

**The Impact of COVID-19 on Cryptocurrency:  
The Hedging Behaviour of Bitcoin**

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## Abstract

Cryptocurrencies have several features that set them aside from traditional currencies. In terms of market capitalization, the top five cryptocurrencies are considered for the analysis to strengthen the research's validation. The most successful crypto asset, being Bitcoin, possesses several characteristics that pose advantages and disadvantages in the financial markets. Digital convenience ensures the safety and ease of use for Bitcoin users, while decentralization also poses a primary benefit. Extreme volatility and the impact of negative externalities on the value of Bitcoin contribute to the assessment of Bitcoin trends in the market. The recent outbreak of the coronavirus (COVID-19) has shown evidence of influencing Bitcoin prices as the virus is spread across continents, leaving the global financial environment in turmoil. The classification of Bitcoin as a hedge is dependent on various factors, including global economic uncertainty. The extent to which the coronavirus impacts cryptocurrencies' hedging capabilities, especially that of Bitcoin's, is of particular interest during the 2020 pandemic. Analyzing the literature on the influence of crisis on Bitcoin movement will explain why COVID-19 has had such a significant impact on the global financial markets, especially that of cryptocurrencies. The performance of Bitcoin, Ethereum, XRP, Tether, and Bitcoin Cash is compared to that of seven factors including commodities and indices: gold, USD, S&P 500 index, SSE index, world and emerging markets MSCI indices, and Economic Uncertainty, to better understand the hedging capabilities throughout the time of the crisis. This is done using four different multivariate GARCH specifications that account for the nature of the interaction between the cryptocurrencies and the financial variables. Although previous research finds that Bitcoin should act as a hedge during times of economic turmoil, the performance observed during COVID-19 suggests otherwise.

## 1. Introduction

Cryptocurrencies are being positioned in the highest ranking of importance in the global financial markets. This form of currency exists only in the digital world as a medium of exchange. There are several cryptocurrencies available over the internet, the most popular one being Bitcoin. Cryptocurrencies that were introduced after the success of Bitcoin are known as Altcoins and have some characteristics compared to those of the successful digital currency and others tremendously differing.

There are over 5,000 cryptocurrencies in existence as of February 2020 (Frankenfield, 2020). Based on their market capitalization, the top 5 cryptocurrencies include Bitcoin, Ethereum, XRP, Tether, and Bitcoin Cash (*CoinDesk 20 Digital Assets and Cryptocurrencies*, 2020). While some of these cryptocurrencies have token limits, others have quicker transfer speeds. These differing properties contribute to the advantages and disadvantages for investors holding these particular cryptocurrencies. Although the cumulative market capitalization of these Altcoins is high, it is incomparable to that of Bitcoins'.

Being the first-ever type of cryptocurrency declared in 2009, Bitcoin has become exceptionally popular over the years due to its unique properties. Not only is it the first form of a decentralized peer-to-peer payment network in existence, but it is also solely controlled by Bitcoin users all over the world. Without having any central authority monitoring the transactions, Bitcoin allows its users to be in full control while maintaining identity protection. More explicitly, there is no connection between a bitcoin and the bitcoin owner beyond possession, implying that the identity of the individuals involved in a Bitcoin transaction is virtually anonymous (Brito & Castillo, 2013). Thus, security is an essential advantage to Bitcoin, alongside many other positive features such as the ease to use and transfer of the currency and the speed of the transfer.

Aside from the several advantages of Bitcoin, several disadvantages also exist. One of the main properties of Bitcoin is, in fact, extreme volatility. The volatility of this cryptocurrency can be

significant in any given hour of the day (Franklin, 2016). The risk-return trade-off theory of finance states that high volatility comes with high expected returns. While some of these crypto-assets may have specific properties, they don't need to be the same. Each cryptocurrency is created for a different purpose, and for this reason, the interest in cryptocurrencies is significant.

The current debate in this area of research investigates whether the investment in cryptocurrencies is for portfolio diversification, to act as a hedge or a safe haven. Global economic uncertainty is found to have an effect on the classification of cryptocurrencies into these three categories; In fact, several negative externalities can impact the role and value of these digital assets.

One of the most recent economic uncertainties has been caused by the Novel Coronavirus, also termed COVID-19; China officially declared this pneumonia-type virus in 2019. By January 23, 2020, Wuhan, China, the source of coronavirus, was placed under quarantine as the virus uncontrollably spread to several countries and continents (Bouoiyour & Selmi, 2020). As COVID-19 spread rapidly across the country, it turned into a national crisis leading to significant shutdowns of industries and businesses. Since China's global trade share is as high as 14% (Bouoiyour & Selmi, 2020), the impact on the worldwide scale of financial markets is much more significant than any past economic uncertainties have been. During the SARS outbreak in 2003, sourced from China, its share of global trade was only 5% (Bouoiyour & Selmi, 2020). Therefore, the effect of COVID-19 on the financial markets is much more significant now than it was in 2003. Stock markets have experienced an unprecedented decline in share prices, and cryptocurrencies have also experienced severe volatility. As such, the global implications of COVID-19 have become a topic of interest not only in the health sector but also in the fields of economics and finance.

This thesis aims to identify the extent to which negative externalities, particularly the coronavirus of 2019-2020, impact the hedging expectations of cryptocurrencies, predominantly that of Bitcoin. To do so, a large sample and previous time-series data are used alongside an

empirical design proposed by Guesmi et al., 2019. The proposed models are used to examine the conditional volatility dynamics of the financial assets and measure the conditional cross effects between them, using variations of the *VARMA (1,1) – DCC – GARCH* time series model. Using gold, the US Dollar (USD) index, the Standard & Poor's 500 (S&P 500) index, the Shanghai Stock Exchange (SSE) index and the Morgan Stanley Capital International (MSCI) index, as well as global economic uncertainty and COVID-related total cases and total death statistics, the nature of the relationship between the cryptocurrencies and the financial variables and their transmission mechanisms are taken into account when analyzing the hedging effectiveness. By understanding the dynamics of the network, the framework of the coronavirus outbreak of 2019 will be established, using it as an asset in determining the performance of Bitcoin, specifically-during the global pandemic.

The empirical results suggest that *VARMA (1,1) – DCC – JGR – GARCH* is the best-specified model used to describe the interaction of the cryptocurrencies, especially between Bitcoin and the various financial assets. It is found that the hedging strategies involving gold, USD index and the stock indices and a cryptocurrency, say Bitcoin, reduce a portfolio's variance significantly, as compared to the risk of a portfolio composed of gold, USD index and stock indices only. Therefore, the results show that Bitcoin may regularly offer hedging benefits before the coronavirus, but it has proven the opposite during the pandemic.

The remainder of this research will be organized as follows: Section 2 includes a profound analysis of recent literature. Section 3 will develop a conceptual framework, combining all of the literature presented to form reasonable hypotheses. Section 4 will discuss the data and structural methodology, while Section 5 will identify the main empirical results. Finally, Section 6 will provide concluding remarks.

## 2. Theoretical Framework

### 2.1. Cryptocurrency

The crypto world consists of many dimensions and characteristics, giving it unique importance in the financial markets. The rise of crypto assets presents more options to investors when it comes to storing value. Dr. Usman Chohan, in his paper *Cryptocurrencies: A Brief Thematic Review*, stated that:

“A crypto-asset exists in a dimension that is not physical and can only exist in a digital form. Furthermore, the value is derived from supply and demand forces instead of outside intervention, while offering the utmost privacy.”

(Chohan, 2017)

Crypto assets are segregated into four distinct categories: platform tokens, utility tokens, transactional tokens, and cryptocurrencies. The latter classification will be thoroughly explained and identified as it represents the foundation of this analysis. Cryptocurrencies were introduced as a new form of currency and, over time, grew into a billion-dollar market. Even though they can be used as a medium of exchange with monetary value, they have other applications beyond payment. The payment network and transactions are secured through cryptography, the methodology used to identify a cryptocurrency. “The term ‘cryptography’ is a derivative of two Greek words ‘Kryptos’ and ‘Graphein,’ which translates into ‘Secret’ and ‘Writings’”(Edge & O’Donnell, 2016). The process of encrypting words and numbers has been common in the past, and now, the process is often done digitally.

The exclusion of financial institutions and other third parties served as an advantage of these digital currencies, allowing their users to control their transactions (Shahzad et al., 2019b). Cryptocurrencies are not the only form of digital currency: PayPal, virtual game money and even

loyalty points also account for digital currency (Grinberg, 2012). A concise definition of the digital currency states that:

“Cryptocurrencies are peer-to-peer electronic cash systems which allow online payments to be sent directly from one party to another without going through a financial institution.”  
(Corbet et al., 2019)

In general, cryptocurrencies are considered to have emerged in 2008 in response to the Global Financial Crisis (GFC) (Vojtko & Cisár, 2020), the most successful one being Bitcoin.

#### 2.1.1. Bitcoin: bitcoin

The design of Bitcoin was developed by Satoshi Nakamoto, an alleged pseudonym of one person or group of persons (Kliber et al., 2019). The purpose of this particular cryptocurrency was to work as a medium of exchange in order to buy and sell goods and services. What is important to note is that Nakamoto did not control Bitcoin; he was simply another user in the network that established this particular form of cryptocurrency. This successful cryptocurrency was launched in 2009, suggesting that its creation was a response to the GCF. The smallest denomination of bitcoin is called a “satoshi,” representing 0.0000001 of a bitcoin (Grant & Hogan, 2015). Approximately 25 Bitcoins are created every 10 minutes, through a mining process, with every transaction saved in the transaction log, or blockchain (Franklin, 2016). The total number of bitcoins that can be mined is 21 million, with the last satoshi expected to be mined in year 2140 (Brito & Castillo, 2013). Nakamoto is expected to hold approximately 1 million bitcoins, approximately 5% of the total possible bitcoins. As of July 20, 2020, 18,418,100 bitcoins have been mined (*How Many Bitcoins Are There? How Many Left to Mine? (2020)*, 2020).

“Bitcoin is a virtual currency that began as a white paper in November 2008 and transitioned from an idea to reality in 2009 with the mining of the first bitcoin.” (Grant & Hogan, 2015)

Bitcoin has gained traction over the years for several reasons, with its market capitalization increasing from \$1.4 billion on April 28, 2013, to \$169 billion on July 20, 2020 (*Bitcoin (BTC) Historical Data*, 2020). Bitcoin, as an asset, enables complete transactions and also acts as an investment opportunity. Investors are attracted to the Bitcoin network because of its exclusive properties. Altcoins also possess unique characteristics that pose as advantages and disadvantages for investors. Each cryptocurrency has at least one differing trait, allowing it to be more attractive than other cryptocurrencies to any particular investor.

### 2.1.2. Ethereum: ether

Ethereum is a decentralized software platform and is often described as “the world computer” (Antonopoulos & Wood, 2018). Vitalik Buterina founded the network in 2013, and on July 30, 2015, the first-ever Ethereum block was mined. This network allows individuals to construct and benefit from the variety of functions and corporations that can use decentralized information exchange platforms, or blockchain, for developing the productivity of their business operations. The digital system supports building and running digital, decentralized applications (dApps) for business and personal use (Frankenfield, 2018b).

“Ethereum attempts to offer a decentralized and democratized solution, much like the present-day Internet, but free from the control of any central authority. Instead of running on a few computers owned by an organization, it runs on the global network of hundreds

of computers called nodes that are owned and operated by anonymous but reliable volunteers, thus creating a kind of “Global Super Computer.””

(Seth, 2018)

The cryptocurrency that belongs to Ethereum is known as ether, which acts as a medium of exchange for network contributors, app developers and users. All operations conducted on the Ethereum platform are done so in exchange for ethers, which have a limited supply capped at 18 million ethers per year (Antonopoulos & Wood, 2018). The market capitalization for this cryptocurrency is recorded \$27.5 billion on July 20, 2020 (*Ethereum (ETH) Historical Data, 2020*), much lower than that of bitcoins’ but a lot higher than other altcoins.

### 2.1.3. Ripple: XRP

XRP is the name of the cryptocurrency that is often referred to as Ripple; however, Ripple is the name of the company and the network that backs the cryptocurrency (Reiff, 2020). Founded in 2012, the goal of Ripple was to create an internet of value, to stimulate globalization (“ValueWalk: Chris Larsen Of Ripple (XRP) @Google,” 2018). Co-founder Chris Larsen explained that Ripple is the only enterprise solution for blockchain since it allows institutions to send money globally in a fast, frictionless and cheaper way. He also emphasized that globalization is not complete without the existence of an internet of value. Larsen uses the analogy of shipping containers and describes the internet of value as a shipping container of value, whereas blockchain is just one shipping truck amongst several others. The formation of Ripple believed that the internet was essential to “democratize finance,” especially during the spike of interest in fintech industries (“ValueWalk: Chris Larsen Of Ripple (XRP) @Google,” 2018).

XRP is known to have lower processing times and transaction charges than many other cryptocurrencies, including bitcoin (*CoinDesk 20 Digital Assets and Cryptocurrencies, 2020*).

While it takes bitcoin approximately 1 hour to process a transaction, depending on the transaction fee, which is approximately \$40, it takes XRP only 3 to 5 seconds, with a transaction fee of around \$0.004 (*Ripple Vs. Bitcoin*, 2020). While the Ripple network is considered to be decentralized, it is still operated and owned by the company Ripple (Reiff, 2020).

With 60 million of the 100 billion tokens being owned by Ripple, XRP is still able to achieve a market capitalization of \$8.7 billion on July 20, 2020 (*XRP (XRP) Historical Data*, 2020). Because the market share changes every second, the ranking of the cryptocurrencies changes also. While bitcoin continues to hold the largest market share, followed by ether, XRP is usually ranked third, followed by other altcoins with market shares less than half of that of theirs.

#### 2.1.4. Tether

Founded in 2014, initially named RealCoin, Tether was created to moderate the “friction of moving real currency throughout the cryptocurrency ecosystem” (*CoinDesk 20 Digital Assets and Cryptocurrencies*, 2020). It was one of the first cryptocurrencies created with the purpose of pegging its market value to a fiat currency (Frankenfield, 2019), labelling it, and other cryptocurrencies in similar nature, as ‘stablecoins.’ Tether was initially established under the Tether network, and was created to work within the Bitcoin network but continued to expand into other networks, including Ethereum, Bitcoin cash and others (*CoinDesk 20 Digital Assets and Cryptocurrencies*, 2020).

With no limits on the number of tokens issued, Tether converts digital money into traditional money, usually US Dollars (USD), Euros, or Japanese Yen (*Comparison of Different Cryptocurrencies*, 2019), making it a highly-traded digital currency with low transaction fees. This crypto asset is designed to be stable for volatile markets, although it does pose several risks, including counterparty default risks and more tokens than dollars in the bank (*Comparison of Different Cryptocurrencies*, 2019).

Tether is the largest stablecoin measured by market capitalization, observed at \$9.2 billion on July 20, 2020 (*Tether (USDT) Historical Data*, 2020). In fact, 80% of all bitcoin trading is conducted in Tether, allowing it to be a major source of liquidity for the cryptocurrency market (Frankenfield, 2019). The market share of other altcoins often increase over that of Tether's, demonstrating the volatility in the cryptocurrency ecosystem: on August 1, 2020, the market share of Tether increased to \$10 billion, but its ranking fell from fourth to sixth, with Stellar and ChainLink leading with market shares around \$11 billion (*CoinDesk 20 Digital Assets and Cryptocurrencies*, 2020).

#### 2.1.5. Bitcoin Cash

Bitcoin is known to be the most successful cryptocurrency to date, and for that reason, thousands of cryptocurrencies have been released thereafter. Bitcoin cash was created due to a the splitting of Bitcoin in 2017, allowing more transactions to be processed due to the increased size of the blocks (Frankenfield, 2018a).

“As proposed by Bitcoin inventor Satoshi Nakamoto, Bitcoin was meant to be a peer-to-peer cryptocurrency that was used for daily transactions. Over the years, as it gained mainstream traction and its price surged, Bitcoin became an investment vehicle instead of a currency. Its blockchain witnessed scalability issues because it could not handle the increased number of transactions. The confirmation time and fees for a transaction on bitcoin's blockchain surged. This was mainly due to the 1MB block size limitation for bitcoin. Transactions queued up, waiting for confirmation, because blocks could not handle the increase in size for transactions.

Bitcoin Cash proposes to remedy the situation by increasing the size of blocks to between 8 MB and 32 MB, thereby enabling processing of more transactions per block. The average number of transactions per block on Bitcoin is between 1,000 and 1,500. The number of transactions on Bitcoin Cash's blockchain during a stress test in September 2018 surged to 25,000 per block.”  
(Frankenfield, 2018a)

Overall, Bitcoin Cash is more memory intensive, with a faster processing speed, while performing essentially the same functions as Bitcoin (*Comparison of Different Cryptocurrencies*, 2019). Its market capitalization rose from \$6.2 billion on August 1, 2017, on its launching day, to around \$66 billion on December 20, 2017 of the same year (*Bitcoin Cash (BCH) Historical Data*, 2020). It then declined to \$4.2 billion by July 20, 2020, showing that the volatility of cryptocurrencies can occur to any asset at any time.

The properties of the top five cryptocurrencies outline their basic advantages and disadvantages. Table 1 in the Appendix summarizes the properties of these top five cryptocurrencies. The remainder of this research will focus on Bitcoin, analyzing its strengths and weaknesses, to determine its hedging capabilities in times of economic turmoil. The altcoins will be used as comparative mechanisms to better understand the performance of the successful cryptocurrency during a specific time of global distress.

## 2.2. Advantages of Bitcoin

Digital convenience serves as one of the main advantages of Bitcoin. Although Bitcoin may not be able to perform as a dominant global currency, it can still play a significant role due its ease of use and ability to work in developing markets (Franklin, 2016). Bitcoin has witnessed a great deal of acceptance because it is a network run on computer programs, which are more commonly

used nowadays than in the past (Grant & Hogan, 2015). The ability to complete transfers almost immediately at any given time of any day, may it be a holiday, serves as a great incentive for Bitcoin users, as they have more control over their own assets (*FAQ - Bitcoin*, 2020); for users to be in full control of the transactions without having any intermediary merchant adding any unnecessary charges is an additional advantage to the cryptocurrency (*FAQ - Bitcoin*, 2020).

Furthermore, the extraordinarily quick speed of Bitcoin transfers protects the users from chargeback fraud (Dumitrescu, 2017). Because transfers are instantaneous, once they are complete, they are final (Twitter et al., 2019). There are no boundaries for Bitcoin transfers in the sense that international and domestic transfers are not subject to foreign currency exchange rates and fees.

The absence of a central authority poses yet another key identifying property of Bitcoin (Franklin, 2016). Decentralization allows for cryptography to control Bitcoin creation and management, rather than having a central bank, or any other form of authority, do so (Kliber et al., 2019). This implies that Bitcoin is independent of the possibility of the central authority devaluing the currency through arbitrary currency creation (Grant & Hogan, 2015), and of inflation (Shahzad et al., 2019b).

Also, Dumitrescu, 2017 identified personal data protection as one of the primary advantages of Bitcoin. It was stated that the anonymity of the users is better ensured through encrypted mathematical algorithms, thus firewalling security breaches. This result is similar to that of Kayal & Rohilla, 2019 in that payments are protected and verified through electronic transfer and that the privacy of the user is delinked from the actual transaction.

Furthermore, the low transaction costs as a result of decentralization is another incentive for joining the Bitcoin network. Symitsi & Chalvatzis, 2019 estimate the economic gains of the transaction costs associated to Bitcoin transfers. They study the effect of these gains both with and without transaction costs and find that economic gains are not reduced after introducing transaction costs. This suggests that the cost of Bitcoin transactions are reasonably priced.

Dumitrescu, 2017 finds that on average, the transaction costs are over five times lower than those of credit cards. Transaction costs are also unrelated to the amount transferred, implying that the transaction cost is constant for sending 1 bitcoin or any number of bitcoins. Thus, transaction costs serve as another key advantage of Bitcoin.

### 2.2.1. Bitcoin Classification: Advantages for the Investor

There are several reasons for investors to accept Bitcoin trading as an attractive business. These reasons are more broadly defined as the roles, or classifications of the Bitcoin asset itself. While some investors will participate in the crypto market because Bitcoins are considered to be an asset that is useful for portfolio diversification, others partake of the market activities because they consider Bitcoin either as a hedge or a safe haven. Several recent studies consider the classification of Bitcoin dependent on several factors and impacts.

### 2.2.2. Hedge

This classification of Bitcoin is defined by Jana & Das, 2020 as an investible asset that is either uncorrelated or negatively correlated with another investible portfolio instrument on average. The risk return mechanism allows for the maximization of expected profits. Several past studies have evaluated the role of Bitcoin under different circumstances to determine whether it acts as a hedge or has any other role.

Bitcoin was found to act as a weak hedge for both Bitcoin-friendly economies and all other markets included in the study by Kliber et al., 2019. This result is similar to that of Jana & Das, 2020, where they found Bitcoin to be a weak hedge for all markets. Stensås et al., 2019 observe that Bitcoin acts as a hedge for investors in most of the developing countries like Brazil, Russia,

India and South Korea but a diversifier for other countries and commodities, while Urquhart & Zhang, 2019 conclude that Bitcoin can be an intraday hedge for some currencies, while a diversifier for others. Because these results are theoretically accepted, when Bitcoin behaves differently, several questions arise.

Bitcoin is commonly compared with different commodities, like oil and gold, and its behavior is tested by comparing it to the behavior of these other commodities. Shahzad et al., 2019a and Bouoiyour & Selmi, 2020 find that Bitcoin and gold do not move in the same direction. These two assets are generally viewed as a hedge and a safe haven in times of economic turmoil, however, the factors driving the price of Bitcoin and the price of gold may be different. This result implies that Bitcoin can act as an effective hedge for energy commodities but not for non-energy commodities. Shahzad et al., 2019a conclude that gold is a better hedge than Bitcoin, similar to the conclusion of Pal & Mitra, 2019, that gold is found to provide a better hedge against Bitcoin when compared to wheat, a non-energy commodity. Das et al., 2019 study the comparison of Bitcoin with oil and find that Bitcoin is not superior to other assets when hedging oil-related uncertainties. Investors may prefer different investment instruments to hedge the downside risk in different economic situations and market states. In fact, Bitcoin is found to better hedge the demand-side shocks than the supply-side shocks.

The classification of Bitcoin as a hedge is also dependent on the economic uncertainty. Fang et al., 2019 find that global economic policy uncertainty has a significantly negative impact on the Bitcoin-bonds correlation and a positive impact on both Bitcoin-equities and Bitcoin-commodities correlations, suggesting the possibility of Bitcoin acting as a hedge under specific economic uncertainty conditions. Kayal & Rohilla, 2019 and Al Mamun et al., 2020 conclude that during the period of high policy uncertainty and worsening economic conditions, Bitcoin investors are better off to hedge their portfolio with gold and not with other financial assets. The identification of Bitcoin as a hedge is complex in its foundations, depending on several underlying factors and situations that need to be assessed.

### 2.2.3. Portfolio Diversification

Portfolio diversification is one of the primary reasons that investors invest in any sort of asset. It is defined as an investible instrument that is positively, but imperfectly correlated with another instrument in the portfolio (Jana & Das, 2020). Diversification is commonly practiced in order to moderate the risk that one investment type may perform poorly when multiple assets are invested in. Vojtko & Cisár, 2020, Al-Yahyaee et al., 2019, Shahzad et al., 2019b and Kayal & Rohilla, 2019 conclude that Bitcoin is classified as an asset used for portfolio diversification. Further, Jana & Das, 2020 and Klein et al., 2018 discuss the differences of Bitcoin impacts on equity and on other assets and find that the results are consistent. Bitcoin is found to be an effective diversifier of the downside risk in equity markets in the study conducted by Shahzad et al., 2019b.

Further analyses were conducted to better understand the classification of Bitcoin under various circumstances and across different countries. Bouoiyour & Selmi, 2020 studied the role of Bitcoin and concluded that it could act as an effective diversifier against movements in energy commodities but not for non-energy commodities. On the other hand, Stensås et al., 2019 evaluated the difference in the role of Bitcoin in major developed and developing countries and found that Bitcoin acted as a diversifier only for investors in developed countries, but for all commodities. While Ji et al., 2019 and Shahzad et al., 2019a also found that the diversification role of Bitcoin was not necessarily as strong as commonly believed, Symitsi & Chalvatzis, 2019 concluded that their results were statistically significant for the diversification benefits of Bitcoin. In fact, Urquhart & Zhang, 2019 took one step further and evaluated the role of Bitcoin against world currencies at an intraday level, due to the extreme volatility of the asset. They concluded that Bitcoin acted as an intraday hedge for some currencies, while it acted as a diversifier for others.

An increasing number of analyses find that the presence of Bitcoin in a portfolio enhances its performance by improving the risk-return profile of the portfolio. While Vojtko & Cisár, 2020, Al-Yahyaee et al., 2019, Shahzad et al., 2019b and Kayal & Rohilla, 2019 along with several others found that Bitcoin acted as both a hedge and a diversifier, and consequently the next digital gold, Jana & Das, 2020, Klein et al., 2018 and others found that Bitcoin behaves quite the opposite. They found that Bitcoin and stock market returns were positively correlated during the periods of downward markets. Therefore, the evidence on the classification of Bitcoin as a portfolio diversifier is still under investigation.

#### 2.2.4. Safe Haven

Bitcoin is often considered a safe haven asset for many investors. A safe haven is an investible asset that is negatively correlated with other instruments in the portfolio, as defined by Jana & Das, 2020. It is a financial instrument that is expected to retain or gain value during periods of economic uncertainty. Recent studies have aimed to classify this role of Bitcoin by comparing it to different commodities and by analyzing the network under several conditions and in various locations.

Some researchers, such as Bouoiyour & Selmi, 2020 and Al Mamun et al., 2020, say that Bitcoin is classified as a safe haven. Bouoiyour & Selmi, 2020 examined whether Bitcoin exhibited a safe haven property during global uncertainty. The results found using a twenty-day time span indicated that Bitcoin was considered a crypto safe haven and that Bitcoin reinforced its status as a digital gold. On the other hand, Al Mamun et al., 2020 found that Bitcoin is not necessarily a safe haven investment like gold but the correlation between the two is positive and significant during a deteriorating economic situation. This suggests that when investors look for a safe haven, Bitcoin performs as good as gold. Given the global economic uncertainty observed in 2020, the

researchers were able to capture the classification of Bitcoin as a safe haven based on its market behaviour.

Several other studies have been performed to determine whether or not Bitcoin should be classified as a diversifier, a hedge or a safe haven. Vojtko & Cisár, 2020, Luis et al., 2019, and Stensås et al., 2019 find that Bitcoin is not a safe haven for investors in their analyses. Evidently, Vojtko & Cisár, 2020 concluded that Bitcoin is not a preferred asset to hold during times of stress because its price behaves like the price of the stock market index, which is volatile during financial crises. Similarly, Luis et al., 2019 find that Bitcoin behaves as a speculative asset in the short-term but in the long-term, speculation does not seem to influence Bitcoin behavior. Rather, the demand for Bitcoin may be driven by its future capabilities as a medium of exchange and therefore, it is not regarded as a safe haven or a means of payment.

To continue this analysis further, several studies consider the comparison of Bitcoin to other commodities, such as gold or oil, to determine Bitcoin's classification as a safe haven, similar to when evaluating the assets role as a hedge or diversifier. Jana & Das, 2020, Stensås et al., 2019, Klein et al., 2018, Shahzad et al., 2019b and Shahzad et al., 2019a, along with several other researchers, conclude that Bitcoin is not the new gold. Bitcoin and gold have distinct characteristics and generally, one of the main properties of gold is being a safe haven. Therefore, in terms of protection during global uncertainty, gold outperforms Bitcoin.

Shahzad et al., 2019a investigate the behavior of gold and Bitcoin for the G7 countries and find that gold is an indisputable safe haven and hedge for several G7 stock indices, whereas Bitcoin takes these two roles only in the case of Canada. Comparatively, Shahzad et al., 2019b find that each of Bitcoin, gold, and the commodity index can be considered as a weak safe haven asset in some cases. The roles of these commodities vary across time and also differ between economies. Developed markets find gold as the only weak safe haven asset while gold and commodities play the same role in emerging markets, and Bitcoin serves as a diversifier. Therefore, it can be stated that gold and Bitcoin may perform similarly at a given time but vary

due to other features such as geographical differences. Kliber et al., 2019 study the difference in Bitcoin performance for energy and non-energy commodities and find that Bitcoin was considered only a safe haven in the case of Venezuela. Bitcoin may also serve as a safe haven in emerging financial markets, similar to the findings of Shahzad et al., 2019b. Again, it becomes evident that Bitcoin classification is dependent on the time of the study and the market status in the country of analysis, developed or emerging.

When comparing the classification of Bitcoin, gold and other commodities to the Oil Implied Volatility Index (OVX), Das et al., 2019 find that the US Dollar (USD) is a better alternative to hedge the OVX than Bitcoin. The cryptocurrency is found to outperform gold and other commodities in hedging the OVX, while gold acts as a better safe haven to the OVX when compared to Bitcoin. Stensås et al., 2019 finds that Bitcoin acts as a safe haven for only a few national equity indices, regional indices and commodities but that in most cases, Bitcoin is not found to be a strong safe haven. Klein et al., 2018 explicitly announce that Bitcoin is not the new gold because although its volatility dynamics share some aspects with gold and silver from a diversification perspective, it differs in that Bitcoin does not serve as a safe haven, which is a prominent feature of gold.

### 2.3. Disadvantages of Bitcoin

Bitcoin possesses several properties that identify it as a unique financial asset that can serve many purposes. Not only are there several advantages associated to the concept, but there are also several shortcomings underlying the foundation of the asset. Bitcoin is understood to continuously fluctuate in value over time, thus leading to a great deal of uncertainty in the market. Extreme volatility fluctuations and negative externalities pose as disadvantages of Bitcoin. These weaknesses are discussed to enhance the characteristics of Bitcoin, in order to better understand its reaction to various externalities.

### 2.3.1. Extreme Volatility

Extreme volatility has been found to be a great concern when investing in cryptocurrencies. Vojtko & Cisár, 2020 conclude that Bitcoin is not stable because of its high volatility, while similarly, Kayal & Rohilla, 2019 discuss the volatility of Bitcoin and find it to be thirty times more volatile than other currencies, particularly US dollars, Euros and Yens. Bitcoin is declared to be unfit as a currency since the high volatility feature adversely affects its store of value property. Urquhart & Zhang, 2019 report that Bitcoin volatilities are observed at an hourly frequency since it experiences immense volatility fluctuations throughout the day. Furthermore, Franklin, 2016 concludes that Bitcoin is considered a new currency that is not actively traded as traditional currencies, and therefore, the volatility can be significant in any given hour of the day. He goes on to mention that there are ways to manage this risk through a profound investment strategy known as portfolio diversification. Landry, 2020 discusses the implications of stability: Bitcoin's consistency is questioned between August 8 to August 15, 2019, where the digital currency lost more than 20% of its value, going from \$12,000 to \$9,500 without any evident economic uncertainty.

Other studies examine investor attention and the speculative influence of Bitcoin trading on volatility. Fang et al., 2019 conclude that Bitcoin's high volatility is not caused by speculative trading. In fact, the effect on the volatility of Bitcoin is different from that of any other asset. For Bitcoin investors, the volatility predictions are enhanced by considering the state of global economic uncertainty. In comparison, Urquhart, 2018 examines the relationship between investor attention and Bitcoin fundamentals. Realized volatility and volume are significant drivers of next day investor attention but investor attention offers no significant predictive power in forecasting realized volatility, volume or returns of Bitcoin. Kayal & Rohilla, 2019 highlight that Bitcoin experiences a higher number of bubbles and crashes than other financial assets.

### 2.3.2. Externalities: Historical Incidences

Bitcoin is known to experience extreme volatility both during times of economic uncertainty and times of economic stability. The impact of externalities, such as SARS and the Novel Coronavirus, on Bitcoin is a major concern that greatly influences the financial markets. Studying the efficiency of Bitcoin by considering the Efficient Market Hypothesis (EMH) and reviewing the results generated from previous studies with regards to externalities and market uncertainties contributes to a more comprehensive understanding.

The Efficient Market Hypothesis suggests that once information is recognized, it spreads rapidly and is incorporated into the price of the securities without delay (Malkiel, 2003). The EMH is a theoretical model with a strong foundational history of development and is currently evolving and applied to many situations on a daily basis. Gronwald, 2019 conducts a number of non-linearity tests in his study and finds that Bitcoin markets are inefficient. Furthermore, Urquhart, 2016 conducted a distinct report on the efficiency of Bitcoin and found that Bitcoin returns are not consistent with market efficiency over the full sample considered for the analysis. However, when the sample is split into two subsample periods, some tests indicate that Bitcoin is efficient in the latter period. Also, Bouoiyour & Selmi, 2020 concluded that the adjustment of Bitcoin prices is inconsistent with EMH. Bitcoin is far from being closer to efficiency due to its speculative and volatile behavior. The returns do not respond immediately to coronavirus, and therefore, it would be reasonable to infer that Bitcoin is in an inefficient market but may be in the process of moving towards efficiency

Externalities in the form of market uncertainty are also deemed as negative influencers of Bitcoin. Albulescu, 2020 finds that financial volatility has different sources: economic conditions, institutional issues or market uncertainty. Fang et al., 2019 declare that for Bitcoin investors, the results suggest the ability to use evidence about the state of global economic uncertainty to

improve the predictions of Bitcoin volatility. Comparably, Al Mamun et al., 2020 state that the geopolitical risk and global economic policy uncertainty command a risk premium, particularly in distressed market conditions. In fact, throughout the period of high policy uncertainty and deteriorating economic circumstances, Bitcoin investors can only hedge their portfolio with gold and not with other financial assets. The consequence of geopolitical risk and both global and US economic uncertainty is far more significant during unfavorable economic conditions. Geopolitical risk is the most significant feature that contributes to the volatility and risk premia of Bitcoin. The effect of the US economic policy uncertainty is insignificant while global economic policy uncertainty is significant in explaining Bitcoin risk premia.

Considering historical events that have greatly impacted the value of Bitcoin in the past contributes to a concrete understanding of the behavior of Bitcoin as a result of its classification. Stensås et al., 2019 considered past global externalities, such as the burst of Chinese market bubble in 2015, the US election in 2016, and the Brexit referendum in 2016. Bitcoin acted as a safe haven asset for both the US and non-US investors in these situations but the volatility observed in response to these events was extreme. Bouoiyour & Selmi, 2020 also discussed that the recent Bitcoin rally associated with the 2020 global pandemic can be due to heightened global economic uncertainties consisting of increasing worries over the US-China war, US-Iran tensions, Brexit concerns as well as tensions between Japan and South Korea. All of these factors have boosted Bitcoin prices, but the coronavirus is clearly the most important catalyst as of yet. This externality poses a threat to the performance of the cryptocurrency.

The impact of the negative externalities and the volatile movement of Bitcoin values together identify the fundamentals of the network. While the behavior of Bitcoin depends on time-varying measures, as well as market developments, the externalities suggest a strong impact on the observed volatility and price behavior of Bitcoin. The coronavirus of 2020 is found to have the most significant impact as of yet.

### 2.3.2.1. *Coronavirus (COVID-19)*

Recently, a flu-like virus had affected several residents in the city of Wuhan severely. Within days, the virus spread across the whole world as a cataclysmic event. The Novel Coronavirus, known as COVID-19, has infected over 1.5 million people across the world as of April, 2020, claiming the lives of almost ninety thousand individuals (*Coronavirus Update (Live): 1,518,719 Cases and 88,502 Deaths from COVID-19 Virus Pandemic—Worldometer, 2020*).

As with past crises, the consequences of the coronavirus can also be felt in the global economy as well as in the financial markets. Many analysts such as Bouoiyour & Selmi, 2020, Kayal & Rohilla, 2019 and Yue et al., 2020 compare the coronavirus to the 2003 SARS outbreak. While this can provide useful information, there are several dissimilarities between the two periods to account for. China currently has a much larger share of the global economy and markets than it did 17 years ago. China's share of global trade increased to almost 14% in 2019 compared to 5% in 2003 (Bouoiyour & Selmi, 2020). Furthermore, its share of the MSCI Emerging Markets Index has risen to almost 35% in 2019 from 8% in 2003 (Bouoiyour & Selmi, 2020).

Bouoiyour & Selmi, 2020, Kayal & Rohilla, 2019 and Yue et al., 2020 report that when past disease outbreaks occurred, they were quickly contained. The economic consequences were relatively moderate, and the equities were modestly affected. For example, the outbreak of SARS in 2003 killed 774 people, but it was contained and the stock market rose by more than 20 percent that year (Bouoiyour & Selmi, 2020). However, things are likely to be much different with the coronavirus; the global economy currently appears to be very precarious and an extended disease outbreak might tip the aging business cycle into a global recession. This outbreak aggravates the uncertainty surrounding the global economic outlook.

Current news reports consistently discuss the decline in value of the global stock markets as a result of the COVID-19 outbreak, leading to an increase in the number of investors that are in search of a safe haven for their investments. Bouoiyour & Selmi, 2020 find that the Bitcoin price

has witnessed a rapid increase from January 23 to February 9, 2020. Albuлесcu, 2020 points out that the Bitcoin price has not experienced such an increase in almost 3 months. In this context, Bitcoin is regarded as a safe haven asset within the timeframe considered, as observed by Jana & Das, 2020. Even though there may be various important factors driving it, the emergence of the coronavirus as a determining factor cannot be overlooked, as mentioned by Kayal & Rohilla, 2019. Much significant research has been conducted to investigate the responses of Bitcoin to uncertainty over different externalities including the US presidential elections, the Brexit Referendum, the oil market crash, the Asian financial crisis and many more such events.

The financial volatility that has resulted from the coronavirus until now shows to be significant and may be the possible source for a new financial crisis, as investigated by Albuлесcu, 2020. Market uncertainty is found to be a determining factor of financial volatility through the results obtained from a regression on the infection ratios and death ratios performed with data within China, outside of China and overall on a global scale. The higher the number of affected countries, the higher the financial volatility. While the effects within China on financial volatility were negative and those outside of China were positive. Therefore, the global effect remains inconclusive. Yue et al., 2020 discuss the implications of risk management on the coronavirus and offer suggestions on how to mitigate the risk felt on a global level. It is important to acknowledge that COVID-19 is continuously spreading at rapid speeds while this paper is being developed and therefore, once the virus has stabilized, the classification role of Bitcoin may differ.

The information about the coronavirus takes time to be reflected in the Bitcoin prices, which highlights the inefficiencies it implies. Bouoiyour & Selmi, 2020 find that the adjustment of Bitcoin prices is inconsistent with the EMH. In fact, Bitcoin is far from being close to efficiency due to its speculative and volatile behavior. They find that the returns do not respond immediately to coronavirus, similar to the findings of Jana & Das, 2020, Albuлесcu, 2020, Kayal & Rohilla, 2019 and Urquhart, 2016.

Bouoiyour & Selmi, 2020 mention that one of the reasons that the Bitcoin price may be increasing as the new virus spreads is because 65 percent of Bitcoin mining takes place in China. More accurately, coronavirus exerts a significant influence on mining activity, which may thereafter be driving up the Bitcoin price. Kayal & Rohilla, 2019 discuss this reasoning in their literary study. This observation, however, is only valid during the first few months of the pandemic; as the virus makes its way around the globe, damaging several economies, the value of the cryptocurrency declines rapidly.

The implications of COVID-19 are found to not only significantly affect the economic markets, but also the financial markets. Bitcoin has witnessed a great deal of volatility over the past few months because of the virus. The investor attention in response to the search of a safe haven asset is one of the main reasons for the extreme volatility observed by Bitcoin. The behavior of this cryptocurrency is dependent on several underlying factors that appear as the advantages and disadvantages of the asset, as well as the economic uncertainties that are faced on national and international levels.

#### *2.3.2.2. Coronavirus and financial markets' volatility*

Albulescu, 2020 examines the impact of the virus on financial market volatility and its potential to emerge as a new financial crisis. The author hypothesizes that good and bad macroeconomic announcements impact the volatility index (VIX) asymmetrically. The findings indicate that the death ratio positively influences the VIX, mostly contributed to by the countries aside from China, and that the higher the number of affected countries, the higher the financial volatility.

Furthermore, new reported cases have a marginally negative effect on volatility in China, whereas outside of China, coronavirus contributes to an increase in volatility. The overall situation reveals inconclusive results about the total number of new coronavirus cases on the VIX.

Therefore, the increasing spread of the coronavirus accelerates the volatility and the persistence of COVID-19 might generate a new episode of international financial stress.

#### *2.3.2.3. Hedging and safe haven potentials of Bitcoin during the Coronavirus outbreak*

The global economy appears fragile; therefore, an extended outbreak of the disease might tip the contemporaneous aging business cycle into a global recession. The risk to investors may be much more pronounced. There is an onset of anxiety in the financial markets about the virus. If an effective remedy is not found promptly, it can spell disaster for the global market.

Jana & Das, 2020 investigate the following questions: Does Bitcoin provide diversification benefits when the Chinese equity portfolio investors do not? Given this, does Bitcoin outperform gold? Is the price increase in Altcoins due to the quivering equity markets in China or a mere spillover from Bitcoin? Could Bitcoin have been used to diversify oil and commodity investments? They show that Bitcoin is a weak hedge during the overall period studied and a weak safe haven on the onset of the crisis. Bitcoin is a weak hedge, diversifier and a weak safe haven for the sectoral equity indexes, while gold outperforms Bitcoin in its hedging and safe haven roles. These results parallel those of Bouoiyour & Selmi, 2020. Altcoin price increments are mainly due to the spillover from Bitcoin prices.

In another study, Bouoiyour & Selmi, 2020 analyze the following questions: Does Bitcoin exhibit a safe-haven property against heightened uncertainty? Did the initial news of the coronavirus outbreak lead to the increased volatility of Bitcoin? Does Bitcoin immediately react on publicly announced information? They find Bitcoin to be a crypto safe haven during the time span of January 1 to February 15, 2020, right before the major decline in the value of the cryptocurrency. The virus is found to intensify the volatility of Bitcoin due to a search by investors for alternative asset classes amid concerns about the coronavirus, also discussed by Kayal & Rohilla, 2019.

When the global markets fall in general, it is naturally expected that investors will look for a safe haven. The Bitcoin price has witnessed a rapid rise from January 23, 2020 to February 9, 2020, due to the coronavirus, which means that Bitcoin can act as a safe haven during this time period. If Bitcoin follows the EMH, its prices would adjust with the emergence of unforeseen events, but these price adjustments would become less pronounced after the announcement day. The results show that Bitcoin prices react positively to coronavirus, reinforcing its status as a digital gold or safe haven.

The money velocity of Bitcoins in circulation exerts a negative impact on the Bitcoin price. The exchange-trace ratio is positively and strongly correlated with the price of Bitcoin. Bitcoin and gold do not move in the same direction. A negative effect of the hash rate on the Bitcoin price is observed which means that the higher number of miners that join the Bitcoin network, the more important the network hash rate is. Mining could be seen as a type of Bitcoin investment.

Using the theoretical foundations of the Bitcoin literature and the idea of hedging, Harvey, 2020 discusses the financial implication of the coronavirus and compares the situation to that of the global financial crisis. Due to the pandemic, many individuals have lost their income and wealth and have gone into debt. Therefore, they are likely to turn to another avenue to source income. Interest rates currently being very low, it is difficult to convince individuals to consider bond-based financing. This is where cryptocurrencies have an opportunity to be analyzed in the modern setting. Harvey, 2020 concludes that while gold has a long history and is volatile, it is an unreliable hedge due to the fact that it has a long holding time, of almost centuries. During COVID-19, it also does not serve as an effective hedge.

Harvey, 2020 also addresses cryptocurrencies, that too are not a hedge because they are not linked to any fundamental; Cryptocurrencies are essentially computer programs. Since cryptocurrencies are fairly new, there is no history that would guarantee the hedging capabilities of the digital currency. Therefore, due to its extreme volatility and classification as a risky asset, Bitcoin is not considered to be an effective hedge, especially during times of economic turmoil.

To assess this statement, the predicted outcomes and measurements used in the research, followed by a discussion on the variables and methodology will follow.

### 3. Conceptual Framework

#### 3.1. Development

Based on the literature reviewed, the foundation of cryptocurrencies offers valuable insight into the advantages and disadvantages of these assets. When investigating the performance of Bitcoin, these characteristics suggest that the asset may serve as a hedge, portfolio diversifier or a safe haven, depending on the economic situation at the time. From the discussion presented, it can be observed that during economic turmoil, Bitcoin should act as a hedge and safe haven. Additionally, when compared to gold, past research suggests that gold is a better hedge and safe haven than Bitcoin.

Given the literary analysis identifying the influence of Bitcoin properties on its behavior to global economic uncertainties, this study is able to provide an interpretation as to why Bitcoin responded to the outbreak of the coronavirus of 2020 the way that it did. Cryptocurrencies are known to be volatile and yet they are expected to be attractive investible assets with several purposes. When considering the coronavirus, the pandemic was found to greatly affect not only the economy, but also the financial markets. This experience was the first of its kind to impact the performance of cryptocurrencies to the extent to which their classifications were questioned.

While past research suggests that Bitcoin performs as a hedge during economic downturn, may it be a weak hedge or a strong hedge, the coronavirus is expected to observe the opposite. In this study, the hypothesis is that the top five cryptocurrencies, especially Bitcoin, will not act as a successful hedge due to the coronavirus outbreak of 2019. The coronavirus has impacted both the economic and financial markets across the globe in the matter of only a few months.

Therefore, as it continuously leads to the shutdown of businesses and industries around the world, the coronavirus is expected to influence the values of cryptocurrencies to fall rather than rise, similar to that of the share prices on the stock market. This is the unique characteristic of the coronavirus when compared to other negative externalities throughout history: rather than having the externality affect only a small part of the economy, like the global financial crisis (GFC) which was a big firm problem, the pandemic, which was mainly a small firm problem, affected every individual, every business and every industry across the world (Harvey, 2020).

This analysis will briefly look into the hedging expectations of Bitcoin, to determine whether or not it serves as a hedge. As it was previously mentioned, a hedge is defined by Jana & Das, 2020 as an investible asset that is either negatively correlated or uncorrelated with another investible portfolio instrument on average. The risk return mechanism possesses the purpose of maximizing profits. The top five cryptocurrencies will be considered alongside financial assets: gold, the USD index, the S&P 500 stock index, the SSE index, the MSCI Emerging Markets Index and MSCI Global Markets Index (also referred to as MSCI World Markets Index), as well as the Economic Uncertainty. The reason for comparing the cryptocurrencies to these commodities is to be able to observe the correlation between them and to understand the performance of cryptocurrencies when compared to different financial assets.

Since Bitcoin is considered a 'virtual gold,' it is best to include the commodity of gold to verify this statement. In fact, Dyhrberg, 2016b shows that Bitcoin exhibits many similarities to not only gold, but also to the USD; he found that the cryptocurrency could be used as a hedging tool against the USD in the short run. Bitcoin is also found to be able to offer opportunities of hedging gold, allowing the digital asset to be categorized somewhere between gold and USD (Dyhrberg, 2016a). Dyhrberg, 2016b used a T-GARCH model to explore the hedging capabilities of Bitcoin and found that Bitcoin could be used as a hedging tool against the stock markets during a period of economic turmoil. The USD index is used to determine whether the cryptocurrency is able to hedge against traditional money during the time of the global

pandemic. The inclusion of the S&P 500 index is mainly to determine whether there is a possibility that the market of cryptocurrencies resembles that of the stock market. The SSE is considered for similar reasons, including the fact that since the coronavirus was sourced from China, the expectation for that financial market to be impacted the most is assumed to be much higher than for other exchanges around the world.

All five crypto assets, individually and collectively, will be assessed against the commodities in order to compare and contrast their performance with each other. A profound empirical design will be established in section 4, to describe the mathematical possibilities of determining the hedging capability of the cryptocurrencies. All five cryptocurrencies are also analyzed against global economic uncertainty. This methodology will be able to identify the effectiveness of the cryptocurrencies to perform as a successful hedge during the time period chosen to study the coronavirus. Furthermore, the relationship between the number of COVID related global cases and global deaths are compared to the cryptocurrencies to indicate the extent of the impact of COVID-19 on the financial markets: if the number of COVID cases and deaths are high, it would be expected that the economies will still be operating at minimum capacity due to the severity of the virus i.e. city-wide lockdown, thus negatively impacting the values of the cryptocurrencies.

Once these analyses are complete, the graphical trends of each interaction will be collectively assessed to determine the classification of each cryptocurrency individually. If Bitcoin is found to be an unsuccessful hedge during the coronavirus, the expectation holds that the altcoins will also show similar results. As time progresses during the range considered for this study, if the commodity prices decrease, then the value of the cryptocurrency considered must also decrease in order to confirm the hypothesis. The positive correlation between the variables would suggest that the coronavirus is a special case of the possible externalities that leads to results that differ from past research. This would be a great contribution to academic research in the field of finance.

### 3.2. Measurement Technique

Using time series analysis through the various specifications of the GARCH model, an in-depth empirical investigation will be conducted between all variables. The specifications of the model will be defined in the next section. Once the returns are obtained from the data, it is possible to investigate the extent to which the coronavirus impacts the hedging capabilities of the cryptocurrencies, especially of Bitcoin's. While the data collection outlined the basic methodology used to analyze the question of interest, a well-defined research design must be explained to guide the investigation efficiently.

This exploratory research will examine the relationship between cryptocurrencies- the dependent variables- and the indices and commodities, including economic uncertainty and COVID-related statistics- the independent variables. It will clarify the ambiguous situations in order to develop new ideas as potential opportunities for future research. The criteria for the design depend on several important concepts. First, the component of time suggests that the study is longitudinal, in that it takes place over multiple points in time. In the context of this study, the independent variables are used to determine the effects of the coronavirus on the economic model. The results will determine whether or not the cryptocurrencies serve as a hedge during the specific period of economic downturn. If they do serve as a hedge, then it would be accurate to say that the coronavirus was yet another episode that supports past academic research in fintech.

The correlations between the variables will be able to determine if the factors are able to perform in a synchronised manner. The fact that correlation does not imply causality is essential to this study, in that it should be accepted that the performance of the cryptocurrencies does not mean that the coronavirus directly impacted them. Rather, there could be other external factors such as the shutdown of businesses and industries around the world that may or may not have

impacted the performance of the financial markets. This research aims to provide the best approximation to the truth, or validity, based on the information and data provided.

Once the foundations have been set in place, the reliability and validity of the of the measurement techniques must be assessed (Zikmund et al., 2013). Consistency is the key to evaluating reliability, whereas validity defines the accuracy of the measure. A good measure must be both accurate and consistent. Although it may be possible that other factors could potentially influence the hedging abilities of the cryptocurrencies, this threat to internal validity must be addressed.

What differentiates the present research from prior studies is that the analysis will simply be conducted on the top five cryptocurrencies pre- and post-COVID. Because this virus is still ongoing during the writing of this thesis, the data used will give results that may differ when the impacts of different time periods of the virus are studied in the future. Therefore, this research will be one of the first academic insights to better understand the performance of cryptocurrencies as hedging mechanisms resulting from the immediate aftermath of extreme economic turmoil, specifically the Novel Coronavirus. The following section will provide an insight on the various data sources and sampling methodology used to conduct the study.

#### 4. Data and Methodology

As with any study that aims to analyze the impact between financial and economic variables, endogeneity can be a concern which may question the overall validity of the results.

Endogeneity can be caused by omitted variables or unobserved heterogeneity. In order for this

research to obtain correct and valuable economic inferences, the study develops the most suitable economic tools to ensure the stability of the diagnosis.

#### 4.1. Empirical Design

Autoregressive conditional heteroscedasticity (ARCH) models have become the most prevalent specifications in modeling time series volatility, since the influential paper of Engle, 1982 was published. Several studies have used financial time series to address new findings in the economic and financial markets such as Glosten et al., 1993, Bollerslev et al., 1992, Klein et al., 2018 and Guesmi et al., 2019. Since then, multivariate general autoregressive conditional heteroscedasticity (GARCH) models have been established, suggesting a superior ability in modeling volatility dependence between time series. There are several types of multivariate GARCH models, including the constant conditional correlation GARCH (*CCC – GARCH*) model (Bollerslev, 1990), the *BEKK – GARCH* model, named after Baba, Engle, Kraft and Kroner (R. F. Engle & Kroner, 1995), and the dynamic conditional correlation GARCH (*DCC – GARCH*) model (R. Engle, 2002).

GARCH models are generally used to analyze a number of different types of financial and economic data, such as predicting the volatility of returns for stocks, bonds and market indices (Ruppert, 2011). In this study, various specifications of the GARCH model are implemented to investigate the hedging capabilities of the cryptocurrencies against the other commodities and indices during the coronavirus. In particular, the following four base specifications are used to model the data: *VARMA (1,1) – DCC – GARCH*, *VARMA (1,1) – DCC – EGARCH*, *VARMA (1,1) – DCC – GJR – GARCH* and *VARMA (1,1) – cDCC – FIAPARCH*. *VARMA* represents the vector autoregressive moving average models, which are used predominantly in time series evaluations, to expose the cross-correlations between series, exceeding the isolated analysis of the data series (Simionescu, 2013). Several characteristics have been added to the models, to replicate those of Guesmi et al., 2019, in order to fit the model to the data chosen for

this study. The most suitable model will be recognized and used to analyze the cryptocurrencies', particularly Bitcoin's, hedging effectiveness.

#### 4.1.1. VARMA (1,1)-DCC-GARCH

The VARMA (1,1) – DCC – GARCH model was introduced through the research carried out by Bollerslev, 1990, acknowledging time varying correlation, and assuming constant conditional correlations (ccc). The VARMA – GARCH model itself was presented by Ling & McAleer, 2003. Before the model is explained, the basic design of an AR (1) – DCC – GARCH(1,1) model is presented, with its conditional mean being:

$$z_t^{i/Bitcoin} = \begin{cases} r_t = c + \Omega r_{t-1} + \varepsilon_t \\ \varepsilon_t = H_t^{1/2} \eta_t \end{cases} \quad (1)$$

where  $r_t$  is a time series vector of returns on the financial assets and Bitcoin prices,

$z_t$  is the conditional mean of the AR (1) – DCC – GARCH(1,1) model

$\Omega$  is a (N x N) matrix of coefficients,

$c$  is the vector of constant terms,

$\varepsilon_t$  is the vector of the error terms of the conditional mean equations for the different financial variables and Bitcoin returns,

$\eta_t$  represents a series of independently and identically distributed (*i.i.d.*) random errors, and

$H_t$  is the conditional variance-covariance matrix of the financial variables and Bitcoin returns.

When  $y_t$  denotes the (N x 1) time-series vector of interest, and contains the time varying conditional covariance matrix,  $H_t$ , then:

$$y_t = E(y_t | \varphi_{t-1}) + \varepsilon_t \quad (2)$$

$$Var(\varepsilon_t | \varphi_{t-1}) = H_t \quad , \quad (3)$$

where  $\varphi_{t-1}$  is the  $\sigma$ -field generated by all the available information up to time  $t - 1$ .

If  $h_{ijt}$  is the  $ij^{th}$  element in  $H_t$ ,  $y_{it}$  is the  $i^{th}$  element in  $y_t$ , and  $\varepsilon_{it}$  is the  $i^{th}$  element in  $\varepsilon_t$ , then, as suggested by Bollerslev, 1990, a natural scale invariant measure of the coherence between  $y_{it}$  and  $y_{jt}$ , evaluated at time  $t - 1$  is given by the conditional correlation:

$$\rho_{ij,t} = h_{ij,t} / \sqrt{h_{ii,t} h_{jj,t}} , \quad (4)$$

where  $-1 \leq \rho_{ij,t} \leq 1$  for all  $t$ . Since  $H_t$  varies over time,  $\rho_{ij,t}$  is time varying also.  $H_t$  is further defined as:

$$H_t = D_t P_t D_t' , \quad (5)$$

where  $P_t$  defines the  $(N \times N)$  symmetric matrix of dynamic conditional correlations (DCC), with element  $\rho_{ij} \sqrt{\omega_i \omega_j}$ , and  $D_t$  represents the  $(N \times N)$  diagonal stochastic matrix of conditional standard deviations for each return series, with elements  $\sigma_1, \dots, \sigma_N$ .  $H_t$  will only be positive definite for all  $t$  if each of the  $N$  conditional variances are well defined, and if  $P_t$  is positive definite (Bollerslev, 1990). This diagonal matrix is determined by estimating a univariate GARCH process given by:

$$h_{ii,t} = z_i + \alpha_i \varepsilon_{ii,t-1}^2 + \beta_i h_{ii,t-1} \quad (6)$$

$$\text{with } \forall i = 1, \dots, N ,$$

where  $\alpha_i$  and  $\beta_i$  represent positive time invariant scalars, and  $\varepsilon_{ii,t-1}^2 > 0$  for all  $t$ . Equation (6) defines the *CCC – GARCH* model of Bollerslev, 1990.

Using maximum likelihood estimation (MLE) with a joint normal density, the parameters for models (1) to (6) can be obtained by:

$$\theta = \arg \min_{\theta} \frac{1}{2} \sum_{t=1}^n (\log |Q_t| + \varepsilon_t' Q_t^{-1} \varepsilon_t), \quad (7)$$

where  $\theta$  represents the vector of parameters to be estimated on the conditional log-likelihood function, and

$|Q_t|$  denotes the determinant of  $Q_t$ , which is a (N x N) variance-covariance matrix of standard residuals  $u_t = \frac{\varepsilon_t}{\sqrt{h_t}}$ , and is defined by:

$$Q_t = (1 - \theta_1 - \theta_2) \bar{Q} + \theta_1 u_{t-1} u_{t-1}' + \theta_2 Q_{t-1} \quad (8)$$

where  $\bar{Q} = E(u_t u_t')$  is a (N x N) symmetric positively defined matrix of the unconditional variance-covariance of standard residuals, and

$\theta_1$  and  $\theta_2$  are the unknown parameters that need to be determined, and the sum of these two parameters must be less than one in order to secure the positivity of matrix  $Q_t$ .

It is essential to note that when  $\eta_t$ , from equation (1), does not follow a joint distribution, the estimators are defined as the Quasi-MLE (QMLE) (C.-L. Chang et al., 2010).

The DCC process requires the decomposition of the conditional covariances, such that they become the product of conditional standard deviations and conditional correlations between two markets,  $i$  and  $j$ :

$$h_{ijt} = c + \sqrt{h_{iit} h_{jtt}}, \quad (9)$$

Finally, the conditional correlation at time  $t$ , for markets  $i$  and  $j$  is described as:

$$\rho_{ijt} = \frac{(1 - \theta_1 - \theta_2)\bar{q}_{ij} + \theta_1 u_{i,t-1} u_{j,t-1} + \theta_2 q_{ij,t-1}}{[(1 - \theta_1 - \theta_2)\bar{q}_{ii} + \theta_1 u_{i,t-1}^2 + \theta_2 q_{ij,t-1}]^{1/2} [(1 - \theta_1 - \theta_2)\bar{q}_{jj} + \theta_1 u_{j,t-1}^2 + \theta_2 q_{jj,t-1}]^{1/2}}, \quad (10)$$

where  $q_{ij}$  is the element on the  $i^{\text{th}}$  line and  $j^{\text{th}}$  column of the matrix  $Q_t$ . This methodology allows for the formation of the *VARMA (1,1) – DCC – GARCH* model that will be used in the analysis.

#### 4.1.2. VARMA (1,1)-DCC-EGARCH

An alternative asymmetric GARCH model is introduced by Nelson, 1991. The *VARMA (1,1) – DCC – EGARCH* model accounts for the asymmetric volatility spillovers and is captured by the variance-covariance matrix, which represents a generalization of the DCC model by R. Engle, 2002. This representation captures asymmetric correlations and is defined as:

$$H_t = D_t \rho_t D_t', \quad (11)$$

where  $H_t$  is the conditional variance-covariance matrix of the financial variables and Bitcoin returns,

$D_t$  represents the (N x N) diagonal stochastic matrix of time-varying standard deviations for each return series, with elements  $\sigma_1, \dots, \sigma_N$ , and

$\rho_t$  denotes the time-varying symmetric correlation matrix.

Using the DCC general equation, the dynamic correlations can be observed:

$$Q_t = \bar{\theta} + A'\bar{\theta}A - B'\bar{\theta}B - C'\bar{N}C - A'Z_{t-1}Z'_{t-1}A + B'\theta_{t-1}B + C'\eta_t\eta_t' C, \quad (12)$$

where  $\bar{\theta}$  and  $\bar{N}$  are the conditional correlation matrices of  $Z_t$  and  $\eta_t$ ,  
 $Z_t$  and  $\eta_t$  represent a series of independently and identically distributed (*i.i.d.*) random errors,  
 $\theta_t$  is a positive definite with probability one if  $[\bar{\theta} + A'\bar{\theta}A - B'\bar{\theta}B - C'\bar{N}C]$  is positive definite,  
and

matrices A, B and C are diagonal to be able to estimate the model.

Through the final term of (10), the time-varying correlations will respond asymmetrically to positive or negative shocks in each market, as mentioned by Guesmi et al., 2019.

By scaling  $\theta_t$ , the correlation matrix  $\rho_t$  is observed:

$$\rho_t = \theta_t^{*-1} \theta_t \theta_t^{*-1}, \quad (13)$$

It is important to note that although a standard multivariate EGARCH model is able to study both the volatility spillover and the asymmetry effects among financial elements, it is not practical to apply this design to the conditional correlations. This is because it would restrict the conditional correlations to always be positive and also because the model contains an excess number of parameters. The DCC generalization of equation (12) does not bear these difficulties while allowing for the possibility of asymmetric effects.

#### 4.1.3. VARMA (1,1)-DCC-GJR-GARCH

The *VARMA (1,1) - DCC - GJR - GARCH* model is named after its founders Lawrence R. Glosten, Ravi Jagannathan, and David E. Runkle (Glosten et al., 1993). The purpose of the model was to be able to account for nonlinearity when modeling the conditional variance of time

series. It is assumed that the model shows evidence of the leverage effect, where the impact of negative shocks is more pronounced than the positive ones. The variance-covariance matrix that displays this effect is:

$$H_t = D_t R_t D_t' , \quad (14)$$

with

$$D_t = \mathbf{diag} (\sqrt{h_{ii,t}}, \sqrt{h_{jj,t}}) \text{ and}$$

$$R_t = (1 - \theta_1 - \theta_2)R + \theta_1 \varphi_1 + \theta_2 R_2 \text{ with } \theta_1 + \theta_2 < 0 ,$$

where  $R_t$  represents the DCC symmetric matrix and

$D_t$  is the diagonal matrix conditional standard deviations recorded from the return series from the following GJR- GARCH by Glosten et al., 1993:

$$h_{ii,t} = w_i + \alpha_i \varepsilon_{ii,t-1}^2 + \beta_i h_{ii,t-1} + \gamma_i I_{i,t} \varepsilon_{ii,t-1}^2 , \quad (15)$$

where  $\beta_i$  is the coefficient that measure persistence,

$I_{i,t}$  is the indicator variable that determines the asymmetry in the coefficient estimates, denoted by  $\gamma_i$ . When  $\gamma_i < 0$ , then the negative residuals are more effective than the positive ones when it comes to increasing the variance.

$\theta_1$  and  $\theta_2$  denote the unknown parameters that must be deduced from the model. If two markets, market  $i$  and market  $j$ , are considered a pair, then their conditional correlation is:

$$\rho_{ij,t} = (1 - \theta_1 - \theta_2)\rho_{ij} + \theta_2 \rho_{ij,t-1} + \theta_1 \frac{\sum_{m=1}^M u_{i,t-m} u_{j,t-m}}{\sqrt{(\sum_{m=1}^M u_{i,t-m}^2)(\sum_{m=1}^M u_{j,t-m}^2)}} , \quad (16)$$

where  $u_t = \frac{\varepsilon_t}{\sqrt{h_t}}$  is the standardized residual. Then the estimation of the unknown parameters,  $\theta_1$  and  $\theta_2$  is determined by the quasi-likelihood estimation method, which is “robust to departures from normality under some regular conditions” (Bollerslev & Wooldridge, 1992).

#### 4.1.4. VARMA (1,1)-cDCC-FIAPARCH

The *VARMA (1,1) - cDCC - FIAPARCH* model was developed to improve the consistency and the potential bias in the estimated parameters. The multivariate fractionally integrated asymmetric power ARCH (*FIAPARCH*) generally provides a framework that allows one to recognize how “financial volatilities move together over time and across markets” . Aielli, 2008 proposed the *AR (1) - cDCC - FIAPARCH* model with the hopes of improving the *DCC - GARCH* model introduced by R. Engle, 2002. A corrected Dynamic Conditional Correlation (*cDCC*) model within a *GARCH* model is similar to the *DCC - GARCH* model, except that the correlation process  $Q_t$  is corrected to become:

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q}_t + \theta_1\eta_t^*\eta_t^{*'} + \theta_2Q_{t-1} , \quad (17)$$

where  $\eta_t^* = \mathbf{diag}\{Q_t\}^{1/2}$ .  $\theta_1, \theta_2$ , and  $\eta_t$  are as defined in the former models.

Based on past studies that use multivariate *GARCH* models, it is reasonable to state that the most common model in finance to depict a time series of daily returns is the vector autoregression (VAR) of order 1 (Karanasos et al., 2016). With  $r_t$  and  $\varepsilon_t$  defined in the previous models, the configuration of the VAR(1) mean with cross effects is formulated by Karanasos et al., 2016 as:

$$r_t = \phi + \Phi r_{t-1} + \varepsilon_t , \quad (18)$$

where  $\phi = [\phi_i]_{\forall i=1,\dots,N}$  is an  $(N \times 1)$  vector of constants,

$\Phi$  is the  $(N \times N)$  coefficient matrix, that allows for the cross effects, and

$\varepsilon_t$  is assumed to be conditionally student-t-distributed with mean vector 0 and covariance matrix

$\Sigma_t = \mathbb{E}(\varepsilon_t \varepsilon_t' | \mathfrak{S}_{t-1}) = [\sigma_{ij,t}]_{i,j=1,\dots,N}$  and variance vector  $\sigma_t = \mathbb{E}(\hat{\varepsilon}_t^2 | \mathfrak{S}_{t-1}) = [\sigma_{ii,t}]_{i=1,\dots,N}$ . Then

it is said that  $\sigma_t$  follows a multivariate *FIAPARCH*  $(1, d, 1)$  model (Karanasos et al., 2016).

The univariate *FIAPARCH* is known to identify the structure of the conditional volatility, which then allows for the computation of time-varying standard deviations, as specified by Tse, 1998.

By combining and extending the *FIGARCH* and *APARCH* models of Baillie et al., 1996 and Ding et al., 1993, respectively, the *FIAPARCH* model accounts for the asymmetric reactions of the volatility to economic and financial shocks. Then the *FIAPARCH*  $(1, d, 1)$  model is estimated as a power transformation of the conditional standard deviation as:

$$h_{i,t}^{\delta_i/2} = \omega_i + \{1 - (1 - \psi_i(L))^{-1} \phi_i(L) (1 - L)^{d_{v_i}}\} (|\varepsilon_{i,t}| - \gamma_i) \quad (19)$$

$$\forall i = 1, \dots, N$$

where  $h_{i,t}$  is the conditional variance of  $x_{i,t}$  and  $h_{i,t} \geq 0$  for  $\forall i = 1, \dots, N$

$\omega_i$  is the mean of the process and  $\omega_i > 0$

$\psi_i(L)$  and  $\phi_i(L)$  are the lag polynomials of order P and K respectively,  $\psi_i(L) \geq 0$ ,  $\phi_i(L) \geq 0$ ,

$d_{v_i}$  is the fractional degree of integration of  $h_{i,t}$ , and

$\delta_i$  is the vector of leverage coefficients.

Although this model is able to perform parameter estimation and study the asymptotic properties of the estimates, it is not able to determine the impact of violations in the conditional normality (Sáfadi & Pereira, 2010). Overall, the *VARMA*  $(1,1) - cDCC - FIAPARCH$  is known to

be a more powerful multivariate GARCH because of its ability to capture the volatility and correlation processes much more thoroughly.

Multivariate GARCH models are advantageous, due to their ability to compute returns that are conditional on past history. In being able to analyze time series data, the different variations of the multivariate GARCH models assist in determining the ability of cryptocurrencies to hedge during the coronavirus.

#### 4.2. Cryptocurrencies- Dependent Variable

The data used for this analysis consists of the daily cryptocurrency prices from June 15, 2018 to July 20, 2020 (from <https://ca.finance.yahoo.com>). The data is collected during this time period because that is when all five cryptocurrencies observe data, as some of these assets were launched earlier than others. The goal is to observe the performance of these digital currencies before the outbreak of COVID-19, as well as during the time leading up to the onset and aftermath of the pandemic, i.e. from November 18, 2019 to July 20, 2020. However, the number of COVID-related cases and deaths are only officially recorded starting December 31, 2019, forcing the data to be measured from that date onwards, instead of the actual date. The observed trends are able to justify the results, and to either validate or dispute previous research relating to negative externalities. Because Bitcoin was created in response to the GFC, the performance is expected to differ tremendously during coronavirus, as this pandemic has resulted in the next greatest financial market instability since then.

Since cryptocurrency transactions are observed almost every second of every day, the data must be sorted to be consistent across all measures. Weekend data is removed, and only daily data is included. Assuming that the prices of these cryptocurrencies change continuously, the daily rate of return,  $r_t$ , of the closing prices is computed using log returns,

$$r_t = \ln \left( \frac{P_t}{P_{t-1}} \right), \quad (20)$$

where  $P_t$  is the current price and  $P_{t-1}$  is the previous price.

Log returns are computed for each variable in order to obtain comparable metrics across all assets included in the study and for continuous compounding across the course of the period. The benefits of the returns are normalized, supporting the “evaluation of analytic relationships between two or more variables, despite originating from a price series of unequal values” (*Why Log Returns | Quantivity*, 2011). Conditional mean specifications can be determined when log returns are computed for the model specifications.

### 4.3. Commodities and Indices- Independent Variables

#### 4.3.1. Gold, USD Index, and Stock Market Indices

The data for the commodities is then gathered. The data for gold, GC=F, is extracted from <https://ca.finance.yahoo.com>. The statistics for the USD index, DX-Y, S&P 500 index (GSPC) and SSE index (000001.SS) are obtained from the same source. The weekend data is again removed for all of the commodities, and log returns are computed to stimulate consistency in the analysis. Data is smoothened through the jump method: missing weekday data is replaced with previous known prices. For the SSE index, there were many instances where weekday data was absent for four to five consecutive days, as well as random single days, throughout the time period analyzed.

Once the log returns are generated for the commodities, the cryptocurrencies can be measured alongside them. With both assets being measured in similar units, the analysis can be conducted appropriately. The log returns for Bitcoin, Ethereum, XRP, Tether and Bitcoin Cash are individually modelled alongside the log returns for gold, USD, S&P 500 index and SSE

index. 20 graphs will result from this methodology, providing the graphical representation necessary to visualize the performance of the cryptocurrencies.

#### 4.3.2. MSCI Index

The MSCI index is a large equity index that represents both mid and large-cap equity performances on a global level (A. K.-H. Chang, 2005). It consists of indices that measure both developed and emerging markets individually and collectively. For the purpose of this study, two separate indices will be consulted, in order to observe the differences between the different economies. The MSCI World Index considers the securities from 23 countries around the world but excludes the emerging economies. It is a weighted stock market index of approximately 1,603 stocks from the companies included in the measurement (*MSCI World Historical Rates - Investing.Com Canada, 2020*).

On the other hand, the MSCI Emerging Markets Index is used to measure equity market performance in developing economies around the world. This index measures data from 26 countries around the world, including China, India and the United Arab Emirates (*MSCI Emerging Markets Index (MSCIEF) - Investing.Com Canada, 2020*).

The data for both of these indices are extracted from <https://ca.investing.com>, from June 18, 2018 to July 20, 2020, to observe regularity between the other data used for this study. Because the MSCI index only measures equity performance on weekdays, the weekend data is already removed. Log returns will be computed to ensure consistency in this study and the jump method will be used to fill in any gaps in the dataset. These indices will provide a global representation of the impacts of the coronavirus on the performance of the cryptocurrencies, allowing this study to determine the hedging effectiveness particularly during the time of the pandemic.

### 4.3.3. Economic Uncertainty

To enhance the methodology of the analysis, the monthly relationship between cryptocurrencies and economic uncertainty must be analyzed. This factor is measured by the economic policy uncertainty database (from [http://policyuncertainty.com/global\\_monthly.html](http://policyuncertainty.com/global_monthly.html)). This variable is measured in two ways: (a) based on current-price GDP measures and (b) based on PPP-adjusted GDP (*Economic Policy Uncertainty Index, 2020*). Once this data is documented, the monthly data for each crypto asset must be determined, in order to draw conclusions based on the assessment of the situation. Monthly computations are conducted in order to provide consistency in the measurement, as the PPP-adjusted GDP is the only variable that does not have daily data, but is essential for the analysis chosen to be conducted.

To begin, a monthly average return for each cryptocurrency is computed by

$$\frac{\sum_1^n R_t}{n}, \quad (21)$$

where  $R_t$  represents the return of the crypto asset at time  $t$ , and

$n$  represents the number of weekdays in the month associated to the returns.

The sum of all weekday returns in each month is divided by the total number of weekdays per month to obtain a monthly average return, which will be used to understand the economic uncertainty in the markets during the coronavirus. With this new data, the relationship between cryptocurrencies and economic uncertainty can be examined.

Alongside the cryptocurrencies, the other commodities (gold, USD, SP500 index and SSE index) are also compared to the economic uncertainty, to observe the effectiveness, or non-effectiveness, of the hedging abilities during the extremities of COVID. If there is a negative

correlation between any one of the commodities and the economic uncertainty, then it would be accurate to say that the commodity acts as a hedge during the time of crisis. Analyzing the economic situation is effective in understanding the role of assets in the economy, however, consulting another variable that directly represents the coronavirus would be beneficial in understanding the value of hedging during COVID.

#### 4.4. Additional Variable: COVID-Related Cases and Deaths

We also look at the relationship between the number of COVID-related cases and deaths worldwide compared to the performance of cryptocurrencies and the other commodities. The extent of the impact of COVID-19 on the financial market can then be determined and be used to explain the relationships in the market. The data is available starting only from December 2019 and is gathered from <https://ourworldindata.org/covid-deaths>. Then, the daily data is converted to monthly data so that a compressed analysis can be performed from December 2019 until July 2020. The top five cryptocurrencies are compared to the COVID cases and COVID deaths, in two separate analyses, to observe the performance of the digital assets during the core of the pandemic. The behaviour would be sufficient to determine the abilities of the cryptocurrencies to hedge during such an extreme case of global economic and financial instability. It will also be possible to determine whether commodities or cryptocurrencies are a better hedge to use during the times of severe financial and economic volatility.

The sampling methodology adopted for this research can be referred to as a multistage design since it involves obtaining samples in stages. Starting from selecting the top five cryptocurrencies ranked in terms of market capitalization, to determining the most relevant commodities to compare, and including an economic uncertainty index and COVID-related measures outlines the formation of a successful sampling methodology. Once the analysis has

been put into place, a series of graphs are generated and included in the Appendix as figures. The results are outlined and explained in the next section.

## 5. Empirical Findings

Using the theoretical foundations of cryptocurrency literature, including that of Bitcoin's, and the hedging mechanisms that are used to analyze commodities, the statistical results defining the implications of COVID-19 on the performance of these digital currencies are assessed. A detailed graphical analysis will be included, to observe the trends in the behavior of the financial assets over time. In order to conduct the empirical analysis, the statistical software OxMetrics 7.2 is used to provide integrated solutions for the time series models considered in this study. This software is able to evaluate both univariate and multivariate GARCH models and is specifically used for economic and financial data development.

### 5.1. Graphical Analysis

#### 5.1.1. Cryptocurrencies

To begin, the data is first modelled graphically to show the volatility of each of the five cryptocurrencies: Bitcoin, Ether, XRP, Tether, Bitcoin Cash, as well as for the list of indices and commodities: gold, USD Index, S&P 500 Index, SSE Index, Economic Uncertainty, MSCI Emerging Markets Index and MSCI World Index. This volatility is observed over the whole timespan of the study- from June 5, 2018 to July 20, 2020. It can be observed from Figure 1.a to 1.e that while some volatility clusters are consistent amongst the top five cryptocurrencies, others are variable. For example, between February and March of 2020, all five cryptocurrencies saw extreme volatility jumps in comparison to their volatility trends over time;

Bitcoin recorded volatility between -0.3 and 0.2, similar to that of XRP and Ether, while Tether recorded volatility between -0.015 and 0.015, and Bitcoin Cash between -0.5 and 0.25. On the other hand, between September and October of 2019, XRP observed a sharp volatility jump of almost 200% while volatility showed to be more consistent during that time period for Bitcoin, Ether and Bitcoin Cash. Overall, the cryptocurrencies show similar trends, as shown by the monthly averages recorded over time, from December 31, 2020 to July 20, 2020 in Figure 2. This supports the hypothesis that the implications of COVID-19 on Bitcoin hedging can be assumed to apply to the other cryptocurrencies.

### 5.1.2. Commodities and Indices

Furthermore, Figures 3.a to 3.d are also observed to show similar performance trends over the timespan of the study. Gold, the USD index, and the two stock market indices- the S&P 500 and the SSE index- all experience a significant volatility jump between February 2020 and May 2020. The MSCI world and emerging markets indices both show similar patterns in Figures 4.a and 4.b, where the performance for the emerging markets is more amplified than that of the developed markets. Both of these indices acknowledge an enormous jump beginning February 2020 and although the performance is close to returning to the historical trend observed, it is still very volatile. For example, the volatility for the MSCI world index generally lies between -0.03 and 0.03 up to February 2020, after which the volatility is observed between -0.10 and 0.08, and near July 2020, between -0.05 and 0.03. Similar is the case for the MSCI emerging markets index.

### 5.1.3. Economic Uncertainty

Economic uncertainty is known to exist in all countries around the world and is measured by the frequency of Economic (E), Policy (P) and Uncertainty (U) related articles in the countries of interest. The global economic uncertainty is mathematically defined and classified as the Purchasing Power Parity (PPP) -adjusted global GDP and its trend is summarized by Figure 5. In June 2018, the PPP-adjusted GDP is approximately 173 and near the beginning of the pandemic in November 2019, is found sitting around 266. The trend thereafter is interesting and is found to increase to almost 360 in April 2020 and then begin decreasing to around 330 in July 2020.

#### 5.1.4. MSCI Indices

Figure 6.a and 6.b illustrate the performance of the MSCI emerging markets and developed markets using monthly data to better visualize the market trends. The trends observed by both indices are more or less similar in nature. While the emerging markets show a sharp decline from essentially 0 to -0.08 from March to April of 2019, the world markets show a similar movement from essentially 0 to -0.065 in the same period. Both markets immediately recover back to essentially zero between May and June of 2019 and only slightly decline to -0.01 between January and March of 2020, after which they re-stabilize close to zero once again.

#### 5.1.5. COVID- Related Statistics

The synopsis of the COVID-related cases and deaths on a global scale is found in Figures 7.a and 7.b. Data pertaining to COVID-related statistics was not recorded until December 31, 2019, causing the dependence on this variable to be deemed as weaker than the other variables. Both the number of cases and deaths show a steady incline from when the data was

first recorded onwards. While the number of COVID-related cases follows a convex trend with the inflection point near 5 million cases in April 2020, the COVID-related deaths identify a concave trend with an inflection point near 400,000 deaths between April and May of 2020. As of July 2020, the number of recorded COVID-related cases and deaths have surpassed 15 million cases and 500,000 deaths, respectively. Figure 8 combines the data and focusses on the performance of Bitcoin with respect to gold, the USD Index, the S&P 500 Index and the MSCI World Index. This graph summarizes the behavior of cryptocurrencies, commodities and indices during the world pandemic of 2019-2020.

#### 5.1.6. Bitcoin Hedging: Economic Uncertainty

Once all of the data is assessed individually, a graphical representation of the data is used to support the goals of this study. Since Bitcoin will represent the other cryptocurrencies, and gold will be used to reflect the performance of the other commodities and indices since their movement over time is similar, these two assets will be modelled alongside the global economic uncertainty in Figure 9. Using OxMetrics, the means and ranges of the data are scaled so that the movement in the variables can be compared. Figure 9 shows consistent movement between Bitcoin and Gold throughout the time period of this study, while its relationship with the economic uncertainty differs; while Bitcoin's performance declines beginning September 2018, the PPP GDP is shown to improve. Similar is the case between these two financial variables from January 2020 through to July 2020. Bitcoin and gold are confirmed to be moving consistently throughout time, with a few dissimilarities after January 2020, from April onwards. As per this interpretation, Bitcoin has not shown much change in its hedging capability to economic uncertainty throughout the pandemic.

### 5.1.7. Bitcoin Hedging: MSCI Index

Similarly, Bitcoin and gold are compared against the MSCI world index using monthly averages of the data in Figure 10. The MSCI world and emerging markets index perform similarly and therefore, only one of the two need to be used to fit the data for this diagnostic. Figure 10 confirms the movement of Bitcoin and gold in cyclical motion, while the performance of the MSCI index is countercyclical to the two up until January 2020. After this point, both Bitcoin and gold are found to move in a pattern resembling that of the MSCI index. This implies that the implications of COVID-19 on the hedging capabilities of Bitcoin did exist; while Bitcoin could have previously acted as a hedge against the MSCI index, due to its negative correlation with the variable after the outbreak of the coronavirus, this hedging relationship is shown to be very weak, or almost negligible due to the positive correspondence.

### 5.1.8. Bitcoin Hedging: COVID Statistics

Finally, the trends between Bitcoin and COVID-related cases and deaths are observed in Figure 11. As discussed earlier, the relationship between Bitcoin and gold is found to be cyclical. Once the COVID-related statistics are released in December 2019, the trends of Bitcoin can possibly be explained; in February 2020, the value of Bitcoin is shown to rapidly increase, its log returns moving from -0.015 to 0.02 within the span of 1 month. During the same time period, the number of COVID-related deaths is found to increase by 100%. While Bitcoin log returns decline yet again, the deaths incurred due to the pandemic continue to rise at almost a constant rate for the remainder of the study. The Bitcoin returns are not as volatile after April 2020 and show to almost plateau, similar to the trend showed in the COVID-related deaths; although this variable is increasing, the rate of increase begins to decline after April 2020. This

is yet another implication that the consequences of the coronavirus have affected the performance of cryptocurrencies, including the hedging capabilities of Bitcoin.

## 5.2. Empirical Investigation

Using OxMetrics, the daily data is used to analyze the financial models to understand the performance of the cryptocurrencies during the pandemic. The models will be assessed during the overall time period of the study and their descriptive statistics are found in Table 2 in the appendix for both the daily data used. The data used in this analysis consists of nine variables; gold, USD index, S&P 500 index, SSE index, PPP GDP as a proxy for economic uncertainty, MSCI Global and Emerging Market Indices, and COVID-related statistics, i.e. number of cases and number of deaths. The data used in the empirical analysis will be daily data in order to provide enough observations to perform the computations.

The software, OxMetrics 7.2, is efficient and ideal for evaluating the data considered in this study. One of the features of this software is its G@RCH application, allowing researchers and academicists to use integrated technology to analyze univariate and multivariate General Auto Regressive Conditional Heteroscedasticity (GARCh) time series data. One of the features of this particular application is the availability of “ARCH “in-means” models” (Laurent, 2013). The GARCh models are generally fitted by the method of maximum likelihood. In order to select the best model, various criteria must be considered. These criteria are briefly summarized below:

The Akaike information criterion is developed by Akaike, 1974 and defined by

$$AIC = 2k - 2 \ln L(\hat{\theta}), \quad (22)$$

where  $k$  denotes the number of unknown parameters,

$\theta$  is the vector of unknown parameters, and

$\hat{\theta}$  is their maximum likelihood estimates.

The Bayesian information criteria was established by Schwarz, 1978 and is expressed as

$$BIC = k \ln n - 2 \ln L(\hat{\theta}) \quad , \quad (23)$$

where  $n$  denotes the number of observations.

Bozdogan, 1987 developed the Akaike information criteria in order to develop the Consistent Akaike Information Criteria (CAIC) defined by

$$CAIC = -2 \ln L(\hat{\theta}) + k (\ln n + 1). \quad (24)$$

The Corrected Akaike Information Criteria (AICc) was generated by Hurvich & Tsai, 1989 and is computed as

$$AICc = AIC + \frac{2k(k+1)}{n-k-1}. \quad (25)$$

Furthermore, the Hannan-Quinn criterion is established by Hannan & Quinn, 1979 and is defined by

$$HQC = -2 \ln L(\hat{\theta}) + 2 k \ln \ln n . \quad (26)$$

Finally, the Shibata criterion developed by Shibata, 1976 is expressed by

$$SIC = -2 \ln L(\hat{\theta}) + \ln(n + 2k) . \quad (27)$$

The smaller the values of these measures, the better the fit of the model. This methodology was adopted in the study performed by Chu et al., 2017. For this study in particular, the Akaike, Schwarz Bayesian, Shibata and Hannan-Quinn Information Criterion will be used. Following the methodology used by Guesmi et al., 2019, only four of the several multivariate GARCH models will be used to test the hedging capabilities of cryptocurrencies, especially that of Bitcoin's, during the global pandemic. The dynamics of the conditional returns and volatilities of these models are included in Table 3.

The four models- *VARMA (1,1) - DCC - GARCH*, *VARMA (1,1) - DCC - EGARCH*, *VARMA (1,1) - DCC - GJR - GARCH*, *VARMA (1,1) - cDCC - FIAPARCH* - all record data from mid-June 2018 until July 20, 2020, in order to account for the trends of the market variables before, during and after the outbreak of COVID-19. The data for all five cryptocurrencies is available starting June 5, 2018, due to different launching dates of these digital currencies, making the start date of the data collection more reliable.

Table 2 outlines the summary statistics of all the series, including the Jarque-Bera test for normality. This statistic helps determine that on average, the volatility of Bitcoin is less important than all equity assets, hindering the cryptocurrency's ability to be used as a medium of exchange. The kurtosis statistics suggest that the tail behaviours are flat for all variables through the positive and high results. When assessing the time period leading up to the pandemic, as well as when considering the aftereffects, the cryptocurrencies, stock market indices and MSCI indices are all skewed to the left, while gold and the USD index are skewed to the right. The consistency of these results support the Jarque-Bera test, supporting the rejection of normality for the data.

Table 3 reports the estimation results of the four multivariate GARCH models chosen for this study. All four models confirm significant returns and volatilities based on the four different information criteria used for the analysis. However, *VARMA (1,1) - DCC - GJR - GARCH* is found

to be the best fitting model to the data that models the dynamics of different financial variables with the cryptocurrencies. Figure 12 depicts the conditional variances of the financial assets under the analyzed model, suggesting similar trends during the pandemic. Figures 9 to 11 validate the empirical framework, in that cryptocurrencies are historically classified as a strong hedge but once the number of COVID-related number of cases and deaths increase, their hedging capabilities are severely affected. These results agree, in part, with prior research regarding the hedging classification of cryptocurrencies in times of economic distress, however, the performance during the 2019 world pandemic has shown to provide differing results. This supports the hypothesis in that Bitcoin does not serve as a hedge during the coronavirus. Because the altcoins are shown to follow the trends of that of Bitcoin's, a generalization can be made; the hedging capabilities of cryptocurrencies due to the implications of COVID-19 on the financial markets have been negatively affected. Cryptocurrencies do not act as a hedge during this episode of economic and financial turmoil.

## 6. Conclusions

There are several properties underlying the foundation of Bitcoin's existence. These properties are generalized into advantages and disadvantages and are useful when examining Bitcoin behavior and responses to macroeconomic uncertainty. Bitcoin properties extend beyond its transactional roles, such as digital convenience, ease of use and quick speed. The decentralization of the cryptocurrency encourages safe and secure transactions because of the anonymity of the Bitcoin users through encryption. The classification of Bitcoin as either a portfolio diversifier, hedge or safe haven is considered when discussing the reaction of Bitcoin under various situations. While Bitcoin can be defined as a hedging asset, termed as an investible asset that is either uncorrelated or negatively correlated with other financial instruments in the investor's

portfolio, a portfolio diversifier is expressed as an investible instrument that is positively, but imperfectly correlated with the other assets, as defined by (Laurent, 2013). They also define a safe haven as an investible asset that is negatively correlated with other instruments in the portfolio.

Considering these definitions, the impact of the disadvantages of Bitcoin have numerous implications for the cryptocurrency. The extreme volatility of the digital currency can be viewed as a disadvantage under risk aversion. Most of these externalities include historical events with uncontrollable effects on the global and financial markets. The main externality considered is the Novel Coronavirus of 2019. This global pandemic has caused great economic uncertainty and financial discomfort. Developing a cure for COVID-19 is found to be the only way to reduce the anxiety of this uncertainty.

The use of multivariate GARCH modeling on time series data allows for an empirical representation of the data in a professional manner. While four different models are consulted for this study, there are several other experiments that can be conducted, that may or may not be more efficient. This study replicates the design used by Guesmi et al., 2019 due to the efficiency of the simulations to produce meaningful results that are relevant to this research. From the models considered, the *VARMA (1,1) – DCC – JGR – GARCH* is found to be the most efficient model, due to its ability to analyze the dataset to the best of its ability. This model is able to statistically determine the impacts of COVID-19 on the hedging ability of the cryptocurrencies, especially that of Bitcoin's. As the hypothesis suggests, Bitcoin, as well as the altcoins studied, is not an effective hedge during the coronavirus. This result disputes previous research that claims the cryptocurrency should prove to be an effective hedge during economic turmoil.

The Efficient Market Hypothesis is used to examine the severity of the coronavirus. The inefficiency that is inferred from recent empirical studies suggests that the time span of the analysis is the key in determining the long term effects: When the entire time span is considered in the analysis, inefficiency is recorded, whereas when the sample time is split into two, the latter

subsample is found to show efficiency. Without conducting a thorough investigation of the entire time span of the virus, beginning with the onset of the crisis and ending with the development of a successful remedy, the results remain inconclusive. Therefore, the impact of Bitcoin's reaction to the coronavirus pandemic is essentially dependent on the entire timeframe of the coronavirus. During the writing of this thesis, the aftermath of the pandemic is still being suffered by all economies around the world. While many researchers conclude that Bitcoin is a 'digital gold' in the past and can be thought of as an effective hedge, the results based on the outbreak of COVID-19 indicated otherwise.

This study contributes to the literature on the performance of cryptocurrencies, specifically relating to the hedging capabilities. However, this research does have limitations that are essential to address. Because this academic work is being written during the pandemic, the full data cannot be accounted for; while the financial data is available for the variables up until a certain date, the effects of the coronavirus on the economy are still changing on a daily basis. Different samples will result in different outcomes and the study will not be complete until a biological solution to the virus will be implemented. Once the economy re-stabilizes, may it be in a few months, or even a few years, only then will the overall performance of cryptocurrencies during this time be successfully analyzed. As of now, all research pertaining to the implications of COVID-19 on the global economy and financial markets is as relevant and updated as can be.

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## 8. Appendix

### 8.1. Tables

Table 1. Summary of Properties: Top 5 Cryptocurrencies

	Bitcoin (BTC)	Ether (ETH)	Ripple/XRP (XRP)	Tether (USDT)	Bitcoin Cash (BCH)
			 XRP		 BitcoinCash
Launch Date	2009	2015	2012	2014	2017
Market Capitalization Billions (2020)	\$169	\$27.5	\$8.7	\$9.2	\$4.2

Current Token Circulation (2020)	18.5 million	102 million	44.9 billion	10.2 billion	18.4 million
Token Limit	21 million	None	100 billion (Pre-Mined)	None	21 million
Network	N/A	Ethereum	Ripple Net	Bitcoin & Ethereum	N/A
Approximate Block Time	10 minutes	15 seconds	Instant	15 seconds (Bitcoin Network) and 10 minutes (Ethereum Network)	10 minutes

Sources: Compiled from resources used in this thesis, especially [www.coindesk.com](http://www.coindesk.com), [www.investopedia.com](http://www.investopedia.com), and <https://www.getsmarter.com/blog/market-trends/eight-types-of-cryptocurrencies-compared/>.

Table 2. Descriptive Summary Statistics of Daily Data

Variable	L_BTC	L_XRP	L_ETH	L_USD T	L_BCH	L_GOL D	L_USD	L_SP5 00	L_SSE	L_MSCIEM ERG	L_MSCIWO RLD
Observations	555	555	555	555	555	555	555	555	555	555	555
Minimum	- 0.31595	- 0.28904	- 0.42357	- 0.024543	- 0.43885	- 0.047386	- 0.016262	- 0.12765	- 0.080392	- -0.069425	- -0.10441
Maximum	0.21335	0.33732	0.26837	0.021286	0.37826	0.073632	0.015786	0.089683	0.055542	0.055737	0.084062
Mean	0.00033314	0.0022539	0.0017041	2.13E-06	0.0029513	0.00060933	3.69E-05	0.0003028	0.00011212	-0.0001215	0.00017222
Standard Deviation	0.044211	0.050964	0.056451	0.0035216	0.06953	0.0098202	0.0036867	0.015833	0.012676	0.011839	0.013248
Skewness	- 0.62073	0.27992	- 0.78384	- 0.055442	- 0.42288	0.96944	0.32065	0.99201	- 0.62908	-1.0067	-1.4752
Kurtosis	7.258	6.4574	7.566	14.867	9.5904	11.734	2.5668	16.141	5.6742	7.4798	18.608
Jarque-Bera	1253.8	971.5	1380.6	5111.4	2143.5	3270.9	161.87	6116	781.16	1387.5	8208.9
ARCH LM Test (1)	0.23287	6.8481*	0.59758	91.475*	4.9575*	128.12**	113.91*	189.65*	0.16341	48.668**	72.591**
ARCH LM Test (5)	9.0788**	3.7339*	7.7500*	22.018*	3.2970*	21.316**	39.695*	72.678*	0.51274	54.092**	53.776**
ARCH LM Test (10)	4.8622**	2.0035*	4.2970*	11.453*	2.0122*	19.597**	28.176*	40.912*	1.4175	28.146**	33.266**
LB-Q (5)	4.58559	2.01268	5.66450	9.42705	5.69786	3.61277	4.01454	4.74302	6.55971	6.64131	3.22404
LB-Q (10)	8.93694	3.08567	10.5528	11.3466	10.1271	9.07009	16.5342	14.1817	13.8773	17.0278	12.3650
LB-Q (20)	19.8629	14.0502	26.3610	24.4194	26.9132	14.9492	23.3980	21.3217	24.8558	22.4612	23.8435
LB-Q (50)	46.8323	41.7025	55.0073	51.8316	51.2789	47.2813	51.8253	47.0118	48.1990	37.9920	46.1943
LB-Q <sup>2</sup> (5)	52.3882**	21.8188**	45.2416**	152.403**	15.1122**	170.598**	316.615**	498.369**	2.68667	408.598**	373.546**
LB-Q <sup>2</sup> (10)	54.1015**	22.8753*	46.7255**	164.657**	18.8765*	291.468**	586.043**	754.454**	16.1827	620.907**	597.955**
LB-Q <sup>2</sup> (20)	55.1185**	32.5350*	51.5898**	176.557**	28.7740**	404.136**	654.778**	855.063**	19.7660	669.906**	680.859**
LB-Q <sup>2</sup> (50)	70.9643*	64.1197	68.2706*	257.058**	75.9261*	426.905**	663.329**	860.638**	39.7451	686.003**	687.457**

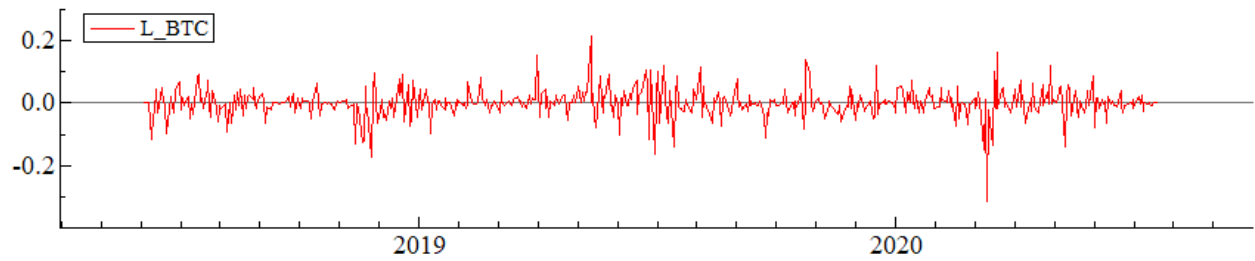
Using daily data for period June 05, 2018 to July 20, 2020 computed on OxMetrics 7.2. Note \*, \*\* and \*\*\* indicate the rejection of the null hypothesis for normality with the Jarque-Bera statistic, the ARCH LM test (when there are no ARCH effects) and for the Ljung-Box Q-Statistic test (when there is no autocorrelation) at the 1%, 5% and 10%, respectively.

Table 3. Dynamics of the Conditional Returns and Volatilities of Multivariate GARCH Models

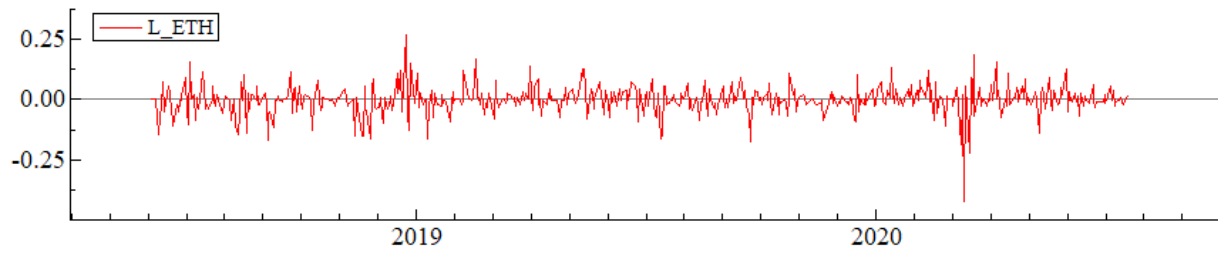
Model Specification	Log-likelihood	AIC	SIC	BIC	HQC
VARMA (1,1)-DCC-GARCH	19422.991	-69.628796	-69.682365	-68.842822	-69.321772
VARMA (1,1)-DCC-EGARCH	18992.160	-67.996975	-68.073325	-67.039798	-67.623074
VARMA (1,1)-DCC-GJR-GARCH	19442.221	-69.658456	-69.723016	-68.786889	-69.317994
VARMA (1,1)-cDCC-FIAPARCH (BBM's) with truncation order 500	19431.425	-69.619551	-69.68411	-68.747975	-69.279088

## 8.2. Figures

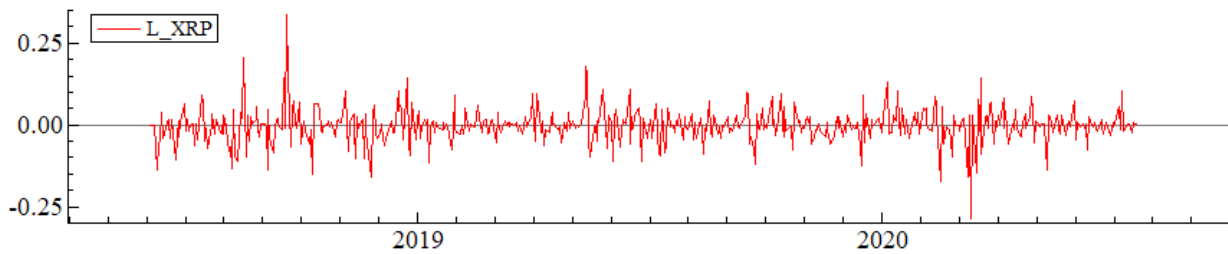
Figure 1.



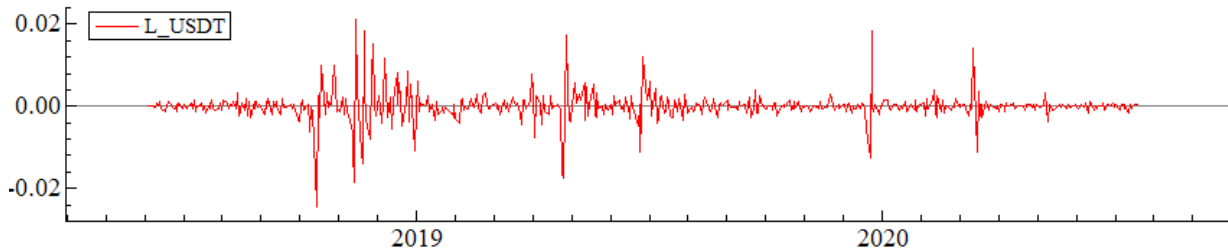
(a) Log returns of Bitcoin, June 2018 to July 2020



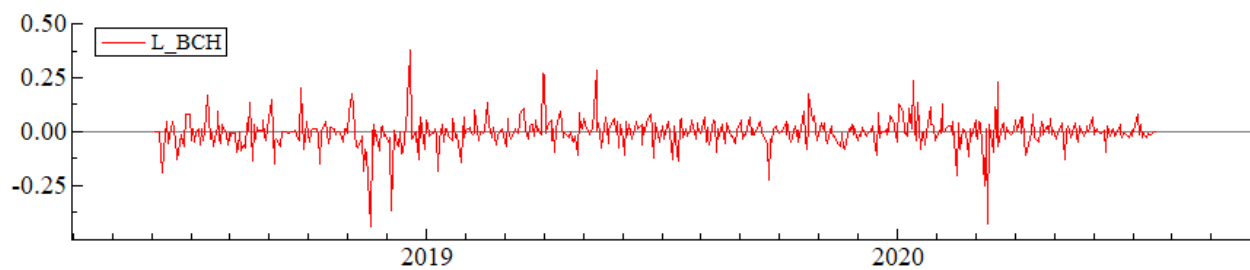
(b) Log returns of Ether, June 2018 to July 2020



(c) Log returns of XRP, June 2018 to July 2020



(d) Log returns of Tether June 2018 to July 2020



(e) Log returns of Bitcoin Cash, June 2018 to July 2020

Figure 2. Cryptocurrency Performance, June 2018 to July 2020

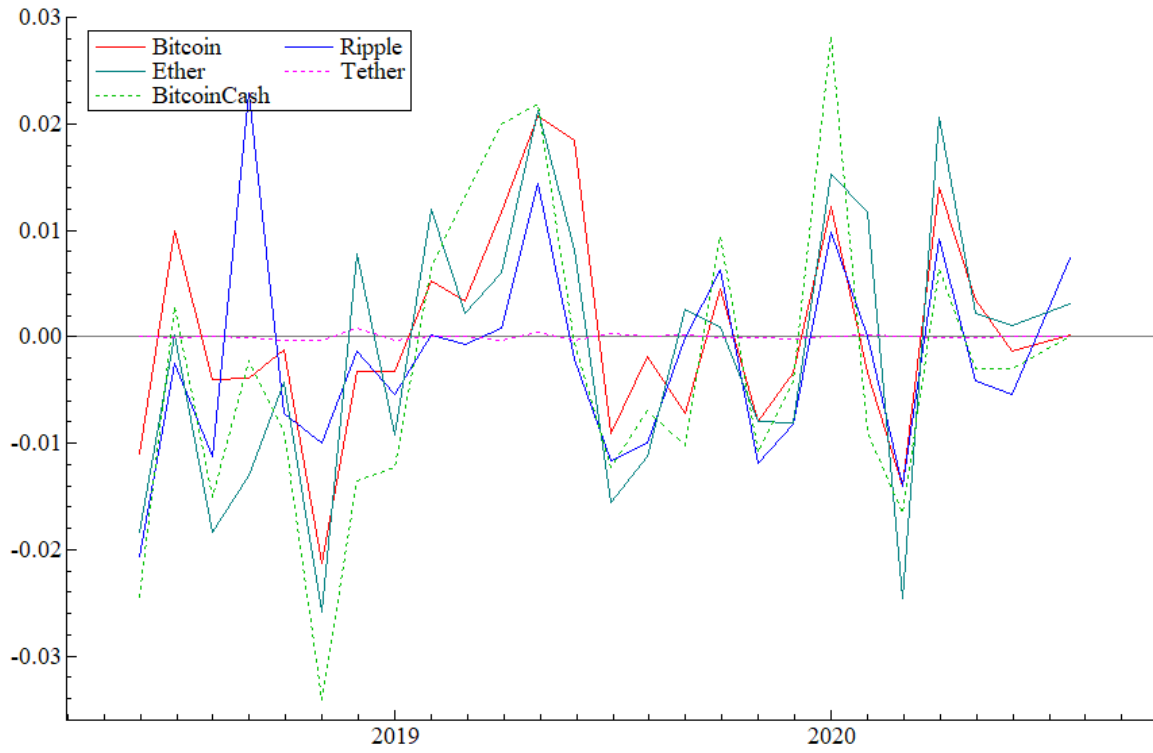
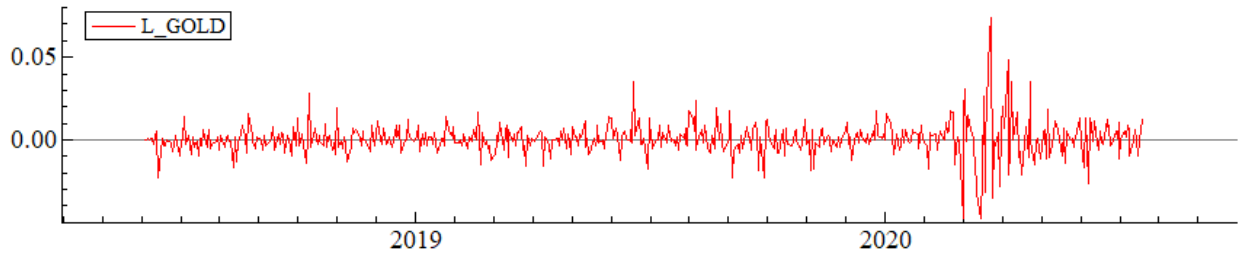
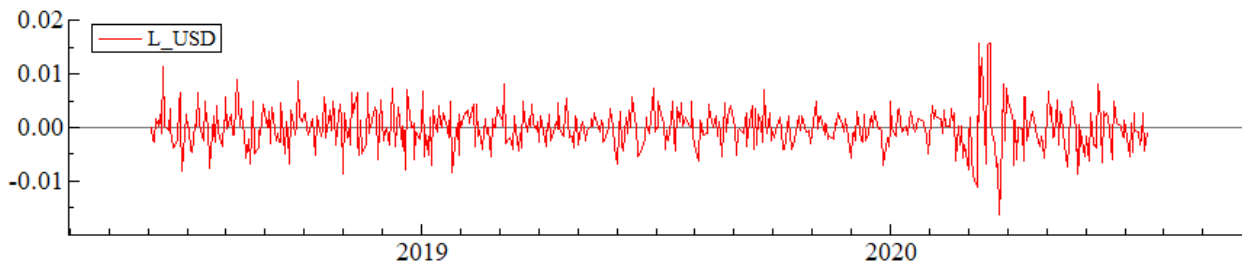


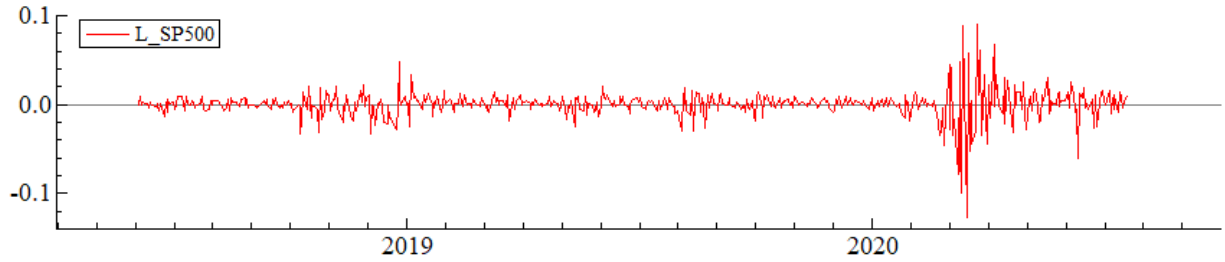
Figure 3.



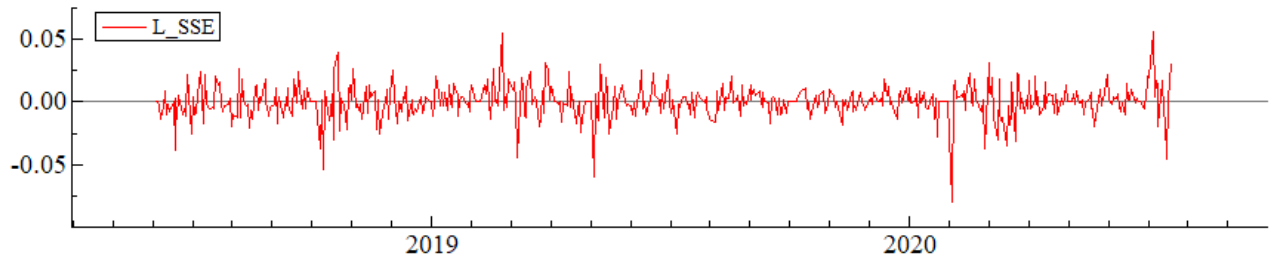
(a) Performance of Gold, June 2018 to July 2019



(b) Performance of USD Index, June 2018 to July 2019

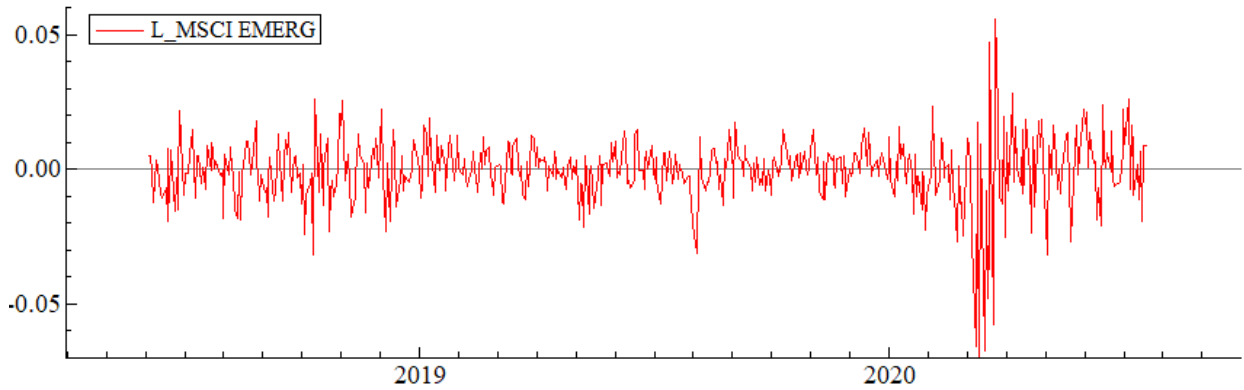


(c) Performance of S&P 500 Index, June 2018 to July 2020

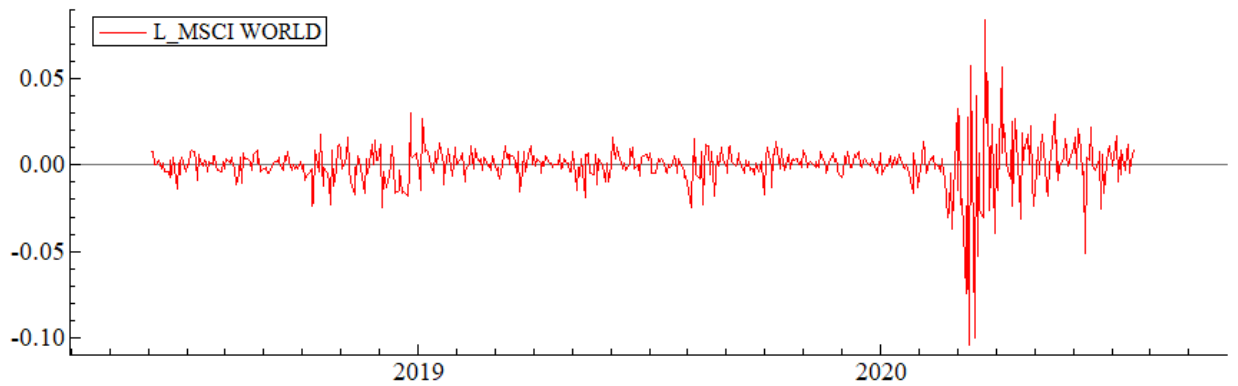


(d) Performance of SSE Index, June 2018 to July 2020

Figure 4.



(a) Performance of MSCI Emerging Markets Index, June 2018 to July 2020



(b) Performance of MSCI World Markets Index, June 2018 to July 2020

Figure 5. The Global Economic Uncertainty from June 2018 to July 2020

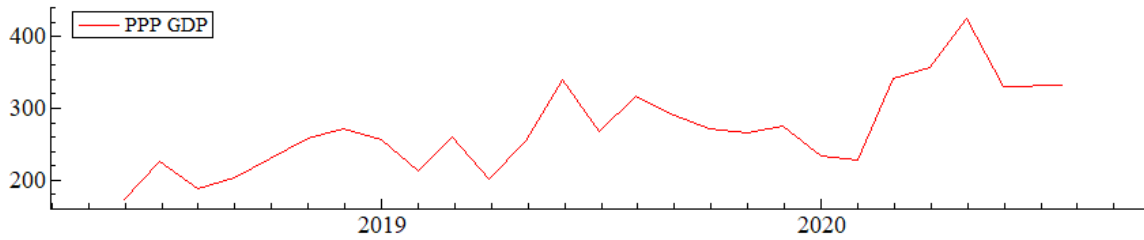
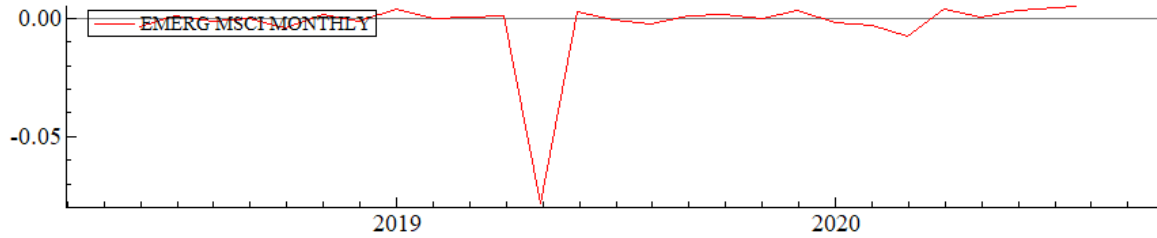
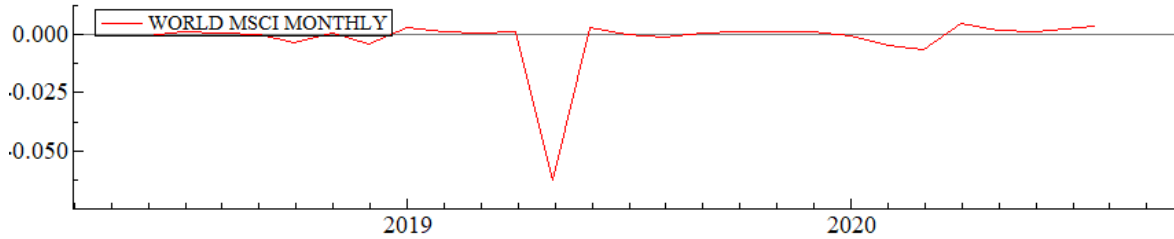


Figure 6.

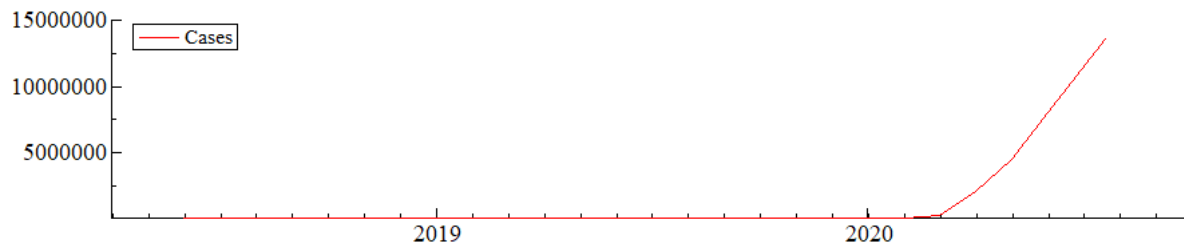


(a) Monthly Data for MSCI Emerging Markets, June 2018 to July 2020

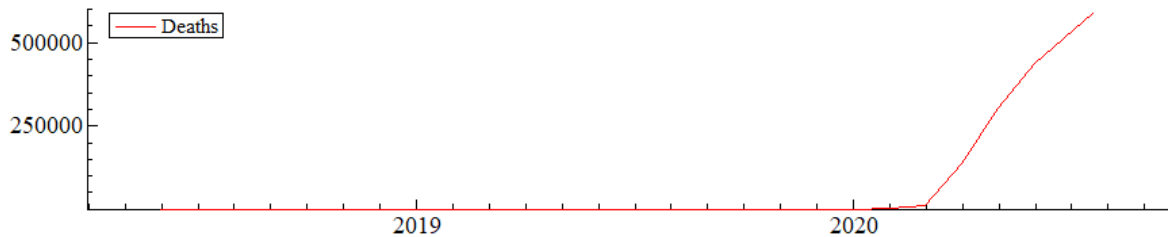


(b) Monthly Data for MSCI World Markets, June 2018 to July 2020

Figure 7.



(a) COVID-Related Cases on a Global Scale, Dec 2019 to July 2020



(b) COVID-Related Deaths on a Global Scale, Dec 2019 to July 2020

Figure 8. Summary of Behaviour: Cryptocurrencies, Commodities and Indices Due to COVID-19

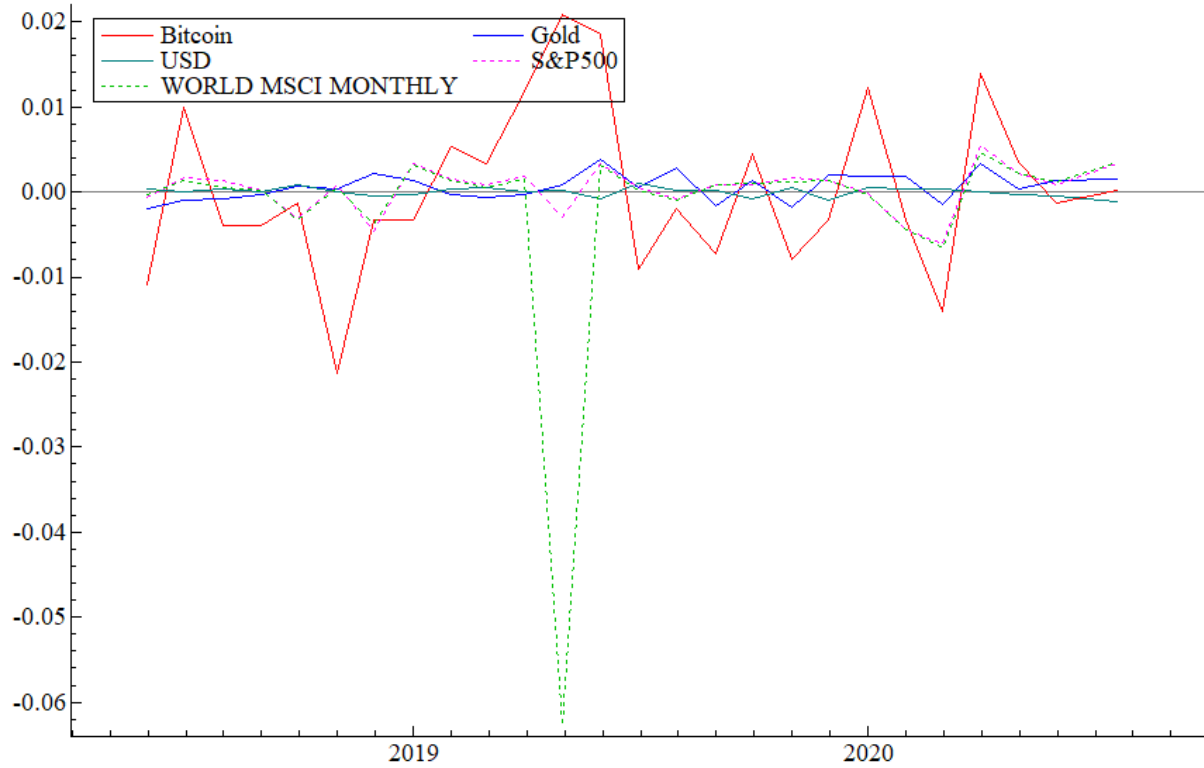


Figure 9. Bitcoin Hedging to Economic Uncertainty

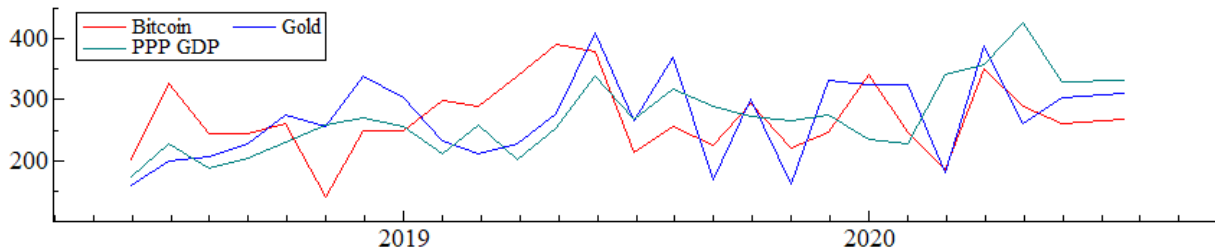


Figure 10. Bitcoin Hedging to MSCI Index

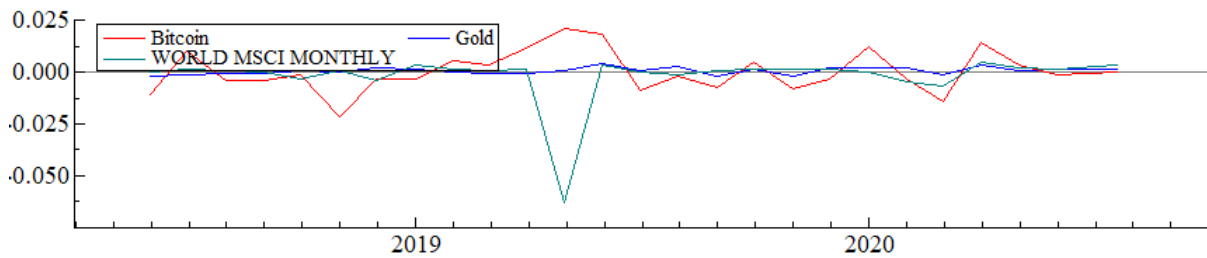


Figure 11. Bitcoin Hedging: Impacts Due to Coronavirus of 2019

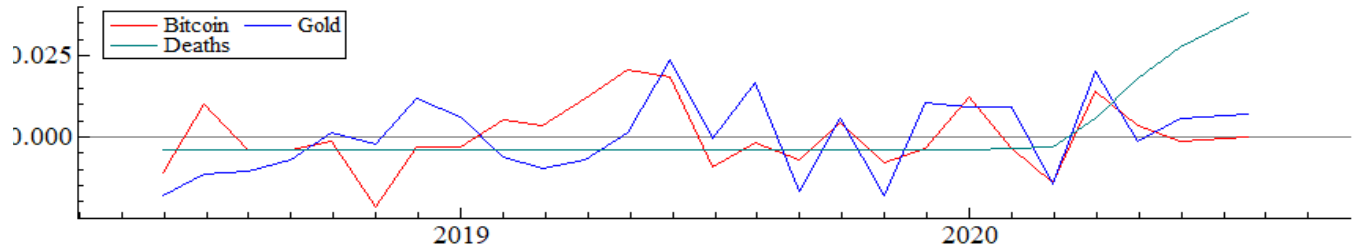


Figure 12. VARMA (1,1) – DCC – GARCH Conditional Variances

