EXAMINING THE VOLATILITY SPILLOVER IN LEADING CRYPTOCURRENCIES AND INVESTIGATING THE HEDGE/SAFE HAVEN PROPERTIES OF ETHEREUM

A Thesis

presented to

the Faculty of Business Administration and Economics

At Notre Dame University-Louaize

In Partial Fulfillment

Of the Requirements for the Degree

Master of Business Administration

by

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DECEMBER 2020

Notre Dame University - Louaize

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ACKNOWLEDGEMENTS

First and foremost, I would like to thank God, the Almighty, for giving me the power and patience during my research to successfully complete it.

Second, I would like to express my sincere gratitude to my supervisor at Notre Dame University, Dr. Etienne Harb for her tremendous support during my research. It was a great privilege and honor to work and study under her guidance. I would like to thank her for the continuous help, motivation, patience and encouraging comments. Her immense, knowledge, sincerity and seriousness helped me accomplishing and writing my thesis.

I would also like to thank the reader of my thesis, Dr. Talie Kassamany, for his tremendous experience, valuable time and constructive comments, which helped me enhance my research skills and aided me in my thesis.

Finally, I would like to express my profound gratitude to my family for their love, prayers, caring and sacrifices for educating and preparing me for the future. I would also like to thank all my friends for their continuous support and motivation.

Thank you.

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ABSTRACT

Purpose: This paper investigates the interconnectedness of the five largest cryptocurrencies in terms of market capitalization namely, Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin through a volatility spillover inspection. It also studies the hedging and/or safe haven capabilities of Ethereum, the second largest cryptocurrency in terms of market capitalization, against the main conventional currencies and the traditional assets in the United States and the European markets.

Design/methodology/approach: In the first part of the research, univariate general autoregressive conditional heteroskedasticity (GARCH) techniques are used to model the volatility of the return series of the cryptocurrencies. Vector autoregressive model (VAR) is then used to examine if volatility spillovers exist between the selected cryptocurrencies. The data retrieved from a reliable website spans from August 2017 until December 2019 with a total of 870 observations. However, in the second part of the research, Ethereum's capability as a hedging and/or safe haven tool in an investor's portfolio is examined using ordinary least squares regressions with percentiles. Crisis event interaction regressions are also performed as a robustness check. We selected three worldwide events that have caused financial turmoil in the market, namely the US presidential election of 2016, the Brexit referendum and the covid-19 to confirm the results of the percentile regressions. The hedging and/or safe haven capability of Ethereum is checked against the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. The return series are retrieved from Thomson Reuters Eikon. For the US market, the data spans from March 2016 until May 2020 with a total of 843 observations while for the EU market, the data spans from March 2016 until May 2020 with a total of 852 observations.

Findings: In the first part of the research, the findings reveal the existence of volatility spillovers between the cryptocurrencies. More particularly, Bitcoin is the most prominent transmitter of volatility shocks followed by Litecoin while Ripple is the top receiver of volatility shocks followed by Litecoin and Ethereum. Additionally, Bitcoin is mainly affected by its own shocks whereas Ethereum, Ripple, Bitcoin Cash and Litecoin are affected by both their own shocks and by shocks from other cryptocurrencies. Moreover, the results show that there are uni-directional volatility spillovers from Bitcoin to

Ethereum, Ripple, Bitcoin Cash and Litecoin, uni-directional volatility spillovers from Ethereum to Litecoin and uni-directional volatility spillovers from Litecoin to Ripple.

In the second part of the research, the results reveal that Ethereum does not act as a hedging and/or safe haven asset against the traditional currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. These results are confirmed in the crisis event interaction model. However, Ethereum seems to act as a safe haven only in some specific events that caused financial turmoil in the market. In this study, during the Brexit referendum event, Ethereum did act as a safe haven against extreme movements in the European bonds.

Practical implications: Our results may be of great help for investors. The results of the research may help them manage the risks of their portfolios since cryptocurrencies are interlinked and volatility spillovers exist among them. Our findings also help investors better understand the behavior of Ethereum. They reveal to investors that Ethereum does not act as a hedge and/or a safe haven in their portfolios against the conventional foreign exchange currencies, the US and EU stock markets, the US and EU bond markets, and the main traded commodities such as the crude oil and the gold. Thus, they should privilege other assets if they want to hedge the risks in their portfolios.

Originality/value: The importance of cryptocurrencies as an alternative asset class has gained a great attention in the financial market in the last decade since the invention of Bitcoin in 2009. Many studies have been performed on the interconnectedness of cryptocurrencies and their interrelation with the traditional assets. Yet, to the best of our knowledge, studies examining volatility spillovers of cryptocurrencies using GARCH-VAR models are still rare. Moreover, most of the researches that study the hedging and/or safe haven potential of cryptocurrencies against traditional assets have focused on Bitcoin, the most prominent cryptocurrency in terms of market capitalization. Very few studies have considered investigating the same properties for Ethereum. Our thesis fills this gap by examining these properties for Ethereum, the second largest cryptocurrency in terms of market capitalization, to date.

Keywords: Cryptocurrencies, volatility spillover, GARCH-VAR, hedge, safe-haven, percentile regressions, crisis event interaction.

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CHAPTER ONE: INTRODUCTION

1.1. INTRODUCTION

This chapter introduces the general topic of the research and highlights its originality and contributions. Section two provides a general background about the topic. The purpose of the study is highlighted in section three. The originality of the research is discussed in section four. Section five presents a summary of the main findings of the research. Section six pinpoints the contribution of the findings to the empirical literature. Section seven provides the structure for the subsequent chapters.

1.2. GENERAL BACKGROUND

Cryptocurrency markets have received a lot of attention from academics and investors since 2009. Cryptocurrencies are digital assets based on blockchain technology. Their main characteristics are their security and their decentralization. It means that they are difficult to counterfeit and function without the intervention of a third party in contrast to the traditional currencies that are ruled by governments or central banks.

Bitcoin is obviously the most popular cryptocurrency with an estimated market capitalization worth $350 billion as of December 2020. Since its introduction in 2009, cryptocurrency markets have rapidly grown with a total of more than 3000 cryptocurrencies to date. Despite its relatively recent launch, Ethereum constitutes the second largest cryptocurrency in terms of market capitalization which is currently estimated at $65 billion (as of December 2020). Although cryptocurrencies have fundamental differences in their functionalities, they are being increasingly traded for investment and speculation purposes.

As investors in cryptocurrencies around the world are exposed to high risks (Gkillas and Katsiampa, 2018), examination of cryptocurrency interconnectedness is crucial in order for them and other market participants to better understand interlinkages within the cryptocurrency market and make more informed decisions. The examination of the hedging and/or safe haven capabilities of the cryptocurrency market against the traditional assets and foreign exchange market is also of utmost importance as cryptocurrencies can present benefits for investors as new hedging and/or safe haven assets and thus provide additional tools to manage the risks of their portfolios.

Thus, due to the importance of the new emerging cryptocurrency market, academics and researchers have been extensively studying the behavior of cryptocurrencies and their relationship with the conventional assets but the researches are still scarce and at their early stage. On one hand, the interconnectedness of cryptocurrencies has been examined in several studies, some revealed that cryptocurrencies are mainly affected by their shocks while others showed that there were volatility spillovers among them. For instance, Koutmos (2018) studied volatility spillovers between cryptocurrencies employing the vector autoregressive model and revealed that Bitcoin, Ethereum, Ripple, and Tether are mainly affected by their own shocks while Litecoin is affected by both its own shocks and by shocks from other cryptocurrencies. Bitcoin is then identified as the most transmitter of volatility shocks whereas Litecoin is the most important receiver of volatility shocks. Additionally, Corbet et al. (2018) also studied volatility spillovers between Bitcoin, Ripple, and Litecoin using a vector autoregressive model, and found that Bitcoin and Ripple are affected by volatility shocks from Litecoin while Bitcoin, Ripple, and Litecoin are mainly affected by their own shocks. Furthermore, Ji et al. (2018) identified volatility spillovers among Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Dash and confirmed that Bitcoin was the largest transmitter of volatility spillovers followed by Litecoin. However, Ethereum and Stellar are the two largest receivers of volatility spillovers.

On the other hand, the few studies addressed the interconnectedness of cryptocurrencies with traditional assets by mainly focusing on Bitcoin. For instance, Baur et al. (2017) studied the hedging and/or safe haven properties of Bitcoin against the traditional foreign exchange currencies and the US stock market using ordinary least squares regression and event crisis interaction. They revealed that Bitcoin was neither a hedge nor a safe haven against conventional or fiat currencies and the US stock market. Conversely, Baumöhl (2018) found that Bitcoin, Ethereum, Ripple, Litecoin, Stellar Lumens, and Nem could be used as hedges against foreign exchange currencies. Finally, Bouri et al. (2019) identified that Bitcoin, Ripple, Litecoin, Stellar, and Monero act as a safe haven against the S&P500 while Ethereum, Dash, and Nem are neither a hedge nor a safe haven against the S&P500.

Consequently, this research fills the gap in the literature by shedding the light on these issues that need to be furtherly investigated, particularly the interconnectedness of cryptocurrencies and more importantly, their interrelation with the real-world assets. Hence, we examine the volatility spillovers among cryptocurrencies having the largest market capitalization and we employ different methodologies than most of previous studies. We also examine the hedging and/or safe haven abilities of Ethereum since the empirical literature mostly focused on Bitcoin.

1.3. PURPOSE OF THE STUDY

This research attempts to study the interconnectedness of cryptocurrencies and their relationship with the conventional assets. Mindful of the importance and infrequent researches of this topic, the objectives of the research are twofold. First, we explore the volatility spillovers among the top five cryptocurrencies in terms of market capitalization namely Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin using general autoregressive conditional heteroskedasticity followed by a vector autoregressive model (GARCH-VAR). Secondly, we examine the hedging and/or safe haven properties of Ethereum, the second largest cryptocurrency in terms of market capitalization, against conventional exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold using percentile regressions followed by an event crisis methodology used as a robustness check. In the latter, we select three events that caused turmoil in financial markets, namely the US presidential election of 2016, the Brexit referendum and the covid-19 pandemic.

This research will answer the following questions:

- *Do volatility spillover activities exist between cryptocurrencies?*
- *Can cryptocurrencies act as hedging and/or safe haven tools against the conventional main currencies and traditional assets in an investor's portfolio?*

1.4. ORIGINALITY OF THE STUDY

The importance of cryptocurrencies as an alternative asset class has gained a great attention in the financial market in the last decade since the invention of Bitcoin in 2009. Yet, most academics, practitioners and investors still ignore its characteristics due to its strange and new nature. Economists have not properly evaluated its behavior yet. Researches on cryptocurrencies are still scarce and at their early development stages. Several studies investigate the interconnectedness between cryptocurrencies (Koutmos, 2018; Corbet et al., 2018; Ji et al., 2018; Katsiampa, 2018; Beneki et al., 2019; Katsiampa et al., 2019b;

Shi et al., 2020). Additionally, many other studies focus on the interconnectedness of cryptocurrencies with the traditional assets and their hedging and/or safe haven potential in an investor's portfolio (Dyhrberg, 2015b; Baur et al., 2017; Baumöhl 2018; Tiwari et al., 2019; Bouri et al., 2019; Stensås et al., 2019**;** Okorie et al., 2020).

Yet, the literature investigating volatility spillovers between cryptocurrencies using GARCH-VAR is still rare. Koutmos (2018), Corbet et al. (2018) and Ji et al. (2019) employ the VAR model to examine return and volatility spillovers among cryptocurrencies. However, they utilize techniques such as the Parkinson (1980) estimator, the 5-day standard deviation and the daily range-based volatility of Diebold and Yilmaz (2016) to calculate the volatilities of the return series. Thus, to the best of our knowledge, this research is one of the few employing univariate GARCH models to obtain the volatilities of the return series.

Additionally, most of the studies that examined hedging and/or safe haven abilities of cryptocurrencies against real world assets have focused on Bitcoin, the most prominent cryptocurrency in terms of market capitalization (Bouri et al., 2016; Baur et al., 2017; Urquhart et al., 2019; Bouri et al., 2020). Yet, to the best of our knowledge, the studies which tackled these properties for Ethereum are scarce and our paper fills this gap. Ethereum is considered one of the most popular cryptocurrencies to date beside Bitcoin and could in later stages constitute a good alternative or even a replacement for the Bitcoin as a hedging and/or safe haven tool in an investor's portfolio, given its lower price and high market capitalization. That is why we have considered studying its behavior against the traditional assets and conventional foreign currencies. Moreover, the models we employ have not yet been used in the analysis of the behavior of Ethereum. We are among the few to mix all real-world assets in the same regression equations while investigating the behavior of extreme values (percentiles). We also consider the biggest two financial markets namely the United States and the European ones. Furthermore, we have extended our main model to include event crisis regressions to check the robustness of our initial models, in order to confirm the safe haven capability of Ethereum in specific and extreme events.

1.5. MAJOR FINDINGS

This study examines the existence of volatility spillovers and thus volatility connectedness among cryptocurrencies for a sample period ranging from August 2017 until December 2019. Moreover, it also tackles the importance of Ethereum as a hedging and/or safe haven cryptocurrency in an investor's portfolio in both the US and the EU markets from March 2016 until May 2020. Our findings are in line with existing literature and support the existence of volatility spillovers and thus connectedness among cryptocurrencies. Specifically, our results report uni-directional volatility spillovers from Bitcoin to Ethereum, Ripple, Bitcoin Cash and Litecoin, uni-directional volatility spillovers from Ethereum to Litecoin and from Litecoin to Ripple. Moreover, Ethereum, Ripple, Bitcoin Cash and Litecoin are affected by their own shocks and by shocks from other cryptocurrencies while Bitcoin is the only cryptocurrency that is mainly affected by its own shocks. Finally, we confirm that Bitcoin is the most transmitter of volatility shocks followed by Litecoin while Ripple is the top receiver of volatility shocks followed by Litecoin and Ethereum.

Additionally, the regression results reveal that Ethereum does not act as a hedge and/or a safe haven for all the assets considered in the study namely the conventional main currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. However, our study reveals that Ethereum presents only some weak safe haven potential in some specific and extreme events. For instance, in our sample, Ethereum acted as a safe haven during the Brexit referendum against the extreme movements in the European bonds.

1.6. STRUCTURE OF THE STUDY

The rest of the thesis is organized as follows: Chapter two introduces the currency risk, the blockchain technology and the roots of money. Cryptocurrencies are then defined along with their types and their benefits. Then the relevant literature review is provided which covers the interconnectedness of cryptocurrencies and their behavior with traditional assets. Chapter three describes in detail the methodology used. It mainly tackles the philosophical dimension, the orientation and the strategy used in this research. Moreover, it shows the development of hypotheses, variables measurement, the diagnostic tests, the empirical methodology, the source of data and the sampling procedures. Chapter four presents the interpretation of the results for both parts and their discussion. It begins with the GARCH-VAR analysis. In this part, the descriptive statistics is first provided. Then, the diagnostics tests are presented. The results of the univariate General Autoregressive Conditional Heteroskedasticity (GARCH) models are presented followed by the results of the vector autoregressive model (VAR). Finally, the results are discussed and compared to the proposed hypotheses. In the second part of this chapter, the results and interpretation of the ordinary least squares (OLS) regressions with percentiles and the crisis event interaction analyses are presented. First, the descriptive statistics and diagnostic tests are reported. Then, the results of the percentile regressions along with the event crisis interaction are presented. Finally, the results are discussed and linked to the hypotheses. Chapter five summarizes the results, presents the limitations of the study, discusses the practical implications and paves the way for further research.

CHAPTER TWO: LITERATURE REVIEW

2.1. INTRODUCTION

This chapter aims at providing a general overview about the volatility of currencies and the blockchain technology, types and natures of cryptocurrencies and a review of the existing empirical literature that addressed their correlation and their hedging and/or safe haven abilities. Section two gives a general overview about currency risk. Section three covers key concepts about blockchain technology, then it goes through the definition of blockchain technology and its functionality to better understand the operation of cryptocurrencies. Section four gives a historical background about the roots of money. Section five introduces cryptocurrencies, their types and their advantages over traditional currencies. The sixth section examines peer reviewed articles that investigated the correlation of cryptocurrencies, their volatility spillover and their hedging and/or safe haven abilities against traditional assets in the market. Section seven concludes.

2.2. CURRENCY RISK

Currency risk or “currency volatility” arises from the change of one currency in relation to another. Investors or multinational corporations (MNCs) that have assets or business operations across national borders are exposed to currency risk that may create unpredictable profits and losses (Chen, 2020). The volatility of currencies can be affected by the prices of stocks, bonds, other currencies and commodities. Furthermore, currency risk is also affected by macroeconomic news, inflation rates and interest rates.

In fact, several studies have linked macroeconomic news announcements to jumps in exchange rates. Goodhart et al. (1993) study the volatility of the USD/GBP exchange rate by taking a one year high-frequency data and two specific events which are the U.S. trade figure announcement and the U.K. interest rate change. They find that in each case the news caused an exchange rate jump. Similarly, Almeida et al. (1998) study the effects of news announcements on DEM/USD exchange rate jumps using three years of high frequency data and shows that there exist short-lived effects. Moreover, Anderson et al. (2003) also show that news affect exchange rates.

Other studies have focused on the interconnection between stock markets and exchange rates and the effect of stock markets on currency volatility. Among them, Kanas (2000) studies the interdependence between the stock returns and the exchange rate changes of six countries, namely U.S., U.K., Japan, Germany, France and Canada through volatility spillover. He finds that currency volatility is affected by all the stock markets except Germany. Moreover, Yang et al. (2004) study the interaction between stock prices and exchange rates for the G-7 countries and find that movements in stock prices will affect future exchange rate movements. Moreover, Kabigting et al. (2011) state that the stock exchange market affects the foreign exchange market in the ASEAN 5 (Philippines, Indonesia, Thailand, Malaysia and Singapore). Consistent with the previous studies, Reboredo et al. (2016) show that there is a positive relationship between stock prices and currency values in emerging economies with respect to the US dollar and the Euro, with downside and upside spillover risk effects transmitted both ways.

Many other factors may affect the volatility of currencies. In their study, Sari et al. (2010) examine the interrelation between gold, silver, platinum, palladium, oil price and the USD/EUR exchange rate. They find a strong correlation between the price returns of the commodities and the changes in the USD/EUR exchange rate in the short-run whereas there seems to be no correlation between the commodities and the exchange rate in the long-run. Moreover, Maitra et al. (2018) investigate the return and volatility spillover among commodities and exchange rates and show that there is a unidirectional volatility spillover and hence a correlation between the multi-commodity exchange (non-agro commodity) and exchange rates.

Given the exchange rate risk, several companies engage in hedging activities especially if they carry considerable amount of debt in foreign currencies and during financial crisis (Buyukkara et al. 2019).

Despite that we expect cryptocurrencies to have similar risk as traditional ones, but they could also be used as tools for hedging and safe haven activities. But before introducing cryptocurrencies, we will present a brief introduction of the blockchain technology on which cryptocurrencies are based.

2.3. BLOCKCHAIN TECHNOLOGY

The blockchain technology is a new technology invented in 2008 and is regarded as the most revolutionary technological innovation since the invention of the internet. It is based on sophisticated encryption algorithms that allows a secure communication between two parties without the intervention of an intermediary. It is becoming more popular and widely used in many areas such as banks, insurance companies and financial markets such as cryptocurrencies. Bitcoin is the first cryptocurrency to use blockchain technology. Thus, in order to better understand the functionality of Bitcoin and other cryptocurrencies, we begin this chapter by introducing the blockchain technology. We first define some important key concepts of a blockchain network such as hashing functions, digital signature, encryption and decryption, peer-to-peer network and distributed ledger. Then we give a brief overview of the functionality of a blockchain network.

2.3.1. DEFINITIONS

2.3.1.1.HASHING FUNCTION

A hashing function is a one-way compression algorithm that transforms any block of data into a fixed output. Thus, each block of data will always have its unique hash and any change in a bit of the block changes the whole hash and generates a completely different new hash. That is why hashes are important for integrity. This means that nobody can change any bit in the block of data without the knowledge of the whole network (Singhal et al., 2018).

2.3.1.2.DIGITAL SIGNATURE

A digital signature is used to sign a message and verify it using a public-private key pair. It provides non-repudiation and trust. Using the private key, the transmitter signs it and the receiver verifies the signature using the public key.

2.3.1.3.ENCRYPTION AND DECRYPTION

A public-private key pair is used to encrypt and decrypt a message. It is a secure and confidential mathematical algorithm. The public and private keys are inverse of each other. The public key is used to encrypt a message at the transmitter. Only the one who has the private key can decrypt the encrypted message.

2.3.1.4.PEER-TO-PEER NETWORK

In general, there are two types of networks. The traditional switched network which is a connection of computers (nodes) linked to a central switch. If this server switches off, all the network goes down. However, a peer-to-peer network is a decentralized network in which all the nodes are connected to each other. The only way to switch off the network is to shut down all the nodes.

2.3.1.5.DISTRIBUTED LEDGER

A ledger is the history of all transactions made within the blockchain in the peer-to-peer network. A copy of the blockchain is shared among all miners in the network. A miner is the network participant who keeps a copy of the entire blockchain and verifies the transactions before adding them on the blockchain (Singhal et al., 2018).

2.3.2. WHAT IS A BLOCKCHAIN?

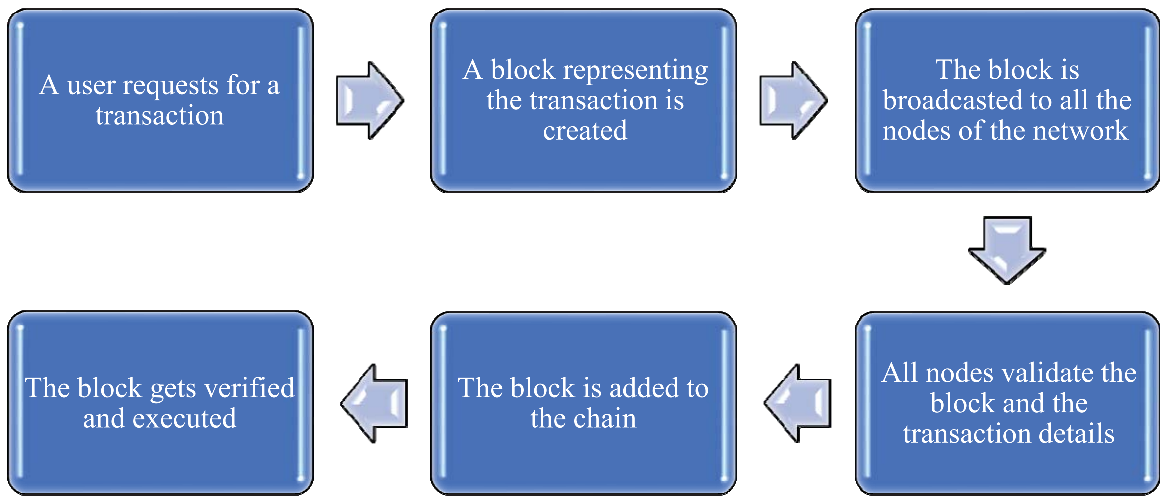
A blockchain is a shared, trusted, public and distributed peer-to-peer ledger that maintains a continuously growing list of transactional records between parties. It uses many encryption algorithms such as public-private key pairs and hashing functions in order to secure any transaction between two parties. Every block contains information such as the time of transaction, its amount and the digital signatures of the two parties. It also stores its own hash and the hash of the previous block to form a blockchain.

2.3.3. HOW DOES A BLOCKCHAIN WORK?

Before a block of data is sent through the network, it first gets hashed. Then, the generated hash gets signed. When the transmitter signs the hash, he cannot deny later that he did not send the block. Then, the block gets encrypted so that only the appropriate party can receive it and decrypt it.

When the block is sent through the network and before the block is added to the ledger, it is spread among all miners. They check if the transaction is legitimate or not. In other words, they verify all transaction details of the block. If most of the miners accept the new block, it is added to the blockchain (Xu et al., 2019).

Figure 2.1: Summary of Blockchain Functionality



2.4. DEFINITION OF CRYPTOCURRENCIES

According to Frankenfield (2020), cryptocurrencies are digital currencies based on the blockchain technology. The term "Crypto" shows the high security of cryptocurrencies which indicates that they are difficult to counterfeit. Additionally, cryptocurrencies are decentralized meaning that there is no governmental or financial intervention between two parties during a transaction in contrast to the traditional currencies which are ruled by governments and financial institutions.

2.4.1. TYPES OF CRYPTOCURRENCIES

Bitcoin is the most popular cryptographic currency to date. According to Baumöhl (2018), the price of Bitcoin showed a high volatility. It was 300 USD at the end of 2014. But after three years, at the end of 2017, its price increased to almost $20,000 and dropped down again at the beginning of 2018. Furthermore, the market capitalization of Bitcoin increased dramatically since its introduction and reached 300 billion US dollars as of December 2020.[1]

The success of Bitcoin has led to the introduction of new cryptocurrencies or so-called altcoins or meta-coins and stablecoins such as Ethereum, Ripple, Tether, Bitcoin Cash, Bitcoin SV and Litecoin. Ethereum has been for long the second cryptocurrency in terms of market capitalization with a total estimated value of 60 billion US dollars (as of December 2020)[1]. Bitcoin and Ethereum together represent approximately 60% of the total estimated cryptocurrency market capitalization[1]. As of December 2020, there exists more than 3000 cryptocurrencies in the market with a market capitalization of more than 500 billion US dollars.[1]

2.4.2. BENEFITS OF CRYPTOCURRENCIES

Cryptocurrencies have many benefits over fiat currencies. According to Chuen et al. (2018), cryptocurrencies are decentralized with no intermediary between two parties during any transaction. This is in contrast to fiat currencies or platform-based digital currencies which are centralized and regulated by governments and central banks. This decentralized nature of cryptocurrencies makes the transactions between two parties more transparent, faster with lower transaction fees. They clarify these features by stating that every transaction will be broadcast to the entire network. This process will only take few seconds. Then, all miners verify the transaction, which will only take about 10 minutes. The transactions are usually free of charge but sometimes the owner can decide to pay extra money for a faster transaction.

[1] According to www.investing.com

Another feature of cryptocurrencies is that many countries have begun to accept it as alternative payment methods to traditional currencies. Bouri et al. (2018) declare that Chicago Mercantile Exchange (CME) and Chicago Board Options Exchange (CBOE) have legitimized Bitcoin by introducing future contracts based on the price of Bitcoin. In the same content, Feng et al. (2018) state that many retailers and internet companies such as Subway and Microsoft are accepting payments in Bitcoin.

On the other hand, many drawbacks exist among cryptocurrencies. There are many security breaches related to the cryptocurrency transactions observed in the past. Huang et al. (2014) state that Mt. Gox and BitFinex have been hacked in 2014 and 2015, respectively. Moreover, Vasek et al. (2016) declare that cryptocurrencies are being stolen by hacking wallet passwords.

In addition to the security considerations, Foley et al. (2019) state that illegal activities with Bitcoin reach up to a value of 76 billion US dollars per year. They mention that about a quarter of Bitcoin users and half of Bitcoin transactions are related to illegal purchases.

2.5. EXISTING LITERATURE

2.5.1. INTERCONNECTEDNESS OF CRYPTOCURRENCIES

Cryptocurrency users and investors need to understand the connectedness of cryptocurrencies in order to make better decisions about the selection of assets for risk management of their portfolios, especially that cryptocurrency is a new asset class and its behavior is still ambiguous to investors. Cryptocurrency market is young and volatile and the studies that examined it are still scarce. Hence, there is an ongoing need to investigate the relation of cryptocurrencies and their interconnection with other traditional assets. In the present subsection, we review the articles that address the connectedness of cryptocurrencies and in the next one, we examine their interconnection with real assets to study their safe haven and/or hedging potential.

As a summary of the empirical literature, most of the studies performed on cryptocurrencies show a strong interconnection between them. Many methodologies have been used by many researchers such as Beneki et al. (2019), Katsiampa (2019) and Shi et al. (2020) and many more and they have found the same conclusion; a strong interrelation in the cryptocurrency market. However, when studying the interconnection of cryptocurrencies with other assets and the hedging and safe haven properties of cryptocurrencies (mainly Bitcoin), the results are heterogenous. Some of the authors like Baumöhl (2018) and Tiwari et al. (2019) find that Bitcoin and other cryptocurrencies are uncorrelated or negatively correlated during normal times and/or during times of economic fallouts with particular traditional assets giving them hedging and/or safe haven ability against those assets. Others like Dyhrberg (2015a) and Stensås et al. (2019) show that cryptocurrencies are positively correlated with other traditional assets which indicates that they can only be used as diversifiers in an investor's portfolio. In the following, we will give a summary of the main articles tackling these issues.

Employing the autoregressive distributed lag (ARDL) model, Ciaian et al. (2017) study the relationship between cryptocurrencies using daily data of seventeen cryptocurrencies consisting of Bitcoin, six major alternative cryptocurrencies in terms of market capitalization (Ethereum, Ripple, Litecoin, Monero, Dash and Nem) and ten minor alternative cryptocurrencies (Dogecoin, Peercoin, Namecoin, Novacoin, Nxt, Counterparty, Mintcoin, Qora, Supernet and Bitshares) for the period 2013-2016. They find that, in the long-run, Bitcoin price does not impact all cryptocurrencies. Only the cryptocurrencies similar to Bitcoin in their price formation mechanisms namely, Ethereum, Namecoin, Nxt and Supernet seem to be positively related to Bitcoin price. However, in the short-run, Bitcoin price has a positive impact on all of the alternative cryptocurrencies except Dash. Thus, they conclude that the relationship between Bitcoin and the alternative cryptocurrencies is stronger in the short-run than in the long-run.

From another perspective, by adopting random matrix theory and minimum spanning trees, Stosic et al. (2018) investigate the behavior of 119 cryptocurrencies using daily price returns from 26th of August 2016 until 18th of January 2018. Their results reveal the presence of multiple collective behavior in the cryptocurrency market indicating that cryptocurrencies are correlated. Moreover, by comparing the estimated volatilities and the realized volatilities relying on error statistics, Naimy et al. (2018) show that the EGARCH (1,1) model outperforms both the GARCH (1,1) and EWMA when forecasting the volatility of the Bitcoin/USD exchange rate. They use a sample period that ranges from 1st of April 2013 until 31st of March 2016.

However, considerable studies have focused on return and volatility spillover to examine the interconnection of cryptocurrencies. Different techniques have been applied on different cryptocurrencies to study spillovers. One of the widely used techniques to study spillovers between assets is the vector autoregression (VAR) developed by Diebold and Yilmaz (2009). This technique is utilized by Koutmos (2018) who performs a vector autoregressive analysis to study the return and volatility spillovers of the 18 largest cryptocurrencies in terms of market capitalization using daily data from 7th of August 2015 until 17th of July 2018. The log of the price return is considered while the volatilities are calculated using the Parkinson (1980) estimator. For the return spillovers, his findings reveal that Bitcoin, Ethereum, Ripple and Tether returns are mainly affected by their own shocks. However, Litecoin returns are 55.7% affected by its own shocks and 44.3% affected by shocks from other cryptocurrencies. Moreover, Bitcoin is mainly the biggest transmitter[2] of shocks to other cryptocurrencies while Dogecoin is the most important receiver[3] of shocks from other cryptocurrencies. Similarly, for volatility spillover, the results reveal that Bitcoin, Ethereum, Ripple and Tether volatilities are also mainly affected by their own shocks. However, Litecoin volatility is 44.2% affected by its own shocks and 55.8% affected by shocks from other cryptocurrencies. Moreover, Bitcoin is the most important transmitter of volatility shocks while Litecoin is the most important receiver of volatility shocks. Therefore, as a conclusion, they state that cryptocurrencies are correlated through their return and volatility spillovers. Similarly, Corbet et al. (2018) perform a spillover analysis by employing the vector autoregressive technique to study the degree of interconnectedness between Bitcoin, Ripple and Litecoin. They use daily log changes (returns) and 5-day standard deviation (volatilities) from 2013 until the end of July 2017. For price spillovers, their results reveal that Ripple and Litecoin prices are both affected by Bitcoin prices. However, Bitcoin prices are not affected by Ripple and Litecoin prices. Thus, they conclude that Bitcoin is the main transmitter of return in the market. On the other hand, when they consider volatility spillovers, they find that both Bitcoin and Ripple are affected by volatility shocks from Litecoin. They also mention that Bitcoin, Ripple and Litecoin are mainly affected by their own shocks. Likewise, Ji et al. (2018) study return and volatility spillovers among six cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin,

[2] A transmitter of shocks is a financial asset that transmits market shocks to other assets.
[3] A receiver of shocks is a financial asset that is affected by shocks from other assets.

Stellar and Dash) using daily data from 7th of August 2015 until 22nd of February 2018 and employing the vector autoregressive methodology. The daily returns are calculated as the difference in the log of prices. However, a daily range-based volatility is considered, similar to Diebold and Yilmaz (2016). Their results reveal that the dominant transmitter of return spillover is Litecoin followed by Bitcoin. However, the largest receiver of return spillover is Ethereum followed by Dash and Ripple. Furthermore, when they split the returns into positive and negative returns, they show that the cryptocurrencies are connected more strongly through negative returns. Additionally, they show that Ethereum and Ripple are the top receivers of negative return shocks whereas Litecoin and Bitcoin are the top transmitters of negative return shocks. Regarding volatility spillovers, Bitcoin is the largest transmitter of volatility spillovers followed by Litecoin. However, Ethereum and Stellar the two largest receivers of volatility spillovers. Moreover, Litecoin seems to have a strong influence on other cryptocurrencies. Finally, they demonstrate that Dash is very weakly connected with other cryptocurrencies in terms of volatility spillover meaning that it can be used as a hedging tool in the cryptocurrency market.

Many other articles have focused on the multivariate GARCH models to check for volatility spillovers among cryptocurrencies. For instance, Katsiampa (2018) uses the bivariate diagonal Baba-Engle-kraft-kroner (BEKK)-GARCH model to study the volatility co-movement between Bitcoin and Ethereum. He uses daily price returns from 7th of August 2015 until 15th of January 2018. The author states that the conditional covariance of the two cryptocurrencies is found to be significantly affected by both cross-products of previous news/shocks and previous covariance terms. Thus, he concludes that there is a bi-directional volatility spillover between Bitcoin and Ethereum. Similarly, Katsiampa (2019) employs an asymmetric diagonal BEKK-GARCH model to examine the volatility co-movement between the five cryptocurrencies which are Bitcoin, Ethereum, Ripple, Litecoin and Stellar Lumen using daily data from 7th of August 2015 until 10th of February 2018. They find that the covariances of the cryptocurrencies are affected by both cross products of previous terms and previous conditional covariances. Consequently, they conclude that volatility co-movement exists between the cryptocurrencies. In the same context, Katsiampa et al. (2019a) use eight cryptocurrencies namely Bitcoin, Ethereum, Litecoin, Dash, Ethereum Classic, Monero, Neo and OmiseGo to examine their interlinkages and conditional correlations. They employ the asymmetric BEKK-MGARCH model with an intra-day data spanning from 15th of September 2017 until 1st of July 2018. Their findings reveal that the conditional covariances are affected by both cross product of past error terms and past conditional covariance terms indicating volatility co-movement and consequently interlinkage between the cryptocurrencies. Moreover, Beneki et al. (2019) use a multivariate BEKK-GARCH and a VAR model with daily data from 8th of August 2015 until 10th of June 2018 to study the volatility transmission between Bitcoin and Ethereum. Their findings show that there exists unidirectional volatility spillover from Ethereum to Bitcoin. From the same point of view, Katsiampa et al. (2019b) study the volatility spillover between Bitcoin, Ethereum and Litecoin by adopting a bivariate BEKK model and by using daily data from 7th of August 2015 until 10th of July 2018. They find that there are bi-directional shock spillovers between Bitcoin and both Ethereum and Litecoin and a uni-directional shock spillover from Ethereum to Litecoin. Specifically, they state that for the Bitcoin-Ethereum pair, past news about shocks in Bitcoin positively affects the current conditional volatility of Ethereum while previous shocks of Ethereum have negative impact on the current volatility of Bitcoin. On the other hand, in the case of the Bitcoin-Litecoin pair, lagged shocks in one cryptocurrency negatively affects the current conditional volatility of the other.

Other techniques have also been adopted by authors to study the co-movements between cryptocurrencies. For instance, Aslanidis et al. (2019) use a generalized dynamic conditional correlation model to study the relation between the four most popular cryptocurrencies (Bitcoin, Dash, Monero and Ripple) from 21st of May 2014 until 27th of September 2018. They show that positive correlations exist among the cryptocurrencies, but these correlations differ across time. They also demonstrate that Monero has the most stable correlation across time with every cryptocurrency. Thus, they conclude that cryptocurrencies are interrelated. Another technique used by Mensi et al. (2019) is the wavelet coherence and cross wavelet transform approaches to study co-movements between Bitcoin and major cryptocurrencies. The authors perform the analysis on Dash, Ethereum, Litecoin, Monero and Ripple from 28th of April 2014 until 22nd of January 2018. They identify leading relationships of Bitcoin with Dash, Monero and Ripple, lagging relationship with Ethereum and out-of-phase movements with Litecoin which indicates that the cryptocurrencies are interrelated. Another technique employed by Stosic et al. (2018) and Song et al. (2019) is the agglomerative hierarchical clustering and minimum spanning tree to analyze the structure of the cryptocurrency market before and after filtering the Bitcoin-Ethereum pair. Song et al. (2019) select 76 cryptocurrencies with hourly data from December 2017 until March 2018. Before the filtering process, their findings indicate that a structure of only two clusters appear where most of the cryptocurrencies are connected to Bitcoin and Ethereum. After they eliminate the influence of Bitcoin and Ethereum, they observe six homogenous clusters. They conclude that cryptocurrencies are correlated and that Bitcoin and Ethereum lead the market as major assets.

In line with all previous studies related to volatility co-movements and spillovers between cryptocurrencies, Shi et al. (2020) apply a technique called the multivariate factor stochastic volatility model (MFSVM) with the Bayesian estimation technique to study the correlations between six cryptocurrencies namely, Bitcoin, Dash, Ethereum, Litecoin, Ripple and Stellar. They use daily price returns for a period spanning from 8th of August 2015 until 1st of January 2020. They find that there is a positive correlation between the price volatility of Bitcoin and Litecoin. Furthermore, the volatility of Ethereum is positively correlated with both Ripple and Stellar. Additionally, their results show that there is a positive correlation between the volatility of Ripple and Dash. At the end, they conclude that Ethereum is connected with Ripple, Dash and Stellar whereas Bitcoin is related to Litecoin.

Table 2.1: Summary of Previous Studies

The following table represents a summary of the literature review.

Source	Cryptocurrencies	Sample Period	Main Results
Ciaian et al. (2017)	Ethereum, Ripple, Litecoin, Monero, Dash, Nem, Dogecoin, Peercoin, Namecoin, Novacoin, Nxt, Counterparty, Mintcoin, Qora, Supernet and Bitshares	2013-2016	The cryptocurrencies are interrelated in the short- and long-run.
Stosic et al. (2018)	119 cryptocurrencies	26th of August 2016 until 18th of January 2018	The cryptocurrencies are correlated.
Naimy et al. (2018)	Bitcoin	1st of April 2013 until 31st of March 2016	EGARCH (1,1) outperforms GARCH (1,1) and EWMA when forecasting the volatility of the Bitcoin/USD exchange rate.
Koutmos (2018)	18 cryptocurrencies	7th of August 2015 until 17th of July 2018 Return: log of the price return Volatility: Parkinson (1980) estimator	The cryptocurrencies are connected through return and volatility spillovers.
Corbet et al. (2018)	Bitcoin, Ripple and Litecoin	2013 until the end of July 2017 Return: daily log changes Volatility: 5-day standard deviation	The cryptocurrencies are related through return and volatility spillovers.

Ji et al. (2018)	Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Dash	7th of August 2015 until 22nd of February 2018 Return: Difference in the log of prices Volatility: Daily range-based volatility of Diebold and Yilmaz (2016)	The cryptocurrencies are connected through return and volatility spillovers.
Katsiampa (2018)	Bitcoin and Ethereum	7th of August 2015 until 15th of January 2018	Bi-directional volatility spillover between Bitcoin and Ethereum.
Katsiampa (2019)	Bitcoin, Ethereum, Ripple, Litecoin and Stellar Lumen	7th of August 2015 until 10th of February 2018	Volatility co-movement exists between the cryptocurrencies.
Katsiampa et al. (2019a)	Bitcoin, Ethereum, Litecoin, Dash, Ethereum Classic, Monero, Neo and OmiseGo	15th of September 2017 until 1st of July 2018	Volatility co-movement exists between the cryptocurrencies.
Beneki et al. (2019)	Bitcoin and Ethereum	8th of August 2015 until10th of June 2018	Unidirectional volatility spillover from Ethereum to Bitcoin.
Katsiampa et al. (2019b)	Bitcoin, Ethereum and Litecoin	7th of August 2015 until 10th of July 2018	Bi-directional shock spillovers between Bitcoin and both Ethereum and Litecoin and a uni-directional shock spillover from Ethereum to Litecoin.
Aslanidis et al. (2019)	Bitcoin, Dash, Monero and Ripple	21st of May 2014 until 27th of September 2018	The cryptocurrencies are correlated.
Mensi et al. (2019)	Dash, Ethereum, Litecoin, Monero and Ripple	28th of April 2014 until 22nd of January 2018	The cryptocurrencies are interconnected.
Song et al. (2019)	76 cryptocurrencies	December 2017 until March 2018	The cryptocurrencies are interrelated.
Shi et al. (2020)	Bitcoin, Dash, Ethereum, Litecoin, Ripple and Stellar	8th of August 2015 until 1st of January 2020	The cryptocurrencies are connected through return and volatility spillovers.

In conclusion, despite that previous studies have employed a broad range of methodologies to study the interconnection between cryptocurrencies, including the vector autoregression technique which is used to study return and volatility spillovers between assets, only few studies have focused on the volatility spillover within the cryptocurrency market by using univariate GARCH techniques to model the volatility of every cryptocurrency. For instance, Koutmos (2018) used Parkinson (1980) estimator to calculate the variance of the price returns of the cryptocurrencies. Moreover, Corbet et al. (2018) employed 5-day standard deviation and Ji et al. (2010) utilized the daily range-based volatility of Diebold and Yilmaz (2016). But to the best of our knowledge, few studies used GARCH-VAR modeling techniques in studying volatility spillovers among cryptocurrencies. Thus, this research fills the gap in addition to the use of larger data samples than previous studies for more exact results.

2.5.2. BEHAVIOR OF CRYPTOCURRENCIES WITH OTHER FINANCIAL ASSETS (DIVERSIFIER, HEDGE OR SAFE HAVEN)

According to Ciner et al. (2012), studying the interconnection of cryptocurrencies with other financial instruments is of extreme importance for investors because their portfolio's performance is based on its components and their co-movements.

In this sense, Baur and McDermott (2010) distinguish between diversifiers, hedges and safe havens. They report that if two assets are positively correlated, each of the two assets can be considered as a diversifier. Additionally, an asset acts as a weak hedge if it is uncorrelated with another asset while it is considered as a strong hedge if it is negatively correlated with another asset. Finally, they state that a weak (strong) safe haven is an asset that is uncorrelated (negatively correlated) with another asset during times of market turmoil.

Previous studies have shown the existence of many safe haven assets in the financial market. One of the most popular of them is gold. Among the many research papers that have shown the safe haven behavior of gold are Baur and Lucey (2010), Reboredo (2013) and Baumöhl et al. (2017). However, the literature on the hedging and/or safe haven properties of cryptocurrencies is still scarce. The research on cryptocurrencies has mainly focused on the hedge and/or safe haven properties of Bitcoin, the most prominent cryptocurrency.

From this angle, Dyhrberg (2015a) explores the properties of Bitcoin using GARCH models. The daily data spans from 19th of July 2010 until 22nd of May 2015. The assets included in the study are gold cash, gold futures, USD/EUR, USD/GBP, FTSE index and the federal funds rate. Their results show that Bitcoin have hedging capabilities against the

US dollar. Moreover, they demonstrate that Bitcoin returns and the FTSE index are positively correlated. Finally, they prove that a positive volatility shock to USD/GBP decreases the volatility of Bitcoin returns indicating that Bitcoin acts as a safe haven asset against USD/GBP. Similarly, Dyhrberg (2015b) uses the threshold GARCH model to study the hedging capabilities of Bitcoin against USD/EUR, USD/GBP and FTSE index. He uses daily data from 19th of July 2010 to 22nd of May 2015. His findings reveal that Bitcoin and the stocks in the FTSE index are uncorrelated giving Bitcoin hedging ability against the stocks in the index. Similarly, Bitcoin can also be used as a hedge against the US dollar in the short-run since the results show that Bitcoin is uncorrelated with USD/EUR and USD/GBP.

In the same context, Bouri et al. (2016) use dynamic conditional correlation models followed by quantile regression to study the hedge and safe haven properties of Bitcoin against S&P500, FTSE100, DAX30, NIKKEI225, Shanghai A-share, Morgan Stanley Capital International (MSCI) World, MSCI Europe, MSCI Pacific, Pimco Investment Grade Corporate bond index Exchange-Traded Fund (ETF), US dollar index, Standard and Poor's Goldman Sachs (SPGS) commodity index, brent crude oil and gold spot prices. They use daily and weekly price returns from 18th of July 2011 until 22nd of December 2015. Their results show that, when performing the analysis using daily data, Bitcoin cannot be considered as a weak or strong safe haven against extreme movements in any of the assets under study. They state that Bitcoin can only be considered as an effective diversifier for Asia Pacific stocks and brent crude oil. Moreover, they declare that Bitcoin is a strong hedge for the Japanese stocks, the Asia Pacific stocks and the commodity index. Next, using weekly data, they show that Bitcoin can be regarded as a strong safe haven against extreme movements in Chinese stocks and Asia Pacific stocks. They also demonstrate that Bitcoin can be considered as a strong hedge for Chinese stocks but only acts as a diversifier for the remaining indices except for Japanese and Asia Pacific stocks.

In line with all previous studies examining the hedging and/or safe haven properties of Bitcoin, Bouri et al. (2017) study the capability of Bitcoin to be a diversifier, hedge or safe haven against commodities in general, energy commodities and non-energy commodities. These commodities are represented by the S&P GSCI, the S&P GSCI energy commodities index and the S&P GSCI non-energy commodities index. The methodology used in their study is the pairwise dynamic conditional correlations followed by regression analysis. They use a sample of daily data from 18th of July 2010 to 28th of December 2015 and divide it into two sub-samples (before and after the December 2013 crash). For the entire period, Bitcoin shows to be a strong hedge against commodities in general and energy commodities and is no more than a diversifier for non-energy commodities. However, for the pre-crash period, they demonstrate that Bitcoin is a hedge for commodities and energy commodities whereas it is just a diversifier for non-energy commodities. Finally, after the Bitcoin crash of December 2013, they reveal that Bitcoin is just a diversifier for commodities in general, energy commodities and non-energy commodities.

Moreover, Baur et al. (2017) study the interrelation of Bitcoin with traditional assets including S&P500, EUR/USD, AUD/USD, JPY/USD, GBP/USD, CNY/USD, and HUF/USD. They use daily price returns from July 2010 until July 2015 for Bitcoin and S&P500 whereas they use daily realized volatility across the currency pairs using 5-min midpoint quotes. Their results show that Bitcoin does not act as a hedge or as a strong safe haven to foreign exchange volatility returns and S&P500 returns. Their findings only reveal that Bitcoin is uncorrelated to foreign exchange volatility and S&P500. Moreover, using three types of events dates (financial, Natural and terrorism/war), they show that Bitcoin and S&P500 are positively correlated during the natural disaster. Moreover, they find that Bitcoin and S&P500 are negatively correlated during the terrorism/war event suggesting that there is a weak safe haven effect during this event. In line with Baur et al. (2017), Chan et al. (2018) examine the hedging capability of Bitcoin against different indices including EuroSTOXX, NIKKEI225, Shanghai A-Share, S&P500 and the TSX indices over different data frequencies. They apply GARCH and constant conditional correlation on daily, weekly and monthly returns from October 2010 until October 2017. They demonstrate that Bitcoin is a strong hedge for all the indices considered under monthly return. But for daily and weekly returns, Bitcoin is only a weak hedge.

However, in contrast with all previous studies which focus mainly on studying the properties of Bitcoin against mainstream assets, Corbet et al. (2018) and Baumöhl (2018) extend the previous work to include other cryptocurrencies. Corbet et al. (2018) for example, study the hedging potential of Bitcoin, Ripple and Litecoin with MSC GSCI total return index, the US$ broad exchange rate, S&P500 and the COMEX gold price using the vector autoregression model and a daily data sample spanning from 2013 until end of July 2017. They demonstrate that the correlations between the cryptocurrencies and the assets are very low which means that cryptocurrencies can be used as hedges against the traditional assets. Baumöhl (2018), on the other side, studies the relationship between the six largest market capitalization cryptocurrencies namely, Bitcoin, Ethereum, Ripple, Litecoin, Stellar Lumens and Nem and the six largest forex currencies: Euro, Japanese Yen, British Pound, Swiss Franc, Canadian Dollar and Chinese Yuan using daily data from the

1st of September 2015 until 29th of December 2017. He uses the quantile cross-spectral approach. He identifies negative relations between the forex currencies and cryptocurrencies in both the short- and long-run. Thus, he concludes that cryptocurrencies can be used as hedges against forex currencies.

In the same spirit, Aslanidis et al. (2019) explore the connectedness between four cryptocurrencies which are Bitcoin, Dash, Monero and Ripple and three traditional assets namely, S&P500, S&P US Treasury bond 7-10Y index and Gold Bullion LBM using a generalized dynamic conditional correlation model. The daily data sample spans from 21st of May 2014 until 27th of September 2018. They find that correlations between the cryptocurrencies and the assets are negligible. They also show that the correlation of the assets with Monero is even closer to zero than against other cryptocurrencies. Consequently, they conclude that cryptocurrencies can be used as hedges against the traditional assets. Similarly, Tiwari et al. (2019) examine the time-varying correlations between six cryptocurrencies namely, Ripple, Dash, Stellar, Litecoin, Ethereum and Bitcoin and S&P500 using a copula-ADCC-EGARCH model. The daily data spans from 7th of August 2015 until 15th of June 2018. Their results reveal that overall time-varying correlations are extremely low, indicating that the cryptocurrencies serve as a hedge asset against the risk of S&P500. They also show that volatilities respond more to negative shocks as compared to positive shocks in both markets. Furthermore, they identify Litecoin to be the most effective hedge asset against risk of S&P500.

In parallel with Aslanidis et al. (2019) and Tiwari et al. (2019), Bouri et al. (2019) study the hedging and safe haven properties of eight cryptocurrencies against down movements in the S&P500. They use daily data for eight cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, Nem and Monero) and S&P500 from 7th of August 2015 until 4th of May 2018. Their results show that Bitcoin, Ripple, Litecoin, Stellar and Monero act as a safe haven for the S&P500. However, for Ethereum, Dash and Nem, they are neither a hedge nor a safe haven for the S&P500.

In line with Dyhrberg (2015a) and other authors examining the properties of Bitcoin, the most prominent cryptocurrency so far, Urquhart et al. (2019) study its relationship with six traditional currencies employing an asymmetric dynamic conditional correlation model and OLS regression analysis using intraday data from 1st of November 2014 until 31st of October 2017. They identify Bitcoin as an intraday hedge for Swiss Franc, Euro and British Pound but state that it acts as a diversifier for Australian Dollar, Canadian Dollar and Japanese Yen. They also use the non-temporal threshold regression to prove that Bitcoin is a safe haven during periods of extreme market turmoil for the Canadian Dollar, Swiss Franc and British Pound. Moreover, Kurka (2019) studies the transmission of shocks between traditional assets and Bitcoin. The assets include gold and crude oil, EUR/USD, JPY/USD, S&P500 and US 2-year T-note. The sample period ranges from July 2011 to December 2018. He uses the vector autoregression model to study the volatility spillover. For the unconditional overall connectedness, he finds that spillovers to and from Bitcoin are low which indicates that Bitcoin possess hedging capabilities against the other assets. However, when he performs a time-conditional spillover analysis, he shows that there are moments where there is a strong connection between Bitcoin and the traditional assets showing that Bitcoin is not always a hedge against the traditional assets. Thus, he concludes that the hedging property of Bitcoin is time dependent.

Consistent with the previous studies, Stensås et al. (2019) investigate whether Bitcoin acts as a diversifier, hedge or safe haven tool for investors in major developed and developing markets, as well as for commodities. They employ the GARCH dynamic conditional correlation model and daily observations from 13th of September 2011 until 1st of January 2018. The sample covers seven developed countries namely USA, UK, Japan, Italy, Germany, France and Canada represented by S&P500, FTSE100, NIKKEI225, FTSE MIB, DAX30, CAC40, S&PTSX60 respectively, and six developing countries namely Brazil, Russia, India, China, South Korea, and Zimbabwe represented by IBRX, MICEX10, NIFTY50, Shanghai A-Share, KOSPI, MSCI Zimbabwe respectively, five regional indices from MSCI to represent the World, BRIC, Asia, Pacific and European stocks and commodities which are oil, gold, cotton, corn, coffee and all wheat represented by Standard & Poor's Goldman Sachs (SPGS) World Commodity Index, London Metal Exchange (LME), Merrill Lynch Commodity Index Extra (MLCX) Agriculture and MLCX Energy. Their results show that Bitcoin is only an effective diversifier for investors in the developed market. They also demonstrate that Bitcoin acts as a strong hedge for investors in most of the developing countries such as Russia, India and South Korea and a weak hedge for Brazil. As for safe haven capability, Bitcoin does not appear as a safe haven for investors in most developed and developing countries. They find evidence of Bitcoin being a strong safe haven only for the US, Zimbabwe and Indian stock market. However, during times of crisis as the United States presidential election, Bitcoin acts as a strong safe haven for USA, France and South Korea stocks specially when uncertainties are built up in the days leading up to the US presidential election. Finally, they find that Bitcoin is a strong safe haven for USA, UK, Japan, Germany, France, China, and South Korea and a weak safe haven for all other countries around the Brexit referendum date.

Moreover, Bouri et al. (2020) study the safe haven properties of Bitcoin against world, developed, emerging, USA and Chinese stock market indices using log price returns covering the period of 20th of July 2010 until 22nd of February 2018. Using the wavelet coherence, their results show that Bitcoin is not correlated with all stock indices for the whole period analyzed over almost all frequencies. Therefore, they state that Bitcoin can be considered as a safe haven asset.

However, extending the study to include other cryptocurrencies than Bitcoin, Yen et al. (2020) use regression analysis to investigate the relationship between the economic policy uncertainty index (EPU) of China, United States, Japan and Korea and Bitcoin's, Litecoin's and Ripple's volatility. The daily data used in the analysis spans from February 2014 to June 2019. They show that Bitcoin, Litecoin and Ripple can be used as hedging tools against China's EPU risk since changes in the China's EPU are negatively associated with Bitcoin's and Litecoin's volatility and not correlated with Ripple's volatility. Finally, Okorie et al. (2020) examine the volatility spillover between crude oil spot prices and ten cryptocurrencies which are Bitcoin, Ethereum, Ripple, Bitcoin Cash, Litecoin, Elastos, ReddCoin, BitCapitalVendor, and Stratis. The daily data spans from 29th of April 2013 until 17th of September 2019. Using VAR – MGARCH – BEKK techniques and the Wald tests, they find that crude oil and BitCapitalVendor have bidirectional volatility spillover. They also show that there is a unidirectional volatility spillover between crude oil and Bitcoin Cash. Finally, they demonstrate that Ethereum, Ripple and ReddCoin have unidirectional volatility spillover to crude oil. Furthermore, they state that there is a short-lived hedging capability between crude oil and Ethereum whereas the hedging capability between crude oil and Solve, Elastos and BitCapitalVendor is long-lived. Thus, they conclude that the cryptocurrency market is not completely isolated from the commodity markets. Furthermore, Conlon et al. (2020) examine the safe haven benefits of cryptocurrencies namely, Bitcoin, Ethereum and Tether during the covid-19 bear market against the MSCI world, the S&P500, the FTSE100, the FTSE MIB, the IBEX, and the CSI300 indices. Daily data are used from 11th of April 2019 until 9th of April 2020. The value at risk (VaR) and the expected shortfall (ES) are performed to measure potential losses in a portfolio. Their results reveal that Bitcoin and Ethereum do not act as a safe haven against the international equity markets while Tether is found to act as a safe haven against the traditional assets. In the same context, Bouri et al. (2020) examine the diversification ability of the leading cryptocurrencies namely Bitcoin, Ethereum, Ripple, Litecoin and Stellar against four MSCI equity indices of USA, Europe, Asia-Pacific excluding Japan, and Japan using daily data from 7th of August 2015 until 31st of July 2018. They employ DCC-GARCH model and find that Bitcoin is a hedge in USA, Asia-Pacific and Japan, Ethereum acts as a strong hedge in Asia-Pacific and Japan, Ripple is a hedge in Japan, Litecoin is considered as a hedge in Asia-Pacific in japan and Stellar is found to just be a diversifier against the studied indices. However, their results reveal that none of the cryptocurrencies can be considered as a safe haven against the equity indices. Additionally, in line with all previous studies tackling the properties of Bitcoin, Conlon and McGee (2020) examine the safe haven properties of Bitcoin against the S&P500 using daily return series from July 2010 until March 2020. Using the value at risk (VAR) methodology, they show that Bitcoin does not act as a hedge against the S&P500 index.

Table 2.2: Summary of Previous Studies

The following table represents the summary of the literature.

Source	Sample Period	Main Results
Dyhrberg (2015a)	19th of July 2010 until 22nd of May 2015	Bitcoin acts as a hedge against the US dollar and can be considered as a safe haven against USD/GBP.
Dyhrberg (2015b)	19th of July 2010 until 22nd of May 2015	Bitcoin acts as a hedge against the stocks in the FTSE index and the US dollar.
Bouri et al. (2016)	18th of July 2011 until 22nd of December 2015	Bitcoin only acts as a diversifier for Asia Pacific stocks and Brent crude oil, a strong hedge for the Japanese stocks, the Asia Pacific stocks and the commodity index.
Bouri et al. (2017a)	18th of July 2010 until 28th of December 2015	For the entire period, Bitcoin shows strong hedge capabilities against commodities in general and energy commodities. For the pre-cash period, Bitcoin acts as a hedge for commodities and energy commodities.
Baur et al. (2017)	July 2010 until July 2015	Bitcoin does not act as a strong safe haven to FX volatility returns and S&P500 returns.
Chan et al. (2018)	October 2010 until October 2017	Bitcoin is a weak hedge for EuroSTOXX, NIKKEI225, Shanghai A-share, S&P500 and the TSX indices under daily returns.
Corbet el al. (2018)	2013 - 2017	Bitcoin, Ripple and Litecoin act as hedges against MSC GSCI total return index, the US$ broad exchange rate, S&P500 and the COMEX gold price.
Baumöhl (2018)	1st of September 2015 until 29th of December 2017	Bitcoin, Ethereum, Ripple, Litecoin, Stellar Lumens and Nem act as hedges against the foreign currencies.
Aslanidis et al. (2019)	21st of May 2014 until 27th of September 2018	Bitcoin, Dash, Monero and Ripple can be used as hedges against S&P500, S&P US Treasury bond 7-10Y index and Gold Bullion LBM.
Tiwari et al. (2019)	7th of August 2015 until 15th of June 2018	Ripple, Dash, Stellar, Litecoin, Ethereum and Bitcoin serve as hedges against S&P500.

Bouri et al. (2019)	7th of August 2015 until 4th of May 2018	Bitcoin, Ripple, Litecoin, Stellar and Monero act as a safe haven for the S&P500 while for Ethereum, Dash and Nem, they are neither a hedge nor a safe haven for the S&P500.
Urquhart et al. (2019)	1st of November 2014 until 31st of October 201	Bitcoin is an intraday hedge for Swiss Franc, Euro and British Pound but acts as a diversifier for Australian Dollar, Canadian Dollar and Japanese Yen. Bitcoin is a safe haven during periods of extreme market turmoil for the Canadian Dollar, Swiss Franc and British Pound.
Kurka (2019)	July 2011 until December 2018	For the unconditional overall connectedness, Bitcoin possess hedging capabilities against gold and crude oil, EUR/USD, JPY/USD, S&P500 and US 2-year T-note. However, for the time-conditional spillover analysis, Bitcoin is not always a hedge against the traditional assets.
Stensås et al. (2019)	13th of September 2011 until 1st of January 2018	Bitcoin is a strong hedge in most of the developing countries such as Russia, India and South Korea, a weak hedge for Brazil and a strong safe haven only for the US, Zimbabwe and Indian stock market.
Bouri et al. (2020)	20th of July 2010 until 22nd of February 2018	Bitcoin acts as a safe haven against world, developed, emerging, USA and Chinese stock market indices.
Yen et al. (2020)	February 2014 until June 2019	Bitcoin, Litecoin and Ripple can be used as hedging tools against China's EPU risk.
Okorie et al. (2020)	29th of April 2013 until 17th of September 2019	Ethereum and crude oil show short-lived hedging capability while Solve, Elastos and BitCapitalVendor show long-lived hedging capability against crude oil.
Conlon et al. (2020)	11th of April 2019 until 9th of April 2020	Bitcoin and Ethereum do not act as a safe haven against the MSCI world, the S&P500, the FTSE100, FTSE MIB, IBEX and CSI300. However, Tether is found to act as a safe haven against the assets.
Conlon and McGee (2020)	July 2010 until March 2020	Bitcoin does not act as a safe haven against the S&P500 index.
Bouri et al. (2020)	Bitcoin, Ethereum, Ripple, Litecoin and Stellar	Bitcoin is a hedge in USA, Asia-Pacific and Japan, Ethereum acts as a strong hedge in Asia-Pacific and Japan, Ripple is a hedge in Japan, Litecoin is considered as a hedge in Asia-Pacific in japan and Stellar is found to just be a diversifier against the studied indices.

As a conclusion, since Ethereum has been the second largest cryptocurrency in terms of market capitalization and since all previous work has mainly focused on the hedging and/or safe haven properties of Bitcoin, we fill the gap in the literature by studying these properties for Ethereum as a future alternative hedging and/or safe haven tool to Bitcoin. We employ percentile regressions with crisis event interaction regressions which have not been used yet as a methodology in the few articles that have tackled the properties of Ethereum.

2.6. CONCLUSION

In this chapter, we first introduced the currency risk and the concept of blockchain which is the technology used in cryptocurrencies. Then, we gave a general background about cryptocurrencies, their types and their benefits compared with traditional fiat currencies. We then examined previous research studies that addressed co-movements between cryptocurrencies and their hedging and/or safe haven properties against mainstream assets. According to existing literature, the cryptocurrency market is strongly interconnected. Moreover, Bitcoin is found to be a hedge and/or safe haven against other financial instruments.

In the chapters to come, we will extend the previous work done on this topic, by studying the interconnectedness of the five largest cryptocurrencies in terms of market capitalization through a volatility spillover inspection in the first part. In the second part, we will seek the hedging and/or safe haven properties of Ethereum, one of the most prominent cryptocurrencies beside Bitcoin.

CHAPTER THREE: METHODOLOGY

3.1. INTRODUCTION

Chapter three addresses the methodology employed in studying the interconnection of cryptocurrencies through a volatility spillover inspection and in examining the hedging and/or safe haven properties of Ethereum, the second largest cryptocurrency in terms of market capitalization to date. In section two of this chapter, the philosophical dimension is discussed. Section three highlights the research orientation of the study. In section four, the research strategy is introduced. Section five develops the research hypotheses to be tested. Section six introduces the variables used in the study. Section seven pinpoints the diagnostic tests performed before the analyses. Section eight covers the empirical methodology applied in the analysis. Section nine covers the data sources. The sample size and sampling procedures are discussed in section ten. Finally, section eleven concludes this chapter.

3.2. PHILOSOPHICAL PARADIGM

Research philosophy refers to a system of beliefs and assumptions about the development of knowledge. Two core assumptions that portray philosophical approaches are ontology and epistemology. Ontology refers to assumptions about the "nature of reality" or the "study of being" (Holden and Lynch, 2004). Moreover, Bryman et al. (2011) declare that "ontological assumptions and commitments will feed into the ways in which research questions are formulated and research is carried out". Two extreme positions of ontology exist: objective realism and subjective solipsism. Objective realism assumes that there is a real truth in this world regardless of perceptions and beliefs. However, subjective solipsism believes in a different form of the truth depending on people's perception (Holden and Lynch, 2004).

Furthermore, epistemology refers to assumptions about knowledge, what constitutes acceptable, valid and legitimate knowledge, and how knowledge is communicated to others (Burnell and Morgan, 1980). Furthermore, Audi (2011) states that "Epistemology, or the theory of knowledge, is concerned with how we know what we know, what justifies us in believing what we believe, and what standards of evidence we should use in seeking truths about the world and human experience". Two major research philosophies under epistemology are positivism and interpretivism. Positivists believe that reality is stable and can be observed and described from an objective viewpoint i.e., the truth is only established through scientific method (Randall and Gibson, 1990). However, interpretivists aim to understand the interpretations and meanings people give to actions and focus on trying to gain an insight into the experiences of individuals and groups (Trochim, 2000).

This research aims to study the interconnectedness of cryptocurrencies through inspecting their volatility spillover and to examine the hedging and/or safe haven properties of Ethereum. It is perceived as an external independent reality that could be studied through the observation of data and computation of measurable proxies. Accordingly, this research has a tendency towards objective realism. Furthermore, this study approaches its research questions with a positivist epistemological stand because empirical data that is required for the analysis will be collected from trusted databases, observed and studied within the context of descriptive statistics. This will result in generating meaningful inferences which have been achieved through observations and direct measurements.

3.3. RESEARCH ORIENTATION

Research approach is defined as the way a researcher involves a certain theory in his/her research. The two basic approaches in research are deductive and inductive approaches of reasoning. The difference between the two types of approaches is that deductive reasoning starts with a theory or general idea, narrows it down into specific hypotheses which are tested through observations and measurement and draws out conclusions to confirm the theory or not, whereas inductive approach is the other way around. It starts with specific observations, then moves backward to formulating hypotheses towards generalizing theories. Thus, a deductive approach is called a “top-down” approach since it moves from a general idea to a more specific one. The inductive approach is called a “bottom-up” approach since it moves from specific observations towards broader generalizations or theories (Trochim, 2000).

This study follows the deducting approach of reasoning and thus begins with a theory. In the first part of the research which examines the volatility spillover between cryptocurrencies, a behavioral theory (or herding behavior) is adopted. According to Calderón (2018), prices of cryptocurrencies are driven by herding behavior. However, in the second part of the study in which the hedging and/or safe haven properties of Ethereum is considered, the investor’s decision whether to engage in a hedging and/or safe haven action is based on signaling theory. Then, based on the existing theories, hypotheses are developed and tested through building a research strategy. After statistically testing each hypothesis along with analyzing the results, conclusions are drawn to answer the proposed research questions.

3.4. RESEARCH STRATEGY

A research strategy is a plan set by the researcher to answer the research questions. In social research, there are many strategies adopted by researchers in their papers. The most common are surveys, case studies, experiments, action research, ethnography and archival. Based on the type of research and the strategy used, the researcher then selects the research methodology. The most prominent are questionnaires, interviews, participant observation, documents and content analysis (Trochim, 2000).

Moreover, any research can be conducted using a quantitative and/or qualitative approach depending on the research strategy and methodology used. A quantitative analysis uses mathematical procedures and algorithms to transform the raw data collected into outcomes able to test the hypotheses whereas qualitative analysis relies on describing and analyzing attitudes and beliefs. Therefore, quantitative analysis is objective, confirmatory and deductive in nature. However, qualitative analysis is subjective, exploratory and inductive (Atkinson, 2012).

In this sense, this research follows the archival strategy since it uses secondary data extracted from reliable databases. It also adopts the content analysis because it transforms the raw data collected into outcomes which are able to check the validity of the hypotheses. This is performed through a quantitative analysis whereby mathematical procedures and algorithms such as the generalized autoregressive conditional heteroskedasticity model followed by a vector autoregressive model (GARCH-VAR) and an OLS regression analysis with percentiles are used to transform the data into reliable and interpretable outputs.

3.5. HYPOTHESES DEVELOPMENT

This research tackles the interconnectedness of the five selected cryptocurrencies (Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin) and the behavior of Ethereum against the conventional foreign exchange currencies and traditional assets. Concerning the interconnectedness of cryptocurrencies, Koutmos (2018) shows that Bitcoin, Ethereum and Ripple volatilities are mainly affected by their own shocks. However, he states that Litecoin is affected by both its own shocks and by shocks from other cryptocurrencies. Moreover, Corbet et al. (2018) argue that Bitcoin and Ripple are mainly affected by their own shocks. But in contrast to Koutmos (2018), they find that Litecoin is only affected by its own shocks. Thus, the following hypothesis will be examined:

H_1: Bitcoin, Ethereum and Ripple are mainly affected by their own shocks, while Bitcoin Cash and Litecoin are affected by their own shocks and by shocks from other cryptocurrencies.

Moreover, Corbet et al. (2018) show that there is a bi-directional volatility spillover between Bitcoin, Ripple and Litecoin. Likewise, Katsiampa (2018) argue that a bi-directional volatility spillover exists between the two most prominent cryptocurrencies namely Bitcoin and Ethereum while Beneki et al. (2019) find a uni-directional volatility spillover from Ethereum to Bitcoin. In the same sense, Katsiampa et al. (2019b) find that there is a bi-directional spillover between Bitcoin and Litecoin. Moreover, they find that there is a uni-directional spillover from Ethereum to Litecoin. Thus, the following hypothesis will be tested:

H_2: There are bi-directional volatility spillovers among the five selected cryptocurrencies.

On the other hand, Koutmos (2018) states that Bitcoin is the most relevant transmitter of volatility shocks whereas Litecoin is the dominant receiver of volatility shocks. Similarly, Ji et al. (2018) find that Bitcoin is the largest transmitter of volatility spillover. However, unlike Koutmos (2018) they find that Ethereum is the dominant receiver of volatility spillover. Consequently, the following hypothesis will be developed:

H_3: Bitcoin is the dominant transmitter of volatility shocks whereas Ethereum is the most receiver of volatility shocks.

Concerning the hedging behavior of cryptocurrencies against foreign currencies, Dyhrberg (2015b) find that Bitcoin can be used as a hedge against the US dollar in the short-run since the results show that Bitcoin is uncorrelated with USD/EUR and USD/GBP. However, according to Baur et al. (2017), Bitcoin does not act as a hedge against EUR/USD, AUD/USD, JPY/USD, GBP/USD, CNY/USD and HUF/USD. Furthermore, consistent with Dyhrberg (2015b) and according to Baumöhl (2018), Bitcoin can be considered as a hedge against traditional currencies namely Euro, Japanese Yen, British Pound, Swiss Franc, Canadian Dollar and Chinese Yuan since a negative correlation exists between these currencies and Bitcoin. Similarly, Urquhart et al. (2019) find that Bitcoin can act as an intra-day hedge for Swiss Franc, Euro and British Pound but acts only as a diversifier for Australian Dollar, Canadian Dollar and Japanese Yen. Finally, Kurka (2019) believes that hedging capabilities exist between Bitcoin and EUR/USD and JPY/USD.

However, concerning the hedging behavior of cryptocurrencies against the traditional assets, Bouri et al. (2017) find that Bitcoin shows strong hedging capabilities against the commodities included in the S&P GSCI commodities index specially brent crude oil. However, Baur et al. (2017) show that Bitcoin does not act as a hedge against the stocks in the S&P500 index. In line with Bouri et al. (2017), and according to Corbet et al. (2018), Bitcoin, Ripple and Litecoin act as a hedge against gold and the US stock market because the correlations of the cryptocurrencies with the COMEX closing gold price and S&P500 index are very low. Furthermore, Chan et al. (2018) find that Bitcoin is a weak hedge against S&P500 under daily and weekly returns whereas it can be considered as a strong hedge under monthly returns. Moreover, Aslanidis et al. (2019) show that the correlations of Bitcoin, Ripple, Dash and Monero with gold bullion LBM and S&P500 are negligeable meaning that these cryptocurrencies can be used as hedges against gold and the US stocks. In the same context, Kurka (2019) finds that Bitcoin acts as a hedge against gold, crude oil and S&P500. Finally, Tiwari et al. (2019) show that Bitcoin, Ethereum, Ripple, Dash and Stellar can serve as hedges against S&P500. Based on the previous literature, the following hypothesis will be tested:

H_4: Ethereum acts as a hedge against the foreign exchange currencies and traditional assets.

Concerning the safe haven behavior of cryptocurrencies against foreign exchange currencies, Bouri et al. (2016) consider that Bitcoin cannot be used as a safe haven against the US dollar index. Likewise, Baur et al. (2017) find that Bitcoin does not act as a strong safe haven to the traditional currencies. However, Urquhart et al. (2019) show that Bitcoin is a safe haven during periods of extreme market turmoil for some currencies namely the Canadian Dollar, Swiss Franc and British Pound.

However, concerning the safe haven properties of cryptocurrencies against traditional assets, Bouri et al. (2016) and Baur et al. (2017) find that Bitcoin cannot be considered as a safe haven asset against the stocks in the S&P500 index. On the other hand, Bouri et al.

(2019) show that Bitcoin, Ripple, Stellar and Monero act as a safe haven for the S&P500 whereas Ethereum, Dash and Nem are not safe haven assets for the US market stocks. Consequently, the following hypothesis will be tested:

H_5: Ethereum does not act as a safe haven against the foreign exchange currencies and traditional assets.

3.6. VARIABLES MEASUREMENT

This research is mainly divided into two parts. In the first part, volatility spillovers between the five main cryptocurrencies in terms of market capitalization namely Bitcoin, Ethereum, Ripple, Tether and Bitcoin Cash are studied. But since Tether is a stable coin with a stable value of 1$ per Tether (Dollar-backed), then there is no need to consider it in the analysis as Song et al. (2019) removed it from their study. Instead, Litecoin is selected to replace it. Litecoin falls in the 6th rank in terms of market capitalization. The second part tackles the hedging and/or safe haven properties of Ethereum against traditional financial assets including currencies, stocks, bonds and commodities.

In studying the properties of Ethereum, we consider two main markets, which are the United States and European ones. In both the US and EU markets, we study the effects on Ethereum from the main currencies (EUR/USD, GBP/USD, AUD/USD, CHF/USD, CAD/USD and CNY/USD), S&P GSCI crude oil index and S&P GSCI gold index. However, S&P500 and BND ETF represent the US stock and bond markets, respectively while EuroSTOXX600 and IEAG ETF present the European stock and bond markets, respectively. Table 3.1 below presents a description of the variables.

Table 3.1: Description of Variables

This table represents the variables used in the analysis and their description.

Variables	Description
ETH	Ethereum
BTC	Bitcoin
XRP	Ripple
BCH	Bitcoin Cash
LTC	Litecoin
EUR/USD	Euro / United States Dollar
GBP/USD	Great Britain Pound / United States Dollar
AUD/USD	Australian Dollar / United States Dollar
CHF/USD	Swiss Franc / United States Dollar
CAD/USD	Canadian Dollar / United States Dollar
CNY/USD	Chinese Yuan / United States Dollar
S&P GSCI crude oil	Standard & Poors Goldman Sachs Commodity Index for crude oil
S&P GSCI gold	Standard & Poors Goldman Sachs Commodity Index for gold
S&P500	Standard & Poors 500 index
EuroSTOXX600	STOXX Europe 600 index
BND ETF	Vanguard Total Bond Market Index Fund ETF
IEAG ETF	IShares Barclays Capital Euro Aggregate Bond

3.7. DIAGNOSTIC TESTS

There are tests that should be applied to the data before running the analyses to ensure well-defined models and unbiased results. These tests include the Augmented Dickey-Fuller test for stationarity, the Jarque-Bera test for normality, the Pearson correlation matrix for multicollinearity, the ARCH test for heteroskedasticity and the Ljung-Box test for autocorrelation.

3.7.1. AUGMENTED DICKEY-FULLER TEST FOR STATIONARITY

The Augmented Dickey-Fuller test was first proposed by David Dickey and Wayne Fuller in 1979 (Dickey and Fuller, 1979). It is performed to check whether the time series has a unit root or not. A stationary time series is a series with a constant mean, constant variance and constant covariance for each given lag (Priestley et al., 1969).

A time series should be stationary because it could strongly affect the behavior and properties of the series. If a series is stationary, any shock to the system will disappear after a period of time that is, a shock at time t will have smaller effect in time t+1, then a smaller effect in time t+2 and so on. However, for a non-stationary time series, any shock will hold forever leading to incorrect results. Moreover, non-stationary times series could lead to "spurious regressions" which means valueless results even though the coefficients are significant and the regression has a high R^2 (Brooks, 2008).

Many tests are used to check for stationarity including KPSS, Philips Perron, ADF^{GLS}. In this research, the Augmented Dickey-Fuller test is used.

The Augmented Dickey-Fuller test is given by the following equation:

$$\Delta y_t = \psi y_{t-1} + \sum_{i=1}^{p-1} \alpha_i \Delta y_{t-i} + u_t$$

The test's hypotheses are:

$H_0 : \psi = 0 \rightarrow the\ time - series\ is\ non - stationary$

$H_1 : |\psi| < 0 \rightarrow the\ time - series\ is\ stationary$

If H_0 is rejected, the time series is stationary.

3.7.2. JARQUE-BERA TEST FOR NORMALITY

The Jarque-Bera test for normality was introduced by Carlos Jarque and Anil Bera in 1980 (Jarque and Bera, 1980). It is applied to a time series to check if it follows a normal distribution. According to the authors, a time series is normal if its distribution follows a bell shape, has a skewness equal to zero and a kurtosis equal to three.

There are many tests to check for the normality of the variables and the residuals such as Jarque-Bera test, Kolmogorov's test and Andersson Darling's test. In this research, we will perform the Jarque-Bera test.

The Jarque-Bera t-statistic is given by:

$$JB_{t-statistic} = n\left[\frac{Skewness^2}{6} + \frac{(Kurtosis - 3)^2}{24}\right]$$

where:

$$Skewness = \frac{E(x^3)}{\sigma^2}$$

$$Kurtosis = \frac{E(x^4)}{\sigma^4}$$

n: sample size

The test's hypotheses are given by:

H_0: $Skewness = 0, Kurtosis = 3 \rightarrow W = 0$ (Data is normal)

H_1: $Skewness \neq 0, Kurtosis \neq 3 \rightarrow W \neq 0$ (Data is not normal)

If the p-value of the test is significant (less than 1%, 5% or 10%), the null hypothesis is rejected and the data sample is not normal. Otherwise, it is normal.

3.7.3. PEARSON MATRIX FOR MULTICOLLINEARITY

Multicollinearity occurs when two or more independent variables are very highly correlated with each other. When multicollinearity occurs, the statistical inferences may not be reliable (Brooks, 2008).

One way to test for multicollinearity is to check the Pearson correlation between every pair of the independent variables.

$$Pearson\ correlation\ coefficient = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

X_i : observations of the variable "X"

Y_i : observations of the variable "Y"

$\bar{X}$: mean of variable "X"

$\bar{Y}$: mean of variable "Y"

According to Gujarati and Sangeetha (2007), a significant correlation value higher than 0.8 is a sign for the existence of multicollinearity. If multicollinearity exists, one way to solve the problem is to drop one of the collinear variables.

3.7.4. ARCH TEST FOR HETEROSKEDASTICITY

The ARCH test for heteroskedasticity was first suggested by Robert Engle in 1982 and is similar to the Lagrange multiplier (LM) test for autocorrelation. The ARCH test is used to check if the variance of the residuals is constant or time-varying (Engle, 1982).

The ARCH test is applied to the following error equation:

$$u_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_q u_{t-q}^2 + v_t$$

□ □−□ □

The null and alternative hypotheses are:

$□_0$: $□_1 = 0$ □□□ $□_2 = 0$ □□□ $□_□ = 0$ → □h□ □□□□□□□□□□ □□□ h□□□□□□□□□□□□□□

$□_1$: $□_1 \neq 0$ □□ $□_2 \neq 0$ □□ $□_□ \neq 0$ → □h□ □□□□□□□□□□ □□□

h□□□□□□□□□□□□□□□

If the p-value of the test is less than the significance level (1%, 5% or 10%), the null hypothesis is rejected and the residuals are heteroskedastic. If an ARCH effect exists, ARCH (q) model can be estimated to model the volatility of the residuals.

3.7.5. LJUNG-BOX TEST FOR AUTOCORRELATION

The Ljung-Box test was first proposed by Greta Ljung and Georges Box in 1978. It is used to check if there is any autocorrelation in the residuals of a time series (Ljung and Box, 1978).

The Ljung-Box statistic is:

$$LB_{Q-statistic} = n(n+2)\sum_{m=1}^{h}(n-m)^{-1}\rho^{2}(m)$$

where:

n: sample size

h: number of lags

$\rho^{2}(m)$: sample autocorrelation at lag m

The null hypothesis for the test is:

H_0 : There is no autocorrelation in the residuals

H_1 : There is autocorrelation in the residuals

If the p-value of the test is less than the significance level (1%, 5% or 10%), the null hypothesis is rejected and the residuals are autocorrelated. Otherwise, they are not autocorrelated.

3.8. EMPIRICAL METHODOLOGY

In this section, we present the econometric models used in this research. In the first part, we employ the general autoregressive conditional heteroskedasticity (GARCH) to model the variance of the cryptocurrencies followed by a vector autoregressive model (VAR) to study volatility spillovers among cryptocurrencies. In the second part, we apply the ordinary least squares regression with percentiles along with the event crisis interaction to seek the hedging and/or safe haven capabilities of Ethereum.

3.8.1. UNIVARIATE GARCH MODELS

The Autoregressive Conditional Heteroskedasticity (ARCH) model was introduced by Robert Engle in 1982 to model the time-varying volatility of assets. It is based on the idea that the time-varying volatility of any asset today may be affected by information from the past. He proposed the first model which is the ARCH (q) model. It states that the conditional variance of the residuals depends on its own previous squared error terms (Engle, 1982).

Consequently, the variance equation would look like:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

The conditional variance (h_t) should be positive and stable. It is positive if $\alpha_i \geq 0$ for $i = \{0, \dots, q\}$ and stable if $\sum_{i=1}^{q} \alpha_i < 1$.

Moreover, the ARCH (q) model proposed by Robert Engle was extended by Tim Bollerslev to the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model which states that the conditional variance is affected by its own previous squared residuals and its own previous lags (Bollerslev, 1986).

The variance equation for a GARCH (p, q) is:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$$

Similar to ARCH (q), the conditional variance (h_t) of GARCH (p, q) should be positive ($\alpha_i \geq 0$ for $i = \{0, \dots, q\}$, $\beta_j \geq 0$ for $j = \{1, \dots, p\}$) and stable $(\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j) < 1$).

Furthermore, an extension of the GARCH (p, q) is the EGARCH (p, q) model introduced by Nelson in 1991. It transforms the conditional variance in "log". This relaxes the non-negativity constraint because log (h_t) becomes always positive (Nelson, 1991).

The variance equation for an EGARCH (p, q) is:

$$\log(h_t) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left|\sqrt{\frac{\varepsilon_{t-i}^2}{h_{t-i}}}\right| + \sum_{j=1}^{p} \beta_j \log(h_{t-j})$$

The EGARCH (p, q) model is symmetric like GARCH (p, q). To account for leverage effect in an EGARCH (p, q), the equation becomes:

$$\log(h_t) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left|\sqrt{\frac{\varepsilon_{t-i}^2}{h_{t-i}}}\right| + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{k=1}^{r} \gamma_k \sqrt{\frac{\varepsilon_{t-k}^2}{h_{t-k}}}$$

□−□

If negative shocks have greater impact than positive shocks, then all □′□ should be negative.

Finally, the GJR-GARCH (p, q) extends the GARCH (p, q) model to account for leverage effect. Hence, it is an asymmetric GARCH (p, q). It was introduced by Lawrence Glosten, Rave Jagannathan and David Runkle in 1993 (Glosten et al., 1993).

The variance equation for a GJR-GARCH (p, q) is:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{i=1}^{q} \gamma_i (\varepsilon_{t-i}^2 \times I_{t-i})$$

where $I_{t-i} = 1$ if $\varepsilon_{t-i} < 0$, 0 otherwise.

If negative shocks have greater impact than positive shocks, all $\gamma' s$ should be positive.

3.8.2. VECTOR AUTOREGRESSION MODEL (VAR)

Vector autoregression models were popularized by Christopher Sims in 1972 (Brooks, 2008). It is a system of regressions with more than one dependent variable. Each dependent variable is regressed on its own lags and the lag of the other dependent variables. Thus, a VAR model allows to study the effects that lagged values of a given dependent variable and the lagged values of all other variables have on that dependent variable (Sims, 1972).

The variance decomposition in VAR is used to check for volatility spillovers among variables. It gives the proportion of the movements in the dependent variables that are due to their own shocks, versus shocks to the other variables (Brooks, 2008).

In this research, different GARCH models will be estimated and a battery of selection criteria (Akaike info criterion, Schwarz criterion, Hannan-Quinn criterion, log likelihood, RMSE, MAE and MAPE) will be considered in order to select the best model. Then utilizing the VAR framework of Diebold and Yilmaz (2009) and Koutmos (2018), we check whether volatility spillovers exist among cryptocurrencies.

3.8.3. OLS REGRESSION WITH PERCENTILES

A regression analysis describes and evaluates the relationship between a given variable Y_i, called the dependent variable, and one or more other variables X_i, called the independent variables. Basically, the relation between Y_i and X_i is not completely linear. The objective of the regression is to find a line that correctly approximates all the observations while minimizing the errors. This can be achieved through the ordinary least squares (OLS) method. The main aim of this method is to decrease the distance between the data of the sample and the best fitted line, and thus minimize the sum square of errors.

The simplest form of a linear regression model is:

$$Y_i = \alpha + \beta X_i + \varepsilon_i$$

where:

Y_i: the dependent variable

X_i : the independent variable

□: the intercept

□: the coefficient of the regressor

$□_{□}$: the

residual

Thus, the purpose of the OLS is to estimate □ and □ in the regression equation in order to minimize the sum square of residuals (SSR).

$$SSR = \sum (y_i - (a + bx_i))^2 = \sum_i \varepsilon_i^2$$

Therefore, it can be shown that to minimize SSR, "a" and "b" are given by:

$$a = \frac{\sum y_i \sum (x_i)^2 - \sum (x_i y_i) \sum x_i}{n \sum (x_i^2) - \left(\sum x_i\right)^2}$$

$$b = \frac{\sum (x_i - \bar{x}) y_i}{\sum (x_i - \bar{x}) x_i}$$

In studying the hedging and/or safe haven properties of Ethereum against traditional assets and foreign exchange currencies in both US and EU markets, we develop a variation of a model used by Baur et al. (2017).

The first equation studies the US market and includes Ethereum as the dependent variable and the average volatility of the traditional currencies (EUR/USD, GBP/USD, AUD/USD, CHF/USD, CAD/USD and CHY/USD) called FXVol, S&P500, BND ETF, S&P GSCI crude oil and S&P GSCI gold as independent variables. Concerning the control variables, Baur et al. (2017) used the lagged values of Bitcoin in their developed model as a control variable whereby Bitcoin is the dependent variable. Moreover, Ciaian et al. (2017), Koutmos (2018) and Mensi et al. (2019) among others showed that there is a relationship between Bitcoin returns and Ethereum returns. Therefore, we use the Bitcoin returns and the lagged values of Ethereum returns as control variables. For the EU market, the same independent and control variables are used except that we select EuroSTOXX600 and IEAG ETF to represent the European stock and bond markets, respectively.

***Equation 1*: (US market)**

[illegible]

***Equation 2* : (EU market)**

[illegible]

where:

□□□□□□□: daily Ethereum returns

□□□□□l□: average daily realized volatility across EUR/USD, GBP/USD,

AUD/USD,

CHF/USD, CAD/USD and CHY/USD pairs using R-squared volatility.

□□□□□□: daily S&P500 returns

□□□□□□□□□X□□□□: daily EuroSTOXX600 returns

□□□□: daily BND ETF returns

□□□□□: daily IEAG ETF returns

□&□□□□□□□□□□□□□□□□: daily S&P GSCI crude oil returns

□&□□□□□□□□l□□: daily S&P GSCI gold returns

□□□□□□□: Bitcoin returns used as a control variable

□□□□□□□□−□: lagged values of Ethereum returns used as a control variable

□□□□□X□□l, □□□□□X□□l and □□□□□□X□□l: indicator variables that take a value of 1 for days

where

FX volatility are in the 90th, 95th and 99th percentiles and 0 otherwise. These represent the

days when volatility is the highest.

□□□□&P□□□, □□□&P□□□ and □□□&P□□□: indicator variables that take a value of 1 for days when the S&P500 returns are in the 10th, 5th and 1st percentiles and 0 otherwise. They represent

the days when the return is the lowest.

□, □ and □: indicator variables that take a value of 1 for days when the EuroSTOXX600 returns are in the 10th, 5th and 1st percentiles and 0 otherwise. They represent the days when the return is the lowest.

□, □ and □: indicator variables that take a value of 1 for days when the BND ETF returns are in the 10th, 5th and 1st percentiles and 0 otherwise. They represent the days when the return is the lowest.

□, □ and □: indicator variables that take a value of 1 for days when the IEAG ETF returns are in the 10th, 5th and 1st percentiles and 0 otherwise. They represent the days when the return is the lowest.

□, □ and □: indicator variables that take a value of 1 for days when the S&P GSCI crude oil returns are in the 10th, 5th and 1st percentiles and 0 otherwise. They represent the days when the return is the lowest.

□, □ and □: indicator variables that take a value of 1 for days when the S&P GSCI gold returns are in the 10th, 5th and 1st percentiles and 0 otherwise. They represent the days when the return is the lowest.

Similar to Baur and McDermott (2010) and Baur et al. (2017), the results are interpreted as follows: Ethereum returns act as a hedge for the financial assets if $□_0$ is positive and statistically significant, while $□_0$, $□_0$, $□_0$ and $□_0$ are negative and statistically significant. However, Ethereum acts as a safe haven for all assets if $□_1$, $□_2$ or $□_3$ is positive and statistically significant, $□_1$, $□_2$ or $□_3$ is negative and statistically significant, $□_1$, $□_2$ or $□_3$ is negative and statistically significant, $□_1$, $□_2$ or $□_3$ is negative and statistically significant and $□_1$, $□_2$ or $□_3$ is negative and statistically significant.

Crisis Events Interaction Analysis

To further examine the capabilities of Ethereum as a safe haven against the assets during times of market turmoil, we employ regressions with different events similar to the framework of Baur et al. (2017) and Stensås et al. (2019). We select three specific events that have caused market turmoil during the sample period. The first event is the United States presidential election of 2016 that took place on 8 November 2016. During the presidential election, the financial markets dropped considerably. Wagner et al. (2018) state that the prices of stocks, bonds and exchange rates fell significantly. Furthermore, according to Mullen et al. (2016), Heng Seng index fell by 2.2% and Japan's NIKKEI plunged by 5.4%, when the election's result was announced. The second event examines the Brexit referendum held on 23 June 2016. According to Davidson et al. (2016), U.S. stocks fell 5% as investors were worried about possible disrupted trade relationships with Europe and other countries after the Brexit. Moreover, Poljak (2016) states that global financial markets experienced their worst day on Brexit since the global financial crisis leaving the British pound at its lowest levels since 1985. He announces that the S&P/ASX200 index fell 3.2%, the 10-year US treasury yields dropped to below 1.5% and the Australian yields dropped below 2%. Finally, the last event that created global uncertainty is covid-19 which was declared a pandemic on 11 March 2020. According to Sindreu (2020), during the pandemic, S&P500 fell by 20% in the first quarter of 2020 and U.S. stocks dropped down by 4% during the first six months of 2020. Finally, Treanor et al. (2020) show that during the covid-19 pandemic stock markets suffered as in the worst week of the 2008 financial crisis, with a dramatic decline in FTSE100, Dow Jones and S&P500 by 11%, 12%, 11.5% respectively.

Thus, to investigate the role of Ethereum as a safe haven asset against the conventional foreign exchange currencies and the traditional assets during these events, we define an event period as 20 trading days after the event, covering approximately one calendar month. Then, during these periods, the indicator variable takes a value of 1 and 0 otherwise.

The equations for the US and EU markets are presented below:

***Equation 3:* (US market)**

□□□□□□$_□$ = □$_□$ + (□$_□$ + □$_□$(□□ □□□□□□□□□□□□***l*** □□□□□□□□□□ □□ □□□□□) + □$_□$(□□□□□□□□) + □$_□$(□□□□□□ − □**9**))□□□□□□***l***$_□$

+ (□$_□$ +

□$_□$(□□ □□□□□□□□□□□□***l*** □***l***□□□□□□□ □□ □□□□□) + □$_□$(□□□***x***□□) + □$_□$(□□□□□□ − □**9**))□□□□□□$_□$ + (□$_□$ +

□$_□$(□□ □□□□□□□□□□□□***l*** □***l***□□□□□□□ □□ □□□□□) + □$_□$(□□□***x***□□) + □$_□$(□□□□□□ − □**9**))□□□$_□$ + (□$_□$ +

□$_□$(□□ □□□□□□□□□□□□***l*** □***l***□□□□□□□ □□ □□□□□) + □$_□$(□□□***x***□□) + □$_□$(□□□□□□ − □**9**))□□□□□□□□□□□□□□□□***l***$_□$ + ((□$_□$ +

□$_□$(□□ □□□□□□□□□□□□***l*** □***l***□□□□□□□ □□ □□□□□) + □$_□$(□□□***x***□□) + □$_□$(□□□□□□ − □**9**))□□□□□□□□□□***l***□$_□$ + □$_□$□□□□□□□$_□$ + □$_□$

□□□□□□□$_{□−□}$ + □□$_□$

***Equation 4*: (EU market)**

□□□□□□$_□$ = □$_□$ + (□$_□$ + □$_□$(□□ □□□□□□□□□□□□***l*** □□□□□□□□□□ □□ □□□□□) + □$_□$(□□□□□□□□) + □$_□$(□□□□□□ − □**9**))□□□□□□***l***$_□$

+ (□$_□$ +

□$_□$(□□ □□□□□□□□□□□□***l*** □***l***□□□□□□□ □□ □□□□□) + □$_□$(□□□***x***□□) + □$_□$(□□□□□□ − □**9**))□□□□□□□□□□□□□□□□$_□$ + (□$_□$ +

□$_□$(□□ □□□□□□□□□□□□***l*** □***l***□□□□□□□ □□ □□□□□) + □$_□$(□□□***x***□□) + □$_□$(□□□□□□ − □**9**))□□□$_□$ + (□$_□$ +

□$_□$(□□ □□□□□□□□□□□□***l*** □***l***□□□□□□□ □□ □□□□□) + □$_□$(□□□***x***□□) + □$_□$(□□□□□□ − □**9**))□□□□□□□□□□□□□□□□***l***$_□$ + (□$_□$ +

□$_□$(□□ □□□□□□□□□□□□***l*** □***l***□□□□□□□ □□ □□□□□) + □$_□$(□□□***x***□□) + □$_□$(□□□□□□ − □**9**))□□□□□□□□□□***l***□$_□$ + □$_□$□□□□□□□$_□$ + □$_□$

□□□□□□□$_{□−□}$ + □□$_□$

Similar to Baur and McDermott (2010) and Baur et al. (2017), the results are interpreted as follows: Ethereum acts as a safe haven in crisis events if $\square_1$, $\square_2$, $\square_3$ are positive and statistically significant, $\square_1$, $\square_2$, $\square_3$ are negative and statistically significant, $\square_1$, $\square_2$, $\square_3$ are negative and statistically significant, $\square_1$, $\square_2$, $\square_3$ are negative and statistically significant and $\square_1$, $\square_2$, $\square_3$ are negative and statistically

significant.

3.9. DATA SOURCE

Two types of data exist: primary data and secondary data. Primary data is collected by the researcher whereas secondary data is already gathered by others. The primary data can be collected through interviews, questionnaires and experiments. The secondary data is available in several sources like reports, journals and websites (Bryman et al., 2011).

In this research, we use secondary data consisting of the daily percentage change in the price (price return) of Bitcoin, Ethereum, Ripple, Tether, Bitcoin Cash and Litecoin retrieved from a reliable website[4]. However, we obtain the price returns of the traditional currencies (EUR/USD, GBP/USD, AUD/USD, CHF/USD, CAD/USD, and CNY/USD), the stock indices (S&P500 and EuroSTOXX600), the bond indices (BND ETF and IEAG ETF), the crude oil index (S&PGSCI crude oil) and the gold index (S&PGSCI gold) from Thomson Reuters Eikon which is a platform that provides access to real time market data, news, data analytics and filtering.

[4] www.investing.com

3.10. SAMPLE SIZE AND SAMPLING PROCEDURES

More than 3000 cryptocurrencies exist today. Yet, it is very difficult to consider this enormous number of variables. Thus, in the first part of the research in which we study volatility spillovers between cryptocurrencies, we focus on the top cryptocurrencies in terms of market capitalization and we consider a sample period that ranges from the 3rd of August, 2017 until the 20th of December, 2019. The choice of this period is due to the late birth of cryptocurrencies, especially Ethereum. While Bitcoin is available in the market since 2012, Ethereum is only available from 2016. Due to this limitation, we omit the missing observations in order to have a common sample with the same number of observations for all cryptocurrencies. Thus, this leads to a total of 870 observations.

In the second part of the research, when studying the hedging and/or safe haven properties of Ethereum with traditional assets, we notice that cryptocurrencies are traded 24 hours a day, 7 days a week while traditional assets are open only during the working week. Therefore, we reduce the dataset of cryptocurrencies to match the number of observations and dates of traditional assets. Thus, when studying the US market, the sample ranges from 10th of March 2016 until 28th of May 2020 with a total of 843 observations. However, for the EU market, the study consists of 852 observations ranging from 10th of March 2016 until 28th of May 2020.

3.11. CONCLUSION

In brief, we approach our study's research question with a positivist philosophical stand since it relies on empirical observations to generate meaningful inferences. It also adopts the deductive approach since it starts with signaling and herding theories as its guiding theories and narrows them down into explicit hypotheses. Furthermore, an archival strategy is used since previous data of cryptocurrencies and traditional assets are obtained from archives to be evaluated and analyzed. Moreover, this research also adopts the content analysis because it transforms the raw data collected into outcomes which are able to check the validity of the hypotheses. This is performed through a quantitative analysis whereby mathematical procedures and algorithms are used such as the generalized autoregressive conditional heteroskedasticity model followed by a vector autoregressive model (GARCH-VAR) and an OLS regression analysis with percentiles to transform the data into reliable and interpretable outputs. The secondary data will be collected from two reliable databases. In the first part of the research, the data sample spans from 3rd of August 2017 until 20th of December 2019 for a total of 870 observations. However, in the second part, the data sample for the US market ranges from 10th of March 2016 until 28th of May 2020 with a total of 843 observations while it ranges from 10th of March 2016 until 28th of May 2020 for the EU market with a total of 852 observations.

CHAPTER FOUR: RESULTS AND ANALYSIS

4.1. INTRODUCTION

This chapter presents the empirical results and their discussion. Section two begins with the GARCH-VAR analysis. In the first sub-section, the descriptive statistics of the explanatory variables are presented. The diagnostic tests are reported in the second sub-section. In the third sub-section, the empirical results are provided. In the final sub-section, the discussion of the results and the link to previous researches and developed hypotheses is provided. The third section presents the ordinary least squares with percentiles analysis and the crisis event interaction analysis. The first sub-section begins with the descriptive statistics. The second sub-section discusses the diagnostic tests. The empirical results are presented in the third sub-section. The final sub-section discusses the results and compares them with previous literature and developed hypotheses. Section four concludes the chapter.

4.2. GARCH-VAR

In this section, we present the results of the volatility spillovers between the cryptocurrencies namely Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin. Univariate GARCH models are used to model the volatility of the residuals. Then, a VAR model is applied to determine if volatility spillovers exist between the cryptocurrencies.

4.2.1. DESCRIPTIVE STATISTICS

This section presents the descriptive statistics of the variables used in the study. The mean, median, standard deviation, minimum, maximum, kurtosis and skewness for Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin are reported. The results are shown in table 4.1.

Table 4.1: Descriptive Statistics

This table reports the descriptive statistics for the daily data from August 2017 until December 2019 of the first five cryptocurrencies in terms of market capitalization used in the analysis. The daily return data is retrieved from investing.com website.

	Bitcoin	Ethereum	Ripple	Bitcoin Cash	Litecoin
Mean	0.0021	0.0008	0.0024	0.0024	0.0018
Median	0.0013	-0.0009	-0.0024	-0.0039	-0.0027
Maximum	0.2255	0.2322	0.8558	0.5457	0.6106
Minimum	-0.1705	-0.2018	-0.2981	-0.3807	-0.2650
Std. Dev.	0.0433	0.0523	0.0712	0.0829	0.0634
Skewness	0.2551	0.0043	3.7339	1.6766	2.0413
Kurtosis	5.8953	5.4087	37.4742	13.4206	18.1156

According to table 4.1, the mean of returns of Bitcoin is 0.21% with a standard deviation of 4.33%. The maximum return records 22.55% while the table reports a minimum of -17.05%. Furthermore, the return series has a high kurtosis of 5.8953, which indicates that the distribution is leptokurtic. The distribution's skewness is 0.2551 indicating that the distribution is almost symmetric. Yet, the value of kurtosis implies that the distribution is not normal.

Furthermore, table 4.1 shows that Ethereum return series has a mean of 0.08% with a standard deviation of 5.23%. During the sample period, the maximum and the minimum returns are 23.22% and -20.18%, respectively. The skewness is almost equal to zero which means that the distribution is symmetric around the mean. However, the kurtosis is 5.4087 which indicates that the distribution is leptokurtic. The value of the kurtosis indicates that the return series of Ethereum is not normal.

Moreover, Ripple's mean and standard deviation is 0.24% and 7.12%, respectively. The maximum return is 85.58% while the minimum return is -29.81%. Additionally, the skewness is 3.7339 and the kurtosis is 37.4742. This implies that the return series is not normal but skewed to the right and leptokurtic.

Likewise, the mean and the standard deviation of the return series of Bitcoin Cash are 0.24% and 8.29%, respectively. The minimum and the maximum returns fluctuate between -38.07% and 54.57% during the period under consideration. It has a skewness of 1.6766 which denotes that the distribution is skewed to the right. Additionally, it has a kurtosis of 13.4206 indicating that the distribution is leptokurtic. In conclusion, the distribution is not normal.

Finally, regarding the return series of Litecoin, the mean and the standard deviation are 0.18% and 6.34%, respectively. The series has a maximum of 61.06% and a minimum of -26.5%. The distribution is far from normal since its skewness and kurtosis are 2.0413 and 18.1156, respectively. It is skewed to the right and leptokurtic.

4.2.2. DIAGNOSTIC TESTS

In this section, the diagnostic tests results are presented. These tests are needed to maintain the validity of the analysis and achieve unbiased results. The common tests are augmented Dickey-Fuller test for stationarity, the Jarque-Bera test for normality and the ARCH test for heteroskedasticity (see section 3.7.).

Table 4.2 below presents the results of the ADF test. This test cannot be performed if there is autocorrelation in the residuals. Thus, the number of lags in table 4.2 is the number needed for each of the cryptocurrencies return series to remove autocorrelation from the residuals. All cryptocurrencies have $|\square_{c\square\square\square\square c\square\square\square\ \square\square\square\square\square\square\square}| < |\square_{A\square\square}|$. Thus, the null hypothesis that the return series are not stationary is rejected. Consequently, they are all stationary. Therefore, we use the return series to conduct this study specially that the price series are not stationary. However, the errors from the mean equation are not normally distributed as Jarque-Bera test indicates but this issue is not a problem because given the large data sample, the residuals always follow an asymptotically normal distribution (Brooks, 2008). Moreover, the ARCH test indicates that the residuals are heteroskedastic. Thus, univariate GARCH models can be utilized to model the volatility of the residuals from the mean equation (for more details about the Jarque-Bera and the ARCH tests refer to appendix A).

Table 4.2: Augmented Dickey-Fuller Test Results

This table represents the results of the augmented Dickey-Fuller test for the daily data from August 2017 until December 2019 of the first five cryptocurrencies in terms of market capitalization used in the analysis. The daily return data is retrieved from investing.com website.

	# of lags	1% level	5% level	10% level	ADF t-statistic
Bitcoin	0	-3.4377	-2.8647	-2.5685	-29.6617
Ethereum	2	-3.4377	-2.8647	-2.5685	-15.6190
Ripple	1	-3.4377	-2.8647	-2.5685	-18.2257
Bitcoin Cash	0	-3.4377	-2.8647	-2.5685	-25.7695
Litecoin	0	-3.4377	-2.8647	-2.5685	-28.9691

4.2.3. EMPIRICAL RESULTS

This section shows a detailed presentation of the results (refer to section 3.8.). The first sub-section presents the results of the univariate GARCH models of the five cryptocurrencies. The second sub-section reports the results of the vector autoregressive model including the forecast error variance decomposition. The last sub-section discusses the results and links them to previous studies and developed hypotheses.

4.2.3.1. UNIVARIATE GARCH MODELS

In this section, a detailed presentation of the most appropriate univariate GARCH models of the cryptocurrencies is discussed. Table 4.3 presents the results. For further details, refer to appendix B.

Table 4.3: The Mean and Variance Equations of the Univariate GARCH Models

This table reports the most appropriate univariate GARCH models of the first five cryptocurrencies in terms of market capitalization used in the analysis. P-values are given in parentheses and significant results are marked in bold. ***, **, * denote two-tailed significance at 1%, 5%, and 10% level, respectively.

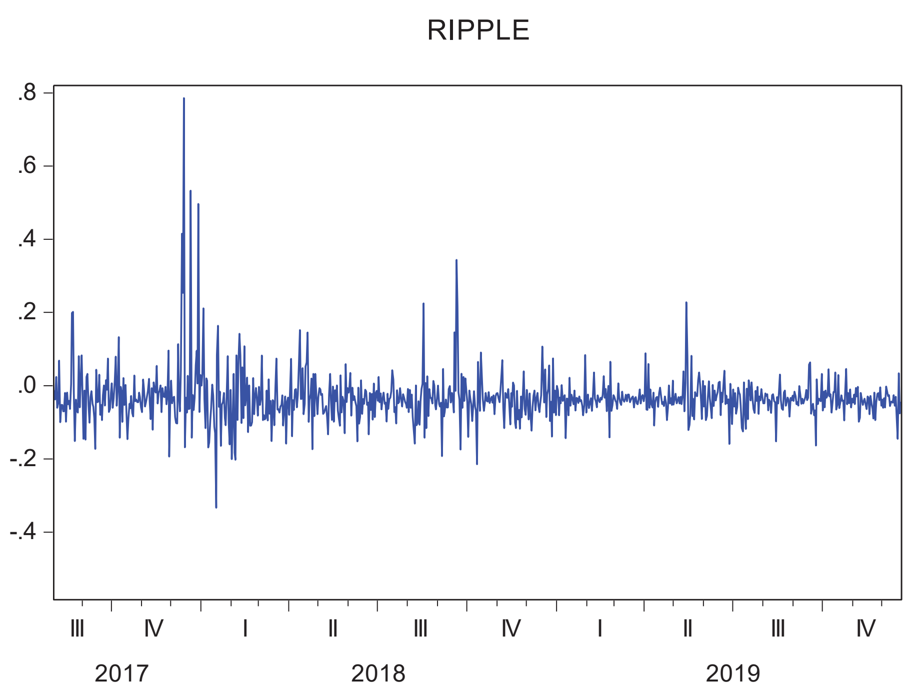
	Bitcoin	Ethereum	Ripple	Bitcoin Cash	Litecoin
	GARCH (1,1)	GARCH (1,1)	EGARCH (1,1)	GARCH (1,1)	GARCH (1,1)
			Mean Equation		
μ	0.0012 (0.3596)	-0.0004 (0.7760)	-0.0021 (0.2583)	-0.0003 (0.8982)	0.0010 (0.6321)
MA (4)		**-0.0759**** (0.0297)			
			Variance Equation		
ω_0	**0.0001***** (0.0000)	**0.0002***** (0.0001)	**-2.0434***** (0.0000)	**0.0003***** (0.0000)	**0.0004***** (0.0000)
α_1	**0.0893***** (0.0000)	**0.0821***** (0.0000)	**0.4691***** (0.0000)	**0.0731***** (0.0000)	**0.0971***** (0.0000)
β_1	**0.8487***** (0.0000)	**0.8294***** (0.0000)	**0.7130***** (0.0000)	**0.8774***** (0.0000)	**0.7896***** (0.0000)
τ			**0.9419***** (0.0000)		
Ljung-Box	(0.0720) *	(0.0140) **	(0.5370)	(0.1140)	(0.8320)
Ljung-Box^2	(0.6840)	(0.9860)	(0.9740)	(0.8500)	(0.5440)

The most appropriate models to represent the volatility of Bitcoin, Ethereum, Bitcoin Cash and Litecoin is GARCH (1,1). As seen in table 4.3, the p-values of α_1 and β_1 are significant at 1%, the variances are stable because $\alpha_1 + \beta_1 < 1$ and the non-negativity constraint is respected ($\alpha_1 > 0$ and $\beta_1 > 0$) for all cryptocurrencies. Note that the moving average MA (4) is added to the mean equation of Ethereum in order to remove autocorrelation from the residuals. Moreover, the results of the Ljung-Box test show that the residuals are not autocorrelated and are homoskedastic.

For the case of Ripple, we notice that ⍰$_1 > 1$ which indicates that the variance is explosive (⍰$_1 = 1.1944$). To solve the problem, outliers are removed from the sample to obtain a stable variance. Figure 4.1 shows the period of the outliers. Thus, a dummy variable is created that takes a value of one from 12/8/2017 until 1/18/2018 (the period of the outliers) and zero otherwise.

Then the dummy variable is included in the analysis. "τ" in table 4.3 is the coefficient of the dummy variable. The results show that EGARCH (1,1) is the most appropriate model to represent the variance of Ripple (for more details, refer to appendix B). The variance is now stable since ⍰$_1 < 1$ and has a significant p-value at 1% and ⍰$_1$ is also significant at 1%. The residuals are not autocorrelated and are homoskedastic at all significant levels.

Figure 4.1: The Period of the Outliers in the Return Series of Ripple



The conditional variance equations are given below with substituted coefficients:

$$h_t = 0.0001 + 0.0893\varepsilon_{t-1}^2 + 0.8487h_{t-1}\ (\text{□□□□□□□□}) \quad (1)$$

$$h_t = 0.0002 + 0.0821\varepsilon_{t-1}^2 + 0.8294h_{t-1}\ (\text{□□}h\text{□□□□□}) \quad (2)$$

$$\log h_t = -2.0434 + 0.4691\left|\sqrt{\frac{\varepsilon_{t-1}^2}{h_{t-1}}}\right| + 0.713\log h_{t-1} + 0.9419\varepsilon_t\ (\text{□□□□□□□}) \quad (3)$$

$$h_t = 0.0003 + 0.0731\varepsilon_{t-1}^2 + 0.8774h_{t-1}(\text{□□□□□□□□ □□□}h) \quad (4)$$

$$h_t = 0.0004 + 0.0971\varepsilon_{t-1}^2 + 0.7896h_{t-1}(\text{□□□□□□□□□}) \quad (5)$$

4.2.3.2. VECTOR AUTOREGRESSION MODEL

Once the models of the five cryptocurrencies have been presented, the variance series are created using the equations from (1) until (5)[5]. These variance series are used in the vector autoregression model to determine whether volatility spillovers exist between cryptocurrencies. A VAR (8) model is used in order to remove autocorrelation from the residuals. Table 4.4 shows the results of the volatility spillover analysis, 25-day-ahead forecast.

[5] The variance series are stationary and no multicollinearity exists between the variables. For details, refer to appendix A.

Table 4.4: Volatility Spillover Results

The following spillover table represents the degree of connectedness between the five cryptocurrencies. Variance decompositions are based upon a daily VAR and a Cholesky factorization with a 25-day-ahead forecast. Volatilities are computed using univariate GARCH models.

To	From					
	BTC_vseries	ETH_vseries	XRP_vseries	BCH_vseries	LTC_vseries	Contribution from others
BTC_vseries	95.2691	0.6580	2.8983	0.0397	1.1350	4.7310
ETH_vseries	45.4652	46.8644	2.6875	0.6071	4.3759	53.1357
XRP_vseries	20.6780	8.1810	39.7705	1.1284	30.2421	60.2295
BCH_vseries	11.8932	1.3465	1.1300	79.4582	6.1722	20.5419
LTC_vseries	36.7574	11.4441	4.2570	2.1596	45.3820	54.6181
Contribution to others	114.7938	21.6296	10.9728	3.9348	41.9252	
Contribution including own	210.0629	68.4940	50.7433	83.3930	87.3072	

Table 4.4 provides an analysis of volatility spillovers for a 25-day-ahead forecast. The reported results are based on the Cholesky factorization. For the case of Bitcoin, it is seen that innovations to Bitcoin volatilities are responsible for 95.3% of the error variance when forecasting 25-day-ahead Bitcoin volatilities, 45.5% of the error variance in forecasting Ethereum volatilities, 20.7% of the error variance in forecasting Ripple volatilities, 11.9% of the error variance in forecasting Bitcoin Cash volatilities and 36.8% in forecasting Litecoin volatilities. Thus, it can be concluded that Bitcoin transmits volatility shocks to Ethereum, Ripple, Bitcoin Cash and Litecoin. Consequently, there are volatility spillovers from Bitcoin to all cryptocurrencies considered in the analysis. Moreover, it is also noticed that Bitcoin is mainly affected by its own shocks since it receives relatively a small proportion of shocks (contribution from others = 4.7%).

Furthermore, as shown in table 4.4, innovations to Ethereum volatilities are responsible for 46.9% of the error variance when forecasting 25-day-ahead Ethereum volatilities and 11.4% of the error variance in forecasting Litecoin volatilities. Consequently, Ethereum transmits volatility shocks only to Litecoin. However, the volatility spillovers from Ethereum to the other effects are negligeable. Additionally, it should be observed that Ethereum is affected by its own shocks (46.9%) and by shocks from other cryptocurrencies (contribution from others = 53.1%).

The cases of Ripple and Bitcoin Cash are quite different from Bitcoin and Ethereum. The findings in table 4.4 indicate that the volatility spillovers from Ripple to the other cryptocurrencies are negligible. However, it can be seen that Ripple is affected by its own shocks (39.8%). Moreover, the contribution from other cryptocurrencies is 60.2% which means that Ripple is also affected by shocks from other cryptocurrencies. For Bitcoin Cash, table 4.4 infers that Bitcoin Cash is mainly affected by its own shocks (79.5%) and by shocks from other cryptocurrencies (contribution from others=20.5%) but does not transmit volatility shocks to other cryptocurrencies.

Additionally, for the case of Litecoin, the findings reveal that innovations to Litecoin volatilities are responsible for 45.4% of the error variance when forecasting 25-day-ahead Litecoin volatilities and 30.2% of the error variance in forecasting Ripple volatilities. Thus, it can be concluded that Litecoin is affected by its own shocks and transmits volatility shocks to Ripple. It should also be noted that Litecoin is affected by shocks from other cryptocurrencies (contribution from others = 54.6%).

Additionally, when comparing “contributions to others”, Bitcoin and Litecoin have the highest values (114.8 and 41.9 respectively) which indicates that Bitcoin is the most prominent transmitter of volatility shocks among the five cryptocurrencies followed by Litecoin. However, when comparing “contributions from others”, it can be seen that Ripple is the top receiver of volatility shocks followed by Litecoin and Ethereum (their respective values of “contribution from others” is 60.2, 54.6 and 53.1). The results obtained from the forecast error variance decomposition are confirmed in the impulse response functions in figure 4.2.

Figure 4.2: The Impulse Response Functions

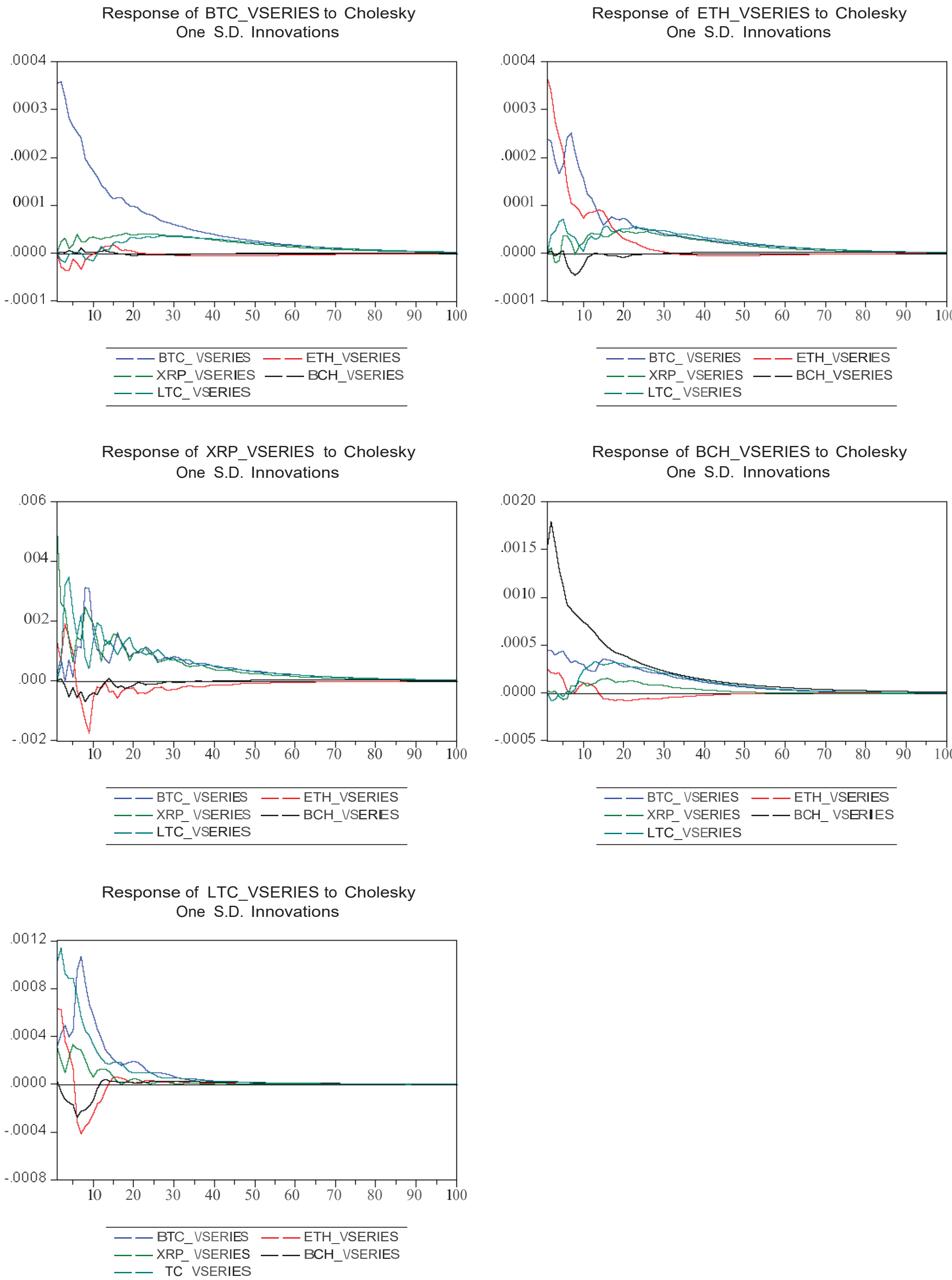


Table 4.5: Summary of the Results

This table represents a summary of the results for the volatility spillover of the five cryptocurrencies namely, Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin.

Results
1) Bitcoin is the most prominent transmitter of volatility shocks followed by Litecoin.
2) Ripple is the top receiver of volatility shocks followed by Litecoin and Ethereum.
3) Bitcoin is mainly affected by their own shocks.
4) Ethereum, Ripple, Bitcoin Cash and Litecoin are affected by both their own shocks and by shocks from other cryptocurrencies.
5) There are uni-directional volatility spillovers from Bitcoin to Ethereum, Ripple, Bitcoin Cash and Litecoin.
6) There is uni-directional volatility spillover from Ethereum to Litecoin.
7) There is uni-directional volatility spillover from Litecoin to Ripple.

4.2.4. DISCUSSION OF THE RESULTS AND HYPOTHESES

One of the aims of this research is to examine the volatility spillovers between the five cryptocurrencies with the highest market capitalization. According to the existing literature, our study hypothesizes that Bitcoin, Ethereum and Ripple are mainly affected by their own shocks while Bitcoin Cash and Litecoin are affected by their own shocks and by shocks from other cryptocurrencies (H_1). We also state that there are bi-directional volatility spillovers between the cryptocurrencies (H_2). Additionally, (H_3) states that Bitcoin is the dominant transmitter of volatility shocks while Ethereum is the most receiver of volatility shocks. Our findings reveal Bitcoin is the only cryptocurrency that is mainly affected by its own shocks while Ethereum, Ripple, Bitcoin Cash and Litecoin are affected by both their own shocks and shocks from other cryptocurrencies. Thus, we partially support (H_1). Furthermore, our results reveal that there is no bi-directional volatility spillover between any cryptocurrency pair. However, the results report that there are only uni-directional volatility spillovers from Bitcoin to Ethereum, Ripple, Bitcoin Cash and Litecoin, a uni-directional volatility spillover from Ethereum to Ripple and from Litecoin to Ripple. Consequently, (H_2) is not supported. Finally, our results reveal that Bitcoin is the most prominent transmitter of volatility shocks while Ripple is the most important receiver of volatility shocks. Thus, (H_3) is partially supported.

These results are in line with many previous studies. For instance, Koutmos (2018) shows that Bitcoin is mainly affected by its own shocks while Litecoin is 44.2% affected by its own shocks and 55.8% affected by shocks from other cryptocurrencies. Moreover, he finds that Bitcoin is the most important transmitter of volatility shocks whereas Litecoin is one of the most prominent receivers of volatility shocks. He also shows that there are volatility spillovers from Bitcoin to both Ethereum and Litecoin. Finally, his results reveal that no volatility spillovers from Ripple to Bitcoin, Ethereum and Litecoin exist. Moreover, Corbet et al. (2018) report that there are volatility spillovers from Bitcoin to Litecoin and from Litecoin to Ripple. They also find that Bitcoin is mainly affected by its own shocks. Furthermore, Ji et al. (2018) find that Bitcoin is the largest transmitter of volatility shocks and Ethereum is one of the largest receivers of volatility spillover. Likewise, Katsiampa et al. (2018) show that a volatility spillover exists from Bitcoin to Ethereum. Finally, Katsiampa et al. (2019) find a uni-directional shock spillover from Ethereum to Litecoin. Their results also reveal that a volatility spillover from Bitcoin to both Ethereum and Litecoin exists.

4.3. OLS REGRESSION WITH PERCENTILES

In this section, we present the results of the ordinary least squares regressions with percentiles in addition to the crisis event interaction analysis. The aim is to determine if hedging and/or safe haven capabilities exist for Ethereum, the second largest cryptocurrency in terms of market capitalization, against the conventional currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold.

4.3.1. DESCRIPTIVE STATISTICS

This section presents the descriptive statistics of the variables used in the analysis. The mean, median, standard deviation, minimum, maximum, kurtosis and skewness are reported for Bitcoin, Ethereum, foreign exchange currencies, S&P500, EuroSTOXX600, BND ETF, IEAG ETF, S&PGSCI crude oil and S&PGSCI gold. The results are shown in table 4.6 for the US sample in panel A and the EU sample in panel B.

Table 4.6: Descriptive Statistics

This table represents the descriptive statistics for two panels. Panel A provides the descriptive statistics of the US sample and Panel B reveals the descriptive statistics of the EU sample both for the period from March 2016 until May 2020.

Panel A: Descriptive statistics of the US sample

	Ethereum	Bitcoin	FXVol	S&P500	BND ETF	S&PGSCI crude oil	S&PGSCI gold
Mean	0.0042	0.0029	2.0985	0.0005	0.0002	-0.0004	-0.0003
Median	-0.0009	0.0021	1.7725	0.0007	0.0001	-0.0013	-0.0002
Maximum	0.2951	0.2556	9.5157	0.0938	0.0422	0.3255	0.0485
Minimum	-0.4455	-0.3918	0.0442	-0.1198	-0.0544	-0.2739	-0.0545
Std. Dev.	0.0615	0.0448	1.4053	0.0127	0.0035	0.0332	0.0088
Skewness	0.1212	-0.4043	1.2393	-0.8144	-2.4152	2.0183	-0.3092
Kurtosis	8.6874	13.5048	4.9342	26.3366	100.4732	40.9953	10.2533

Panel B: Descriptive statistics of the EU sample

	Ethereum	Bitcoin	FXVol	EuroSTOXX 600	IEAG ETF	S&PGSCI crude oil	S&PGSCI gold
Mean	0.0034	0.0026	2.1236	-0.0001	0.0001	-0.0003	-0.0004
Median	-0.0014	0.0020	1.7876	-0.0005	0.0002	-0.0017	-0.0002
Maximum	0.2951	0.2556	9.5157	0.1297	0.0170	0.3255	0.0485
Minimum	-0.4455	-0.3918	0.0442	-0.0775	-0.0357	-0.2739	-0.0545
Std. Dev.	0.0617	0.0447	1.4195	0.0109	0.0024	0.0333	0.0089
Skewness	0.1181	-0.4139	1.2224	2.7914	-3.5156	1.9984	-0.3110
Kurtosis	8.5562	13.4064	4.8346	36.3104	61.2116	40.1993	9.9008

In the US sample in panel A, Ethereum and Bitcoin return series score mean values of 0.42% and 0.29%, respectively with a standard deviation of 6.15% and 4.48% each. The minimum and maximum values of Ethereum are -44.55% and 29.51%, respectively while the minimum and maximum values of Bitcoin are -39.18% and 25.56%, respectively. The skewness of Ethereum is 0.1212 and its kurtosis is 8.6874 while Bitcoin has a skewness and kurtosis figures of -0.4043 and 13.5048, respectively, which indicates that both Ethereum and Bitcoin are not normally distributed.

Furthermore, FXVol data has a mean of 209.85% and a median of 177.25%. The values range from a minimum of 4.42% and a maximum of 951.57%. Its standard deviation is 140.53%. The skewness and kurtosis are respectively 1.2393 and 4.9342. These results show that FXVol distribution is not normal but leptokurtic and skewed to the right.

Moreover, S&P500 and BND ETF return series have mean values of 0.05% and 0.02%, respectively. The median return of S&P500 is 0.07% and that of BND ETF is 0.01%. The minimum and maximum of S&P500 are respectively -11.98% and 9.38%, while the minimum and maximum of BND ETF are -5.44% and 4.22%, respectively. The standard deviation figures of S&P500 and BND ETF are 1.27% and 0.35%, respectively. The skewness of S&P500 is -0.8144 and its kurtosis is 26.3366, which indicates that the distribution is skewed to the left and leptokurtic. However, the skewness and kurtosis of BND ETF are -2.4152 and 100.4732, respectively, which also shows that the distribution is not normal but skewed to the left and leptokurtic.

Finally, the mean values of S&PGSCI crude oil and S&PGSCI gold are -0.04% and -0.03%, respectively. The median value of S&PGSCI crude oil is -0.13% while that of S&PGSCI gold is -0.02%. The values of S&PGSCI crude oil and S&PGSCI gold spread from a minimum of -27.39% to a maximum of 32.55% for S&PGSCI crude oil and -5.45% and 4.85% for S&PGSCI gold. The standard deviation of S&PGSCI crude oil is 3.32%. The standard deviation of S&PGSCI gold is 0.88%. The skewness and kurtosis are 2.0183 and 40.9953, respectively for S&PGSCI crude oil. This indicates that the distribution is skewed to the right and leptokurtic. Finally, the skewness and kurtosis of S&PGSCI gold are respectively -0.3092 and 10.2533. This denotes that the distribution is almost symmetric around the mean but is leptokurtic.

In the EU sample in panel B, the mean and median of Ethereum are 0.34% and -0.14%, respectively with a minimum of -44.55% and a maximum of 29.51%. The standard deviation of the distribution is 6.17%. However, the skewness and kurtosis are 0.1181 and 8.5562 respectively, which means that the distribution is symmetric around the mean but is leptokurtic. Thus, the distribution is not normal.

Moreover, the mean and median values of Bitcoin are 0.26% and 0.2%, respectively. The values range from a minimum of -39.18% to a maximum of 25.56%. The standard deviation of the distribution is 4.47%. The skewness has a value of -0.4139 and a kurtosis of 13.4064. Consequently, the distribution is not normal but leptokurtic.

Furthermore, FXVol has a mean value of 212.36% and a median of 178.76%. Its minimum and maximum values are 4.42% and 951.57%, respectively. The value of its standard deviation is 141.95%. The skewness and kurtosis of the distribution are 1.2224 and 4.8346, respectively which show that the distribution is skewed to the right and leptokurtic consequently not normal.

Likewise, EuroSTOXX600 and IEAG ETF have a mean of -0.01% and 0.01%, respectively. The median of EuroSTOXX600 is -0.05% and that of IEAG ETF is 0.02%. The values of EuroSTOXX600 range from a minimum of -7.75% to a maximum of 12.97% while the minimum and maximum of IEAG ETF are -3.57% and 1.7%, respectively. The standard deviation of EuroSTOXX600 is 1.09% while that of IEAG ETF is 0.24%. The skewness and kurtosis of EuroSTOXX600 are 2.7914 and 36.3104, respectively. However, the skewness and kurtosis of IEAG ETF are -3.5156 and 61.2116, respectively. Therefore, EuroSTOXX600 has a distribution that is skewed to the right and leptokurtic while IEAG ETF has a distribution that is skewed to the left and leptokurtic.

Finally, the mean of S&PGSCI crude oil and S&PGSCI gold are -0.03% and -0.04%, respectively. The median of S&PGSCI crude oil is -0.17% and that of S&PGSCI gold is -0.02%. The minimum and maximum values of S&PGSCI crude oil are -27.39% and 32.55%, respectively while the minimum and maximum of S&PGSCI gold are respectively -5.45% and 4.85%. The standard deviation of S&PGSCI crude oil is 3.33% while that of S&PGSCI gold is 0.89%. The skewness and kurtosis of S&PGSCI crude oil are 1.9984 and 40.1993, respectively, which indicates that S&PGSCI crude oil is not normal but leptokurtic and skewed to the right. Moreover, the skewness and kurtosis of S&PGSCI gold are respectively -0.311 and 9.9008, which also indicates that the distribution is not normal but leptokurtic and almost symmetric around the mean.

4.3.2. DIAGNOSTIC TESTS

In this section, the results of the diagnostic tests are displayed (refer to section 3.7.). Stationarity and multicollinearity tests are performed pre-regression. However, normality and heteroskedasticity tests of the residuals are implemented post-regression. The results of the augmented Dickey-Fuller test for stationarity are shown in table 4.7 below. Panel A presents the results of the US sample while panel B depicts the results of the EU one. As presented in the table, all return series are stationary since $|t_{critical\ values}| < |t_{ADF}|$ at all significance levels in panel A and panel B which indicates that we reject the null hypothesis that the return series are not stationary. Consequently, the return series are stationary. Therefore, we will use the return series to conduct the analysis, especially that the price series are not stationary.

Table 4.7: Augmented Dickey-Fuller Results

This table represents the results of the augmented Dickey-Fuller test for two panels. Panel A reports the augmented Dickey-Fuller test results of the US sample and Panel B represents the augmented Dickey-Fuller test of the EU sample both for the period from March 2016 until May 2020.

Panel A: Augmented Dickey-Fuller results of the US sample

	# of lags	1% level	5% level	10% level	ADF t-statistic
Ethereum	0	-3.4379	-2.8648	-2.5685	-29.4190
Bitcoin	0	-3.4379	-2.8648	-2.5685	-30.1653
FXVol	1	-3.4379	-2.8648	-2.5685	-18.9136
S&P500	3	-3.4379	-2.8648	-2.5685	-15.8155
BND ETF	4	-3.4379	-2.8648	-2.5685	-14.1775
S&PGSCI crude oil	3	-3.4379	-2.8648	-2.5685	-13.8131
S&PGSCI gold	4	-3.4379	-2.8648	-2.5685	-15.2946

Panel B: Augmented Dickey-Fuller results of the EU sample

	# of lags	1% level	5% level	10% level	ADF t-statistic
Ethereum	0	-3.4378	-2.8647	-2.5685	-29.3648
Bitcoin	0	-3.4378	-2.8647	-2.5685	-30.3122
FXVol	1	-3.4378	-2.8647	-2.5685	-19.2338
EuroSTOXX600	4	-3.4378	-2.8647	-2.5685	-11.3947
IEAG ETF	2	-3.4378	-2.8647	-2.5685	-17.8208
S&PGSCI crude oil	3	-3.4378	-2.8647	-2.5685	-13.9028
S&PGSCI gold	3	-3.4378	-2.8647	-2.5685	-15.8244

The results of the correlation matrix are presented in table 4.8. Panel A and panel B present the results of the US and EU samples, respectively. The outcomes of table 4.8 approve that multicollinearity does not exist across the variables since all correlation coefficients are less than 0.8, according to Gujarati and Sangeetha (2007).

Additionally, the Breush-Pagan-Godfrey test for heteroskedasticity shows that the residuals are homoskedastic in both the US and EU samples. Finally, the Jarque-Bera test for normality shows that the residuals follow a non-normal distribution both in the US and the EU models. Yet, the non-normality is not a matter in this research. Given the large sample size, the residuals follow an asymptotically further details about the tests, refer to appendix A.

Table 4.8: Correlation Matrix

This table shows the values of Pearson correlations among each of the variables used in the analysis. The correlation matrix is organized in two panels. Panel A presents the correlation coefficients of the US sample. Panel B reports the correlation coefficients of the EU sample. The p-values are given in parenthesis and significant results are marked in bold. ***, **, * denote two-tailed significance at 1%, 5%, and 10% level, respectively.

Panel A: Correlation coefficients of the US sample

	Bitcoin	BND ETF	FXVol	S&P500	S&PGSCI crude oil	S&PGSCI gold
Bitcoin	1.0000					
BND ETF	**0.2301***** (0.0000)	1.0000				
FXVol	0.0047 (0.8906)	0.0476 (0.1677)	1.0000			
S&P500	**0.1673***** (0.0000)	**0.0604*** (0.0799)	0.0081 (0.8146)	1.0000		
S&PGSCI crude oil	-0.0243 (0.4806)	-0.0194 (0.5744)	0.0338 (0.3270)	0.0494 (0.1517)	1.0000	
S&PGSCI gold	**-0.0602*** (0.0809)	**-0.2647***** (0.0000)	-0.0279 (0.4179)	0.0314 (0.3627)	**0.1349***** (0.0001)	1.0000

Panel B: Correlation coefficients of the EU sample

	Bitcoin	EuroSTOXX 600	FXVol	IEAG ETF	S&PGSCI crude oil	S&PGSCI gold
Bitcoin	1.0000					
EuroSTOXX600	0.0003 (0.9933)	1.0000				
FXVol	0.0101 (0.7691)	0.0302 (0.3789)	1.0000			
IEAG ETF	**0.0902***** (0.0084)	**0.0654*** (0.0562)	0.0044 (0.8988)	1.0000		
S&PGSCI crude oil	-0.0275 (0.4232)	**0.3166***** (0.0000)	0.0286 (0.4051)	-0.0363 (0.2897)	1.0000	
S&PGSCI gold	**-0.0669*** (0.0510)	**-0.0258** (0.4523)	-0.0201 (0.5577)	-0.0178 (0.6048)	**0.1309***** (0.0001)	1.0000

4.3.3. EMPIRICAL RESULTS

This section presents the detailed results of the hedging and/or safe haven potential of Ethereum against the conventional foreign exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold (refer to section 3.8.). Table 4.9 presents the results of the percentile regression and the crisis event interaction regression for the US sample. Table 4.10 presents the results for the EU sample.

Table 4.9: Regression and Crisis Event Interaction Results for the US Sample

The following table represents the results of the ordinary least squares regression and crisis event interaction regression for the hedging and/or safe haven capabilities of Ethereum against the conventional foreign exchange currencies, the US stock and bond markets, the crude oil and the gold. The results of the regression models are represented without and with the control variables.

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Where [illegible]$_0$ is the intercept, and [illegible] represents the residual values. P-values are given in parentheses and significant results are marked in bold.
***,
**, * denote two-tailed significance at 1%, 5%, and 10% level, respectively.

	Ethereum			Ethereum	
Panel A: Percentile Regression			*Panel B: Crisis Event Interaction*		
Intercept	**0.0085*** (0.0749)	0.0054 (0.1757)	Intercept	**0.0062*** (0.0986)	0.0037 (0.2324)
FXVol	-0.0029 (0.2041)	-0.0015 (0.4206)	FXVol	-0.0012 (0.4165)	-0.0010 (0.3997)
FXVol*P90_Fxvol	0.0036 (0.1620)	0.0005 (0.8189)	FXVol* US presidential election of 2016	-0.0014 (0.7842)	-0.0023 (0.5724)
FXVol*P95_Fxvol	-0.0041 (0.1470)	-0.0011 (0.6427)	FXVol*Brexit	0.0056 (0.5075)	0.0036 (0.6038)
FXVol*P99_Fxvol	0.0043 (0.1954)	0.0017 (0.5329)	FXVol*Covid_19	-0.0075 (0.1449)	-0.0049 (0.2470)
S&P500	**0.7452***** (0.0041)	0.3188 (0.1384)	S&P500	**0.5199**** (0.0263)	**0.3494*** (0.0691)
S&P500*P1_S&P500	0.2536 (0.6358)	-0.2754 (0.5330)	S&P500* US presidential election of 2016	1.6481 (0.5285)	1.7824 (0.4064)
S&P500*P5_S&P500	0.5397 (0.5285)	0.0254 (0.9713)	S&P500*Brexit	-0.1677 (0.8992)	0.2005 (0.8535)
S&P500*P10_S&P500	-0.5762 (0.4949)	0.2656 (0.7035)	S&P500*Covid_19	0.4751 (0.2171)	0.0199 (0.9499)
BND ETF	**2.4337**** (0.0102)	**1.4215*** (0.0687)	BND ETF	1.5448 (0.1674)	0.8559 (0.3515)
BND ETF*P1_BND ETF	1.5526 (0.5779)	0.4329 (0.8507)	BND ETF* US presidential election of 2016	-0.4314 (0.9281)	-0.0737 (0.9850)
BND ETF*P5_BND ETF	3.0808		(0 .	4667)	1.2289 (0.7246)

BND ETF*Brexit	0.3685 (0.9514)	-1.6106 (0.7455)

BND ETF*P10_BND ETF	-2.3510 (0.5226)	-1.7274 (0.5684)	BND ETF*Covid_19	2.5773 (0.1002)	0.8589 (0.5054)
S&PGSCI crude oil	0.0854 (0.3064)	0.0566 (0.4104)	S&PGSCI crude oil	-0.0179 (0.8021)	0.0352 (0.5491)
S&PGSCI crude oil* P1_S&PGSCI crude oil	-0.1991 (0.4234)	-0.1716 (0.4070)	S&PGSCI crude oil* US presidential election of 2016	0.2462 (0.6121)	0.2047 (0.6077)
S&PGSCI crude oil* P5_S&PGSCI crude oil	-0.0739 (0.8452)	-0.1184 (0.7051)	S&PGSCI crude oil*Brexit	**1.4057***** (0.0091)	**1.2445***** (0.0049)
S&PGSCI crude oil* P10_S&PGSCI crude oil	0.0815 (0.8110)	0.2427 (0.3878)	S&PGSCI crude oil* Covid_19	0.0787 (0.6281)	0.0015 (0.9912)
S&PGSCI gold	-0.2201 (0.5238)	-0.3875 (0.1738)	S&PGSCI gold	-0.2586 (0.3648)	-0.3074 (0.1905)
S&PGSCI gold* P1_S&PGSCI gold	-0.4734 (0.5496)	-0.1194 (0.8552)	S&PGSCI gold* US presidential election of 2016	-0.6158 (0.6339)	-0.4676 (0.6594)
S&PGSCI gold* P5_S&PGSCI gold	-0.0369 (0.9719)	0.8021 (0.3548)	S&PGSCI gold*Brexit	**2.4515*** (0.0982)	**3.1913***** (0.0088)
S&PGSCI gold* P10_S&PGSCI gold	0.3341 (0.7284)	-0.2512 (0.7514)	S&PGSCI gold*Covid_19	0.0605 (0.9377)	0.4552 (0.4739)
Ethereum (-1)		0.0320 (0.2516)	Ethereum (-1)		0.0274 (0.3209)
Bitcoin		**0.7935***** (0.0000)	Bitcoin		**0.7904***** (0.0000)
Adjusted R_squared	0.0662	0.3673	Adjusted R_squared	0.0728	0.3762
F-test	3.9867	23.1954	F-test	4.3065	24.0498
P-value	0.0000	0.0000	p-value	0.0000	0.0000
NOBS	843	843	NOBS	843	843

Table 4.10: Regression and Crisis Event Interaction Results for the EU Sample

The following table represents the results of the ordinary least squares regression and crisis event interaction regression for the hedging and/or safe haven capabilities of Ethereum against the conventional foreign exchange currencies, the EU stock and bond markets, the crude oil and the gold. The results of the regression models are represented without and with the control variables.

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Where $□_0$ is the intercept and □□ represents the residual values. P-values are given in parentheses and significant results are marked in bold.
***,
**, * denote two-tailed significance at 1%, 5%, and 10% level, respectively.

	Ethereum			Ethereum	
Panel A: Percentile Regression			*Panel B: Crisis Event Interaction*		
Intercept	**0.0093*** (0.0581)	0.0056 (0.1513)	Intercept	0.0049 (0.2076)	0.0032 (0.2916)
FXVol	-0.0022 (0.3480)	-0.0012 (0.5109)	FXVol	-0.0009 (0.5715)	-0.0010 (0.4316)
FXVol*P90_Fxvol	0.0023 (0.3788)	0.0003 (0.8967)	FXVol* US presidential election of 2016	-0.0017 (0.7272)	-0.0020 (0.5951)
FXVol*P95_Fxvol	-0.0024 (0.4051)	-0.0007 (0.7595)	FXVol*Brexit	0.0056 (0.5146)	0.0031 (0.6474)
FXVol*P99_Fxvol	0.0034 (0.3191)	0.0010 (0.7022)	FXVol*Covid_19	-0.0001 (0.9772)	-0.0019 (0.6477)
EuroSTOXX600	-0.1770 (0.4986)	-0.0628 (0.7674)	EuroSTOXX600	0.1382 (0.6302)	0.2605 (0.2570)
EuroSTOXX600* P1_EuroSTOXX600	-0.2157 (0.8027)	0.1469 (0.8308)	EuroSTOXX600* US presidential election of 2016	-1.5800 (0.4596)	-1.2893 (0.4488)
EuroSTOXX600* P5_EuroSTOXX600	-0.0164 (0.9877)	0.5462 (0.5199)	EuroSTOXX600*Brexit	0.0454 (0.9619)	-0.2481 (0.7434)
EuroSTOXX600* P10_EuroSTOXX600	0.9225 (0.3136)	0.1827 (0.8028)	EuroSTOXX600*Covid_19	0.0758 (0.8713)	-0.1795 (0.6329)
IEAG ETF	0.5831 (0.6734)	0.1510 (0.8910)	IEAG ETF	1.8742 (0.1162)	0.5659 (0.5524)
IEAG ETF*P1_IEAG ETF	2.3823 (0.4081)	1.2359 (0.5899)	IEAG ETF* US presidential election of 2016	2.6224 (0.6545)	3.0182 (0.5180)
IEAG ETF*P5_IEAG ETF	-2.5432 (0.5666)	-4.8343 (0.1718)	IEAG ETF*Brexit	-8.8373 (0.1128)	**-8.8119**** (0.0472)

IEAG ETF*P10_IEAG ETF	2.8180 (0.4953)	4.1175 (0.2113)	IEAG ETF*Covid_19	0.6910 (0.7120)	0.5814 (0.6966)
S&PGSCI crude oil	0.0914 (0.3042)	0.0491 (0.4886)	S&PGSCI crude oil	-0.0526 (0.5040)	0.0006 (0.9926)
S&PGSCI crude oil* P1_S&PGSCI crude oil	-0.0869 (0.7345)	-0.0902 (0.6621)	S&PGSCI crude oil* US presidential election of 2016	0.1739 (0.7178)	0.1353 (0.7243)
S&PGSCI crude oil* P5_S&PGSCI crude oil	-0.2198 (0.5721)	-0.1691 (0.5873)	S&PGSCI crude oil*Brexit	0.7953 (0.1626)	0.6391 (0.1592)
S&PGSCI crude oil* P10_S&PGSCI crude oil	0.1410 (0.6878)	0.2332 (0.4041)	S&PGSCI crude oil* Covid_19	**0.3464**** (0.0456)	0.1216 (0.3795)
S&PGSCI gold	**-0.6046*** (0.0769)	-0.3902 (0.1519)	S&PGSCI gold	-0.3471 (0.2347)	-0.2631 (0.2594)
S&PGSCI gold* P1_S&PGSCI gold	-0.7956 (0.3407)	-0.4990 (0.4530)	S&PGSCI gold* US presidential election of 2016	-0.6068 (0.7007)	-0.6873 (0.5846)
S&PGSCI gold* P5_S&PGSCI gold	0.0147 (0.9888)	0.4264 (0.6122)	S&PGSCI gold*Brexit	2.3781 (0.1901)	**2.6006*** (0.0723)
S&PGSCI gold* P10_S&PGSCI gold	0.4413 (0.6421)	0.0637 (0.9338)	S&PGSCI gold*Covid_19	**-1.1029*** (0.0762)	-0.0225 (0.9640)
Ethereum (-1)		0.0414 (0.1426)	Ethereum (-1)		0.0434 (0.1238)
Bitcoin		**0.8435***** (0.0000)	Bitcoin		**0.8411***** (0.0000)
Adjusted R_squared	0.0000	0.3663	Adjusted R_squared	0.0064	0.3702
F-test	0.9998	23.3358	F-test	1.2738	23.7091
P-value	0.4597	0.0000	P-value	0.1879	0.0000
NOBS	852	852	NOBS	852	852

In terms of adjusted R-squared, in both US and EU samples, as shown in tables 4.9 and 4.10, approximately 0% of the variations in Ethereum are explained by the independent variables before accounting for the control variables. However, after including the control variables, R-squared values improve and increase to 37%. It should be noted that low R-squared values are generated but are normal for such regressions including cryptocurrencies, mainly due to their high volatilities. Many previous researches also show low R-squared values such as Baur et al. (2017) and Bouri et al. (2019) among others.

As an interpretation of the results, it is clear that in the US market, Ethereum does not act as a hedge against the foreign exchange market since FXVol shows an insignificant p-value equal to 42.06%. Moreover, Ethereum cannot be considered as a safe haven against the conventional foreign exchange currencies since the 90th, 95th and 99th percentiles of the FXVol are insignificant (81.89%, 64.27% and 53.29% respectively). This result is also supported in the crisis event interaction regression since the three events namely the US presidential election of 2016, Brexit referendum and covid-19 do not show any safe haven capability of Ethereum against the conventional currencies. Their p-values show insignificance and are respectively 57.24%, 60.38% and 24.70%.

Furthermore, the findings reveal that Ethereum does not act as a hedge against US stocks since the S&P500 index has a p-value of 13.84%, which is insignificant. Moreover, it cannot be considered as a haven because the S&P500 index in the 1st, 5th and 10th percentiles have p-values of 53.30%, 97.13% and 70.35% respectively, which are statistically insignificant. This result is also noticed in the crisis event interaction analysis. As shown in Table 4.9, Ethereum does not act as a safe haven against US stock market in the US presidential election of 2016, Brexit referendum and covid-19 because their p-values are statistically insignificant (40.64%, 85.35% and 94.99% respectively).

Turning to the hedging and/or safe haven properties of Ethereum against the US bonds, the results in table 4.9 indicate that Ethereum is not a hedge against the US bonds. The p-value of BND ETF is statistically significant at 10% (6.87%) but with a positive coefficient (1.4215). Furthermore, Ethereum does not act as a safe haven against the US bond market since the 1^{st}, 5^{th} and 10^{th} percentiles of BND ETF are statistically insignificant (85.07%, 72.46% and 56.84% respectively). The same results are given in the crisis event interaction regression because the p-values of the US presidential election of 2016, the Brexit referendum and the covid-19 events are insignificant.

Additionally, the results reveal that Ethereum does not act as a hedge since the p-value of S&PGSCI crude oil is 41.04%, which is statistically insignificant. Moreover, Ethereum does not act as a safe haven against crude oil because the p-values of the 1^{st}, 5^{th} and 10^{th} percentiles of S&PGSCI crude oil show insignificant values (40.70%, 70.51% and 38.78% respectively). It is also noticed that Ethereum is not a safe haven for crude oil in the three events. For the US presidential election of 2016 and the covid-19 events, the p-values are 60.77% and 99.12% respectively, which are both statistically insignificant. However, for the Brexit referendum event, the p-value is statistically significant at 1% (0.49%) but the coefficient is positive (1.2445). However, it should be negative in order to consider Ethereum as a safe haven against the crude oil.

Finally, the results show that Ethereum does not act as a hedge against gold in the US market since the p-value of S&PGSCI gold is insignificant (17.38%). Furthermore, Ethereum is not considered as a safe haven because the p-values of the 1^{st}, 5^{th} and 10^{th}

percentiles of S&PGSCI gold are also statistically insignificant (85.52%, 35.48% and 75.14% respectively). The crisis events interaction results report the same results.

In the same way of analysis as in the US market, the results of the EU market in table 4.10 can be summarized as follows: Ethereum does not act as a hedge and/or a safe haven against all the considered assets in the study. However, it seems to show safe haven capabilities in some specific events that have caused turmoil in the financial market. In this study, for example, during the Brexit referendum event, Ethereum seems to act as a safe haven against the extreme movements in the European bonds.

Table 4.11: Summary of the Results

This table presents a summary of the percentile regression analysis along with the crisis event interaction analysis for both US and EU samples for the hedging and/or safe haven abilities of Ethereum against the conventional foreign exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold.

	US market		EU market	
	Ethereum		Ethereum	
	Hedge	Safe haven	Hedge	Safe haven
Forex currencies	No	No	No	No
Stock market	No	No	No	No
Bond market	No	No	No	No
Crude oil	No	No	No	No
Gold	No	No	No	No

4.3.4. DISCUSSION OF THE RESULTS AND HYPOTHESES

The aim of this research is to examine the hedging and/or safe haven capability of Ethereum, the second largest cryptocurrency in terms of market capitalization, against the conventional foreign exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. According to the existing literature, our study hypothesizes that Ethereum acts as a hedge against the foreign exchange currencies and traditional assets (H_4). Moreover, our next hypothesis (H_5) states that Ethereum does not act as a safe haven against the foreign exchange currencies and traditional assets. Our results report that Ethereum does not act as a hedge for the foreign exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. Thus, (H_4) is not supported. Our findings also imply that Ethereum does not act as a safe haven against the foreign exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. Consequently, (H_5) is supported. These results are in line with few previous studies tackling Ethereum. For instance, Bouri et al. (2019) show that Ethereum is neither a hedge nor a safe haven for the S&P500 index. Moreover, Conlon et al. (2020) find that Ethereum does not act as a safe haven against international equity markets such as the MSCI world, the S&P500, the FTSE100, FTSE MIB, IBEX, and CSI 300. However, Okorie et al. (2020) find that Ethereum acts as a short-lived hedge against crude oil. However, this contradicting result may be due to the fact that they adopt volatility connectedness between Ethereum and the crude oil in their study and not the return connectedness, which can lead to different results and directions as Diebold and Yilmaz (2009) mention that at any given point, return and volatility spillovers may be very different and, more generally, their dynamics may be very different as well. Moreover, among the articles tackling Bitcoin and showing the same results, Baur et al. (2017) find that Bitcoin does not act as a hedge nor a safe haven against EUR/USD, AUD/USD, JPY/USD, GBP/USD, CNY/USD, HUF/USD and S&P500 index or US stock market.

Additionally, our results that Ethereum is neither a hedge nor a safe haven for all the assets considered in the study could be explained that investors still consider the traditional assets as more effective hedges and/or safe havens against any financial instrument in their portfolio. This may be due to the fact that Ethereum is still an ambiguous cryptocurrency for investors and its behavior has not been studied well yet. For instance, Baur and Lucey (2010) find that gold is a hedge against US stocks and a safe haven in extreme stock market conditions. Furthermore, Ciner et al. (2012) show that the bond market is a hedge for the equity market and gold can be regarded as a hedge against the foreign exchange market in the US and the UK samples. Additionally, Reboredo et al. (2014) state that gold serves as a hedge against US dollar depreciation but is a weak safe haven against extreme US dollar movements. Moreover, Agyei-Ampomah et al. (2014) find that copper acts as a hedge and safe haven asset against sovereign bonds.

It should also be noted however, even though investors still prioritize the traditional assets over the new cryptocurrency market, Bitcoin shows some hedging and safe haven properties against few conventional instruments. Thus, when it comes to the cryptocurrency market, it seems that investors still prefer Bitcoin as a hedging or safe haven tool in their portfolios rather than Ethereum even though Ethereum has a cheaper price.

For example, Dyhrberg (2015b) finds that Bitcoin can be used as a hedge against the US dollar in the short-run. Additionally, the findings of Baumöhl (2018) show that Bitcoin acts as a hedge against Euro, Japanese Yen, British Pound, Swiss Franc, Canadian Dollar and Chinese Yuan. The outcomes of Corbet et al. (2018) reveal that Bitcoin can be used as a hedge against the US stocks and the gold. Furthermore, Chan et al. (2018) show that Bitcoin is a strong hedge for EuroSTOXX and S&P500 under monthly return and a weak hedge under daily and weekly returns. Finally, Urquhart et al. (2019) find that Bitcoin is a safe haven during periods of extreme market turmoil for the Canadian Dollar, Swiss Franc and British Pound.

4.4. CONCLUSION

This chapter provides the empirical results, their discussion and their linkages with previous studies and developed hypotheses. In the first part of the research, we examine whether volatility spillovers exist between the five cryptocurrencies with the highest market capitalization. Univariate GARCH models are used to model the volatility of every cryptocurrency. Then a VAR system is utilized to determine volatility spillovers between the cryptocurrencies. The sample period for this study spans from August 2017 until December 2019. In the second part of the study, we inspect the hedging and/or safe haven capability of Ethereum against the conventional foreign exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. Percentile regressions and event interaction crisis regressions are used with a sample period that spans from March 2016 until May 2020.

Our main findings in part one reveal the existence of uni-directional volatility spillovers from Bitcoin to Ethereum, Ripple, Bitcoin Cash and Litecoin, a uni-directional volatility spillover from Ethereum to Litecoin and from Litecoin to Ripple. Moreover, we find that Bitcoin is the main transmitter while Ripple is the main receiver of volatility shocks. Additionally, the findings reveal that Bitcoin is mainly affected by its own shocks while Ethereum, Ripple, Bitcoin Cash and Litecoin are affected both by their own shocks and by shocks from other cryptocurrencies. These outcomes partially support hypothesis (H_1) which states that Bitcoin, Ethereum and Ripple are mainly affected by their own shocks, while Bitcoin Cash and Litecoin is affected by both their own shocks and by shocks from other cryptocurrencies. However, they do not support hypothesis (H_2) which report that there are bi-directional volatility spillovers among the five selected cryptocurrencies.

Additionally, the results partially support (H_3) that Bitcoin is the dominant transmitter of volatility shocks whereas Ethereum is the most receiver of volatility shocks.

Moreover, our main results in the second part show that Ethereum does not act as a hedge and/or a safe haven against the traditional foreign exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. The outcomes do not support hypothesis (H_4) that states that Ethereum acts as a hedge against the foreign exchange currencies and traditional assets. However, our hypothesis (H_5) which states that Ethereum does not act as a safe haven against the foreign exchange currencies and traditional assets is supported.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1. INTRODUCTION

The purpose of this research is to investigate volatility spillovers between the five highest cryptocurrencies in terms of market capitalization, namely Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin. Additionally, it examines the hedging and/or safe haven properties of Ethereum, the second largest cryptocurrency in terms of market capitalization, in both US and EU markets. The second section summarizes the findings. Section three discusses the practical implications of the research. Section four provides the limitations of the study. The last section suggests further research.

5.2. SUMMARY OF THE FINDINGS

This research examines volatility spillovers between the top five cryptocurrencies in terms of market capitalization namely Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin using GARCH-VAR. The main results suggest the existence of volatility spillovers among the selected cryptocurrencies. Specifically, the findings reveal that there are uni-directional volatility spillovers from Bitcoin to Ethereum, Ripple, Bitcoin Cash and Litecoin, uni-directional volatility spillovers from Ethereum to Ripple and from Litecoin to Ripple. Moreover, the results show that Bitcoin is the most important transmitter of volatility shocks and Ripple is the top receiver. Finally, Bitcoin is mainly affected by its own shocks while Ethereum, Ripple, Bitcoin Cash and Litecoin are affected by both their own shocks and by shocks from other cryptocurrencies.

Additionally, the second part of the research examines the hedging and/or safe haven capabilities of Ethereum against the conventional foreign exchange currencies and the real assets using percentile regressions and event crisis analyses. The results reveal that

Ethereum does not act as a hedge and/or a safe haven for the traditional foreign exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. These results are confirmed in the crisis event interaction regressions except that during the Brexit referendum, Ethereum shows a safe haven potential against the extreme movements in the European bonds market.

Table 5.1: Summary of the Findings

This table represents the summary of the findings with the tested hypotheses for both the US and EU samples.

Hypotheses	Findings
H_1: Bitcoin, Ethereum and Ripple are mainly affected by their own shocks, while Bitcoin Cash and Litecoin are affected by their own shocks and shocks from other cryptocurrencies.	Partially Supported
H_2: There are bi-directional volatility spillovers among the five selected cryptocurrencies.	Not Supported
H_3: Bitcoin is the dominant transmitter of volatility shocks whereas Ethereum is the most receiver of volatility shocks.	Partially Supported
H_4: Ethereum acts as a hedge against the foreign exchange currencies and traditional assets.	Not Supported
H_5: Ethereum does not act as a safe haven against the foreign exchange currencies and traditional assets.	Supported

5.3. PRACTICAL IMPLICATIONS

The empirical findings of this research have important implications and provide recommendations for investors and regulators. As cryptocurrencies are increasingly used for investment and speculation purposes, understanding their price volatility movements and co-movements is of great importance, since volatility can affect investment decisions.

In this sense, the results show interlinkages within the cryptocurrency market and could thus help traders and investors better manage the risks of their portfolios.

Additionally, the results of our study do not show any hedging and/or safe haven capability of Ethereum against the conventional exchange currencies, the US and EU stock markets, the US and EU bond markets, the crude oil and the gold. Thus, we recommend to investors who seek protection in their portfolios from downward movements in equity and commodity markets not to consider Ethereum in managing their portfolios against the risks of the aforementioned assets.

In addition to the importance of this study to investors, it would also provide insights to regulators and governments to engage in better understanding the important role of Ethereum in investment decision-making in financial markets.

5.4. LIMITATIONS OF THE STUDY

This study presents two main limitations. The first one is the use of daily data instead of intraday data. The latter was out of reach because intraday data is, unfortunately, not stored in Reuters or Bloomberg or any other data provider for more than three to six months. Otherwise, intraday data for longer periods could be made available by data providers but at a very high cost. The second limitation faced in the present research is the restricted sample size due to the late birth of some cryptocurrencies.

5.5. SUGGESTIONS FOR FUTURE RESEARCH

The results of this study are of great importance for investors and risk managers and consequently deserve further studies. For instance, a major improvement of the study could be through the inclusion of more cryptocurrencies in the examination of the volatility spillovers in the cryptocurrency market to provide the investors with more insights about other good candidates as alternative to the largest two cryptos, namely, Bitcoin and Ethereum. Additionally, one of the major improvements future studies could achieve would be to extend our model to examine how other assets are correlated in percentiles with this new cryptocurrency market. New financial assets could be incorporated in the model to study their effects with Ethereum. For example, the behavior of other commodities, indices and other major currencies could be included to further inspect the capability of Ethereum as a hedging and/or safe haven tool in an investor's portfolio.

Additionally, further studies could be performed to examine the impact of covid-19 and the US presidential election of 2016 on the performance of cryptocurrencies. Also, considering the market performance of Bitcoin and Ethereum under crucial events in several countries other than the ones we considered could be interesting as well. In addition, one could examine the possibility of hedging and/or safe haven potentials of Ethereum to investors, other than in the US and EU markets, such as in the developed and developing countries. Moreover, studying the market performance of Ethereum in relation with the market index and with factor-mimicking portfolios to find any possible opportunity of diversifying risk could be interesting to provide insights to investors and portfolio managers.

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APPENDIX A

Appendix 1: Normality and Heteroskedasticity Tests of the Residuals

This table represents the results of the normality and heteroskedasticity tests of the residuals from the mean equation of the cryptocurrencies. The daily data spans from August 2017 until December 2019.

	Bitcoin	Ethereum	Ripple	Bitcoin Cash	Litecoin
Jarque-Bera test	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
White test	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***

Appendix 2: Augmented Dickey-Fuller Test Results

This table represents the results of the augmented Dickey-Fuller test for the daily data from August 2017 until December 2019 of variance series cryptocurrencies.

	# of lags	1% level	5% level	10% level	ADF t-statistic
BTC_vseries	1	-3.4377	-2.8647	-2.5685	-5.7083
ETH_vseries	0	-3.4377	-2.8647	-2.5685	-6.5572
XRP_vseries	6	-3.4377	-2.8647	-2.5685	-3.6301
BCH_vseries	2	-3.4377	-2.8647	-2.5685	-6.8638
LTC_vseries	3	-3.4377	-2.8647	-2.5685	-7.8762

Appendix 3: Correlation Matrix

This table reports the return correlation between the five cryptocurrencies used in the study. Daily data between August 2017 until December 2019 is used and is retrieved from investing.com website. P-values are given in parentheses and significant results are marked in bold. ***, **, * denote two tailed significance at 1%, 5%, and 10% level, respectively.

	BTC_vseries	ETH_vseries	XRP_vseries	BCH_vseries	LTC_vseries
BTC_vseries	1.0000				
ETH_vseries	**0.6874***** (0.0000)	1.0000			
XRP_vseries	**0.4455***** (0.0000)	**0.5026***** (0.0000)	1.0000		
BCH_vseries	**0.3718***** (0.0000)	**0.3297***** (0.0000)	**0.1649***** (0.0000)	1.0000	
LTC_vseries	**0.5088***** (0.0000)	**0.5995***** (0.0000)	**0.6619***** (0.0000)	**0.1081***** (0.0014)	1.0000

Appendix 4: Breush-Pagan-Godfrey Test Results

This table shows the results of the heteroskedasticity test. ***, **, * denote two-tailed significance at 1%, 5%, and 10% level, respectively.

Model	P-value	Results
US market	0.6351	We do not reject H_0 => residuals are homoskedastic.
EU market	0.3562	We do not reject H_0 => residuals are homoskedastic.
Crisis event interaction in the US market	0.8925	We do not reject H_0 => residuals are homoskedastic.
Crisis event interaction in the EU market	0.7877	We do not reject H_0 => residuals are homoskedastic.

Appendix 5: Normality Test Results

This table shows the results of the normality test. ***, **, * denote two-tailed significance at 1%, 5%, and 10% level, respectively.

Model	P-value	Result
US market	0.0000***	We reject H_0 => residuals are not normally distributed.
EU market	0.0000***	We reject H_0 => residuals are not normally distributed.
Events analysis in the US market	0.0000***	We reject H_0 => residuals are not normally distributed.
Events analysis in the EU market	0.0000***	We reject H_0 => residuals are not normally distributed.

APPENDIX B

Appendix 6: Univariate GARCH Models

This table shows the results of the heteroskedasticity tests. It is organized in five panels. Panel A, panel B and panel C present a comparison of the univariate GARCH models of Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin, respectively. P-values are given in parentheses and significant results are marked in bold. ***, **, * denote two-tailed significance at 1%, 5%, and 10% level, respectively.

Panel A: Comparison of the univariate GARCH models of Bitcoin

	Bitcoin		
	ARCH (4)	GARCH (1,1)	EGARCH (1,1)
	Mean Equation		
□	0.0015 (0.2923)	0.0012 (0.3596)	0.0005 (0.7151)
	Variance Equation		
□□	**0.1366***** (0.0000)	**0.0893***** (0.0000)	**0.2027***** (0.0000)
□□	**0.1068***** (0.0003)		
□□	**0.1102***** (0.0035)		
□□	**0.1279***** (0.0015)		
□□		**0.8487***** (0.0000)	**0.9064***** (0.0000)
Ljung-Box	(0.0380) **	(0.0720) **	(0.0650) **
Ljung-Box^2	(0.1670)	(0.6840)	(0.5120)
Akaike	-3.5240	**-3.5576**	-3.5506
Schwarz	-3.4911	**-3.5357**	-3.5286
Hann-Ouinn	-3.5114	**-3.5493**	-3.5422
RMSE	**0.043273**	0.043276	0.0433297
MAE	**0.029588**	**0.029588**	0.029597
MAPE	112.4718	110.0419	**102.3376**
LL	1538.9230	**1551.5730**	1548.4960

Panel B: Comparison of the univariate GARCH models of Ethereum and Bitcoin Cash

	Ethereum			Bitcoin Cash		
	ARCH (1)	GARCH (1,1)	EGARCH (1,1)	ARCH (1)	GARCH (1,1)	EGARCH (1,1)
Mean Equation						
?	0.0003 (0.8409)	-0.0004 (0.7760)	0.0002 (0.9030)	-0.0003 (0.9288)	-0.0003 (0.8982)	0.0006 (0.8088)
?? (?)	**-0.0763***** (0.0058)	**-0.0759**** (0.0297)	**-0.0723**** (0.0348)			
Variance Equation						
??	**0.1462***** (0.0000)	**0.0821***** (0.0000)	**0.1629***** (0.0000)	**0.3213***** (0.0000)	**0.0731***** (0.0000)	**0.1487***** (0.0000)
??		**0.8294***** (0.0000)	**0.9127***** (0.0000)		**0.8774***** (0.0000)	**0.9599***** (0.0000)
Ljung-Box	(0.0120) **	(0.0140) **	(0.0110) **	(0.3020)	(0.1140)	(0.0640) *
Ljung-Box^2	(0.0370) **	(0.9860)	(0.9690)	(0.4180)	(0.8500)	(0.3390)
Akaike	-3.0872	**-3.1204**	-3.1170	-2.2730	**-2.3706**	-2.3672
Schwarz	-3.0652	**-3.0930**	-3.0896	-2.2565	**-2.3486**	-2.3453
Hann-Ouinn	-3.0788	**-3.1099**	-3.1065	-2.2667	**-2.3622**	-2.3588
RMSE	0.052225	0.052239	**0.052223**	0.082901	0.082904	**0.082879**
MAE	0.036413	**0.036391**	0.036393	0.051006	**0.051000**	0.051089
MAPE	112.2790	111.7208	**110.9675**	99.7648	**99.7276**	101.7296
LL	1346.9210	**1362.3830**	1360.8830	991.7437	**1035.1910**	1033.7330

Panel C: Comparison of the univariate GARCH models of Ripple and Litecoin

	Ripple			Litecoin		
	ARCH (2)	GARCH (1,1)	EGARCH (1,1)	ARCH (2)	GARCH (1,1)	EGARCH (1,1)
			Mean Equation			
?	-0.0022 (0.2258)	-0.0022 (0.2301)	-0.0021 (0.2583)	0.0014 (0.4991)	0.0010 (0.6321)	0.0016 (0.4128)
			Variance Equation			
??	**0.2522***** (0.0000)	**0.2493***** (0.0000)	**0.4691***** (0.0000)	**0.1523***** (0.0000)	**0.0971***** (0.0000)	**0.2373***** (0.0000)
??	**0.1293***** (0.0000)			**0.1526***** (0.0000)		
??		**0.4927***** (0.0000)	**0.7130***** (0.0000)		**0.7896***** (0.0000)	**0.8702***** (0.0000)
Ljung-Box	(0.3920)	(0.5340)	(0.5370)	(0.7570)	(0.8320)	(0.7920)
Ljung-Box^2	(0.7250)	(0.9720)	(0.9740)	(0.0780)	(0.5440)	(0.1680)
Akaike	-2.9607	-2.9801	**-2.9900**	-2.8374	**-2.8549**	-2.8410
Schwarz	-2.9333	-2.9526	**-2.9626**	-2.8155	**-2.8330**	-2.8191
Hann-Ouinn	-2.9503	-2.9696	**-2.9795**	-2.8290	**-2.8465**	-2.8326
RMSE	0.071292	0.071294	**0.071283**	0.063336	0.063340	**0.063335**
MAE	**0.040811**	**0.040811**	0.040812	0.041306	**0.041271**	0.041318
MAPE	120.1934	120.4075	**118.6126**	107.3309	**104.5392**	108.3137
LL	1292.9250	1301.3220	**1305.6650**	1238.2610	**1245.8700**	1239.8440