we can conclude that a unit variation in the BTC generates higher positive volatility in the LTC and the XMR, as was to be expected considering their properties. ETH is also one of the most influenced in terms of its price fluctuation. However, a change in the price of BTC generates a change in the opposite direction at Ripple and Stellar, as was also expected.

Table 14. MGARCH model applied from BTC to other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>z	[95% Conf.Interval]	
reth	0.2011	0.0338	5.94	0	0.134767	0.267427
rxrp	-0.0572	0.0278	-2.06	0.039	-0.11159	-0.0028
rltc	0.3010	0.0352	8.54	0	0.231967	0.370095
rdash	-0.0114	0.0249	-0.46	0.647	-0.06025	0.037401
rxlm	-0.0542	0.0223	-2.43	0.015	-0.09795	-0.01051
rxmr	0.1688	0.0341	4.94	0	0.101867	0.235692
rdoge	0.0683	0.0175	3.9	0	0.033949	0.102697
rxvg	0.0487	0.0170	2.86	0.004	0.01537	0.082041
rnxt	0.1157	0.0235	4.93	0	0.069709	0.161627
_cons	0.0005	0.0011	0.5	0.616	-0.00157	0.002647

Ethereum also increased the strength of the impulse exerted on the remaining cryptocurrencies, being in the COVID period around 0.04 while in the initial sample it rarely reached 0.03 – note that this impact is similar in most assets *(Appendix 58)*. In the pandemic period, a greater impact of ETH on XVG and XLM was noted, which was not visible in the study with the larger temporal sample. The volatility test continues to demonstrate that changes in the price of ETH continue to be largely accompanied by the prices of BTC and LTC (in this sense, ETH-BTC is even higher than in BTC-ETH, as was also noted in the other sample).

In the case of Ripple *(Appendix 59, Appendix 60)*, we can see that when there is a shock, it exerts impulses essentially on the XLM and XVG. Also at the level of MGARCH, we can verify that a variation in XRP will cause a greater variation, in a positive sense, in XRP. Unlike the BTC-XRP coefficient for example (which was negative), all MGARCH values are positive.

The impulses exerted by Litecoin in the remaining ones have effects on the price between the precise moment of the shock and also in the following moment (unlike most until then), especially with ETH, XLM, XRP, and XVG. This currency continues to present a positive coefficient of the MGARCH with the two main cryptocurrencies – as there has always been this greater relationship between the main currencies as we have already seen *(Appendix 61, Appendix 62)*.

A curious thing is observed in the application of multivariate GARCH. The DASH currency has negative coefficients with ETH and NXT *(Appendix 64)*, that is, platforms with their blockchain, which therefore have fluctuations in the opposite direction to DASH. The strongest association that exists is with XMR. XMR also presents impulses with effect up to the moment 2 in several currencies and, accordingly with MGARCH, we verify that its volatility has greater convergence with the main cryptocurrencies *(Appendix 66)*.

The same happened in the opposite pairs, for example, XLM mainly presents impulses in the XLM and XVG at zero moments *(Appendix 67)*. The MGARCH coefficient with the XRP is also highlighted, which is extremely positive, validating the fact of a greater similarity due to the centralization. It only has a negative coefficient with NXT *(Appendix 68)*.

A particular case is DOGE during this pandemic period. This was the golden period of this cryptocurrency, which grew up more than the magnificent performances of the cryptos' sector. This led to less influence, in statistical terms, at the level of impulses generated in other currencies, as the price of Dogecoin often soared on its initiative and even when the market was completely stabilized. Therefore, the IRF graphs are less relevant in this pandemic period than in the total sample and the intensity of shocks is also lower than the average for other currencies *(Appendix 69)*. Surprisingly, the MGARCH analysis showed that a unit variation in the Dogecoin order mainly positively affects XRP *(Appendix 70)*. For the smallest assets by market cap, XVG continued to verify a similar relationship and influence on XRP and XLM, which would not be expected *(Appendix 72)*. On the other hand, NXT is the currency that has the greatest impulses exerted on DOGE, and the MGARCH coefficient *(Appendix 73, Appendix 74)* showed that a variation in its price has high relevance in the volatility of the BTC, in the same direction (coefficient of 0.715). The same NXT has a volatility trend contrary to the XVG when shocks occur.

As a result of the impacts of the forex market currencies on the crypto market currencies, it's possible to conclude that the US dollar has a dynamic IRF in terms of direction *(Appendix 75)*, but not so much relevant because values are close to nullity. Furthermore, the impact is found to be insignificant in all IRFs. Another fact is that a unit variation in the USD generates a variation in the opposite direction of the LTC, only.

GBP, AUD, CAD, and NZD have negative MGARCH coefficients for Monero, which indicates that when one of these fiat currencies has a positive change in price, XMR changes in a downward direction, and vice versa. It should be noted that there are very few conclusions to be drawn since statistically significant outputs are rare *(Appendix 80, Appendix 84, Appendix 88, Appendix 90)*.

4.2. Optimal portfolio

4.2.1. Total sample (2015-2021)

To potentialize the data collected in previous investigations, we will now analyze the constitution of portfolios that have the best risk-return combination, assuming investors' rationality. This study will be based on the application of the Markovitz Efficient Frontier, comparing the Sharpe Ratio obtained between different portfolios, that is, the additional return per unit of risk assumed in this portfolio decision.

This analysis will be performed for the total sample and the COVID period, and then the coefficients generated in both cases will be analyzed. Here are the assets that will be used in this study:

- Gold – because of its hedging and safe haven capacity, recognized by many authors that were already mentioned in the literature review of this work;
- S&P500 – as the world's leading index, with the largest and the most important companies in the world. It is considered a benchmark indicator of the investment market;
- Bitcoin – the most famous cryptocurrency and the one with the best results in terms of Sharpe Ratio. That's why it will be the one with the highest potential to fight with gold in the quest for the best safe-haven;
- Ethereum – to test the presence of two cryptocurrencies in portfolios. It is the second main cryptocurrency, and it also has good Sharpe Ratio values;
- Stock Indexes that may have particular prominence in one of the samples and that may have potential interest in our analysis – in this case, it will be:
    - *Nikkei 225;*
    - *NZX*.

Firstly, although the high annualized returns of cryptocurrencies, they also have high values of the annual variance turning their Sharpe Ratio lower, making them less interesting in this method of analysis. That is why the inclusion of Bitcoin will be the most convenient – it has more stability in its price and is less volatile than others.

Table 15. Sharpe Ratio of used assets (2015-2021)

	Sharpe Ratio
Gold	0.5143
S&P500	0.4751
BTC	1.2823
ETH	1.0929
NZX	1.1016

Second, the S&P500 is the preferred index for portfolio composition but the New Zealand index (NZX) was also used because it is the index with the best risk-return ratio *(Table 15)*.

The first analysis performed was based on Bitcoin, Ethereum, S&P500, and Gold. If the distribution of the weights of the assets were made equally (25% on each investment), the Sharpe ratio would be 1.3633 *(Figure 9)*, that is, per additional unit of risk assumed by the investor, this will be remunerated at +1.3633% of return.

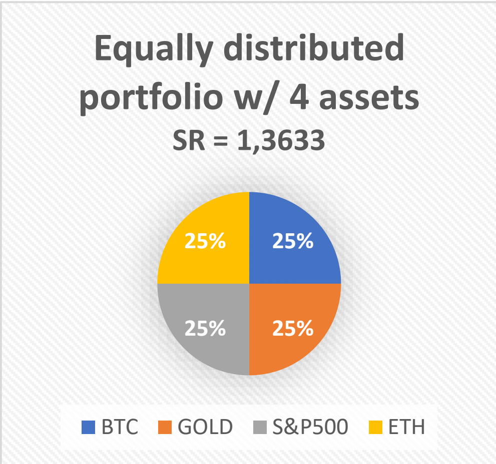

Figure 9. Portfolio with 4 assets with the same weights (2015-2021)

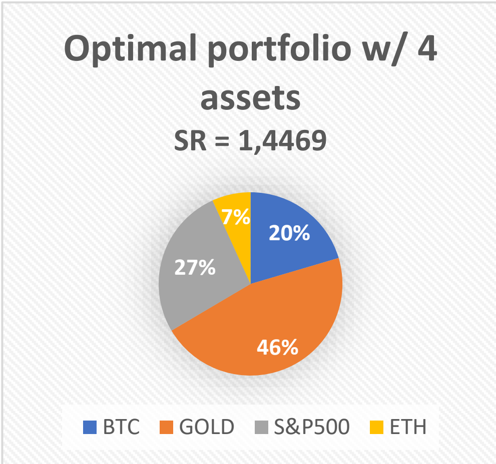

Figure 10. Optimal portfolio with 4 assets (2015-2021)

Using Excel, we calculated the optimal portfolio composition: 46% Gold, 27% S&P500, 20% Bitcoin, and 7% Ethereum *(Figure 10)*. We can conclude that, although gold continues to assume greater importance in portfolios, the two cryptocurrencies accounted for 27% of the total portfolio, which is a very good sign compared to some academic studies that showed that the ideal solution was to have up to 16% of cryptocurrencies in an investment portfolio (Conlon et al., 2020).

If we compose a portfolio with only 3 assets, according to Markovitz, it should allocate 25% to Bitcoin, 28% to S&P500, and 47% to Gold – in this case, cryptocurrencies decrease their influence. The advantage of the American index in this option is also visible when we try to create a portfolio between the S&P500 and Bitcoin, in which 52% of the first asset and 48% of the second must be acquired.

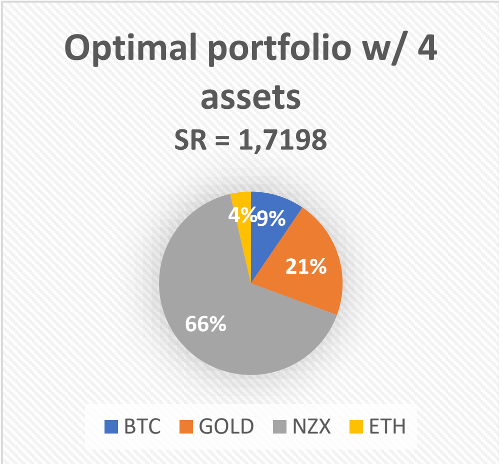

Figure 11. Optimal portfolio with 4 assets, including NZX (2015-2021)

Even in this period of analysis, the behavior of the NZX index stands out, which must be considered. So, we were replacing the S&P500, assuming that the investor's choice would be to opt for New Zealand firms and not the biggest in the world or American ones as previously.

Performing a similar process as the previous one, if we had to create an optimal portfolio with 4 assets from the extended sample of this study it would be composed of 66% NZX, 21% Gold, 9% Bitcoin, and 4% Ethereum *(Figure 11)*. This portfolio would produce a Sharpe ratio of 1.7198, that is, it has an additional return of approximately 1.72% per unit of risk.

4.2.2. Covid-19 Period

Analyzing the process of constitution of portfolios in the COVID-19 period, we can initially say that it has some differences and particularities compared to the larger sample. Firstly, because it was a period with high volatility but, at the same time, it had extraordinary returns.

Table 16. Sharpe Ratio of used assets (Covid-19 period)

	Sharpe Ratio
Gold	0.6278
S&P500	0.3348
BTC	2.0206
ETH	1.7944
NZX	0.4429
Nikkei	0.7710

Looking only at the individual SR of each asset *(Table 16)*, it was predictable that the results would be more promising than in the time analyzed previously. From the outset, the Japanese stock index (Nikkei) stands out with a high Sharpe ratio, followed by the NZX and then the S&P500. Let's see with better detail the relevance of including these same indexes in portfolios.

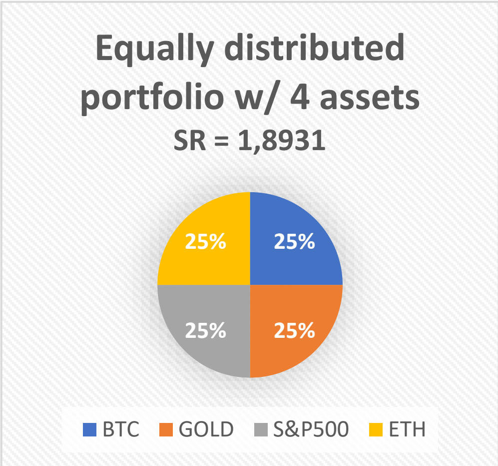

Figure 13. Portfolio with 4 assets with the same weights (Covid-19 period)

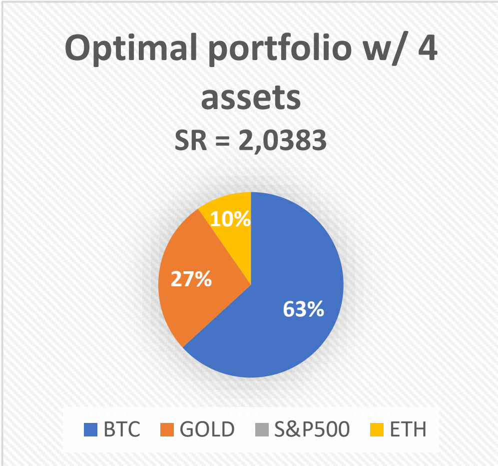

Figure 12. Optimal portfolio with 4 assets (Covid-19 period)

At the first time, let's look at portfolio compositions with the S&P500. If we create a portfolio with equal proportions between Bitcoin, Ethereum, Gold, and S&P500 we obtain a portfolio with an additional return of 1.893% per unit of risk *(Figure 12)*, which is a more profitable option than all those mentioned in the previous study for the period since 2015. According to the Markovitz model, if we build a bi-variable portfolio with Bitcoin and the American index, this portfolio should be composed entirely of Bitcoin. If we try to include Gold in this portfolio as well, then we should have 73% Bitcoin, 27% Gold, and 0% S&P500. Still, the optimal portfolio when we try to include the American index is composed of 63% Bitcoin, 27% Gold, 10% Ethereum, and 0% S&P500 *(Figure 13)*, that is, it is not possible to include the S&P500 despite having a Sharpe Ratio relatively interesting.

However, the S&P500 is not the best index to include in portfolios. The NZX index, which was the best match for the full sample, continues to be attractive, achieving an additional 2.028% return per unit of risk when it pairs 74% Bitcoin with 26% NZX.

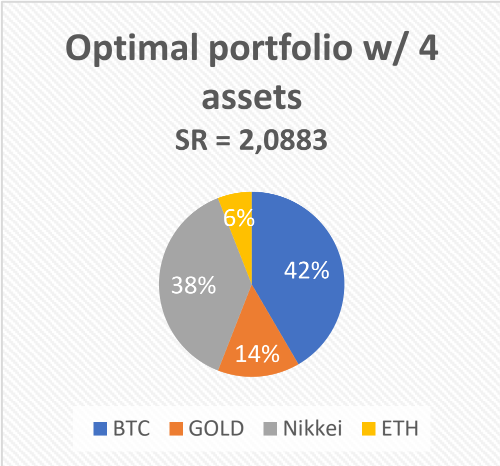

Figure 14. Optimal portfolio with 4 assets, including Nikkei 225 (Covid-19 period)

Nevertheless, the biggest novelty of the analysis in the pandemic period was the inclusion of the Japanese stock index, which accounted for a very significant Sharpe Ratio value. If we were building a bipartite portfolio between Nikkei 225 and Bitcoin, 45% and 55% of the portfolio weights would be distributed to each asset, respectively. Including Gold in this equation, we would conclude that Bitcoin and Nikkei would continue to be the assets with the biggest presence (48% and 38%, respectively), with the remaining 14% of the portfolio referring to Gold. Still, the best combination of the pandemic period comes down to the portfolio comprising 42% Bitcoin, 38% Nikkei, 14% Gold, and 6% Ethereum – which results in a portfolio with an additional return of 2.088% per unit of risk assumed by the investor *(Figure 14)*.

The fact that the Nikkei index is the stock with the highest return per unit of risk is partially justified by the fact that the Japanese yen also had exceptional returns compared to the other forex pairs in this period of COVID (Narayan et al., 2020). On the other hand, Japan already had a negative interest rate before the outbreak of this pandemic, which took some leeway for the Bank of Japan to act through its yield, as most countries worldwide have done - they lowered their interest rates. The fact that Japan did not have the opportunity to use this monetary policy mechanism generated an inflationary process in its assets and markets.

5. Conclusion

This study compared three classes of financial assets - forex, stocks, and cryptocurrencies - and sought to detect correlation or performance relationships between their main assets. This research work contains an extended analysis of five and a half years and for the period of COVID-19, where it was possible to observe different trends in these products with different characteristics. The results obtained have some lines of proximity to the existing literature, but there are also some new conclusions.

Forex pairs proved to be positively correlated with each other, apart from pairs with the USD dollar - the world's main currency. The eight stock indexes are also positively correlated, and it is possible to verify a greater relationship in countries with greater cultural heritage or even geographical proximity. Gold is negatively correlated with stock market indices, which validates its safe-haven property – in line with results obtained by Hussain Shahzad et al. (2020) and Kang et al. (2019). The cryptocurrencies are also positively correlated with each other - it is possible to observe stronger corrections according to the characteristics and functionalities of each one - and with the gold asset. It should be noted that in the pandemic period the correlations were even more expressive than in the broader analysis.

By analyzing the Impulse Response Functions we can draw some conclusions: 1) a shock in one cryptocurrency has a much greater effect on the others (compared to other types of assets) which helps to justify the greater market volatility and evidence the existence of a "trend market" in the cryptos; 2) the size of stock index impulses for cryptocurrencies are stronger than the reverse, so cryptocurrencies do not have much influence on general markets; 3) in cryptocurrencies, impulses vary according to the market cap of the currencies (the most impactful are the largest) and their function; 4) cryptocurrency impulses in forex pairs are residual and vice versa - so the two markets are independent.

Another way to measure the connections between assets is through the analysis of the MGARCH coefficients, which showed that: 1) cryptocurrencies have bigger connections among themselves, reinforcing the fact that they all follow a general market trend; 2) Litecoin volatility exerts the greatest influence on Bitcoin volatility (the highest MGARCH coefficient observed), which may indicate that LTC should be taken as one of the main drivers of the crypto market; 3) The centralized cryptos present an exceptional reality and behave differently from the others; 4) there are no significant relationships between cryptocurrencies and stock markets; 5) the influence of cultural heritage is again observed in terms of stock indexes.

The analysis of the COVID period based on Pearson Correlation, Impulse Response Function, and MGARCH shows practically the same trends mentioned above, but in a more accentuated form. The IRFs were slightly stronger, Ethereum took on a more structural role in the cryptomarket and Dogecoin confirmed the extraordinarily inflationary performance, especially because of the Elon Musk effect.

On the other hand, this study produced new conclusions about portfolio composition. For the period 2015-2021, when compared to the existing literature, our analysis suggests greater investment in cryptocurrencies by investors, when we are given a choice between Gold, S&P500, and any of the cryptocurrencies. In our case, the ideal investment portfolio should contain 20% Bitcoin and 7% Ethereum - more than a quarter of the portfolio should be cryptocurrencies. This result arises from the fact that the profitability per additional risk unit of BTC and ETH are the highest, respectively.

When we carry out the same exercise with the support of the Markowitz model for portfolio composition during the COVID period, we obtain even more impressive results. The most efficient portfolio in terms of risk-return (with the possibility to include S&P500, gold, and any crypto) is composed of 63% Bitcoin and 10% Ethereum, leaving the remaining share of the portfolio for gold. In this ideal portfolio, the S&P500 does not even enter. This surprising conclusion is a result of the huge bull run of cryptocurrencies and the sharper-than-normal volatility in the stock markets. During the study, other excellent portfolios were also presented, more specifically with the inclusion of the Nikkei and NZX indexes, which were the stocks with the highest Sharpe Ratio in this period. In the case of the Japanese index, this happened due to its national currency has appreciated against the other pairs (because the Bank of Japan had the most negative interest rate among the countries under analysis, so it cannot lower its interest rate much more, as other countries have done during the pandemic). Furthermore, the FED's money printing was also more aggressive, and the USD depreciated further against the remaining pairs.

To sum up, according to the Markowitz model, the COVID period was more profitable than the 2015-2021 period.

Even so, some difficulties arose during this work: 1) the inexistence of a risk-free rate for cryptocurrencies and the fact that there are different rates for different countries - difficulty in finding a uniform risk-free interest rate for the entire study; 2) cryptocurrencies that existed in 2015 were included to have a broader sample, but some of them in 2021 are no longer relevant because they lost influence (e.g.: NXT); 3) it is difficult to compare three types of assets that have such different dimensions, characteristics, and performances, which sometimes also limits the reading of the coefficients obtained.

Among some suggestions for future work, the extension of the analysis period is essential to better understand cryptocurrencies in a long-term vision (they are still recent assets) and understand how price fluctuations behave or if it is something speculative. As the annual growth in the number of crypto-assets has increased exponentially, it also makes sense to study more currencies. However, the analysis of certain cryptocurrencies should be done separately (e.g.: Dogecoin) because it has abnormal behavior and has its factors influencing it.

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Appendix

Appendix 1. Pearson Correlation of forex pairs and gold (2015-2021)

	USD	EUR	GBP	JPY	AUD	CHF	CAD	NZD	GOLD
USD	1.0000 ***								
EUR	-0.2048 ***	1.0000 ***							
GBP	-0.1592 ***	0.5480 ***	1.0000 ***						
JPY	-0.1170 ***	0.4463 ***	0.1441 ***	1.0000 ***					
AUD	-0.1379 ***	0.4789 ***	0.5071 ***	0.1740 ***	1.0000 ***				
CHF	-0.2074 ***	0.8163 ***	0.4429 ***	0.5658 ***	0.3568 ***	1.0000 ***			
CAD	-0.1729 ***	0.3681 ***	0.4182 ***	0.0790 ***	0.6656 ***	0.2884 ***	1.0000 ***		
NZD	-0.1403 ***	0.4874 ***	0.4814 ***	0.2606 ***	0.7969 ***	0.3976 ***	0.5697 ***	1.0000 ***	
GOLD	-0.2112 ***	0.0979 ***	0.0523 *	0.0987 ***	0.0896 ***	0.1058 ***	0.0770 ***	0.0805 ***	1.0000 ***

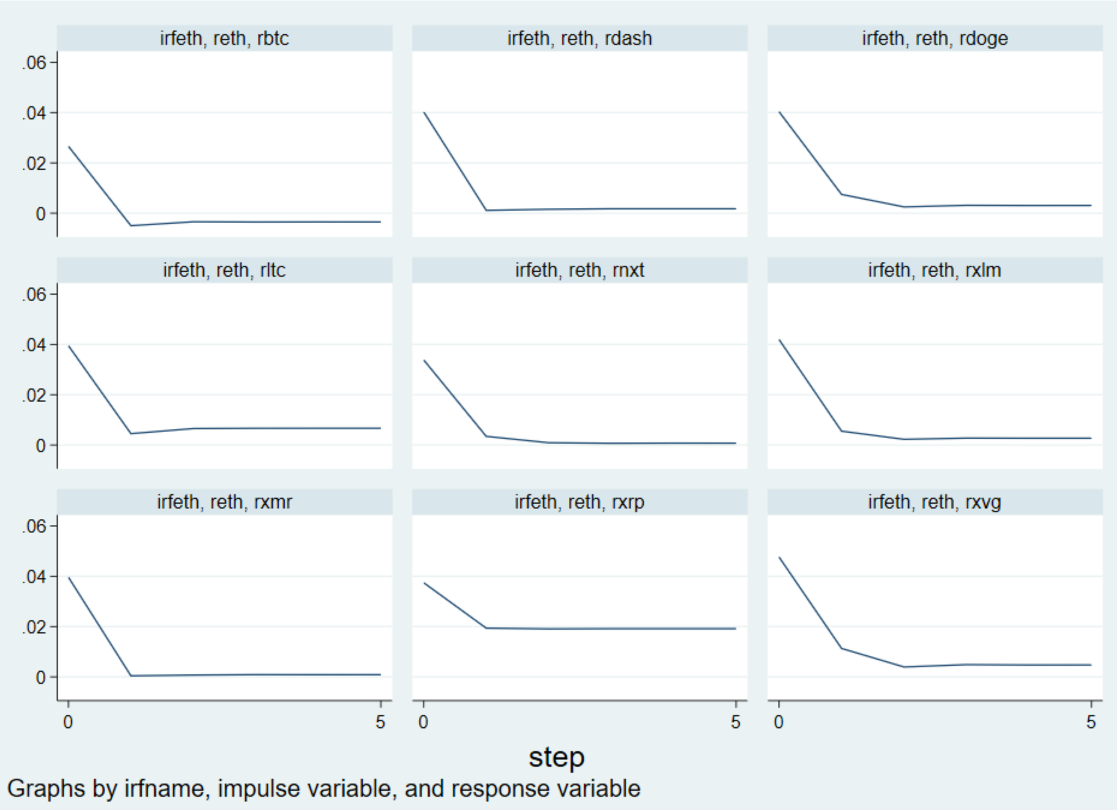
Notes: * - significant at the 10% significance level; ** - significant at the 5% significance level; *** - significant at the 1% significance level

Appendix 2. Pearson Correlation of Stocks indexes and gold (2015-2021)

	SP&500	STOXX	FTSE	NIKKEI	SMI	TSX	ASX	NZX	GOLD
S&P500	1.0000 ***								
STOXX	0.5959 ***	1.0000 ***							
FTSE	0.5802 ***	0.8757 ***	1.0000 ***						
NIKKEI	0.2531 ***	0.4594 ***	0.4186 ***	1.0000 ***					
SMI	0.5656 ***	0.7988 ***	0.7789 ***	0.3770 ***	1.0000 ***				
TSX	0.7738 ***	0.6692 ***	0.6953 ***	0.2983 ***	0.5976 ***	1.0000 ***			
ASX	0.4376 ***	0.4834 ***	0.5140 ***	0.5250 ***	0.4444 ***	0.5176 ***	1.0000 ***		
NZX	0.2339 ***	0.3015 ***	0.3332 ***	0.3790 ***	0.3417 ***	0.2972 ***	0.5028 ***	1.0000 ***	
GOLD	-0.1040 ***	-0.1054 ***	-0.0343	-0.0990 ***	-0.1042 ***	0.0733 ***	-0.0252	0.0028	1.0000 ***

Notes: * - significant at the 10% significance level; ** - significant at the 5% significance level; *** - significant at the 1% significance level

Appendix 3 - Impulse Response Function from Ethereum to other cryptocurrencies (2015-2021)



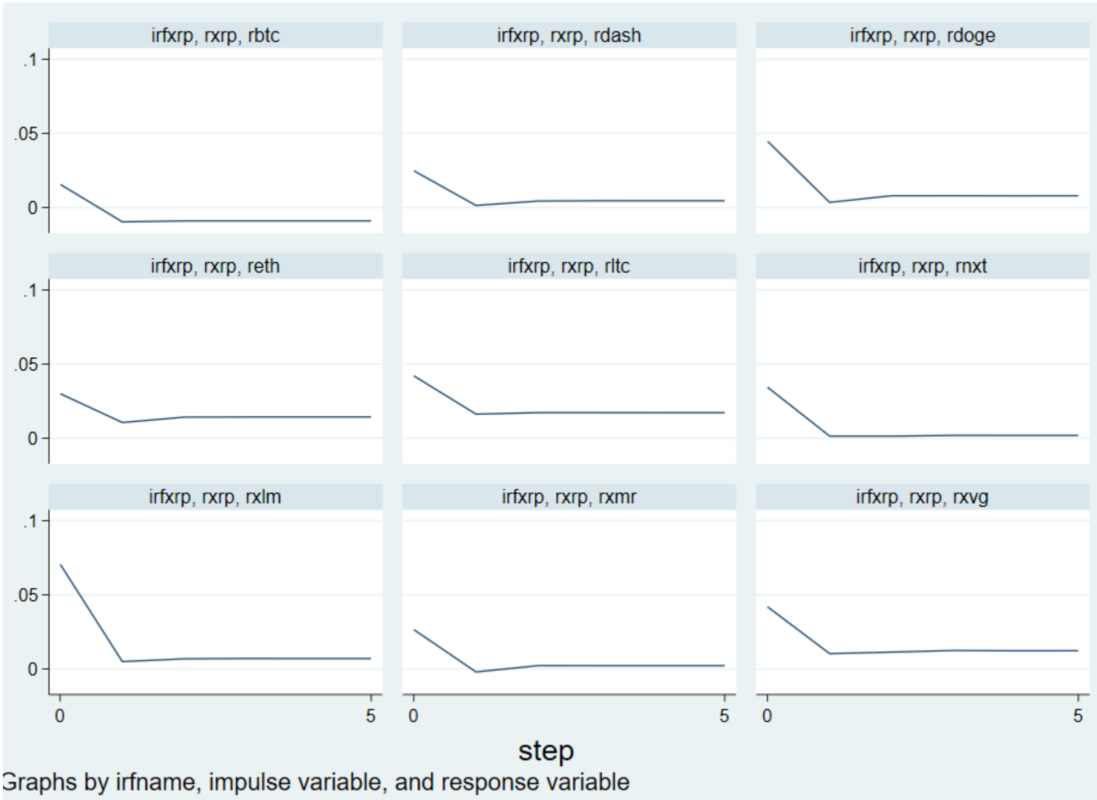
Appendix 4. MGARCH model applied for Ethereum and other cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(**9**) = **3478.34**
Log likelihood = **2068.625** Prob > chi2 = **0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
reth						
rbtc	.396262	.0354993	11.16	0.000	.3266846	.4658394
rxrp	.142638	.0225313	6.33	0.000	.0984775	.1867985
rltc	.2849834	.0277177	10.28	0.000	.2306576	.3393091
rdash	.1203964	.0300096	4.01	0.000	.0615787	.1792141
rxlm	.0365306	.0178322	2.05	0.041	.0015801	.0714811
rxmr	.046886	.0217039	2.16	0.031	.004347	.089425
rdoge	.0035442	.0162168	0.22	0.827	-.0282402	.0353286
rxvg	.0288667	.0118461	2.44	0.015	.0056488	.0520847
rnxt	.0332777	.0186309	1.79	0.074	-.0032382	.0697935
_cons	.0001683	.0009653	0.17	0.862	-.0017236	.0020602
ARCH_reth						
arch						
L1.	.1420962	.0209065	6.80	0.000	.1011203	.1830722
garch						
L1.	.8743544	.0141809	61.66	0.000	.8465603	.9021486
_cons	.0000232	6.03e-06	3.84	0.000	.0000114	.000035

Appendix 5. Impulse Response Function from Ripple to other cryptocurrencies (2015-2021)



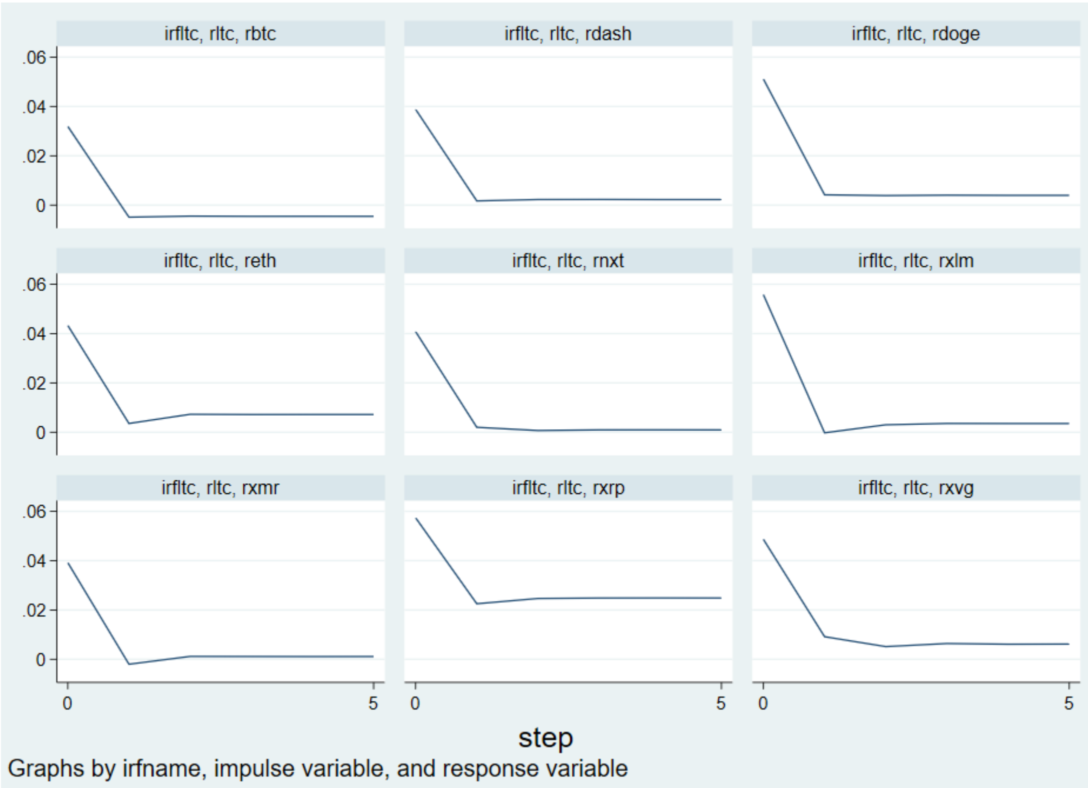
Appendix 6. MGARCH model applied for Ripple and other cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample:	**18aug2015 - 12mar2021**	Number of obs =	**1,238**
Distribution:	**Gaussian**	Wald chi2(**9**) =	**2387.31**
Log likelihood =	**2054.443**	Prob > chi2 =	**0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxrp						
rbtc	.1522077	.0379487	4.01	0.000	.0778297	.2265857
reth	.0727441	.0205177	3.55	0.000	.0325302	.112958
rltc	.1296645	.0287813	4.51	0.000	.0732543	.1860748
rdash	.0203084	.0181603	1.12	0.263	-.0152851	.0559018
rxlm	.2959378	.0206821	14.31	0.000	.2554017	.336474
rxmr	.0847135	.0167109	5.07	0.000	.0519608	.1174662
rdoge	.1181301	.0171389	6.89	0.000	.0845385	.1517218
rxvg	-.018805	.0082232	-2.29	0.022	-.0349221	-.0026879
rnxt	.0130431	.018393	0.71	0.478	-.0230064	.0490926
_cons	-.0038085	.0009771	-3.90	0.000	-.0057235	-.0018935
ARCH_rxrp						
arch						
L1.	.4725513	.0618696	7.64	0.000	.3512891	.5938134
garch						
L1.	.6400135	.0318518	20.09	0.000	.577585	.7024419
_cons	.0001599	.0000299	5.35	0.000	.0001014	.0002185

Appendix 7. Impulse Response Function from Litecoin to other cryptocurrencies (2015-2021)



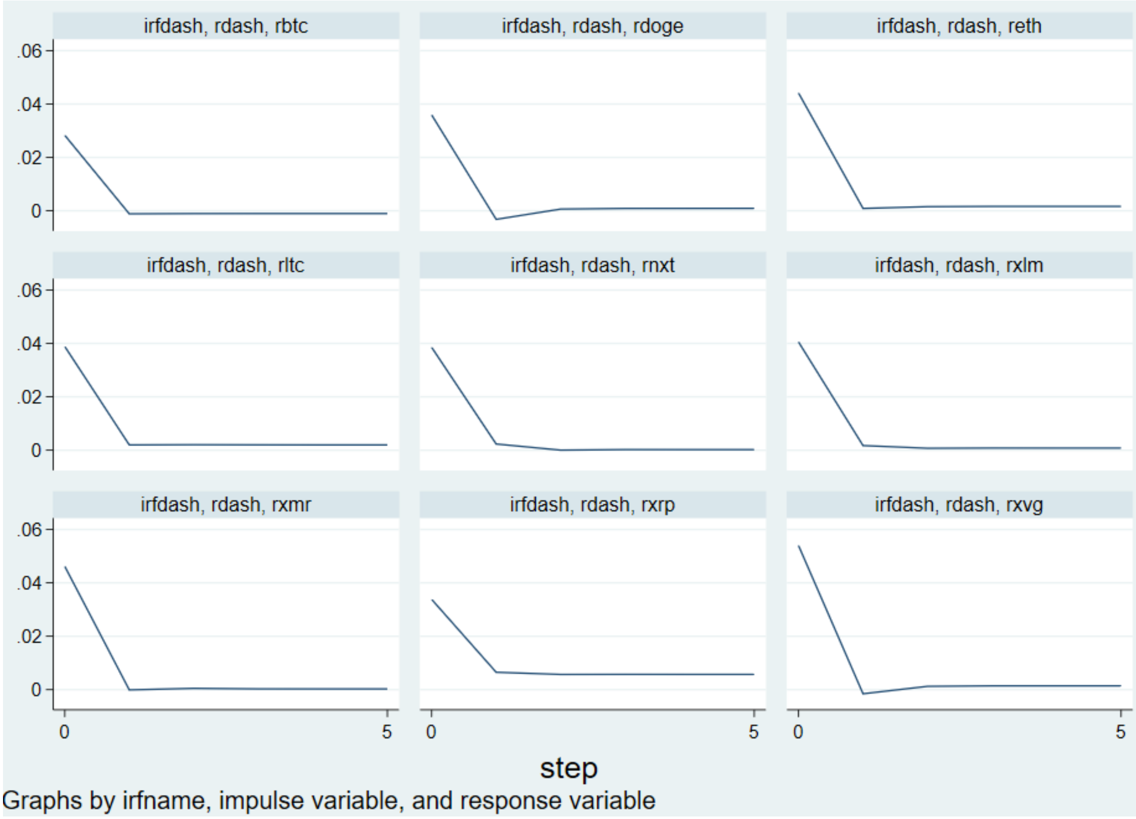
Appendix 8. MGARCH model applied for Litecoin and other cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021**	Number of obs = **1,238**
Distribution: **Gaussian**	Wald chi2(**9**) = **3651.95**
Log likelihood = **2284.654**	Prob > chi2 = **0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rltc						
rbtc	.7061647	.034315	20.58	0.000	.6389086	.7734209
reth	.0423857	.0136825	3.10	0.002	.0155684	.069203
rxrp	.197859	.0196467	10.07	0.000	.1593523	.2363658
rdash	.0704678	.0171965	4.10	0.000	.0367632	.1041723
rxlm	.0286575	.0185115	1.55	0.122	-.0076245	.0649394
rxmr	.0278663	.0147899	1.88	0.060	-.0011213	.0568539
rdoge	.035083	.0138988	2.52	0.012	.0078419	.0623241
rxvg	-.0018219	.0090691	-0.20	0.841	-.0195969	.0159532
rnxt	.0139708	.0162795	0.86	0.391	-.0179364	.045878
_cons	-.0020422	.0009013	-2.27	0.023	-.0038088	-.0002757
ARCH_rltc						
arch						
L1.	.1276435	.0173599	7.35	0.000	.0936187	.1616682
garch						
L1.	.8675127	.0139423	62.22	0.000	.8401863	.8948392
_cons	.0000412	8.74e-06	4.72	0.000	.0000241	.0000583

Appendix 9. Impulse Response Function from Dash to other cryptocurrencies (2015-2021)



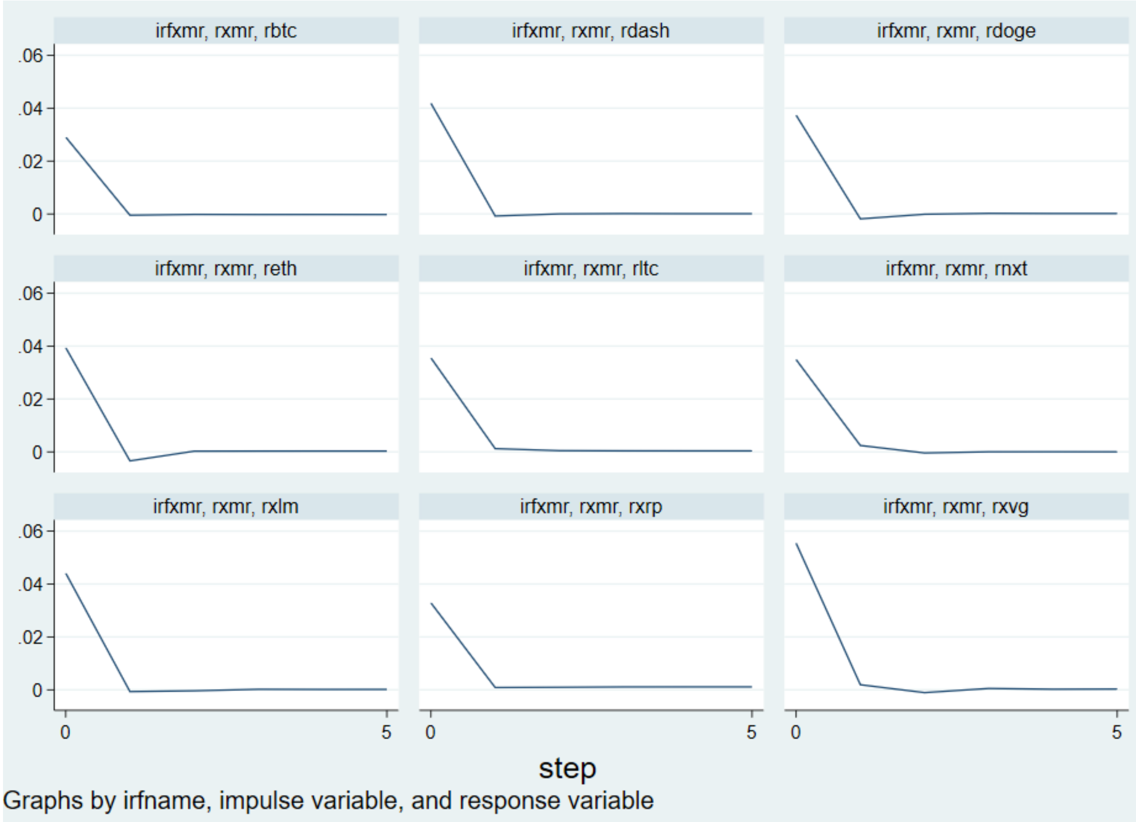
Appendix 10. MGARCH model applied for Dash and other cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021**	Number of obs	=	**1,238**
Distribution: **Gaussian**	Wald chi2(**9**)	=	**1579.81**
Log likelihood = **2019.711**	Prob > chi2	=	**0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rdash						
rbtc	.1562833	.0435929	3.59	0.000	.0708428	.2417239
reth	.1876618	.026589	7.06	0.000	.1355483	.2397752
rxrp	-.016669	.024101	-0.69	0.489	-.0639062	.0305681
rltc	.1402421	.0315148	4.45	0.000	.0784742	.2020101
rxlm	.0253132	.0185326	1.37	0.172	-.0110101	.0616365
rxmr	.2651666	.0235356	11.27	0.000	.2190377	.3112955
rdoge	.0341389	.0183986	1.86	0.064	-.0019218	.0701995
rxvg	.0254347	.0101447	2.51	0.012	.0055514	.045318
rnxt	.0574576	.0182318	3.15	0.002	.0217239	.0931912
_cons	-.0016898	.0011239	-1.50	0.133	-.0038927	.000513
ARCH_rdash						
arch						
L1.	.245485	.0400868	6.12	0.000	.1669164	.3240536
garch						
L1.	.7647641	.029265	26.13	0.000	.7074057	.8221224
_cons	.0001272	.0000281	4.53	0.000	.0000722	.0001822

Appendix 11. Impulse Response Function from Monero to other cryptocurrencies (2015-2021)



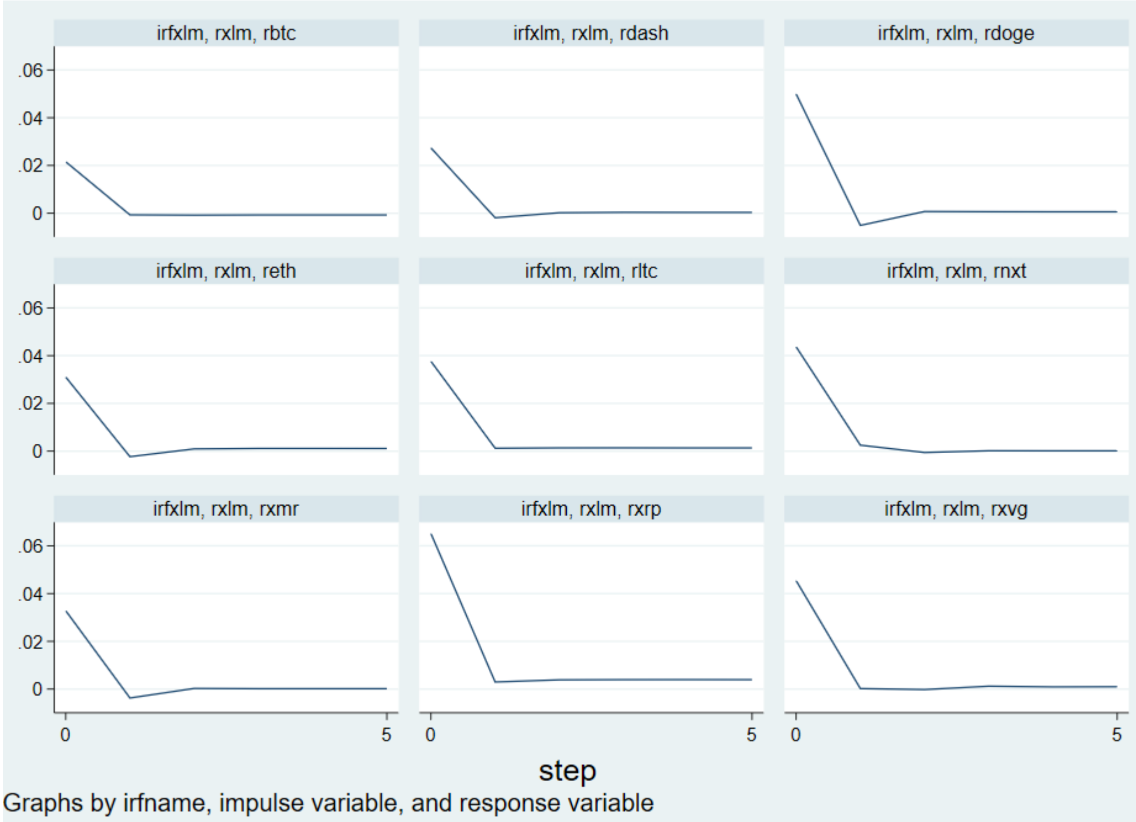
Appendix 12. MGARCH model applied for Monero and other cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(**9**) = **2073.56**
Log likelihood = **1945.565** Prob > chi2 = **0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxmr						
rbtc	.4800182	.0572339	8.39	0.000	.3678418	.5921946
reth	.0620336	.0280255	2.21	0.027	.0071047	.1169625
rxrp	.020685	.0258492	0.80	0.424	-.0299784	.0713485
rltc	.0649447	.0318222	2.04	0.041	.0025742	.1273152
rdash	.3350357	.0276158	12.13	0.000	.2809096	.3891617
rxlm	.0401565	.0250163	1.61	0.108	-.0088746	.0891876
rdoge	.0235764	.0223989	1.05	0.293	-.0203247	.0674775
rxvg	.0538377	.0129235	4.17	0.000	.028508	.0791674
rnxt	-.0207291	.0262037	-0.79	0.429	-.0720874	.0306291
_cons	.0001518	.0011523	0.13	0.895	-.0021066	.0024102
ARCH_rxmr						
arch						
L1.	.0725778	.031926	2.27	0.023	.010004	.1351516
garch						
L1.	.9345336	.0274833	34.00	0.000	.8806673	.9884
_cons	.0000113	9.75e-06	1.16	0.245	-7.78e-06	.0000304

Appendix 13. Impulse Response Function from Stellar other cryptocurrencies (2015-2021)



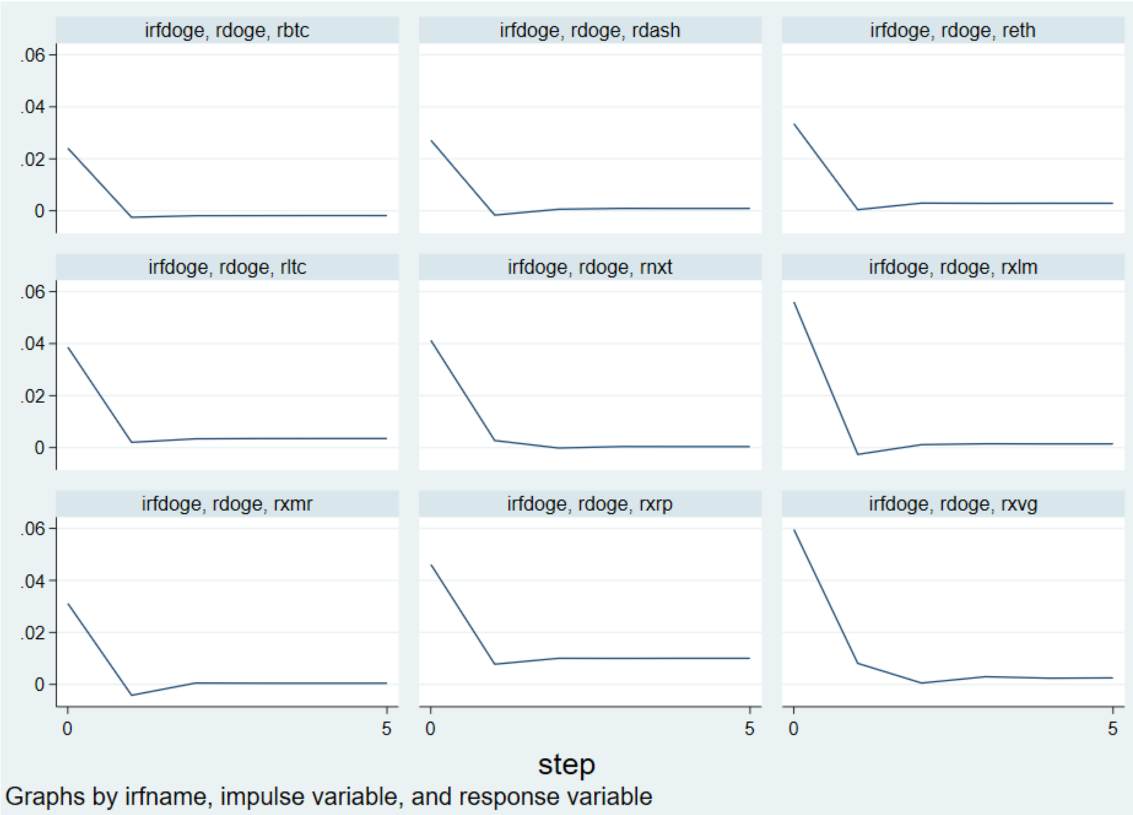
Appendix 14. MGARCH model applied for Stellar and other cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021**		Number of obs =	**1,238**
Distribution: **Gaussian**		Wald chi2(**9**) =	**4131.72**
Log likelihood =	**1749.423**	Prob > chi2 =	**0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxlm						
rbtc	-.1912239	.0569889	-3.36	0.001	-.3029202	-.0795277
reth	.107441	.0263908	4.07	0.000	.0557159	.159166
rxrp	.7352703	.0213357	34.46	0.000	.6934531	.7770874
rltc	.1119853	.0304198	3.68	0.000	.0523636	.171607
rdash	.0367497	.0264603	1.39	0.165	-.0151114	.0886109
rxmr	.0682132	.0225297	3.03	0.002	.0240557	.1123707
rdoge	.0724704	.0123232	5.88	0.000	.0483173	.0966234
rxvg	.0360596	.0124581	2.89	0.004	.0116421	.060477
rnxt	.1211515	.0278314	4.35	0.000	.0666029	.1757001
_cons	.0004186	.0011507	0.36	0.716	-.0018367	.0026739
ARCH_rxlm						
arch						
L1.	.6738256	.0925398	7.28	0.000	.4924509	.8552004
garch						
L1.	.5970599	.0354182	16.86	0.000	.5276416	.6664782
_cons	.000202	.0000382	5.29	0.000	.0001271	.0002768

Appendix 15. Impulse Response Function from Dogecoin to other cryptocurrencies (2015-2021)



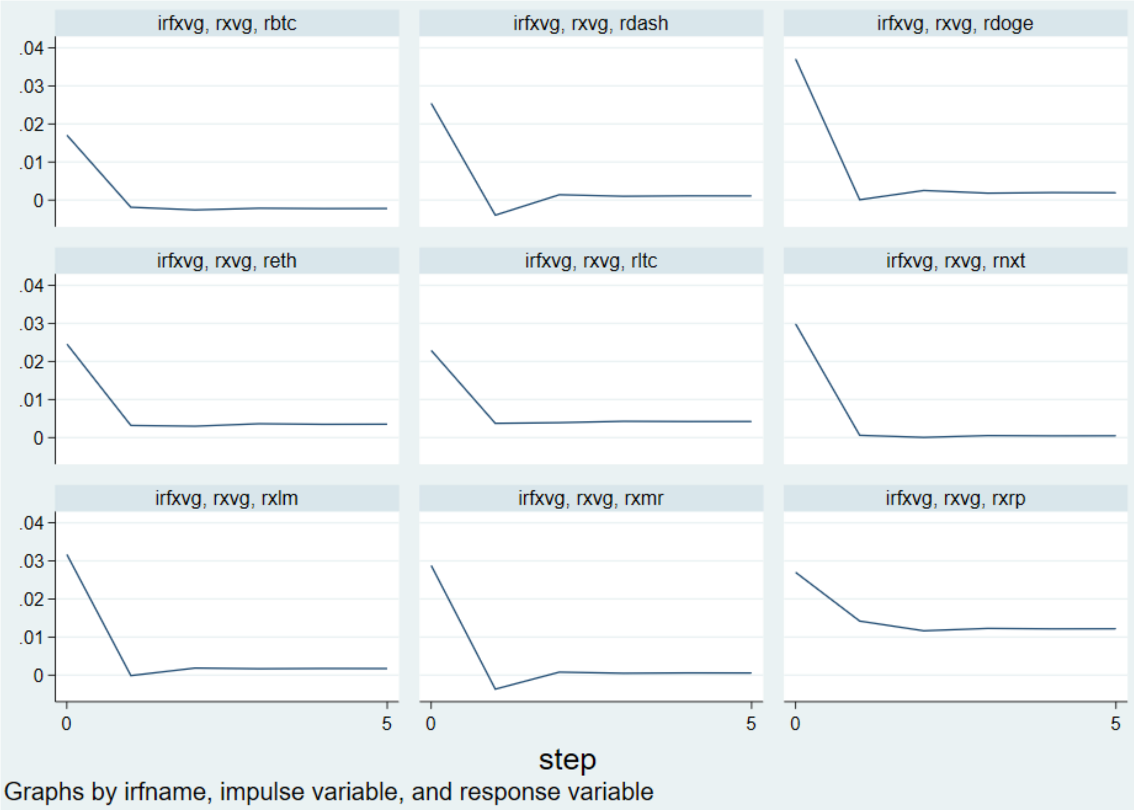
Appendix 16. MGARCH model applied for Dogecoin and other cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021**		Number of obs =	**1,238**
Distribution: **Gaussian**		Wald chi2(**9**) =	**1784.64**
Log likelihood = **2006.827**		Prob > chi2 =	**0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rdoge						
rbtc	.1040605	.0429528	2.42	0.015	.0198746	.1882464
reth	.0283862	.0175966	1.61	0.107	-.0061025	.0628749
rxrp	.2340577	.0186651	12.54	0.000	.1974748	.2706405
rltc	.1130929	.0287265	3.94	0.000	.0567901	.1693958
rdash	.0680346	.022481	3.03	0.002	.0239726	.1120966
rxlm	.0960978	.017651	5.44	0.000	.0615026	.1306931
rxmr	.0093126	.0172292	0.54	0.589	-.024456	.0430812
rxvg	.0270301	.0075044	3.60	0.000	.0123218	.0417385
rnxt	.0713053	.0166319	4.29	0.000	.0387073	.1039032
_cons	-.0008618	.0009498	-0.91	0.364	-.0027233	.0009998
ARCH_rdoge						
arch						
L1.	.4045927	.0420243	9.63	0.000	.3222266	.4869588
garch						
L1.	.7141542	.0180322	39.60	0.000	.6788116	.7494967
_cons	.0000984	.0000157	6.25	0.000	.0000676	.0001292

Appendix 17. Impulse Response Function from Verge to other cryptocurrencies (2015-2021)



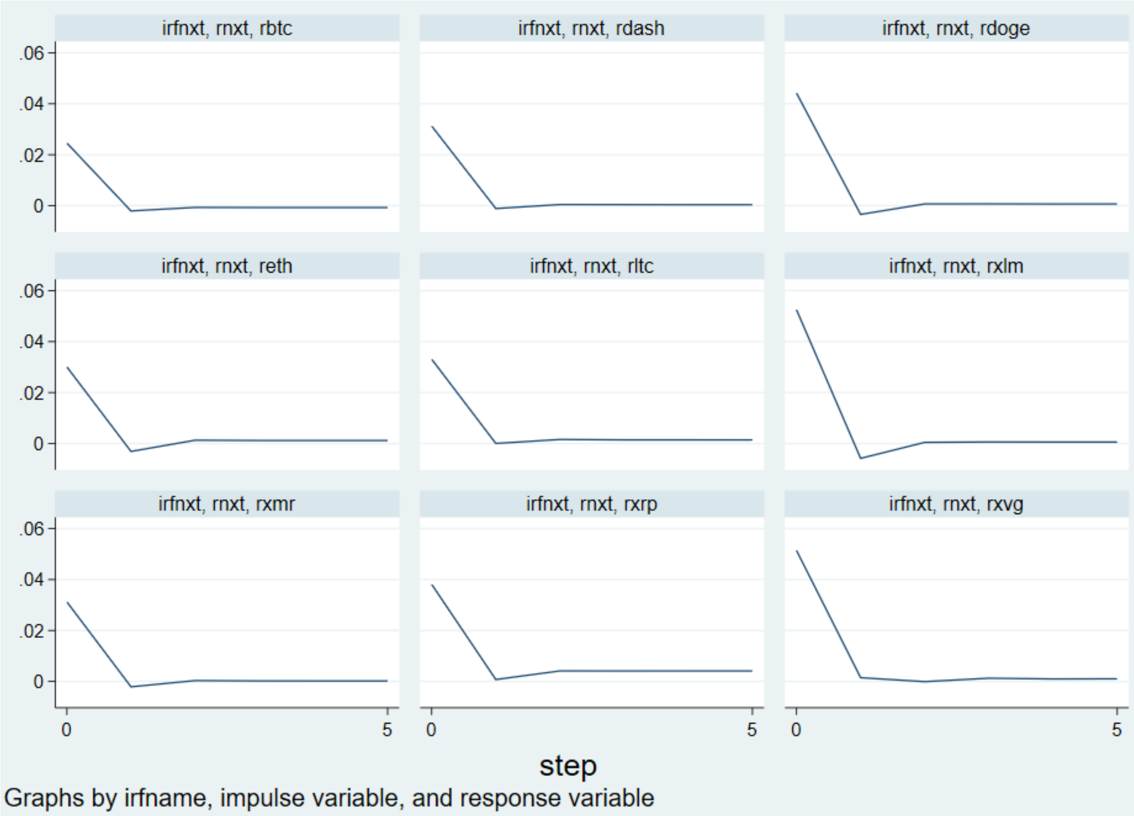
Appendix 18. MGARCH model applied for Verge and other cryptocurrencies (2015-2021)

```
Dynamic conditional correlation MGARCH model

Sample: 18aug2015 - 12mar2021                   Number of obs     =      1,238
Distribution: Gaussian                          Wald chi2(9)      =    1616.09
Log likelihood =  1128.317                      Prob > chi2       =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxvg						
rbtc	.0644002	.0761338	0.85	0.398	-.0848193	.2136197
reth	.1736271	.0568846	3.05	0.002	.0621353	.2851188
rxrp	.2780862	.0461381	6.03	0.000	.1876572	.3685152
rltc	.0134528	.0585769	0.23	0.818	-.1013558	.1282614
rdash	.0891231	.04093	2.18	0.029	.0089018	.1693445
rxlm	.1752562	.0386265	4.54	0.000	.0995498	.2509627
rxmr	.1471648	.0461803	3.19	0.001	.056653	.2376766
rdoge	.1690336	.0290493	5.82	0.000	.1120981	.2259691
rnxt	.0536454	.0360357	1.49	0.137	-.0169834	.1242741
_cons	-.0019347	.0018117	-1.07	0.286	-.0054856	.0016161
ARCH_rxvg						
arch						
L1.	.1603585	.0200746	7.99	0.000	.121013	.199704
garch						
L1.	.8566494	.0135482	63.23	0.000	.8300954	.8832035
_cons	.0000922	.0000246	3.74	0.000	.0000439	.0001405

Appendix 19. Impulse Response Function from Nxt to other cryptocurrencies (2015-2021)



Appendix 20. MGARCH model applied for Nxt and other cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(**9**) = **1879.01**
Log likelihood = **1728.344** Prob > chi2 = **0.0000**

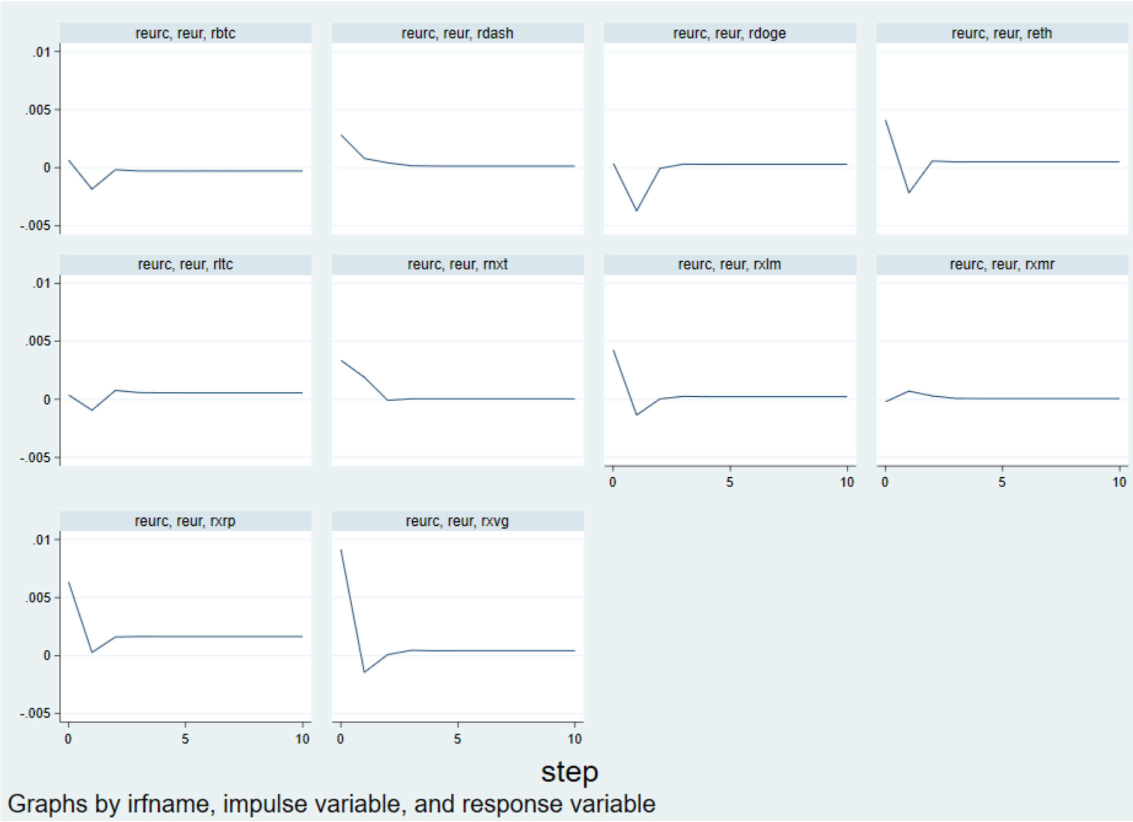
	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rnxt						
rbtc	.4509697	.0585156	7.71	0.000	.3362813	.5656581
reth	.0177951	.0280184	0.64	0.525	-.0371199	.0727101
rxrp	.1160086	.0307778	3.77	0.000	.0556853	.176332
rltc	.0486896	.0400965	1.21	0.225	-.029898	.1272772
rdash	.0493558	.03683	1.34	0.180	-.0228297	.1215414
rxlm	.1375081	.0245435	5.60	0.000	.0894038	.1856124
rxmr	.0393977	.0308801	1.28	0.202	-.0211262	.0999217
rdoge	.1786774	.0177765	10.05	0.000	.1438361	.2135187
rxvg	.0271072	.0122968	2.20	0.027	.003006	.0512085
_cons	-.0028841	.0013598	-2.12	0.034	-.0055493	-.0002189
ARCH_rnxt						
arch						
L1.	.1984649	.0297696	6.67	0.000	.1401175	.2568123
garch						
L1.	.8186076	.0209021	39.16	0.000	.7776402	.8595749
_cons	.0001258	.0000289	4.35	0.000	.0000691	.0001824

Appendix 21. MGARCH model applied for USD and all cryptocurrencies (2015-2021)

```
Sample: 18aug2015 - 12mar2021                    Number of obs    =      1,238
Distribution: Gaussian                           Wald chi2(10)    =      11.20
Log likelihood =  5006.605                       Prob > chi2      =     0.3424
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rusd						
rbtc	.0011252	.0035412	0.32	0.751	-.0058154	.0080659
reth	-.000824	.0022291	-0.37	0.712	-.0051928	.0035449
rxrp	-.0001575	.0018135	-0.09	0.931	-.0037119	.0033969
rltc	-.0018046	.0024137	-0.75	0.455	-.0065353	.0029261
rdash	-.0027043	.0022426	-1.21	0.228	-.0070997	.0016911
rxlm	-.0002586	.0015834	-0.16	0.870	-.003362	.0028448
rxmr	.0054422	.0020647	2.64	0.008	.0013955	.0094889
rdoge	-.0016914	.0014989	-1.13	0.259	-.0046293	.0012464
rxvg	.0003824	.0008978	0.43	0.670	-.0013773	.0021421
rnxt	.0018981	.0016041	1.18	0.237	-.0012458	.005042
_cons	-.0000536	.0001155	-0.46	0.643	-.0002801	.0001728
ARCH_rusd						
arch						
L1.	.0289344	.0068591	4.22	0.000	.0154907	.042378
garch						
L1.	.9624776	.0086553	111.20	0.000	.9455136	.9794416
_cons	1.56e-07	7.73e-08	2.02	0.043	4.70e-09	3.08e-07

Appendix 22. Impulse Response Function from Euro to cryptocurrencies (2015-2021)



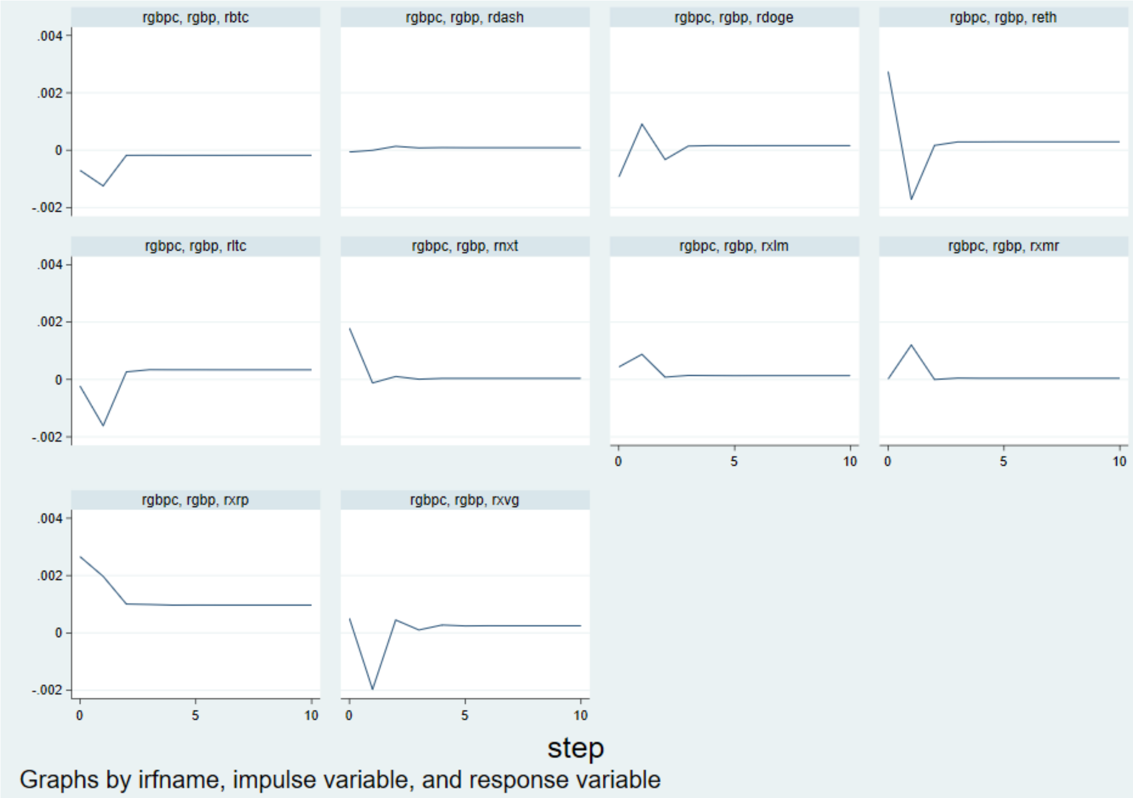
Appendix 23. MGARCH model applied for Euro and all cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(**10**) = **12.50**
Log likelihood = **4819.724** Prob > chi2 = **0.2530**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
reur						
rbtc	.0014909	.004359	0.34	0.732	-.0070526	.0100343
reth	.0042409	.0025842	1.64	0.101	-.000824	.0093058
rxrp	.0042395	.0022601	1.88	0.061	-.0001903	.0086693
rltc	-.00269	.0029675	-0.91	0.365	-.0085061	.0031261
rdash	-.0001175	.0025739	-0.05	0.964	-.0051623	.0049273
rxlm	-.0010207	.0020222	-0.50	0.614	-.0049842	.0029428
rxmr	-.0026465	.002333	-1.13	0.257	-.0072192	.0019262
rdoge	-.0033007	.0017234	-1.92	0.055	-.0066785	.0000771
rxvg	.0013655	.0010859	1.26	0.209	-.0007629	.0034939
rnxt	.0015528	.0019834	0.78	0.434	-.0023347	.0054402
_cons	.0000357	.0001345	0.27	0.790	-.0002278	.0002993
ARCH_reur						
arch						
L1.	.0361134	.0089678	4.03	0.000	.0185369	.05369
garch						
L1.	.9514456	.0116731	81.51	0.000	.9285668	.9743244
_cons	3.20e-07	1.55e-07	2.06	0.039	1.61e-08	6.23e-07

Appendix 24. Impulse Response Function from Pound to other cryptocurrencies (2015-2021)



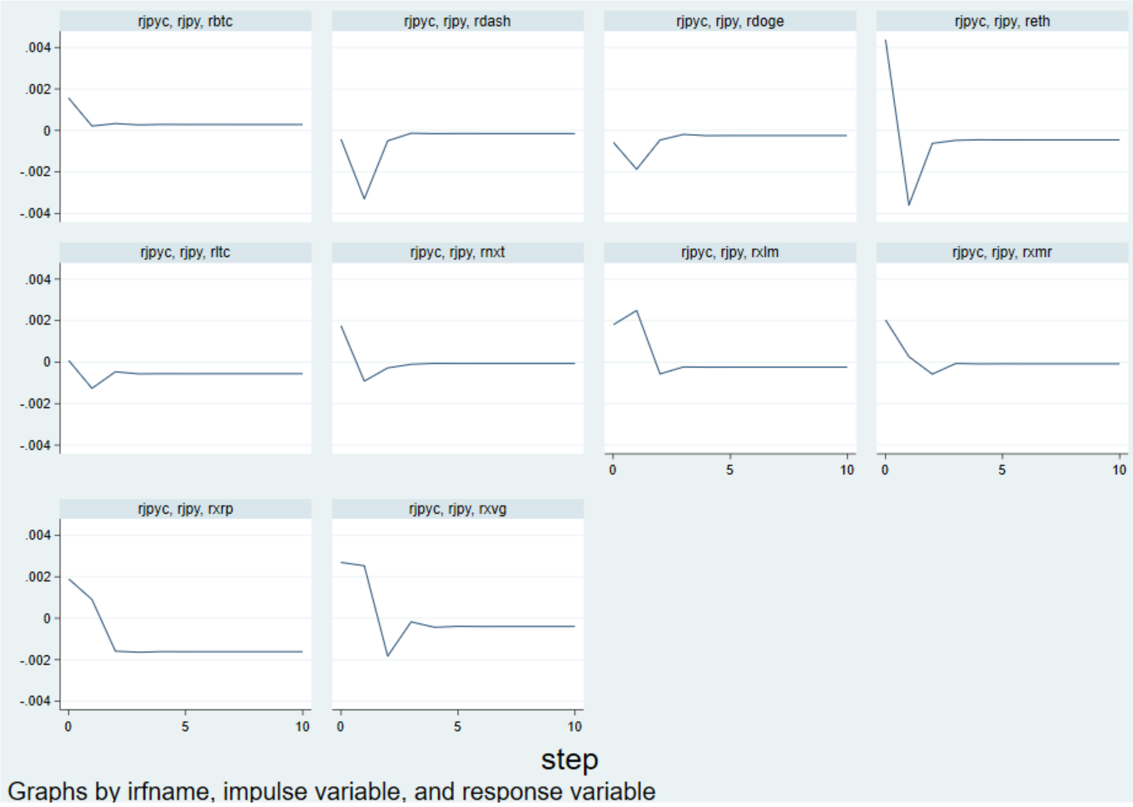
Appendix 25. MGARCH model applied for Pound and all cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(**10**) = **7.55**
Log likelihood = **4521.114** Prob > chi2 = **0.6732**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rgbp						
rbtc	-.0015121	.0051044	-0.30	0.767	-.0115166	.0084924
reth	.0053257	.003	1.78	0.076	-.0005541	.0112055
rxrp	.0036404	.0025556	1.42	0.154	-.0013685	.0086493
rltc	-.0042054	.0034733	-1.21	0.226	-.0110129	.002602
rdash	-.0008647	.0031355	-0.28	0.783	-.0070101	.0052808
rxlm	-.0005073	.0022063	-0.23	0.818	-.0048316	.003817
rxmr	.0001951	.0028264	0.07	0.945	-.0053446	.0057347
rdoge	-.0020628	.0019705	-1.05	0.295	-.0059249	.0017994
rxvg	-2.83e-06	.0012362	-0.00	0.998	-.0024258	.0024201
rnxt	-.0007907	.0023388	-0.34	0.735	-.0053746	.0037932
_cons	-.000042	.0001695	-0.25	0.804	-.0003743	.0002903
ARCH_rgbp						
arch						
L1.	.1417071	.030196	4.69	0.000	.0825241	.20089
garch						
L1.	.7417422	.0527961	14.05	0.000	.6382638	.8452206
_cons	5.31e-06	1.42e-06	3.73	0.000	2.52e-06	8.10e-06

Appendix 26. Impulse Response Function from Yen to other cryptocurrencies (2015-2021)



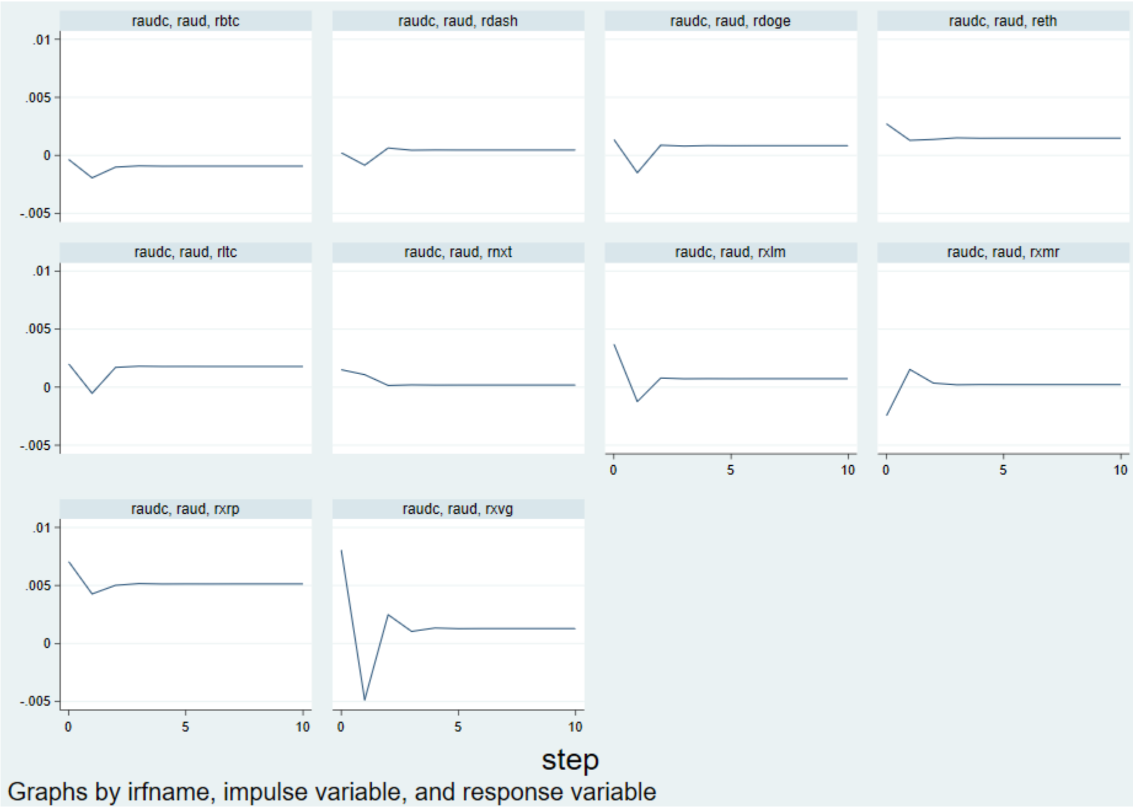
Appendix 27. MGARCH model applied for Yen and all cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(**10**) = **11.06**
Log likelihood = **4720.938** Prob > chi2 = **0.3529**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rjpy						
rbtc	.0000653	.004302	0.02	0.988	-.0083664	.0084971
reth	.0054242	.0026767	2.03	0.043	.0001781	.0106703
rxrp	.0017278	.0020927	0.83	0.409	-.0023739	.0058294
rltc	-.0017279	.0030281	-0.57	0.568	-.0076627	.004207
rdash	-.0069747	.0026831	-2.60	0.009	-.0122334	-.0017159
rxlm	-.000084	.0019495	-0.04	0.966	-.003905	.0037371
rxmr	.0018089	.0027569	0.66	0.512	-.0035945	.0072123
rdoge	-.0018745	.0016493	-1.14	0.256	-.0051071	.0013581
rxvg	.0004039	.0011419	0.35	0.724	-.0018342	.002642
rnxt	.0011694	.0019664	0.59	0.552	-.0026846	.0050234
_cons	5.39e-06	.0001361	0.04	0.968	-.0002613	.0002721
ARCH_rjpy						
arch						
L1.	.0921945	.016532	5.58	0.000	.0597924	.1245966
garch						
L1.	.8887876	.0182882	48.60	0.000	.8529433	.9246319
_cons	7.39e-07	2.29e-07	3.22	0.001	2.89e-07	1.19e-06

Appendix 28. Impulse Response Function from Australian Dollar to other cryptocurrencies (2015-2021)



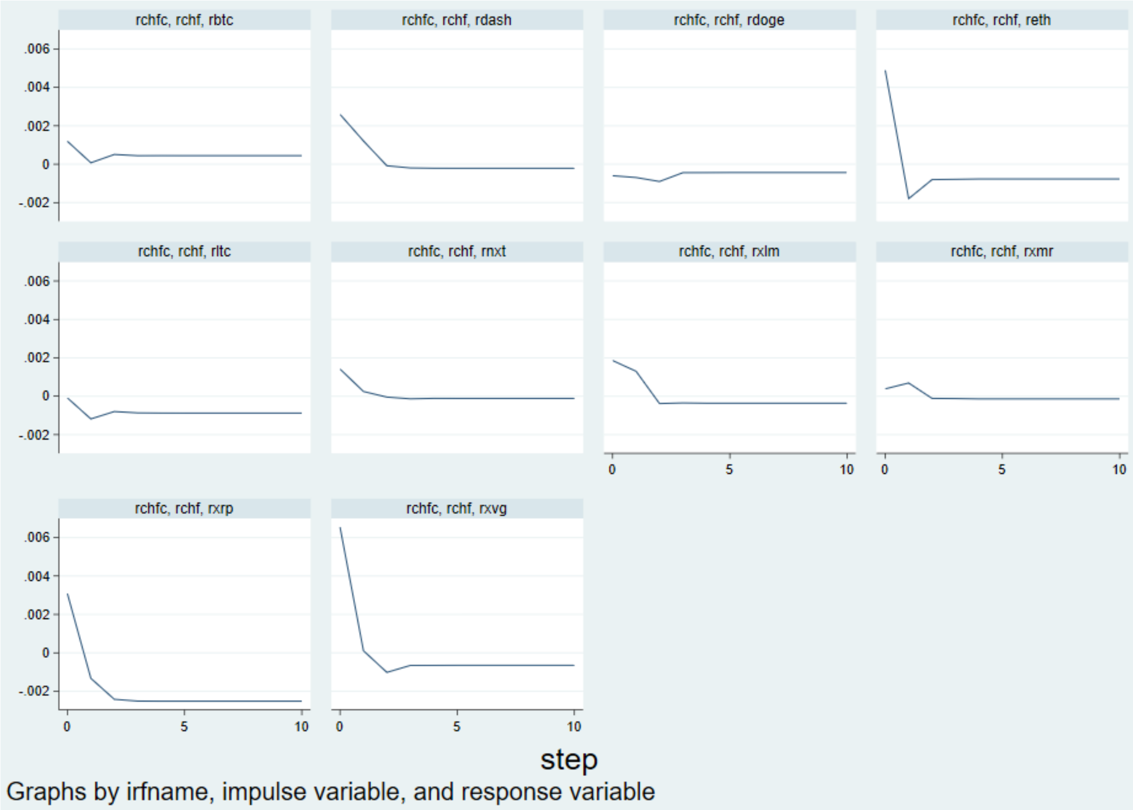
Appendix 29. MGARCH model applied for Australian Dollar and all cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021**	Number of obs	=	**1,238**
Distribution: **Gaussian**	Wald chi2(**10**)	=	**17.12**
Log likelihood = **4521.101**	Prob > chi2	=	**0.0717**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
raud						
rbtc	-.0031179	.0049915	-0.62	0.532	-.0129011	.0066654
reth	.0056022	.0030572	1.83	0.067	-.0003897	.0115942
rxrp	.0049524	.0024687	2.01	0.045	.0001138	.009791
rltc	.0012238	.0032471	0.38	0.706	-.0051405	.0075881
rdash	-.0011367	.0031543	-0.36	0.719	-.0073189	.0050456
rxlm	-.0004983	.0021228	-0.23	0.814	-.004659	.0036624
rxmr	-.0058427	.00289	-2.02	0.043	-.0115071	-.0001783
rdoge	-.0033841	.002268	-1.49	0.136	-.0078292	.001061
rxvg	.0025521	.0011967	2.13	0.033	.0002067	.0048976
rnxt	.0007994	.0021988	0.36	0.716	-.0035102	.005109
_cons	-.0000362	.0001686	-0.21	0.830	-.0003666	.0002942
ARCH_raud						
arch						
L1.	.0524748	.0109415	4.80	0.000	.03103	.0739197
garch						
L1.	.9301514	.0151725	61.31	0.000	.9004139	.9598889
_cons	7.46e-07	3.23e-07	2.31	0.021	1.13e-07	1.38e-06

Appendix 30. Impulse Response Function from Swiss Franc to other cryptocurrencies (2015-2021)



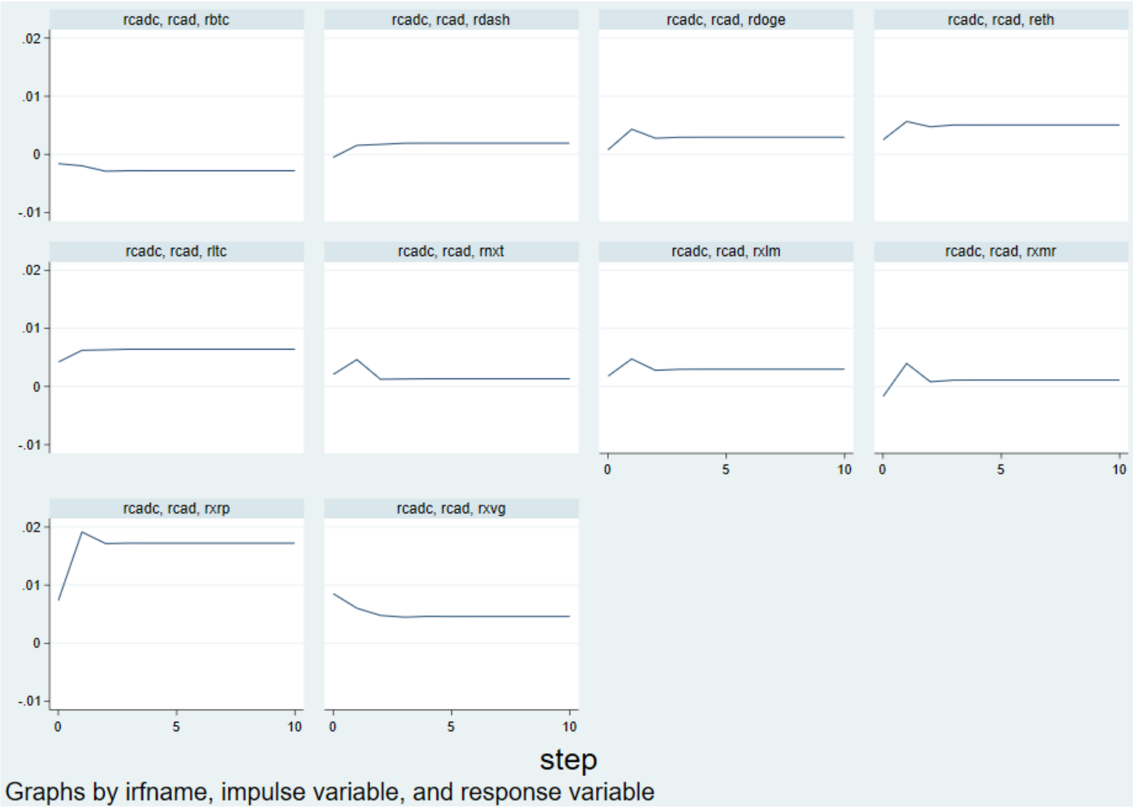
Appendix 31. MGARCH model applied for Swiss Franc and all cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample:	**18aug2015 - 12mar2021**	Number of obs =	**1,238**
Distribution:	**Gaussian**	Wald chi2(**10**) =	**12.13**
Log likelihood =	**4868.213**	Prob > chi2 =	**0.2767**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rchf						
rbtc	.0009855	.0041315	0.24	0.811	-.007112	.0090831
reth	.0050179	.0023529	2.13	0.033	.0004063	.0096295
rxrp	.0034437	.002029	1.70	0.090	-.000533	.0074205
rltc	-.0028019	.0027832	-1.01	0.314	-.0082569	.002653
rdash	.0014128	.0024334	0.58	0.562	-.0033566	.0061822
rxlm	-.0008995	.0018472	-0.49	0.626	-.00452	.002721
rxmr	-.0016579	.0022867	-0.73	0.468	-.0061398	.002824
rdoge	-.0022839	.0016944	-1.35	0.178	-.0056049	.001037
rxvg	.0011016	.0009336	1.18	0.238	-.0007282	.0029313
rnxt	-.000606	.0018723	-0.32	0.746	-.0042755	.0030636
_cons	.0000215	.0001322	0.16	0.871	-.0002376	.0002807
ARCH_rchf						
arch						
L1.	.0575729	.0191689	3.00	0.003	.0200026	.0951432
garch						
L1.	.8807671	.0425726	20.69	0.000	.7973263	.9642078
_cons	1.44e-06	6.68e-07	2.16	0.031	1.32e-07	2.75e-06

Appendix 32. Impulse Response Function from Canadian Dollar to other cryptocurrencies (2015-2021)



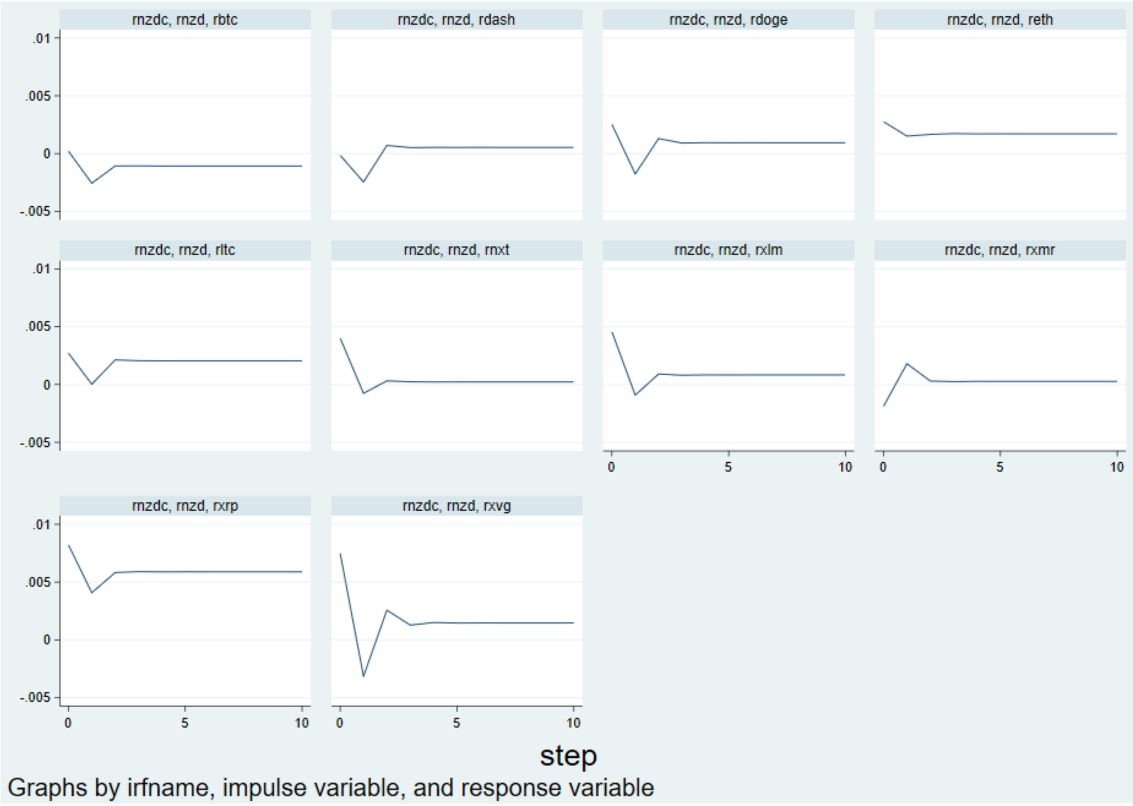
Appendix 33. MGARCH model applied for Canadian Dollar and all cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample:	**18aug2015 - 12mar2021**	Number of obs =	**1,238**
Distribution:	**Gaussian**	Wald chi2(**10**) =	**7.52**
Log likelihood =	**4853.806**	Prob > chi2 =	**0.6753**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rcad						
rbtc	-.002738	.0041405	-0.66	0.508	-.0108532	.0053771
reth	.0030213	.0024451	1.24	0.217	-.001771	.0078135
rxrp	.0002837	.0020512	0.14	0.890	-.0037367	.004304
rltc	.0032931	.0027384	1.20	0.229	-.002074	.0086602
rdash	-.001195	.0024108	-0.50	0.620	-.0059201	.00353
rxlm	.0001086	.0018126	0.06	0.952	-.0034441	.0036612
rxmr	-.0031743	.0024328	-1.30	0.192	-.0079425	.0015939
rdoge	-.0019338	.0017418	-1.11	0.267	-.0053477	.0014801
rxvg	.0014385	.0009704	1.48	0.138	-.0004635	.0033405
rnxt	.0007067	.0018862	0.37	0.708	-.0029901	.0044035
_cons	.0000139	.0001306	0.11	0.915	-.000242	.0002699
ARCH_rcad						
arch						
L1.	.0383851	.0090934	4.22	0.000	.0205625	.0562078
garch						
L1.	.9484904	.0124066	76.45	0.000	.9241739	.9728069
_cons	3.21e-07	1.48e-07	2.17	0.030	3.12e-08	6.11e-07

Appendix 34. Impulse Response Function from New Zealand Dollar to other cryptocurrencies (2015-2021)



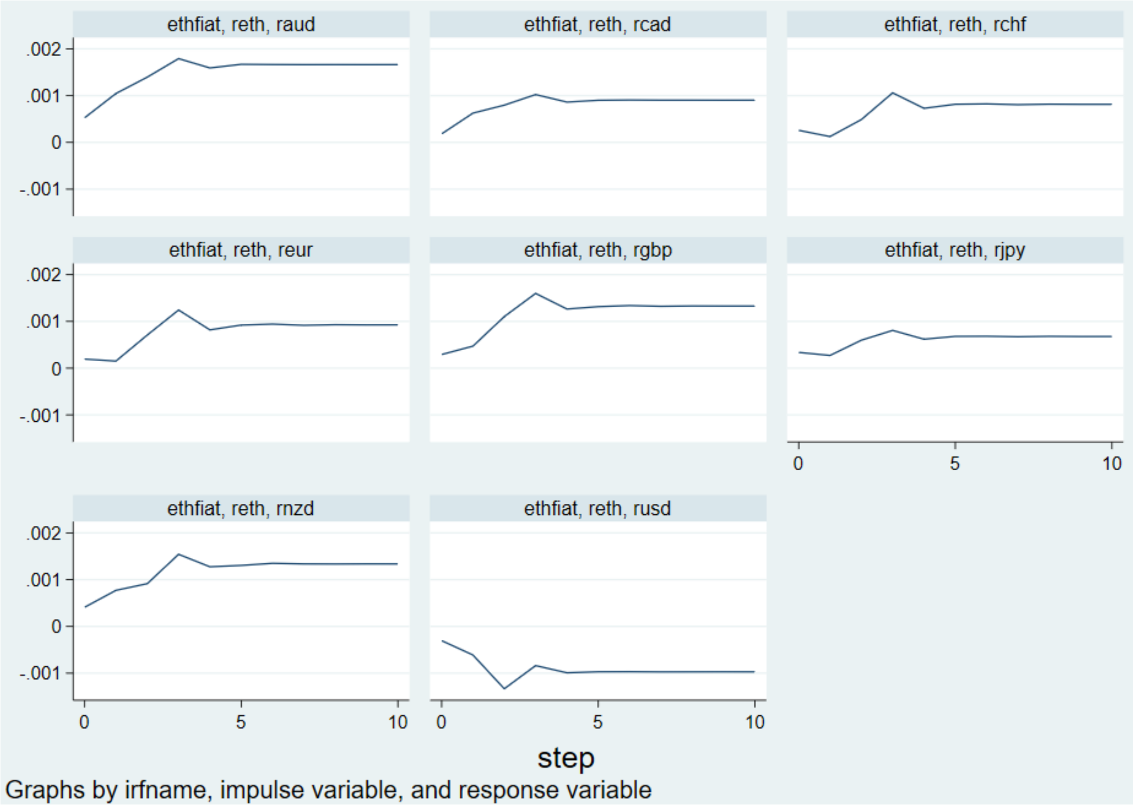
Appendix 35. MGARCH model applied for New Zealand Dollar and all cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(**10**) = **20.75**
Log likelihood = **4458.918** Prob > chi2 = **0.0229**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rnzd						
rbtc	-.0015848	.0052952	-0.30	0.765	-.0119633	.0087937
reth	.0071235	.0032877	2.17	0.030	.0006798	.0135672
rxrp	.0055002	.0026307	2.09	0.037	.000344	.0106564
rltc	.0021531	.0034263	0.63	0.530	-.0045623	.0088684
rdash	-.0035768	.0032925	-1.09	0.277	-.01003	.0028763
rxlm	-.0008214	.00234	-0.35	0.726	-.0054078	.0037649
rxmr	-.0067015	.003148	-2.13	0.033	-.0128714	-.0005316
rdoge	-.0027368	.0023788	-1.15	0.250	-.0073992	.0019255
rxvg	.0016892	.001264	1.34	0.181	-.0007881	.0041665
rnxt	.0029479	.0023934	1.23	0.218	-.001743	.0076388
_cons	-.0000317	.0001792	-0.18	0.860	-.0003829	.0003195
ARCH_rnzd						
arch						
L1.	.0533076	.0128757	4.14	0.000	.0280718	.0785435
garch						
L1.	.9260031	.0189537	48.86	0.000	.8888546	.9631516
_cons	9.47e-07	4.29e-07	2.21	0.027	1.05e-07	1.79e-06

Appendix 36. Impulse Response Function from Ethereum to all forex pairs (2015-2021)



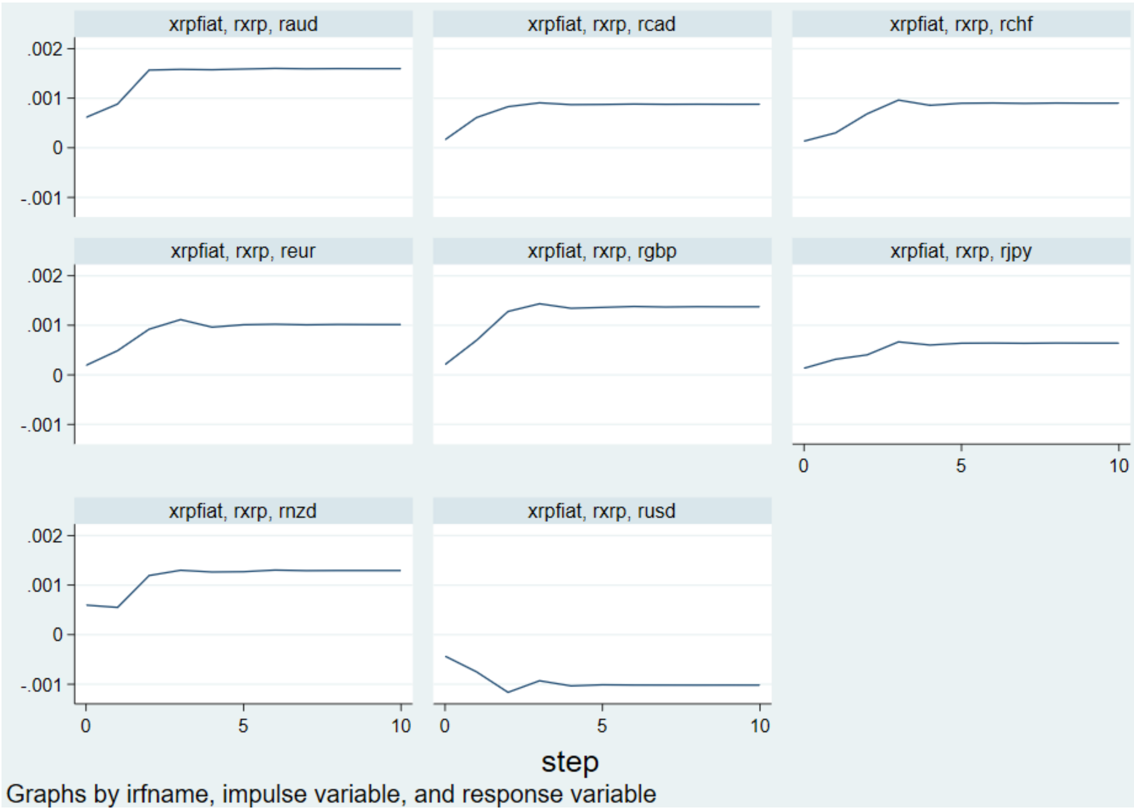
Appendix 37. MGARCH model applied for Ethereum and all forex pairs (2015-2021)

```
Dynamic conditional correlation MGARCH model

Sample: 18aug2015 - 12mar2021                    Number of obs   =      1,238
Distribution: Gaussian                           Wald chi2(8)    =       9.45
Log likelihood =  1423.923                       Prob > chi2     =     0.3055
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
reth						
rusd	-.1894006	.5400337	-0.35	0.726	-1.247847	.869046
reur	-1.462378	.8115162	-1.80	0.072	-3.05292	.1281648
rgbp	.2226091	.4005204	0.56	0.578	-.5623965	1.007615
rjpy	-.0923713	.5301179	-0.17	0.862	-1.131383	.9466407
raud	.2518609	.6229051	0.40	0.686	-.9690106	1.472733
rchf	1.697221	.8483649	2.00	0.045	.034456	3.359985
rcad	.0005008	.6117591	0.00	0.999	-1.198525	1.199527
rnzd	.390891	.5597126	0.70	0.485	-.7061255	1.487908
_cons	.0032568	.0020555	1.58	0.113	-.000772	.0072855
ARCH_reth						
arch						
L1.	.1183218	.0218994	5.40	0.000	.0753998	.1612438
garch						
L1.	.8273981	.0260962	31.71	0.000	.7762505	.8785458
_cons	.0004266	.000098	4.35	0.000	.0002346	.0006187

Appendix 38. Impulse Response Function from Ripple to all forex pairs (2015-2021)



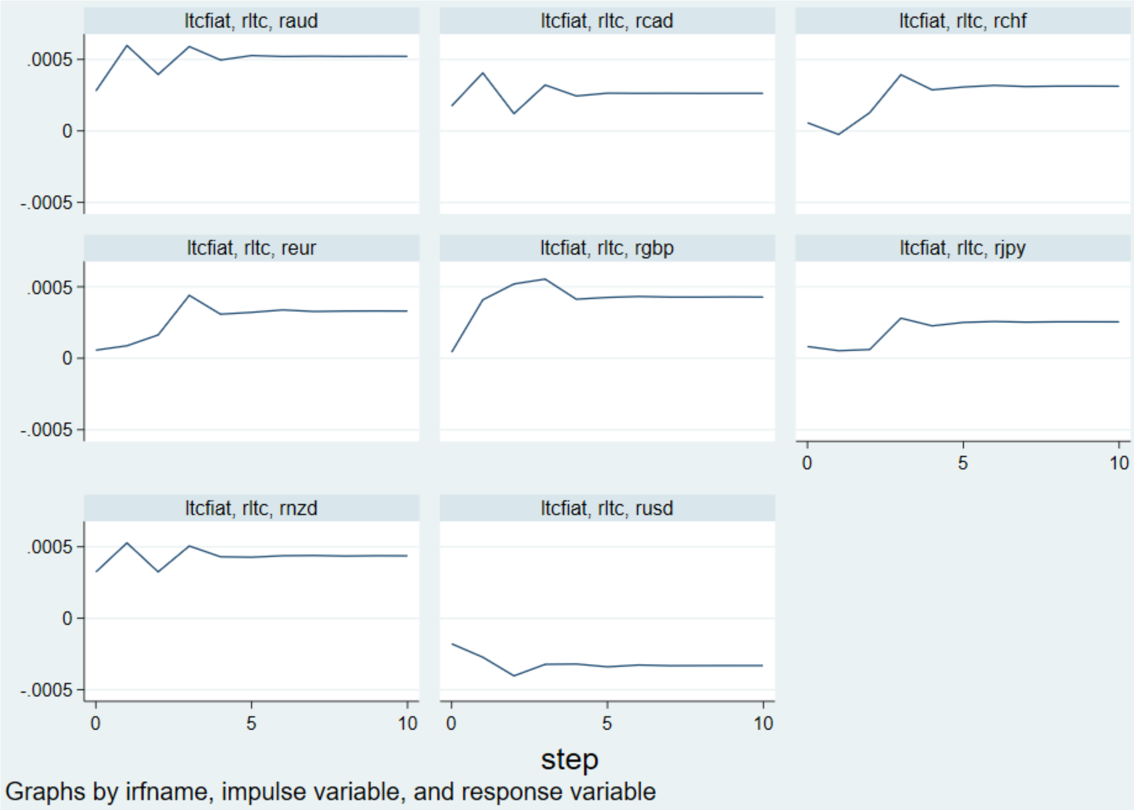
Appendix 39. MGARCH model applied for Ripple and all forex pairs (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(8) = **38.96**
Log likelihood = **1512.333** Prob > chi2 = **0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxrp						
rusd	.2204736	.373825	0.59	0.555	-.51221	.9531572
reur	-.6935009	.5827811	-1.19	0.234	-1.835731	.4487292
rgbp	.4666833	.259362	1.80	0.072	-.0416568	.9750234
rjpy	-.4857896	.294243	-1.65	0.099	-1.062495	.090916
raud	.4196723	.4216067	1.00	0.320	-.4066615	1.246006
rchf	1.757456	.6308075	2.79	0.005	.5210957	2.993816
rcad	-1.153259	.4402585	-2.62	0.009	-2.01615	-.2903678
rnzd	.7310442	.3612517	2.02	0.043	.0230039	1.439085
_cons	-.006126	.0014705	-4.17	0.000	-.0090081	-.0032439
ARCH_rxrp						
arch						
L1.	.5595478	.0689254	8.12	0.000	.4244564	.6946391
garch						
L1.	.6212501	.0271718	22.86	0.000	.5679944	.6745058
_cons	.0004043	.0000676	5.98	0.000	.0002718	.0005367

Appendix 40. Impulse Response Function from Litecoin to all forex pairs (2015-2021)



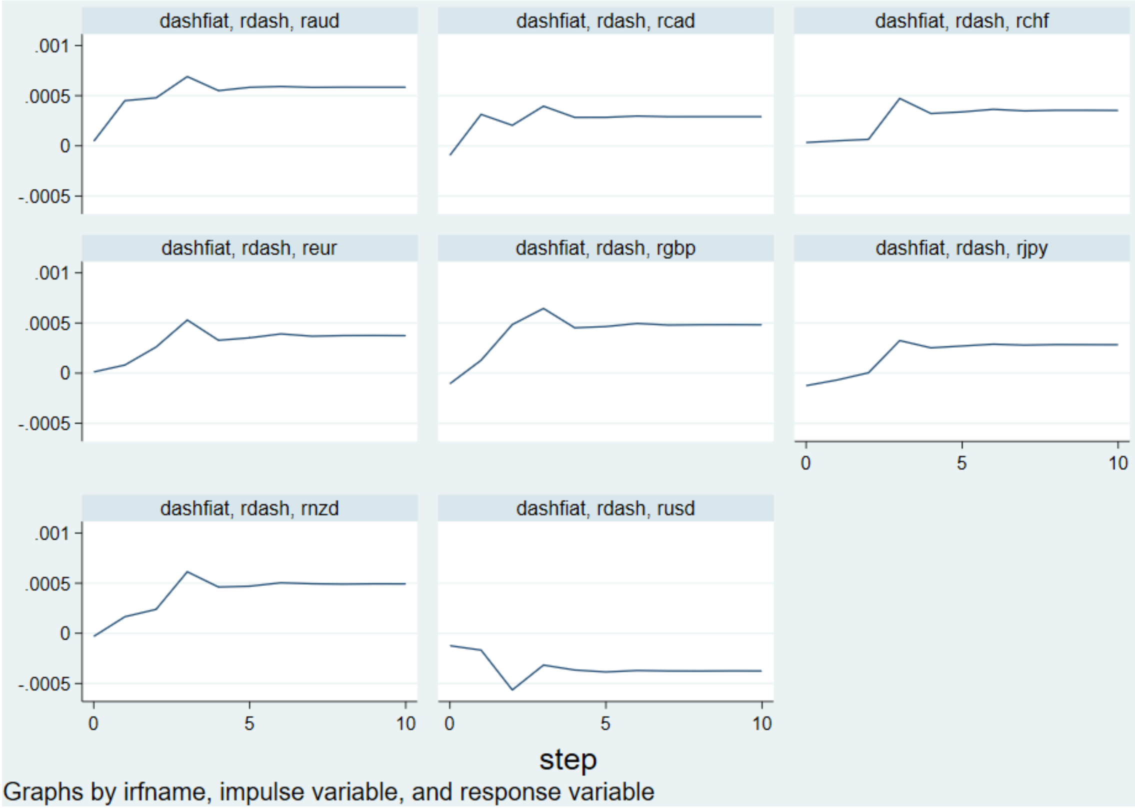
Appendix 41. MGARCH model applied for Litecoin and all forex pairs (2015-2021)

```
Dynamic conditional correlation MGARCH model

Sample: 18aug2015 - 12mar2021                    Number of obs    =      1,238
Distribution: Gaussian                           Wald chi2(8)     =       4.11
Log likelihood =  1567.006                       Prob > chi2      =     0.8472
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rltc						
rusd	-.4797261	.4267699	-1.12	0.261	-1.31618	.3567276
reur	.1720275	.7049367	0.24	0.807	-1.209623	1.553678
rgbp	-.1755746	.3554093	-0.49	0.621	-.872164	.5210148
rjpy	.1716825	.386609	0.44	0.657	-.5860571	.9294222
raud	-.4069271	.4946926	-0.82	0.411	-1.376507	.5626527
rchf	.0995076	.702635	0.14	0.887	-1.277632	1.476647
rcad	.5108364	.4954595	1.03	0.303	-.4602465	1.481919
rnzd	.0969888	.4293147	0.23	0.821	-.7444526	.9384302
_cons	.0012463	.0018511	0.67	0.501	-.0023818	.0048743
ARCH_rltc						
arch						
L1.	.0703747	.013949	5.05	0.000	.0430352	.0977142
garch						
L1.	.8704902	.021575	40.35	0.000	.8282041	.9127764
_cons	.0003223	.0000654	4.93	0.000	.0001941	.0004505

Appendix 42. Impulse Response Function from Dash to all forex pairs (2015-2021)



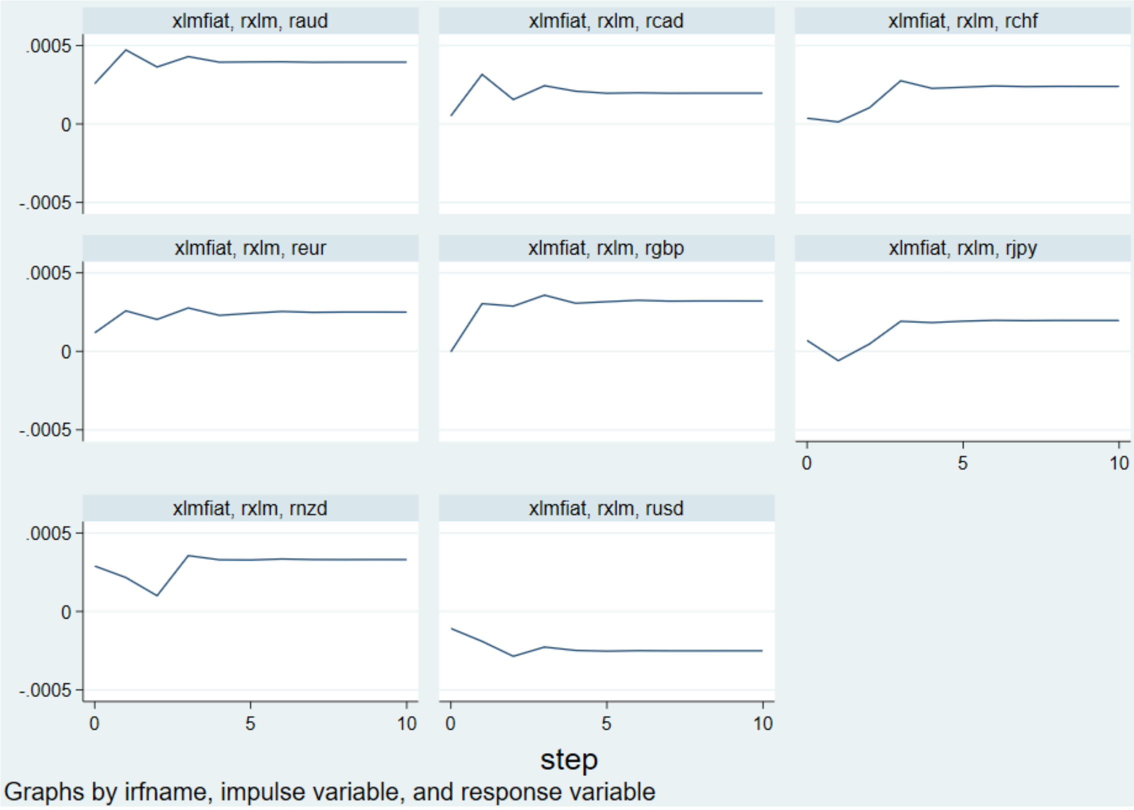
Appendix 43. MGARCH model applied for Dash and all forex pairs (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** — Number of obs = **1,238**
Distribution: **Gaussian** — Wald chi2(8) = **2.78**
Log likelihood = **1531.139** — Prob > chi2 = **0.9471**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rdash						
rusd	.3089384	.4286289	0.72	0.471	-.5311588	1.149036
reur	.2495034	.6619697	0.38	0.706	-1.047933	1.54694
rgbp	.0828346	.3248709	0.25	0.799	-.5539008	.7195699
rjpy	-.1830257	.3723563	-0.49	0.623	-.9128305	.5467792
raud	-.0249508	.4917125	-0.05	0.960	-.9886897	.938788
rchf	.4058982	.6887368	0.59	0.556	-.9440011	1.755797
rcad	-.3361206	.5143749	-0.65	0.513	-1.344277	.6720357
rnzd	.0473979	.4267285	0.11	0.912	-.7889745	.8837703
_cons	.0001011	.0018781	0.05	0.957	-.00358	.0037821
ARCH_rdash						
arch						
L1.	.1501278	.0274209	5.47	0.000	.0963838	.2038718
garch						
L1.	.7978469	.0290664	27.45	0.000	.7408778	.854816
_cons	.000401	.0000906	4.42	0.000	.0002233	.0005786

Appendix 44. Impulse Response Function from Stellar to all forex pairs (2015-2021)



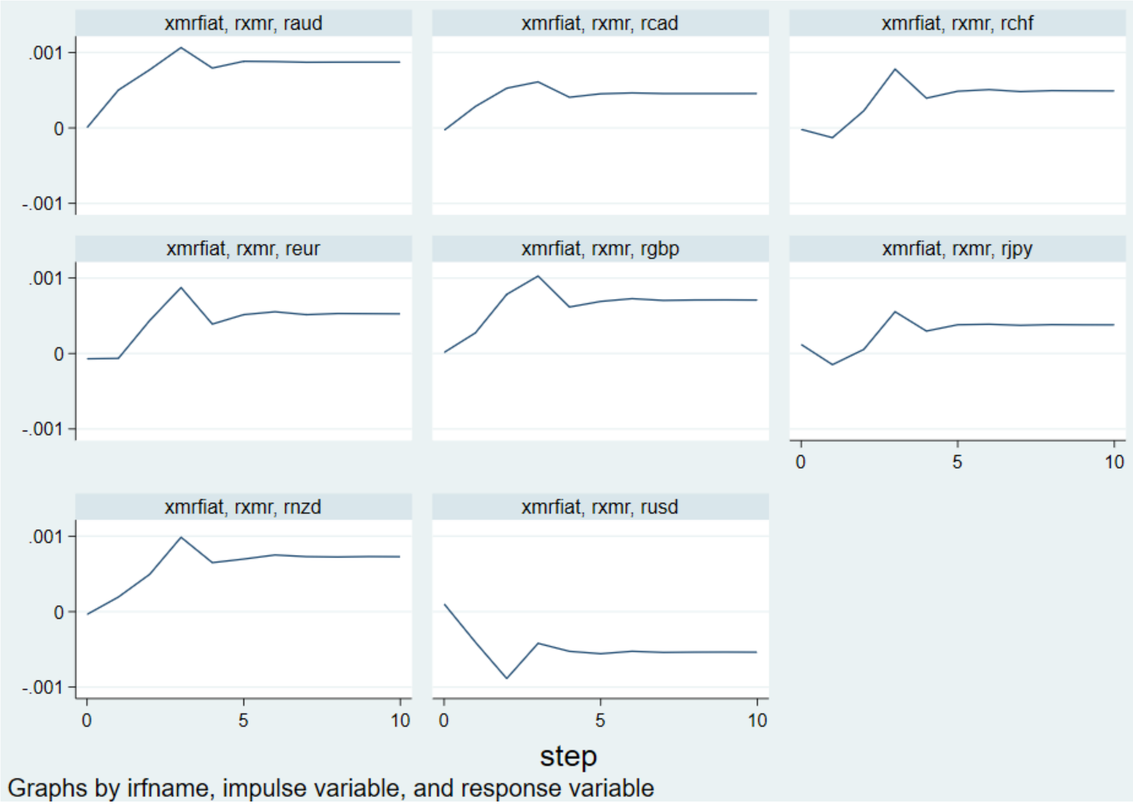
Appendix 45. MGARCH model applied for Stellar and all forex pairs (2015-2021)

```
Dynamic conditional correlation MGARCH model

Sample: 18aug2015 - 12mar2021                    Number of obs    =     1,238
Distribution: Gaussian                           Wald chi2(8)     =    134.59
Log likelihood =   1131.37                       Prob > chi2      =    0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxlm						
rusd	-2.705978	.5418634	-4.99	0.000	-3.768011	-1.643945
reur	-2.401747	.8248863	-2.91	0.004	-4.018495	-.7849999
rgbp	-.8065724	.4193782	-1.92	0.054	-1.628538	.0153937
rjpy	1.897547	.4604086	4.12	0.000	.9951625	2.799931
raud	4.363512	.5312398	8.21	0.000	3.322301	5.404723
rchf	.9867008	.8335259	1.18	0.237	-.6469799	2.620382
rcad	-2.834688	.5631501	-5.03	0.000	-3.938441	-1.730934
rnzd	-1.451483	.4820944	-3.01	0.003	-2.396371	-.5065958
_cons	-.0070406	.0018896	-3.73	0.000	-.0107442	-.003337
ARCH_rxlm						
arch						
L1.	1.210973	.1450746	8.35	0.000	.9266317	1.495314
garch						
L1.	.3194654	.051424	6.21	0.000	.2186762	.4202546
_cons	.0018406	.0003254	5.66	0.000	.0012028	.0024783

Appendix 46. Impulse Response Function from Monero to all forex pairs (2015-2021)



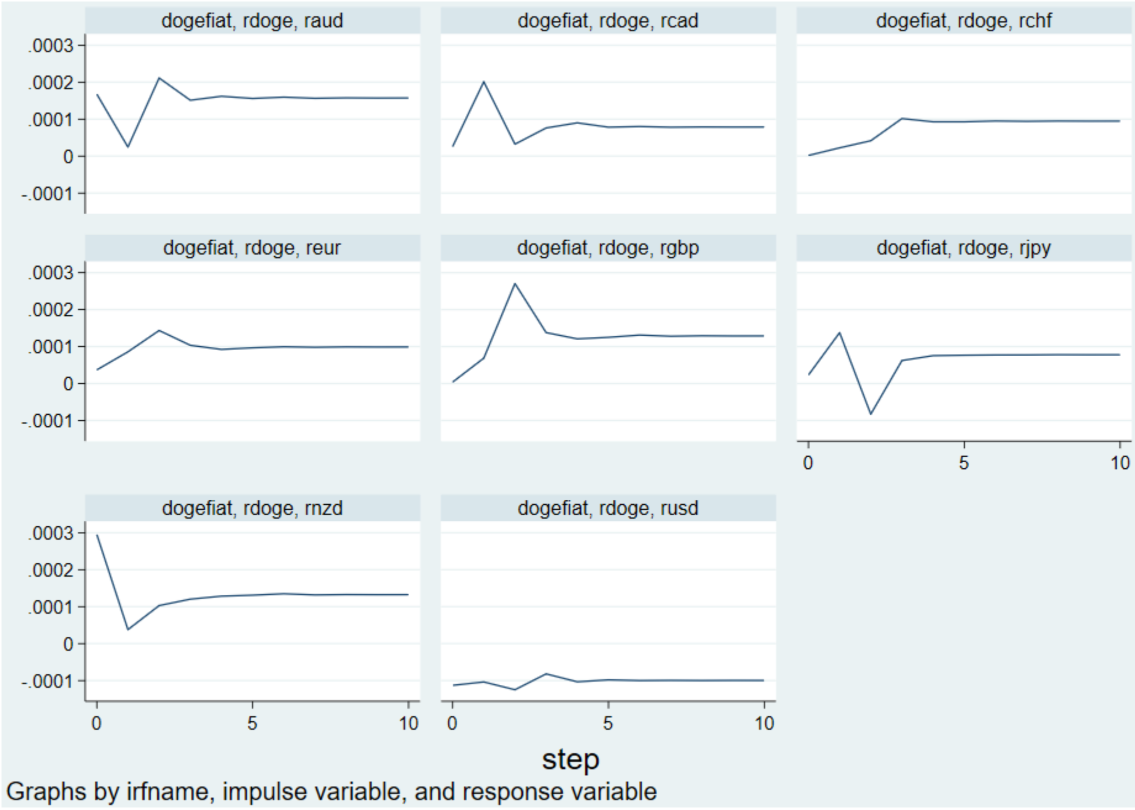
Appendix 47. MGARCH model applied for Monero and all forex pairs (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(**8**) = **11.20**
Log likelihood = **1391.32** Prob > chi2 = **0.1907**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxmr						
rusd	.9590072	.5305651	1.81	0.071	-.0808814	1.998896
reur	-.8421774	.8383135	-1.00	0.315	-2.485242	.8008869
rgbp	.4061057	.4048856	1.00	0.316	-.3874556	1.199667
rjpy	.553984	.4745196	1.17	0.243	-.3760574	1.484025
raud	-.0421705	.5990329	-0.07	0.944	-1.216253	1.131912
rchf	.4511789	.8950602	0.50	0.614	-1.303107	2.205465
rcad	-.7062481	.6228036	-1.13	0.257	-1.926921	.5144244
rnzd	-.1803676	.5219357	-0.35	0.730	-1.203343	.8426075
_cons	.0029799	.0021294	1.40	0.162	-.0011937	.0071535
ARCH_rxmr						
arch						
L1.	.1104473	.0227565	4.85	0.000	.0658455	.1550492
garch						
L1.	.8075116	.0329473	24.51	0.000	.742936	.8720872
_cons	.0006158	.0001531	4.02	0.000	.0003158	.0009159

Appendix 48. Impulse Response Function from Dogecoin to all forex pairs (2015-2021)



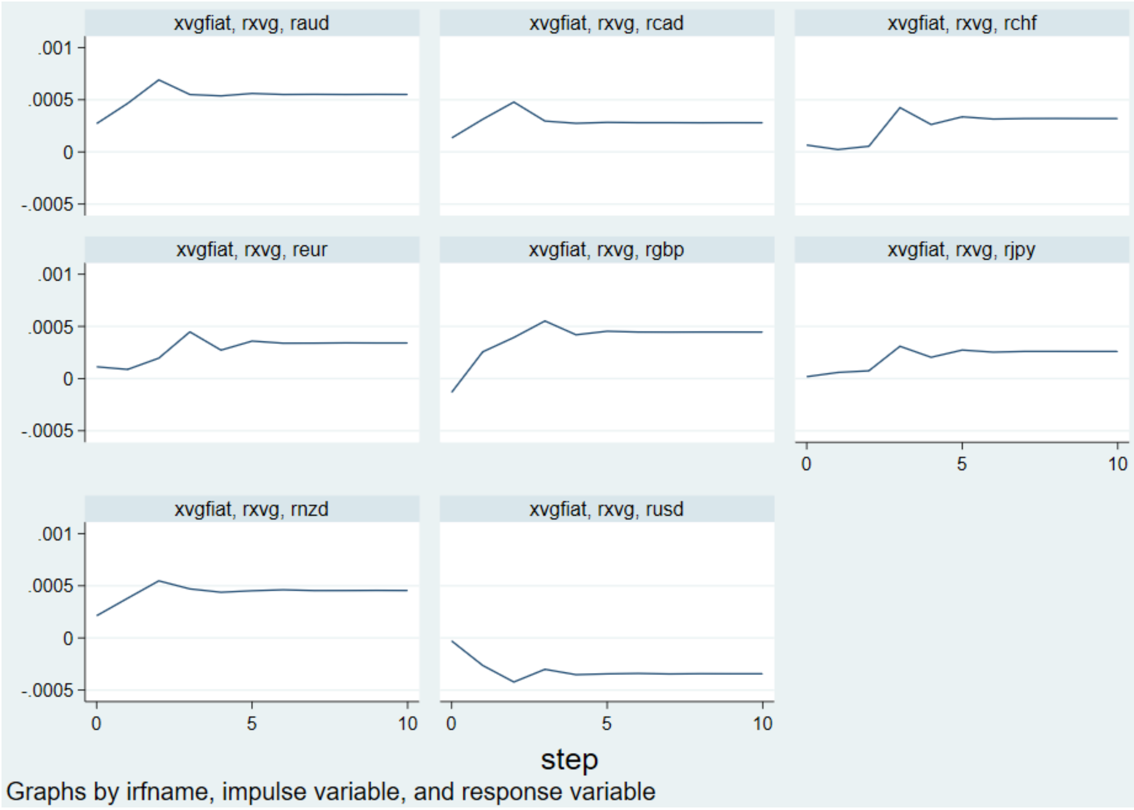
Appendix 49. MGARCH model applied for Dogecoin and all forex pairs (2015-2021)

```
Dynamic conditional correlation MGARCH model

Sample: 18aug2015 - 12mar2021                   Number of obs     =      1,238
Distribution: Gaussian                          Wald chi2(8)      =       7.20
Log likelihood =  1562.213                      Prob > chi2       =     0.5151
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rdoge						
rusd	-.2809866	.3243622	-0.87	0.386	-.9167249	.3547516
reur	-.408938	.4655303	-0.88	0.380	-1.321361	.5034846
rgbp	-.0886274	.2461928	-0.36	0.719	-.5711565	.3939017
rjpy	.2324944	.2698211	0.86	0.389	-.2963453	.7613342
raud	.5890176	.3328943	1.77	0.077	-.0634431	1.241478
rchf	.1806393	.5309593	0.34	0.734	-.8600218	1.2213
rcad	-.4040369	.3474068	-1.16	0.245	-1.084942	.276868
rnzd	-.0093471	.3037519	-0.03	0.975	-.6046899	.5859957
_cons	-.0032724	.001364	-2.40	0.016	-.0059458	-.0005989
ARCH_rdoge						
arch						
L1.	.5219749	.0594267	8.78	0.000	.4055007	.6384492
garch						
L1.	.6594048	.0249996	26.38	0.000	.6104064	.7084031
_cons	.0002794	.0000465	6.01	0.000	.0001883	.0003706

Appendix 50. Impulse Response Function from Verge to all forex pairs (2015-2021)



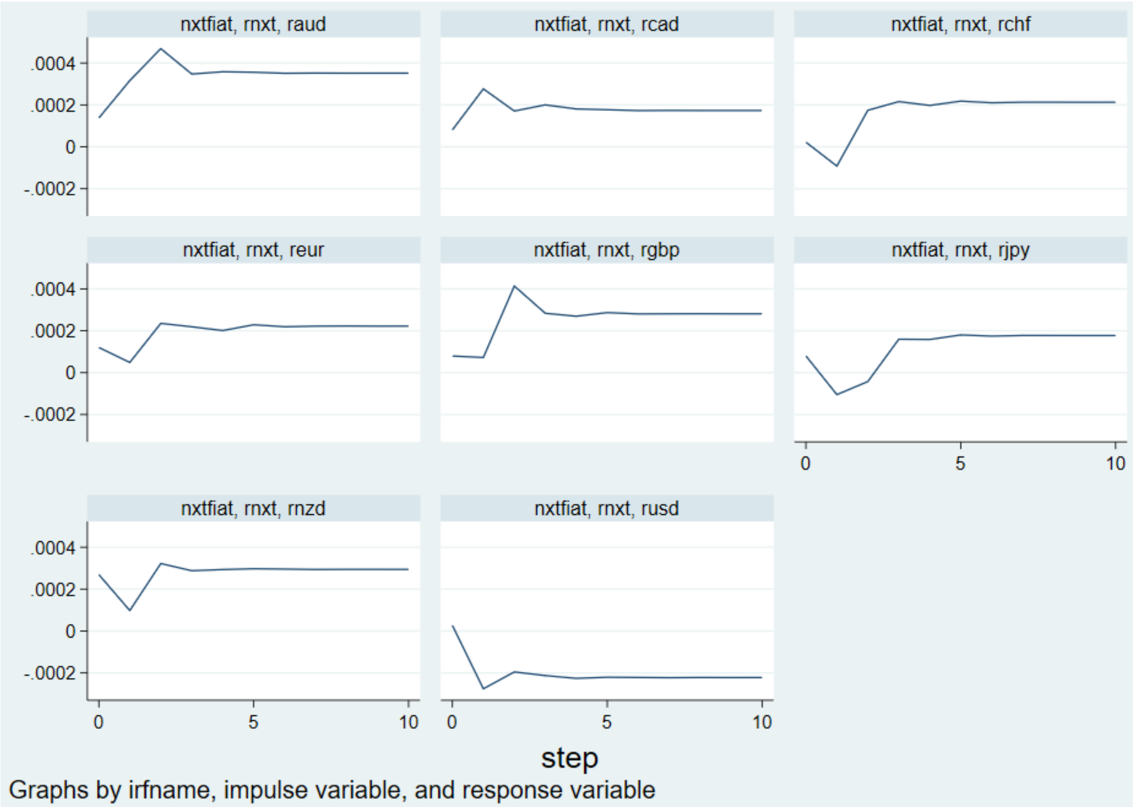
Appendix 51. MGARCH model applied for Verge and all forex pairs (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(8) = **8.82**
Log likelihood = **764.0998** Prob > chi2 = **0.3575**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxvg						
rusd	1.313937	.8390036	1.57	0.117	-.3304799	2.958354
reur	-1.440105	1.256744	-1.15	0.252	-3.903278	1.023067
rgbp	-.2020239	.5898837	-0.34	0.732	-1.358175	.9541269
rjpy	.221359	.796513	0.28	0.781	-1.339778	1.782496
raud	-.6839996	.996103	-0.69	0.492	-2.636326	1.268326
rchf	1.007058	1.289177	0.78	0.435	-1.519682	3.533798
rcad	1.662234	.994551	1.67	0.095	-.2870503	3.611518
rnzd	1.076592	.9116389	1.18	0.238	-.7101877	2.863371
_cons	-.001511	.0030996	-0.49	0.626	-.0075862	.0045642
ARCH_rxvg						
arch						
L1.	.1404082	.0219772	6.39	0.000	.0973336	.1834827
garch						
L1.	.8412021	.0212498	39.59	0.000	.7995532	.8828509
_cons	.0006852	.0001484	4.62	0.000	.0003944	.000976

Appendix 52. Impulse Response Function from Nxt to all forex pairs (2015-2021)



Appendix 53. MGARCH model applied for Nxt and all forex pairs (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021** Number of obs = **1,238**
Distribution: **Gaussian** Wald chi2(8) = **9.06**
Log likelihood = **1373.962** Prob > chi2 = **0.3370**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rnxt						
rusd	.3700759	.5226555	0.71	0.479	-.65431	1.394462
reur	.6264614	.7738514	0.81	0.418	-.8902594	2.143182
rgbp	.1013474	.4693383	0.22	0.829	-.8185387	1.021234
rjpy	.7858021	.448759	1.75	0.080	-.0937494	1.665354
raud	-.2042337	.5593173	-0.37	0.715	-1.300476	.8920081
rchf	-.2523281	.8110556	-0.31	0.756	-1.841968	1.337312
rcad	-.4552651	.5671223	-0.80	0.422	-1.566804	.6562742
rnzd	.2680296	.5208635	0.51	0.607	-.7528441	1.288903
_cons	-.0027853	.0019866	-1.40	0.161	-.006679	.0011084
ARCH_rnxt						
arch						
L1.	.137692	.0207431	6.64	0.000	.0970363	.1783478
garch						
L1.	.8356974	.0197096	42.40	0.000	.7970672	.8743276
_cons	.0003392	.0000643	5.28	0.000	.0002132	.0004651

Appendix 54. MGARCH model applied for S&P500 and all cryptocurrencies (2015-2021)

Dynamic conditional correlation MGARCH model

Sample: **18aug2015 - 12mar2021**	Number of obs = **1,238**
Distribution: **Gaussian**	Wald chi2(**11**) = **89.49**
Log likelihood = **3942.555**	Prob > chi2 = **0.0000**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rsp500						
rbtc	-.0028593	.0070935	-0.40	0.687	-.0167624	.0110437
reth	.0043967	.0041854	1.05	0.293	-.0038066	.0126
rxrp	.0016083	.0033494	0.48	0.631	-.0049563	.008173
rltc	.002215	.0043942	0.50	0.614	-.0063976	.0108275
rdash	.0003486	.0044122	0.08	0.937	-.0082991	.0089963
rxlm	.0011462	.0027502	0.42	0.677	-.0042441	.0065364
rxmr	.0072434	.0036354	1.99	0.046	.0001182	.0143687
rdoge	-.0006981	.0031972	-0.22	0.827	-.0069645	.0055683
rxvg	.0008957	.0015808	0.57	0.571	-.0022026	.003994
rnxt	-.0035829	.0029708	-1.21	0.228	-.0094056	.0022399
rgold	-.2589294	.0299727	-8.64	0.000	-.3176749	-.200184
_cons	.0007347	.0002469	2.98	0.003	.0002507	.0012187
ARCH_rsp500						
arch						
L1.	.1752362	.034555	5.07	0.000	.1075097	.2429627
garch						
L1.	.7931225	.036628	21.65	0.000	.7213328	.8649121
_cons	5.28e-06	1.50e-06	3.51	0.000	2.33e-06	8.22e-06

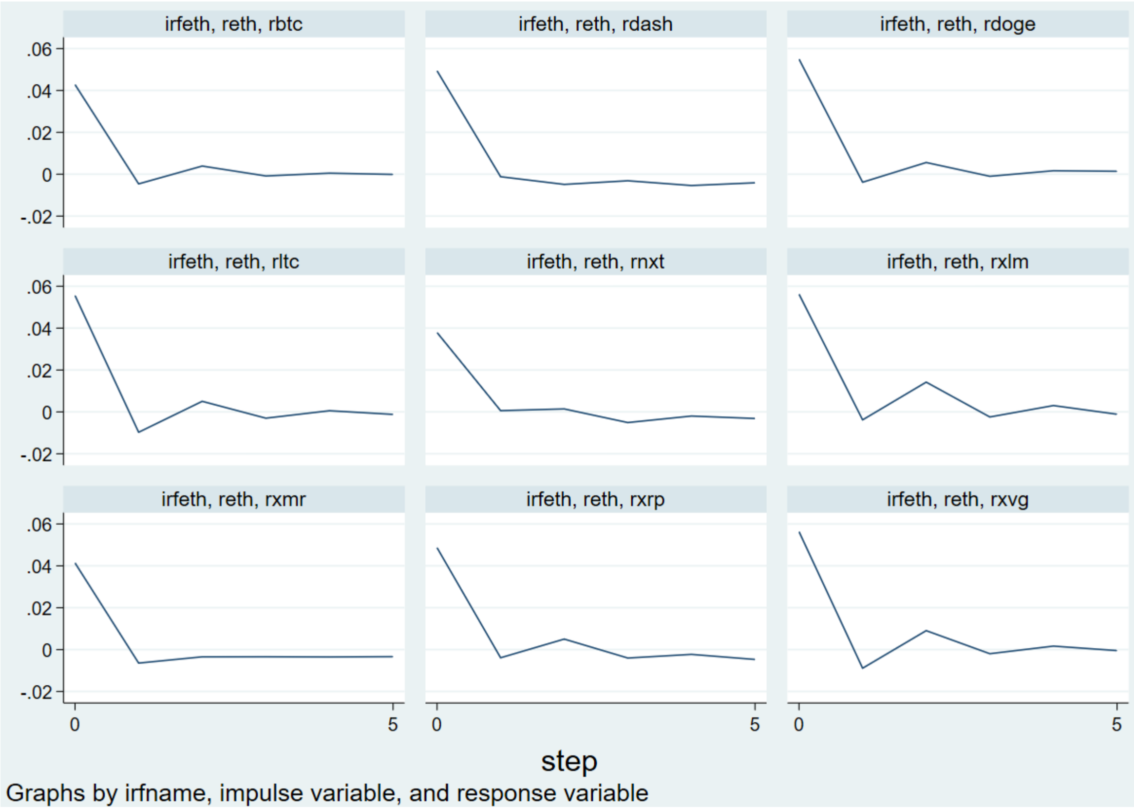
Appendix 55. Pearson Correlation of forex pairs and gold (Covid-19 period)

	USD	EUR	GBP	JPY	AUD	CHF	CAD	NZD	GOLD
USD	1.0000 ***								
EUR	-0.2048 ***	1.0000 ***							
GBP	-0.1592 ***	0.5480 ***	1.0000 ***						
JPY	-0.1170 ***	0.4463 ***	0.1441 ***	1.0000 ***					
AUD	-0.1379 ***	0.4789 ***	0.5071 ***	0.1740 ***	1.0000 ***				
CHF	-0.2074 ***	0.8163 ***	0.4429 ***	0.5658 ***	0.3568 ***	1.0000 ***			
CAD	-0.1729 ***	0.3681 ***	0.4182 ***	0.0790 ***	0.6656 ***	0.2884 ***	1.0000 ***		
NZD	-0.1403 ***	0.4874 ***	0.4814 ***	0.2606 ***	0.7969 ***	0.3976 ***	0.5697 ***	1.0000 ***	
GOLD	-0.2112 ***	0.0979 ***	0.0523 *	0.0987 ***	0.0896 ***	0.1058 ***	0.0770 ***	0.0805 ***	1.0000 ***

Appendix 56. Pearson Correlation of Stock indexes and gold (Covid-19 period)

	SP&500	STOXX	FTSE	NIKKEI	SMI	TSX	ASX	NZX	GOLD
S&P500	1.0000 ***								
STOXX	0.5959 ***	1.0000 ***							
FTSE	0.5802 ***	0.8757 ***	1.0000 ***						
NIKKEI	0.2531 ***	0.4594 ***	0.4186 ***	1.0000 ***					
SMI	0.5656 ***	0.7988 ***	0.7789 ***	0.3770 ***	1.0000 ***				
TSX	0.7738 ***	0.6692 ***	0.6953 ***	0.2983 ***	0.5976 ***	1.0000 ***			
ASX	0.4376 ***	0.4834 ***	0.5140 ***	0.5250 ***	0.4444 ***	0.5176 ***	1.0000 ***		
NZX	0.2339 ***	0.3015 ***	0.3332 ***	0.3790 ***	0.3417 ***	0.2972 ***	0.5028 ***	1.0000 ***	
GOLD	-0.1040 ***	-0.1054 ***	-0.0343	-0.0990 ***	-0.1042 ***	0.0733 ***	-0.0252	0.0028	1.0000 ***

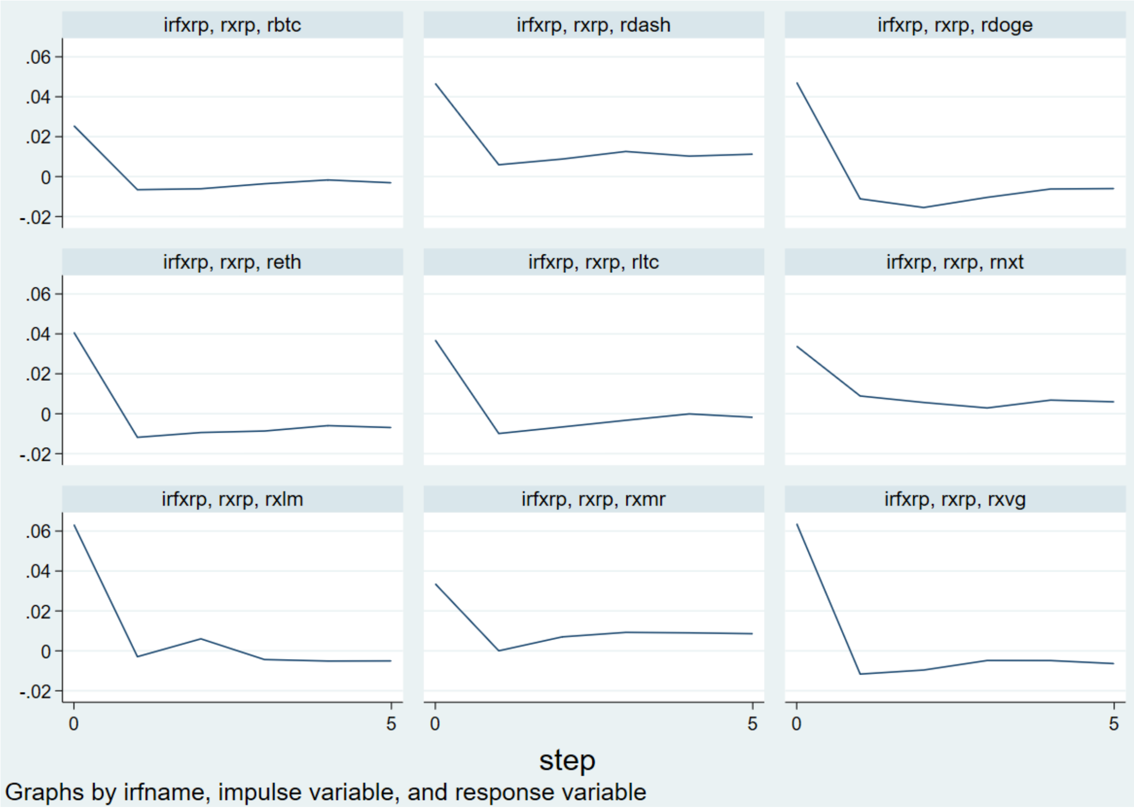
Appendix 57. Impulse Response Function from Ethereum to other cryptocurrencies (Covid-19 period)



Appendix 58. MGARCH model applied for Ethereum and other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
reth						
rbtc	.351196	.0763831	4.60	0.000	.201488	.5009041
rxrp	.0941089	.0369166	2.55	0.011	.0217538	.166464
rltc	.4125014	.0597829	6.90	0.000	.295329	.5296738
rdash	-.0198956	.0267797	-0.74	0.458	-.0723828	.0325915
rxlm	.1490627	.0376391	3.96	0.000	.0752914	.2228341
rxmr	.098952	.0486269	2.03	0.042	.0036451	.194259
rdoge	.002149	.0242292	0.09	0.929	-.0453394	.0496374
rxvg	.0001466	.0219393	0.01	0.995	-.0428537	.0431468
rnxt	.0591338	.0275662	2.15	0.032	.0051051	.1131625
_cons	.0011007	.0015614	0.70	0.481	-.0019595	.004161

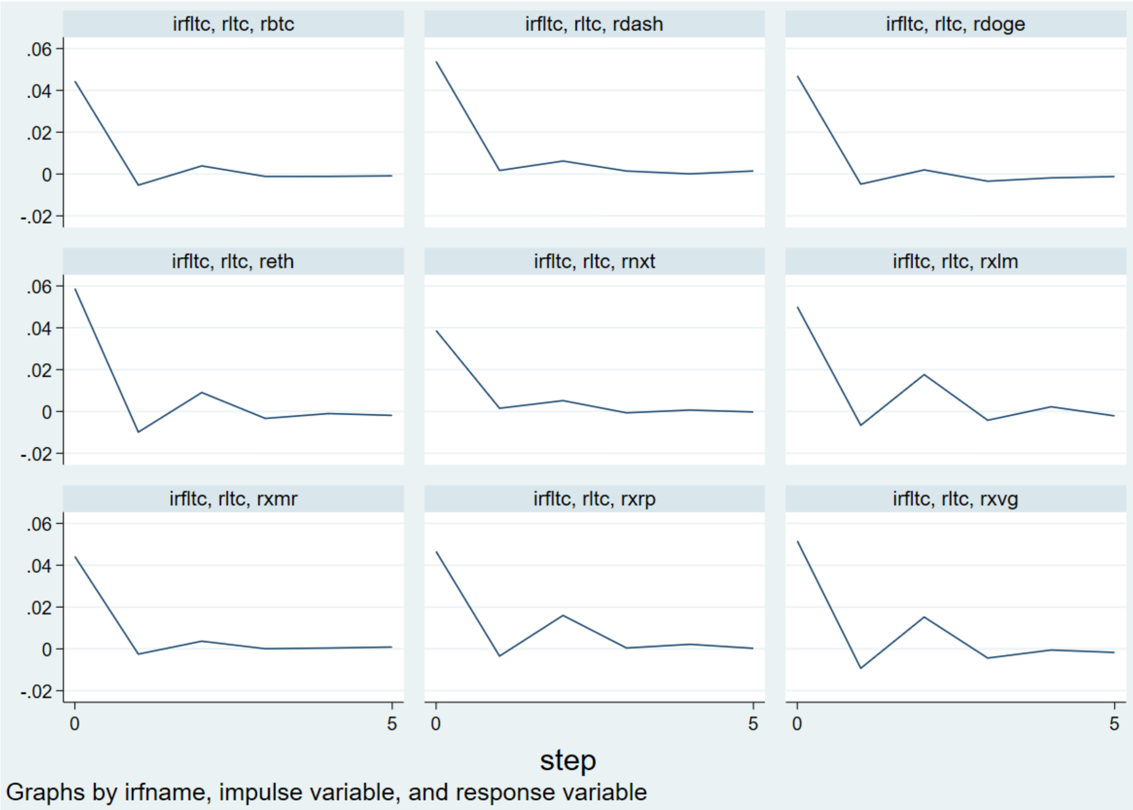
Appendix 59. Impulse Response Function from Ripple to other cryptocurrencies (Covid-19 period)



Appendix 60. MGARCH model applied for Ripple and other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxrp						
rbtc	-.076949	.0448209	-1.72	0.086	-.1647964	.0108983
reth	.1236754	.0437053	2.83	0.005	.0380146	.2093361
rltc	.1548238	.0376654	4.11	0.000	.081001	.2286466
rdash	.0037639	.0145969	0.26	0.797	-.0248455	.0323733
rxlm	.2664264	.0370838	7.18	0.000	.1937436	.3391093
rxmr	.1695556	.0257174	6.59	0.000	.1191503	.2199608
rdoge	.0985183	.0244787	4.02	0.000	.050541	.1464955
rxvg	.0418852	.0159655	2.62	0.009	.0105934	.073177
rnxt	.0799933	.022699	3.52	0.000	.035504	.1244826
_cons	-.0038945	.0009621	-4.05	0.000	-.0057802	-.0020088

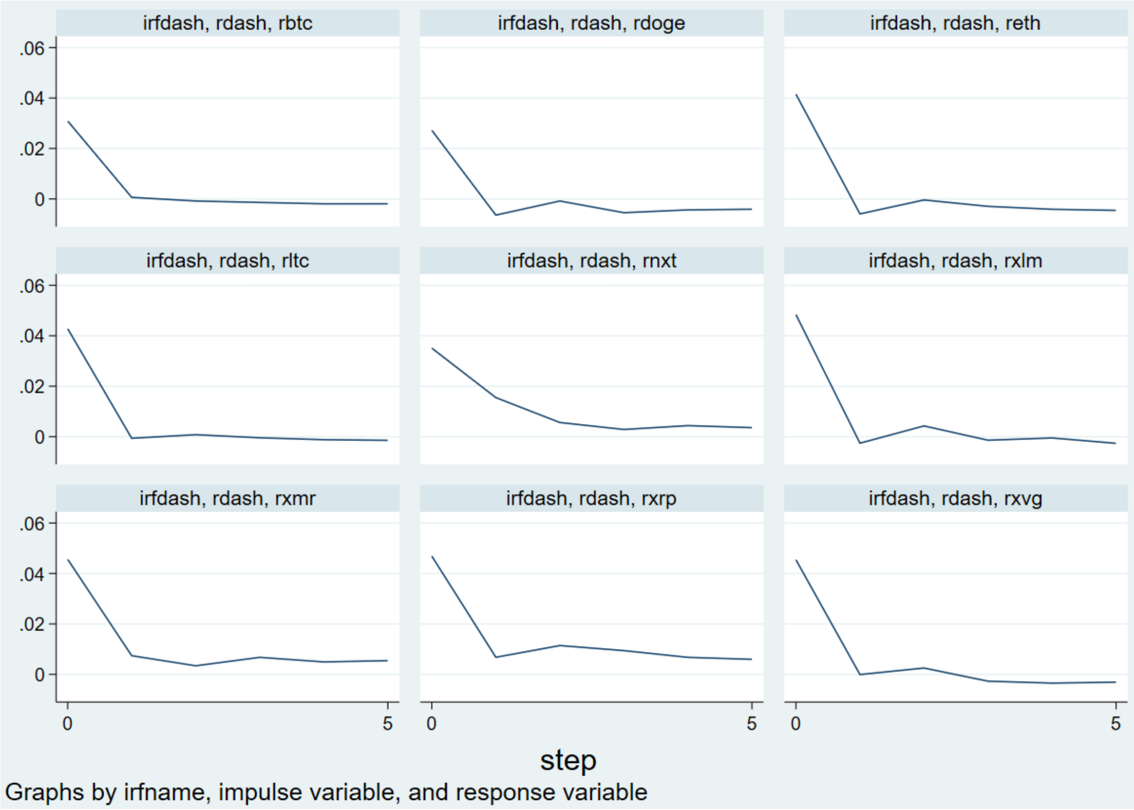
Appendix 61. Impulse Response Function from Litecoin to other cryptocurrencies (Covid-19 period)



Appendix 62. MGARCH model applied for Litecoin and other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rltc						
rbtc	.5262261	.0820607	6.41	0.000	.3653901	.6870621
reth	.3080469	.0616065	5.00	0.000	.1873005	.4287934
rxrp	.1219936	.0482971	2.53	0.012	.0273331	.2166541
rdash	.09742	.028408	3.43	0.001	.0417414	.1530987
rxlm	.0125036	.0503718	0.25	0.804	-.0862234	.1112306
rxmr	.04501	.0475066	0.95	0.343	-.0481013	.1381213
rdoge	-.0008305	.0191488	-0.04	0.965	-.0383615	.0367005
rxvg	-.0277609	.0235733	-1.18	0.239	-.0739637	.018442
rnxt	-.0218754	.0320245	-0.68	0.495	-.0846423	.0408915
_cons	-.0013594	.0014353	-0.95	0.344	-.0041726	.0014539

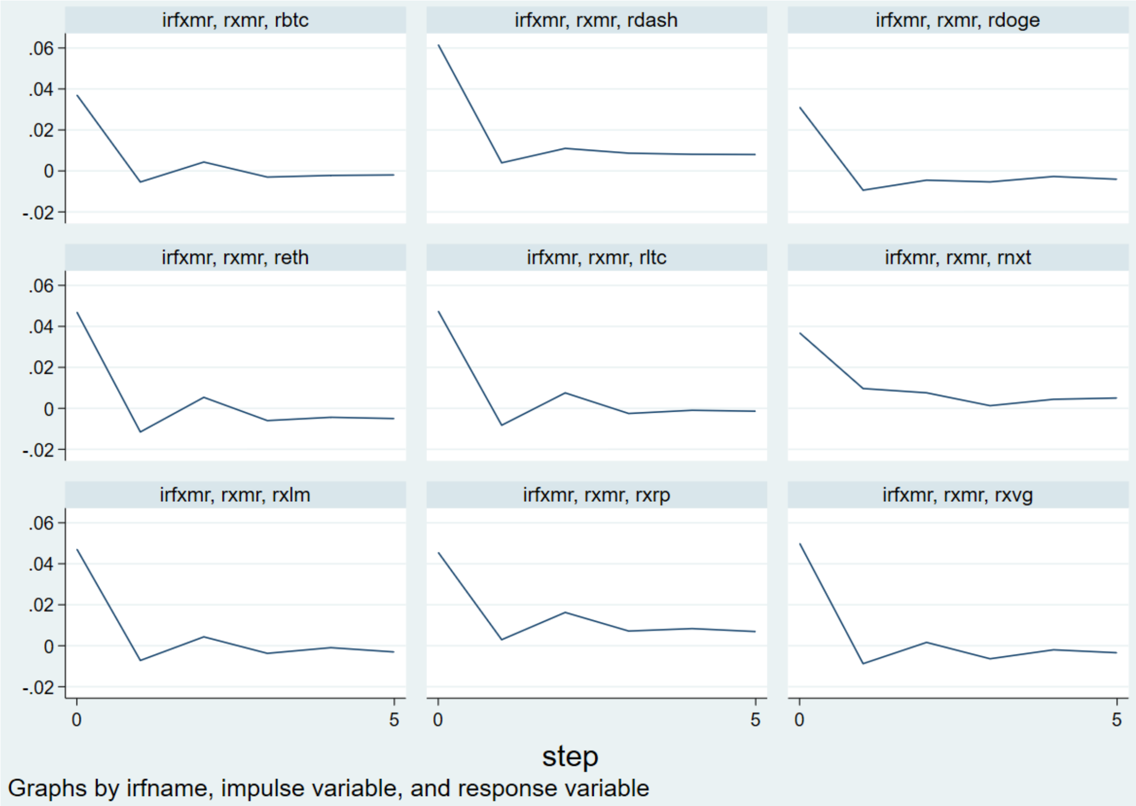
Appendix 63. Impulse Response Function from Dash to other cryptocurrencies (Covid-19 period)



Appendix 64. MGARCH model applied for Dash and other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rdash						
rbtc	.0748409	.0904961	0.83	0.408	-.1025282	.25221
reth	-.1340381	.048739	-2.75	0.006	-.2295649	-.0385114
rxrp	.0338876	.0340271	1.00	0.319	-.0328043	.1005796
rltc	.2703843	.0683031	3.96	0.000	.1365128	.4042558
rxlm	.279218	.0311805	8.95	0.000	.2181054	.3403306
rxmr	.5302772	.0871533	6.08	0.000	.3594598	.7010946
rdoge	-.009244	.0122254	-0.76	0.450	-.0332054	.0147174
rxvg	-.0400078	.0259598	-1.54	0.123	-.0908881	.0108726
rnxt	-.0901456	.0326772	-2.76	0.006	-.1541917	-.0260994
_cons	-.0032098	.0021431	-1.50	0.134	-.0074102	.0009906

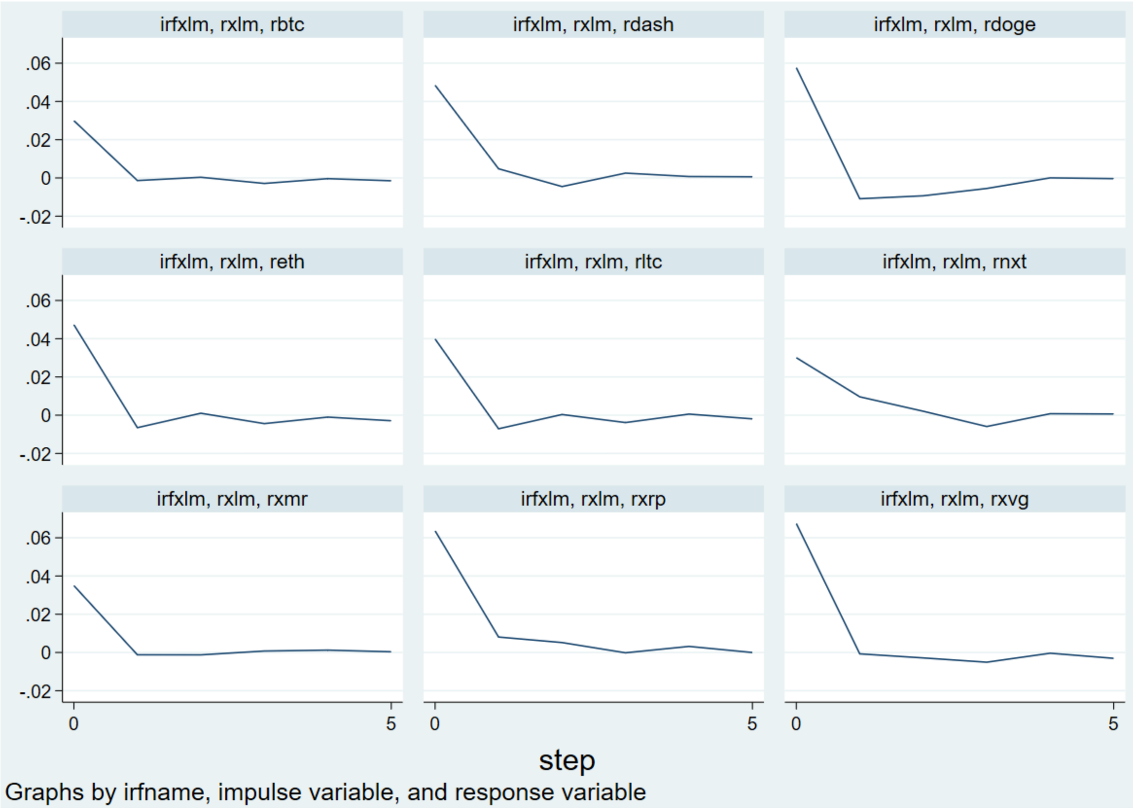
Appendix 65. Impulse Response Function from Monero to other cryptocurrencies (Covid-19 period)



Appendix 66. MGARCH model applied for Monero and other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxmr						
rbtc	.2400419	.0928647	2.58	0.010	.0580305	.4220533
reth	.1369716	.0573324	2.39	0.017	.0246021	.2493411
rxrp	-.0226741	.0398795	-0.57	0.570	-.1008365	.0554882
rltc	.1179216	.0642192	1.84	0.066	-.0079458	.2437889
rdash	.364175	.0362931	10.03	0.000	.2930419	.4353081
rxlm	.0006331	.0436219	0.01	0.988	-.0848642	.0861304
rdoge	-.0135966	.0147051	-0.92	0.355	-.042418	.0152249
rxvg	.0335793	.0251375	1.34	0.182	-.0156893	.0828478
rnxt	.0492732	.032473	1.52	0.129	-.0143728	.1129191
_cons	-.0003306	.001738	-0.19	0.849	-.0037369	.0030758

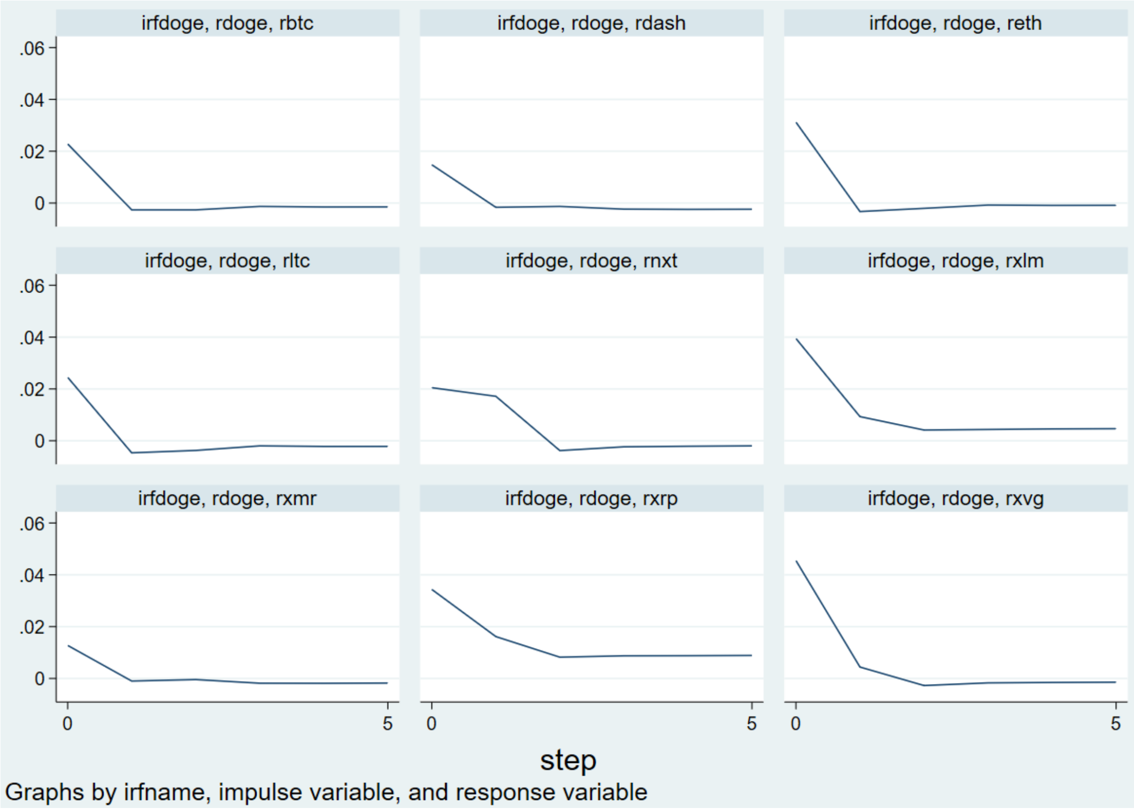
Appendix 67. Impulse Response Function from Stellar to other cryptocurrencies (Covid-19 period)



Appendix 68. MGARCH model applied for Stellar and other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxlm						
rbtc	-.1367203	.0945884	-1.45	0.148	-.3221101	.0486695
reth	.1778285	.0640363	2.78	0.005	.0523196	.3033373
rxrp	.7087336	.0359152	19.73	0.000	.6383411	.7791261
rltc	-.0246621	.0659943	-0.37	0.709	-.1540085	.1046843
rdash	.110715	.0395979	2.80	0.005	.0331046	.1883254
rxmr	.0975957	.0510894	1.91	0.056	-.0025376	.197729
rdoge	.0640798	.0155276	4.13	0.000	.0336463	.0945133
rxvg	.0912206	.0404627	2.25	0.024	.0119151	.1705261
rnxt	-.1044482	.0341505	-3.06	0.002	-.1713819	-.0375145
_cons	.0016589	.0017845	0.93	0.353	-.0018386	.0051564

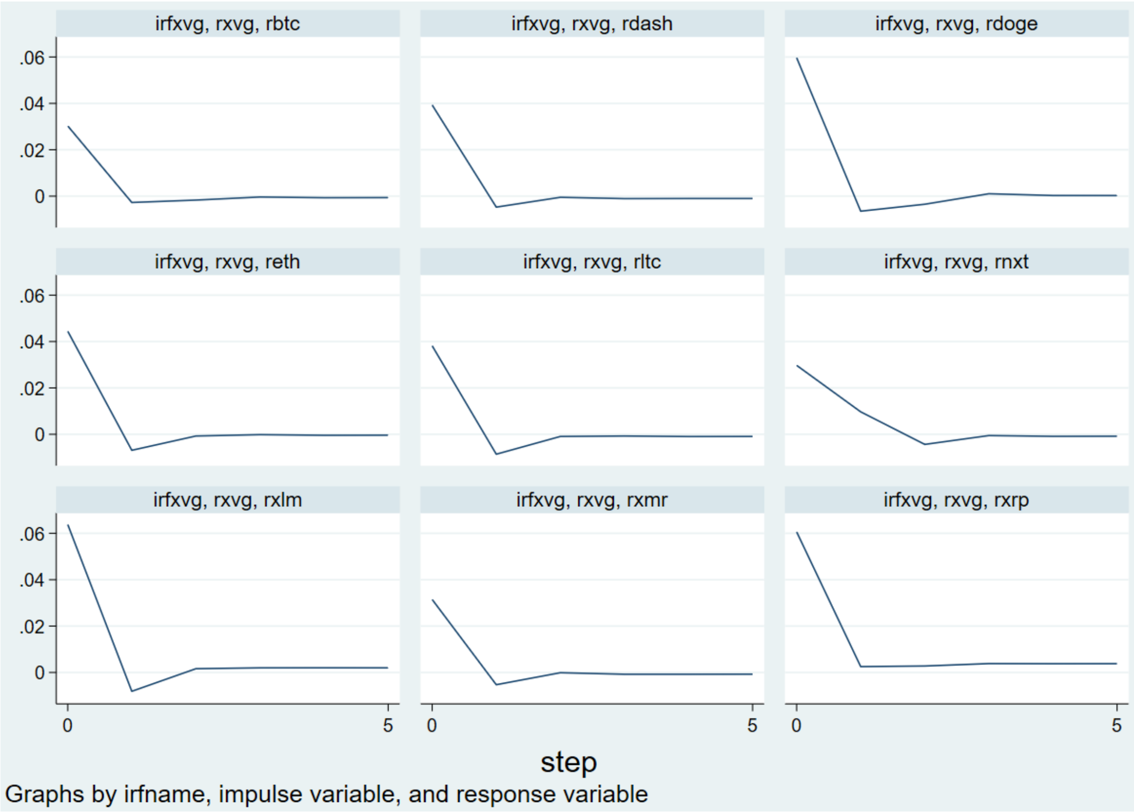
Appendix 69. Impulse Response Function from Dogecoin to other cryptocurrencies (Covid-19 period)



Appendix 70. MGARCH model applied for Dogecoin and other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rdoge						
rbtc	.1623516	.0650482	2.50	0.013	.0348594	.2898437
reth	.1510541	.0310649	4.86	0.000	.090168	.2119402
rxrp	.3683739	.0274303	13.43	0.000	.3146116	.4221363
rltc	-.0710869	.0334348	-2.13	0.033	-.1366179	-.005556
rdash	.0387855	.0359151	1.08	0.280	-.0316067	.1091777
rxlm	.0099833	.0254802	0.39	0.695	-.0399569	.0599235
rxmr	-.0133731	.0327499	-0.41	0.683	-.0775618	.0508155
rxvg	-.0160395	.014775	-1.09	0.278	-.044998	.012919
rnxt	.0793876	.0226217	3.51	0.000	.0350498	.1237253
_cons	-.0031294	.0009554	-3.28	0.001	-.0050021	-.0012568

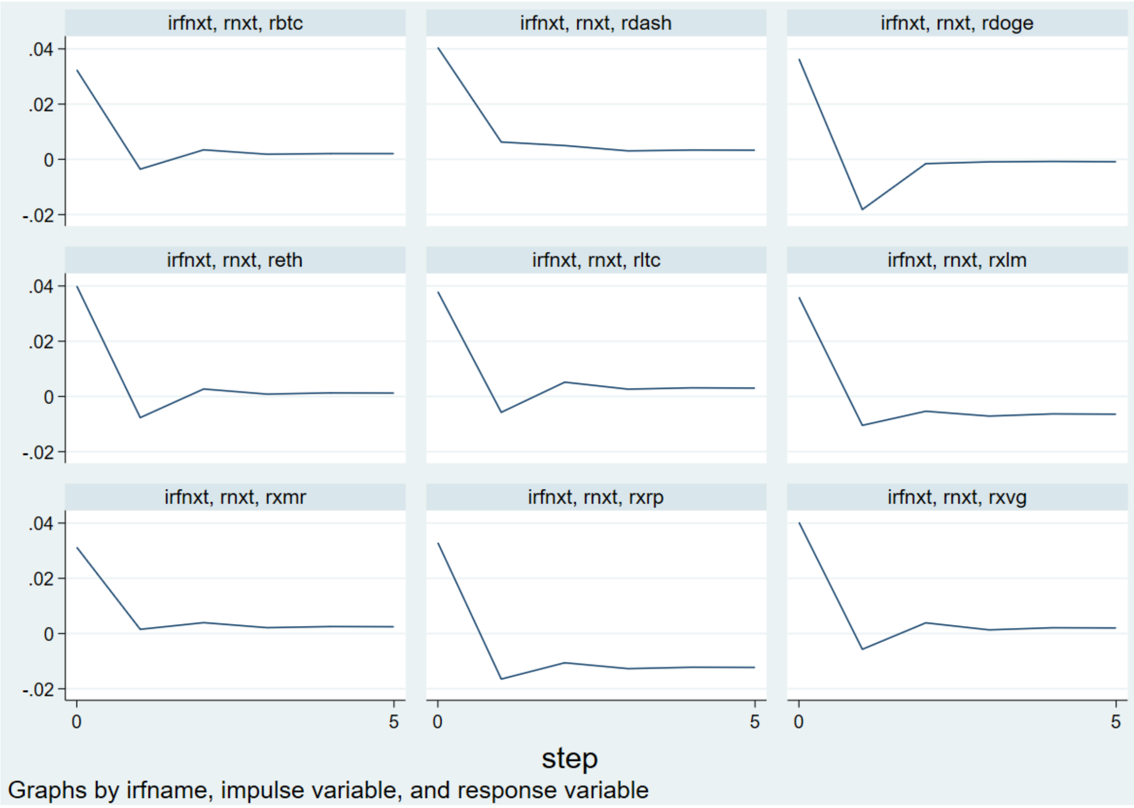
Appendix 71. Impulse Response Function from Verge to other cryptocurrencies (Covid-19 period)



Appendix 72. MGARCH model applied for Verge and other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rxvg						
rbtc	.3152985	.1504515	2.10	0.036	.0204189	.610178
reth	.0231406	.0941728	0.25	0.806	-.1614348	.207716
rxrp	.3414643	.0762017	4.48	0.000	.1921118	.4908169
rltc	-.0666487	.1033799	-0.64	0.519	-.2692696	.1359723
rdash	-.0229285	.0547714	-0.42	0.675	-.1302784	.0844214
rxlm	.3363928	.0518996	6.48	0.000	.2346714	.4381141
rxmr	.1427408	.1027147	1.39	0.165	-.0585763	.3440579
rdoge	.1025344	.0808288	1.27	0.205	-.0558872	.260956
rnxt	.0248536	.0558394	0.45	0.656	-.0845896	.1342969
_cons	-.0052068	.0032793	-1.59	0.112	-.0116341	.0012204

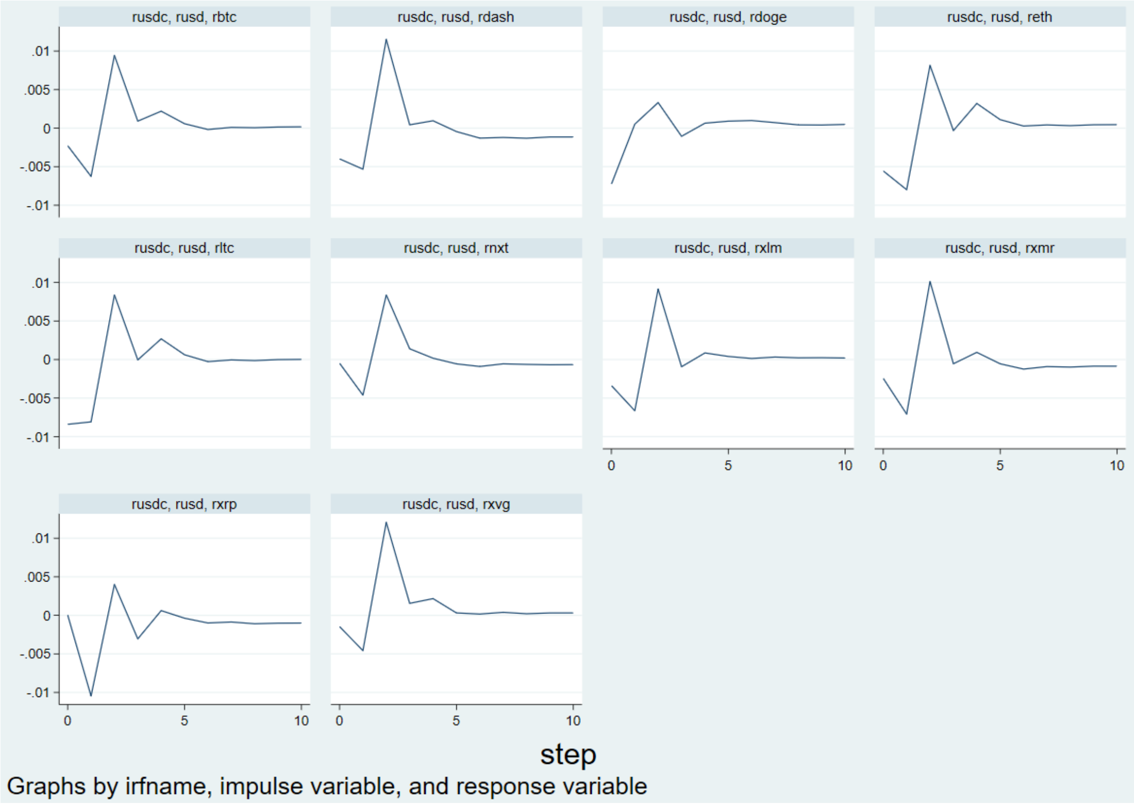
Appendix 73. Impulse Response Function from Nxt to other cryptocurrencies (Covid-19 period)



Appendix 74. MGARCH model applied for Nxt and other cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rnxt						
rbtc	.7151085	.0908457	7.87	0.000	.5370542	.8931629
reth	.0992001	.0675034	1.47	0.142	-.0331043	.2315044
rxrp	.2007745	.0298575	6.72	0.000	.142255	.2592941
rltc	-.0750397	.0870362	-0.86	0.389	-.2456275	.095548
rdash	-.0061766	.0325108	-0.19	0.849	-.0698967	.0575434
rxlm	.0183063	.04199	0.44	0.663	-.0639925	.1006051
rxmr	.0434474	.0629664	0.69	0.490	-.0799644	.1668592
rdoge	-.0200355	.0249697	-0.80	0.422	-.0689753	.0289042
rxvg	-.0656729	.0390233	-1.68	0.092	-.1421571	.0108113
_cons	-.0082366	.0022108	-3.73	0.000	-.0125697	-.0039036

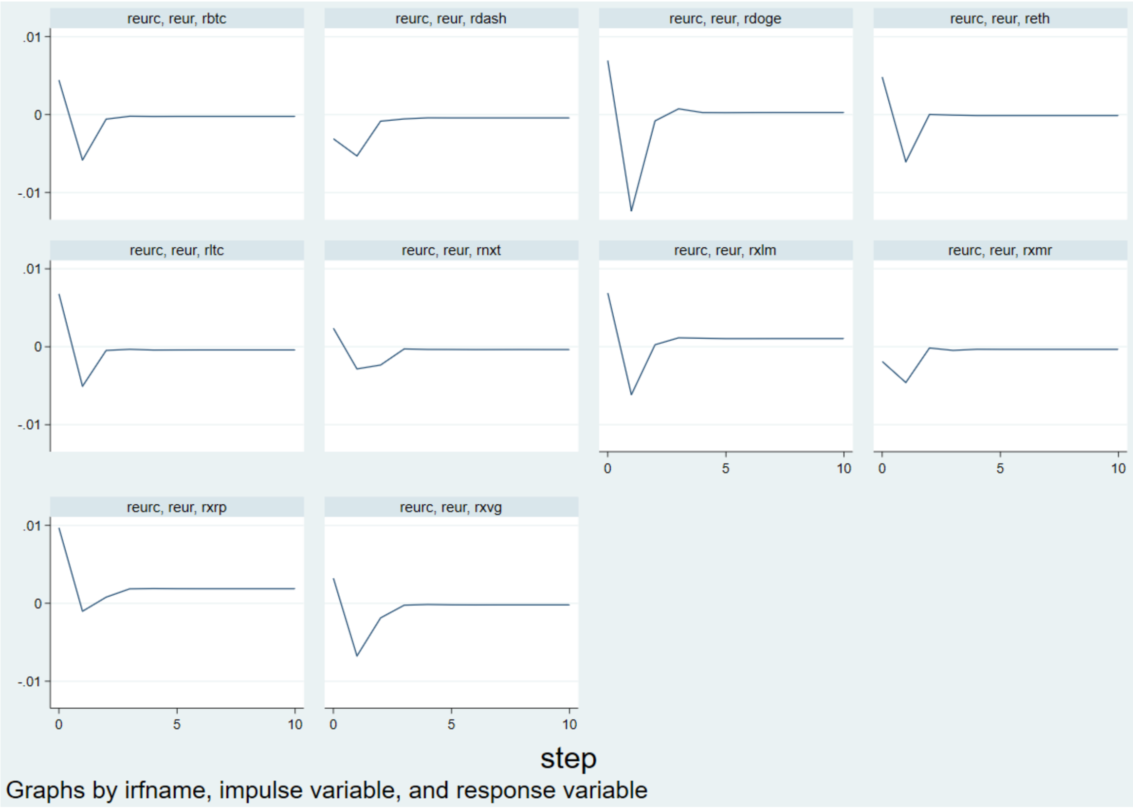
Appendix 75. Impulse Response Function from USD to all cryptocurrencies (Covid-19 period)



Appendix 76. MGARCH model applied for USD and all cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rusd						
rbtc	.0171899	.0107313	1.60	0.109	-.0038431	.0382229
reth	-.0077243	.0072397	-1.07	0.286	-.0219138	.0064652
rxrp	.003224	.0043984	0.73	0.464	-.0053966	.0118447
rltc	-.0222091	.0077284	-2.87	0.004	-.0373565	-.0070617
rdash	-.0017821	.0041821	-0.43	0.670	-.0099788	.0064146
rxlm	-.0016265	.0045707	-0.36	0.722	-.0105849	.0073319
rxmr	.0057484	.0063925	0.90	0.369	-.0067807	.0182775
rdoge	-.0017745	.0022213	-0.80	0.424	-.0061281	.0025791
rxvg	.003976	.0038422	1.03	0.301	-.0035546	.0115066
rnxt	.0031665	.0039932	0.79	0.428	-.0046601	.010993
_cons	-.0002354	.0002472	-0.95	0.341	-.0007199	.0002491

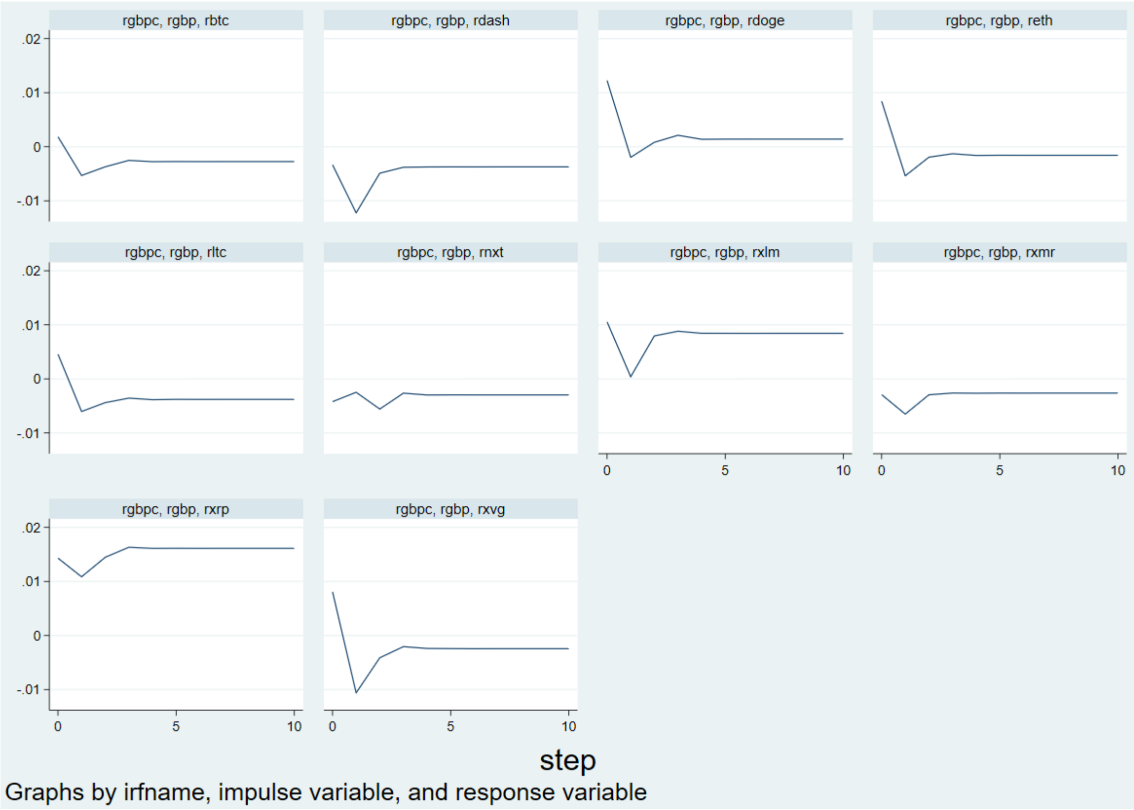
Appendix 77. Impulse Response Function from Euro to all cryptocurrencies (Covid-19 period)



Appendix 78. MGARCH model applied for Euro and all cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
reur						
rbtc	.0175489	.0110246	1.59	0.111	-.004059	.0391567
reth	-.0087694	.0076064	-1.15	0.249	-.0236777	.0061388
rxrp	.0070851	.0045139	1.57	0.117	-.0017619	.0159321
rltc	.0092087	.0082597	1.11	0.265	-.00698	.0253975
rdash	-.0045081	.0043675	-1.03	0.302	-.0130682	.0040519
rxlm	.0019053	.0048056	0.40	0.692	-.0075136	.0113241
rxmr	-.0111904	.0066593	-1.68	0.093	-.0242425	.0018617
rdoge	-.0011141	.0022424	-0.50	0.619	-.005509	.0032809
rxvg	-.0024744	.0042575	-0.58	0.561	-.0108191	.0058702
rnxt	-.0012877	.0043861	-0.29	0.769	-.0098844	.0073089
_cons	.0002402	.0002674	0.90	0.369	-.0002838	.0007643

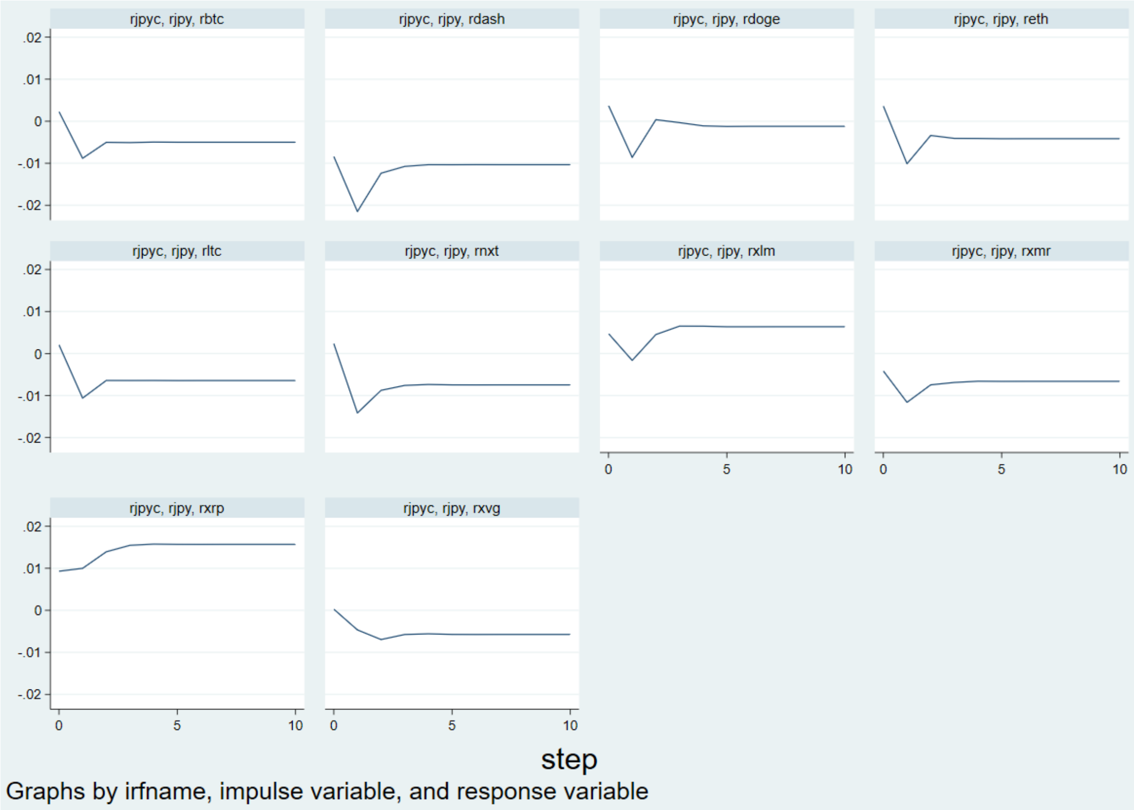
Appendix 79. Impulse Response Function from Pound to all cryptocurrencies (Covid-19 period)



Appendix 80. MGARCH model applied for Pound and all cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rgbp						
rbtc	.0118453	.0150203	0.79	0.430	-.017594	.0412846
reth	.0105518	.0106217	0.99	0.321	-.0102664	.03137
rxrp	.0054825	.0062402	0.88	0.380	-.006748	.0177131
rltc	.0004717	.0112352	0.04	0.967	-.0215489	.0224924
rdash	-.0007054	.0065846	-0.11	0.915	-.0136109	.0122001
rxlm	.0039876	.0062419	0.64	0.523	-.0082464	.0162215
rxmr	-.0192504	.0096768	-1.99	0.047	-.0382166	-.0002842
rdoge	-.0005818	.0027616	-0.21	0.833	-.0059943	.0048308
rxvg	-.0008281	.0052988	-0.16	0.876	-.0112135	.0095573
rnxt	-.0089047	.0058469	-1.52	0.128	-.0203644	.002555
_cons	.0004935	.000353	1.40	0.162	-.0001983	.0011854

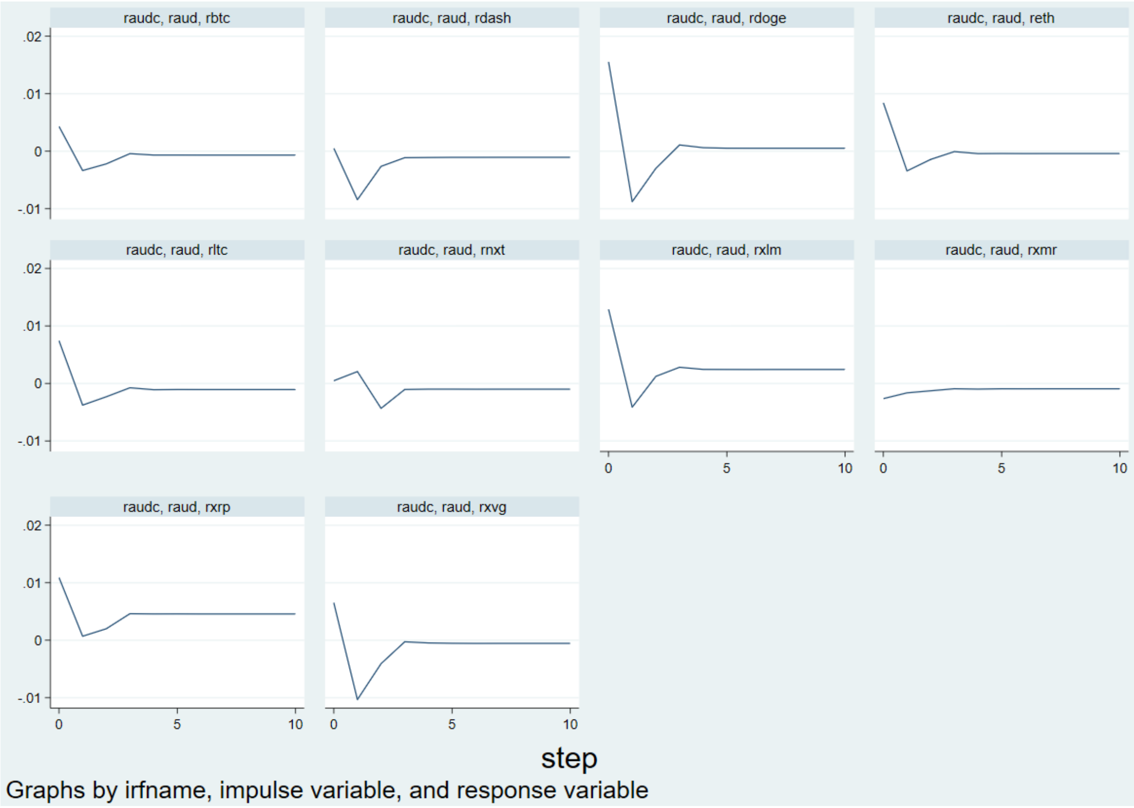
Appendix 81. Impulse Response Function from Yen to all cryptocurrencies (Covid-19 period)



Appendix 82. MGARCH model applied for Yen and all cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rjpy						
rbtc	.0125323	.0113966	1.10	0.271	-.0098046	.0348692
reth	-.001467	.007276	-0.20	0.840	-.0157277	.0127936
rxrp	.0022285	.0041668	0.53	0.593	-.0059383	.0103953
rltc	.0029264	.0084493	0.35	0.729	-.0136339	.0194867
rdash	-.0071535	.0046595	-1.54	0.125	-.0162859	.0019789
rxlm	.0025658	.004401	0.58	0.560	-.0060599	.0111916
rxmr	-.0061167	.0068675	-0.89	0.373	-.0195767	.0073433
rdoge	-.0004127	.0020885	-0.20	0.843	-.0045061	.0036807
rxvg	-.0051489	.00403	-1.28	0.201	-.0130476	.0027499
rnxt	.0004178	.0039908	0.10	0.917	-.0074041	.0082397
_cons	-.0001642	.000252	-0.65	0.515	-.0006581	.0003296

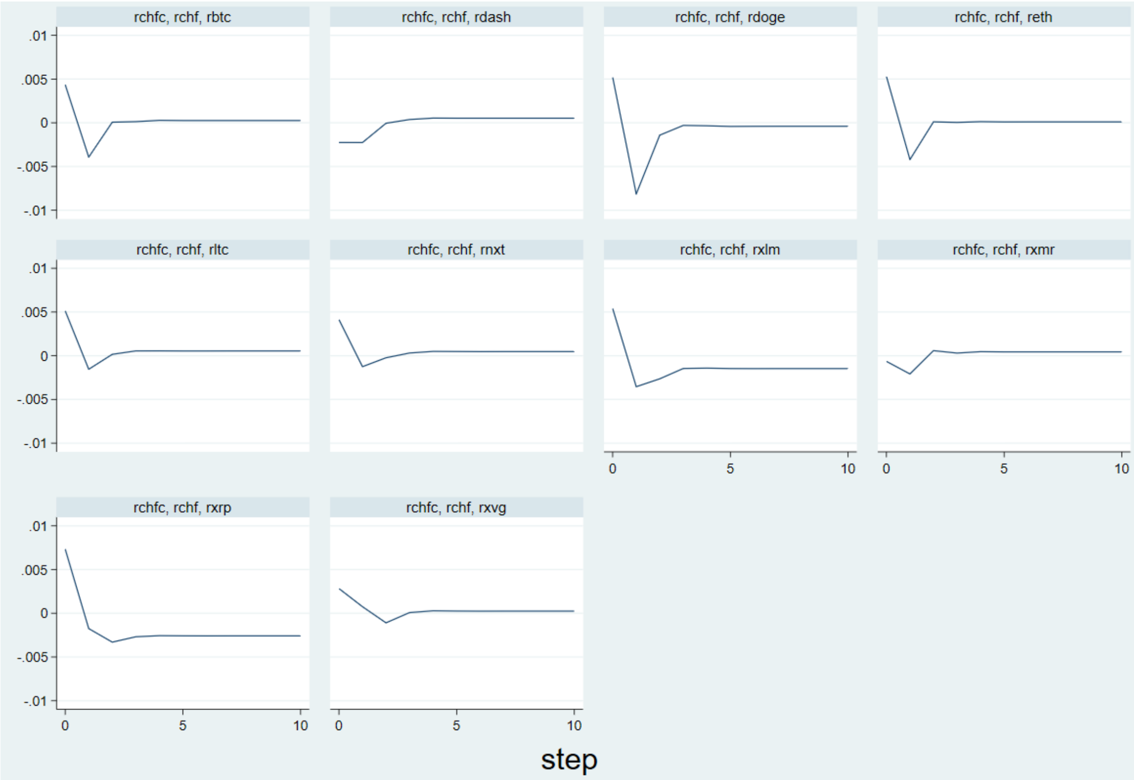
Appendix 83. Impulse Response Function from Australian Dollar to all cryptocurrencies (Covid-19 period)



Appendix 84. MGARCH model applied for Australian Dollar and all cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
raud						
rbtc	.027049	.0165887	1.63	0.103	-.0054643	.0595623
reth	.0061139	.0119902	0.51	0.610	-.0173865	.0296142
rxrp	.0049928	.006623	0.75	0.451	-.0079881	.0179737
rltc	.0066556	.0120325	0.55	0.580	-.0169276	.0302388
rdash	.0065735	.0066421	0.99	0.322	-.0064448	.0195917
rxlm	.0090884	.0066842	1.36	0.174	-.0040123	.0221891
rxmr	-.0421504	.0105423	-4.00	0.000	-.0628129	-.0214878
rdoge	-.0004291	.0036118	-0.12	0.905	-.0075081	.0066499
rxvg	-.0070935	.0065584	-1.08	0.279	-.0199476	.0057606
rnxt	-.0006895	.0065058	-0.11	0.916	-.0134406	.0120616
_cons	.0003824	.0004083	0.94	0.349	-.0004179	.0011826

Appendix 85. Impulse Response Function from Swiss Franc to all cryptocurrencies (Covid-19 period)

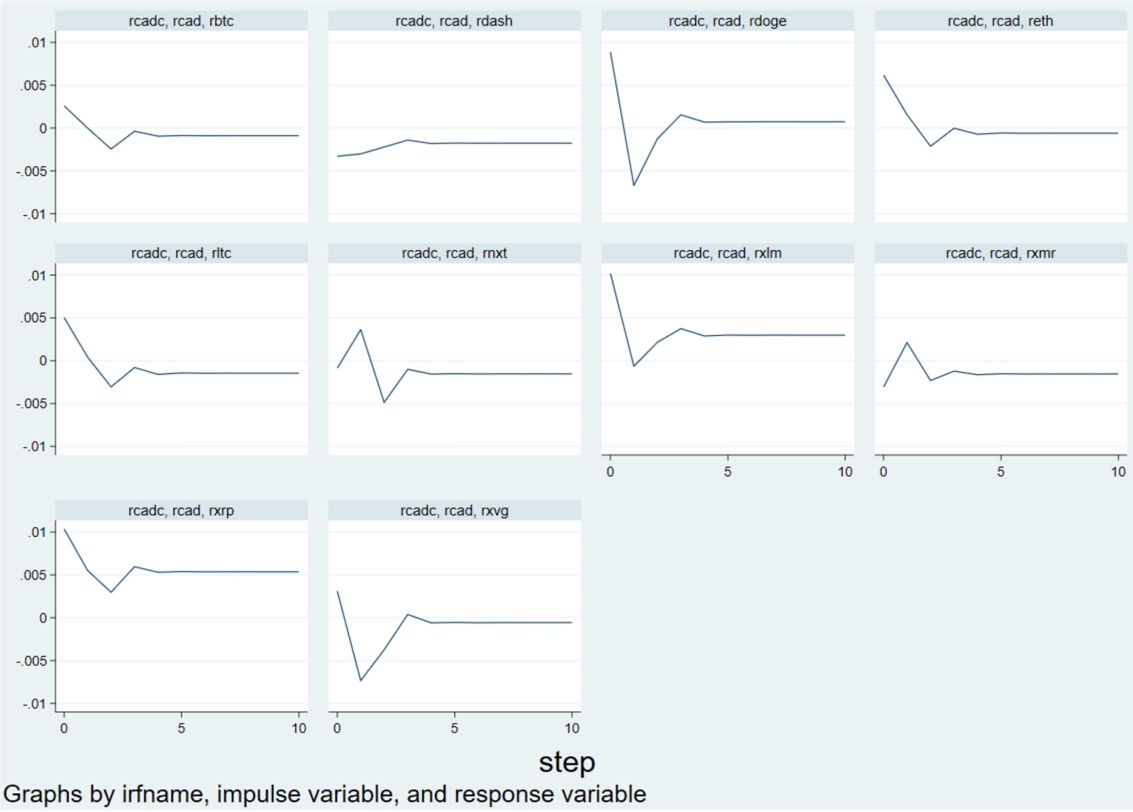


Graphs by irfname, impulse variable, and response variable

Appendix 86. MGARCH model applied for Swiss Franc and all cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rchf						
rbtc	.0197286	.0120786	1.63	0.102	-.003945	.0434022
reth	-.0004011	.0083112	-0.05	0.962	-.0166907	.0158884
rxrp	.0056756	.004842	1.17	0.241	-.0038147	.0151658
rltc	-.0029141	.0093373	-0.31	0.755	-.021215	.0153867
rdash	-.0039389	.0048407	-0.81	0.416	-.0134266	.0055487
rxlm	.0013755	.0050751	0.27	0.786	-.0085716	.0113225
rxmr	-.0057647	.0077416	-0.74	0.456	-.0209379	.0094085
rdoge	-.0011697	.0024543	-0.48	0.634	-.00598	.0036406
rxvg	-.0013634	.0043488	-0.31	0.754	-.0098868	.00716
rnxt	-.0013368	.0045548	-0.29	0.769	-.0102639	.0075904
_cons	.000173	.0002969	0.58	0.560	-.0004089	.000755

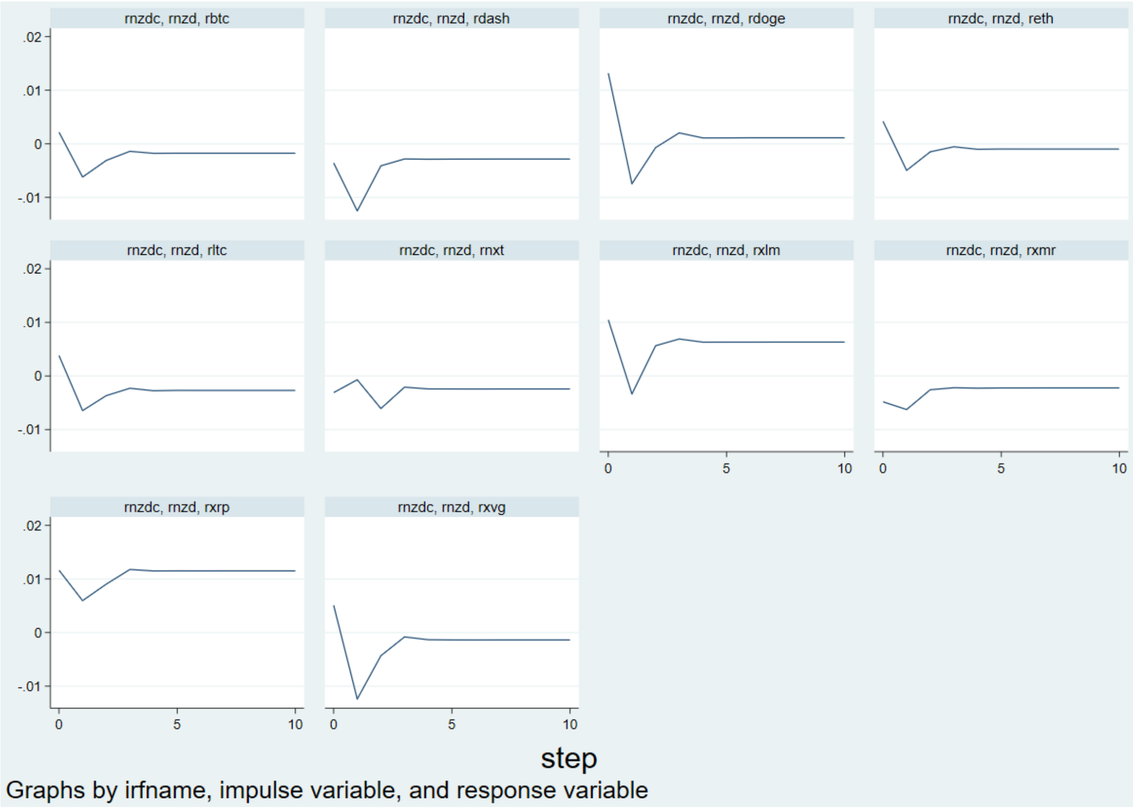
Appendix 87. Impulse Response Function from Canadian Dollar to all cryptocurrencies (Covid-19 period)



Appendix 88. MGARCH model applied for Canadian Dollar and all cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rcad						
rbtc	.0090625	.0120514	0.75	0.452	-.0145579	.0326828
reth	.0049831	.0082009	0.61	0.543	-.0110904	.0210566
rxrp	.005037	.0048964	1.03	0.304	-.0045598	.0146339
rltc	.003156	.0088215	0.36	0.721	-.0141337	.0204458
rdash	-.0036334	.0043847	-0.83	0.407	-.0122273	.0049605
rxlm	.0050741	.0049196	1.03	0.302	-.0045681	.0147164
rxmr	-.0138747	.0076355	-1.82	0.069	-.0288399	.0010906
rdoge	-.0010309	.0025258	-0.41	0.683	-.0059814	.0039197
rxvg	-.0058421	.0043709	-1.34	0.181	-.014409	.0027247
rnxt	-.0004628	.0047278	-0.10	0.922	-.0097293	.0088036
_cons	.0002594	.0002776	0.93	0.350	-.0002847	.0008034

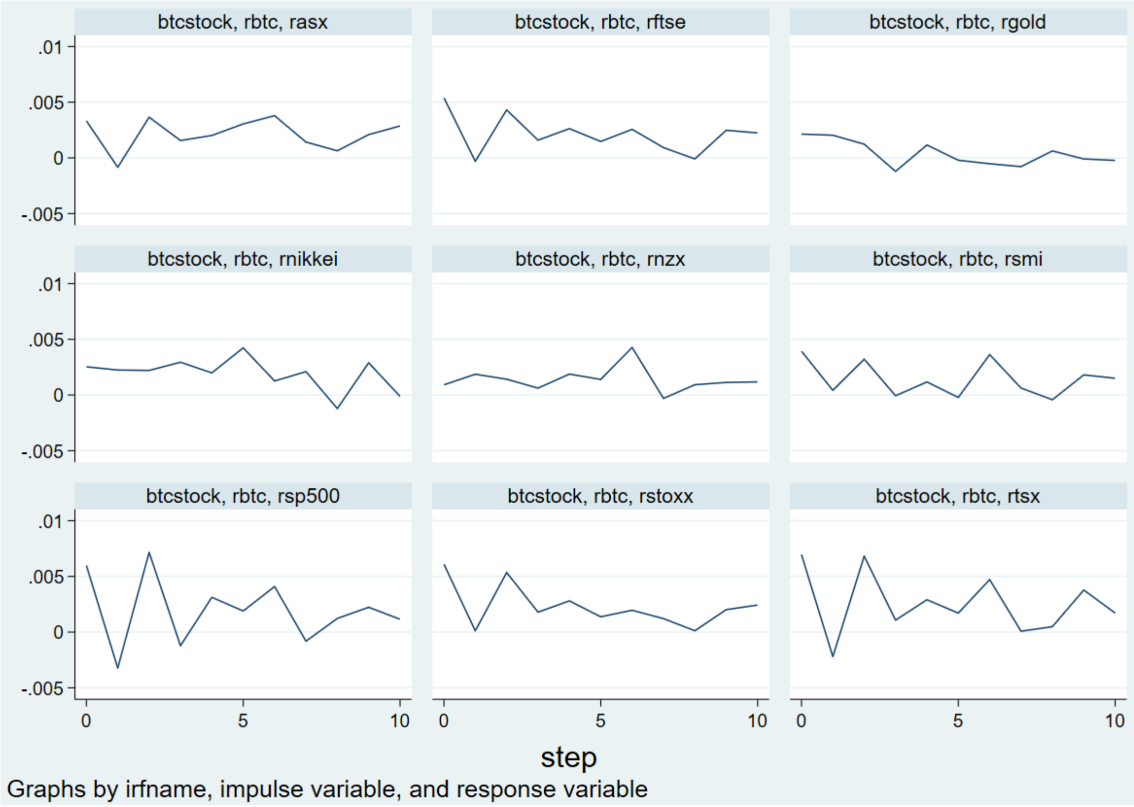
Appendix 89. Impulse Response Function from NZ Dollar to all cryptocurrencies (Covid-19 period)



Appendix 90. MGARCH model applied for NZ Dollar and all cryptocurrencies (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rnzd						
rbtc	.0330192	.0167799	1.97	0.049	.0001312	.0659072
reth	-.0045803	.0120232	-0.38	0.703	-.0281454	.0189848
rxrp	.007434	.0065539	1.13	0.257	-.0054115	.0202794
rltc	.0028337	.0119897	0.24	0.813	-.0206657	.026333
rdash	.0009388	.0062189	0.15	0.880	-.01125	.0131276
rxlm	.0068757	.006633	1.04	0.300	-.0061247	.0198761
rxmr	-.0324833	.0099357	-3.27	0.001	-.0519569	-.0130096
rdoge	.0000671	.0035056	0.02	0.985	-.0068037	.006938
rxvg	-.0038442	.0065608	-0.59	0.558	-.0167031	.0090146
rnxt	-.0057006	.0062911	-0.91	0.365	-.0180309	.0066297
_cons	.0003602	.0003936	0.92	0.360	-.0004112	.0011316

Appendix 91. Impulse Response Function from Bitcoin to all Stock indexes (Covid-19 period)



Appendix 92. MGARCH model applied for Bitcoin and all Stock indexes (Covid-19 period)

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
rbtc						
rsp500	.0922243	.291812	0.32	0.752	-.4797167	.6641652
rftse	-.1051259	.3577915	-0.29	0.769	-.8063844	.5961325
rstoxx	-.284758	.3246575	-0.88	0.380	-.9210751	.3515591
rnikkei	.1081701	.1829114	0.59	0.554	-.2503296	.4666699
rsmi	-.1024899	.2966814	-0.35	0.730	-.6839747	.4789949
rtsx	1.431703	.3922849	3.65	0.000	.6628386	2.200567
rasx	.2084624	.1906525	1.09	0.274	-.1652095	.5821344
rnzx	-.5294191	.2335881	-2.27	0.023	-.9872433	-.0715949
rgold	.7977732	.1824427	4.37	0.000	.440192	1.155354
_cons	.0041927	.0021656	1.94	0.053	-.0000518	.0084373

Appendix 93. Pearson correlation of cryptocurrencies and Stock indexes (2015-2021)

	rbtc	reth	rxrp	rltc	rdash	rxlm	rxmr	rdoge	rxvg	rnxt
rsp500	0.1325 ***	0.1279 ***	0.1110 ***	0.1353 ***	0.1140 ***	0.1044 ***	0.1267 ***	0.0667 ***	0.0873 ***	0.0942 ***
rstoxx	0.1499 ***	0.0912 ***	0.1060 ***	0.1368 ***	0.1227 ***	0.1122 ***	0.1197 ***	0.0671 **	0.0970 ***	0.1163 ***
rftse	0.1466 ***	0.0891 ***	0.1008 ***	0.1428 ***	0.1272 ***	0.1073 ***	0.1349 ***	0.0536 *	0.0847 ***	0.0931 ***
rnikkei	0.0199	-0.0052	0.0322	0.0395	0.0683 **	0.0753 ***	0.0584 **	-0.0018	0.0101	0.0546 *
rsmi	0.1173 ***	0.0730 ***	0.0996 ***	0.1216 ***	0.1116 ***	0.0956 ***	0.1146 ***	0.0413	0.0548 *	0.0916 ***
rtsx	0.1985 ***	0.1584 ***	0.1394 ***	0.1637 ***	0.1572 ***	0.1329 ***	0.1537 ***	0.0847 ***	0.1225 ***	0.1353 ***
rasx	0.1088 ***	0.0697 ***	0.0451	0.0980 ***	0.0762	0.0499	0.0840	0.0246	0.0192	0.0688 **
rnzx	0.0967 ***	0.0526 *	0.0540 *	0.0922 ***	0.0618 **	0.0490 *	0.0782	0.0157	0.0212	0.0341