St. Petersburg State University

Graduate School of Management

Master in Corporate Finance Program

THE APPLICATION OF CRYPTOCURRENCIES FOR HEDGING AND DIVERSIFICATION OF INVESTMENT PORTFOLIOS

Submitted by the 2nd year student:

Vladislav Kovalevskiy

Research advisor:

Vitaly L. Okulov

Candidate of Physics and Mathematics, Associate Professor of the Department of Finance and Accounting

Saint Petersburg

2022

ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

Я, Ковалевский Владислав Юрьевич, студент второго курса магистратуры направления «Менеджмент», заявляю, что в моей магистерской диссертации на тему «Применение криптовалют для хеджирования и диверсификации инвестиционных портфелей», представленной в службу обеспечения программ магистратуры для последующей передачи в государственную аттестационную комиссию для публичной защиты, не содержится элементов плагиата.

Все прямые заимствования из печатных и электронных источников, а также из защищенных ранее выпускных квалификационных работ, кандидатских и докторских диссертаций имеют соответствующие ссылки. Мне известно содержание п. 9.7.1 Правил обучения по основным образовательным программам высшего и среднего профессионального образования в СПбГУ о том, что «ВКР выполняется индивидуально каждым студентом под руководством назначенного ему научного руководителя», и п. 51 Устава федерального государственного бюджетного образовательного учреждения высшего образования «Санкт-Петербургский государственный университет» о том, что «студент подлежит отчислению из Санкт-Петербургского университета за представление курсовой или выпускной квалификационной работы, выполненной другим лицом (лицами)».

____

31.05.2022

STATEMENT ABOUT THE INDEPENDENT CHARACTER OF

THE MASTER THESIS

I, Vladislav Kovalevskiy, second year master student, Master in Corporate Finance program «Management», state that my master thesis on the topic «The Application of Cryptocurrencies for Hedging and Diversification of Investment Portfolios», which is presented to the Master Office to be submitted to the Official Defense Committee for the public defense, does not contain any elements of plagiarism.

All direct borrowings from printed and electronic sources, as well as from master theses, PhD and doctorate theses which were defended earlier, have appropriate references. I am aware that according to paragraph 9.7.1. of Guidelines for instruction in major curriculum programs of higher and secondary professional education at St. Petersburg University «A master thesis must be completed by each of the degree candidates individually under the supervision of his or her advisor», and according to paragraph 51 of Charter of the Federal State Institution of Higher Education Saint-Petersburg State University «a student can be expelled from St. Petersburg University for submitting of the course or graduation qualification work developed by other person (persons)».

31.05.2022

АННОТАЦИЯ

Автор	Ковалевский Владислав Юрьевич
Название ВКР	Применение криптовалют для хеджирования и диверсификации инвестиционных портфелей
Образовательная программа	Менеджмент
Направление подготовки	Корпоративные финансы
Год	2022
Научный руководитель	Окулов Виталий Леонидович
Описание цели, задач и основных результатов	Цель данного исследования - определить, обладают ли изучаемые криптовалюты свойствами для диверсификации или могут служить для «незначительного» или «значительного» хеджирования инвестиционных портфелей базирующихся на выбранных фондовых индексах. Говоря о практической полезности результатов, потенциальный инвестор должен получить более глубокое понимание эффекта включения изученных криптовалют в инвестиционный портфель. Задачи: 1. Изучить и проанализировать существующие научные статьи. 2. Определить набор криптовалют и фондовых индексов для анализа и установить временные рамки для набора данных. 3. Собрать и сформировать набор данных для анализа. 4. Выбрать эконометрическую модель для проведения анализа и обосновать ее выбор. 5. Провести анализ и выяснить, какие свойства демонстрируют выбранные криптовалюты по отношению к выбранным фондовым индексам. 6. Продемонстрировать, как добавление криптовалюты в портфель инвестора, базирующегося на каждом фондовом индексе, влияет на показатели риск-скорректированной доходности. 7. Объяснить академическую и практическую полезность полученных результатов. Основные результаты: • Bitcoin, Ethereum и BNB могут быть использованы для диверсификации портфеля, имитирующего индекс развитых рынков MSCI • Bitcoin, Ethereum и BNB могут быть использованы для «незначительного» хеджирования портфеля, имитирующего индекс развивающихся рынков MSCI. • Ethereum может быть использован для диверсификации портфеля, имитирующего индекс MSCI Russia

	• Bitcoin и BNB могут могут быть использованы для «незначительного» хеджирования портфеля, имитирующего индекс MSCI Russia. Более того, чтобы получить представление о том, как добавление каждой криптовалюты в портфель инвестора, представленного каждым индексом фондового рынка, влияет на показатели риск-скорректированной доходности, были построены и проанализированы портфели, состоящие из криптовалюты и каждого фондового индекса. В результате, скорректированные на риск показатели портфелей, имитирующих Индекс развитых рынков MSCI, Индекс развивающихся рынков MSCI и Индекс MSCI Russia, показали положительную динамику вследствие добавления любой из изученных криптовалют. Однако, портфели включающие криптовалюту BNB продемонстрировали наилучшие показатели риск-скорректированной доходности.
Ключевые слова	Криптовалюта, Bitcoin, Ethereum, BNB, диверсификация, хеджирование, фондовый индекс MSCI

ABSTRACT

<table>
<tr><td>Master Student’s Name</td><td>Kovalevskiy Vladislav Iurevich</td></tr>
<tr><td>Master Thesis Title</td><td>The Application of Cryptocurrencies for Hedging and Diversification of Investment Portfolios</td></tr>
<tr><td>Educational Program Management</td><td>Management</td></tr>
<tr><td>Main field of study</td><td>Corporate finance</td></tr>
<tr><td>Year</td><td>2022</td></tr>
<tr><td>Academic Advisor’s Name</td><td>Vitaly L. Okulov</td></tr>
<tr><td>Description of the goal, tasks, and main results</td><td>The goal of this research is to identify whether the selected cryptocurrencies have diversifier, weak hedge, or strong hedge properties for selected stock market indices. Considering the applicability of results obtained in this paper, the potential investor should gain a deeper understanding of the effects of including studied cryptocurrencies in investment portfolios.
Tasks:
1. To get an understanding of current state of research in the studied field by reading and analyzing existing academic papers.
2. To define the set of cryptocurrencies and equity indices for analysis and to set a timeframe for a dataset.
3. To collect data and form a dataset for analysis.
4. To choose the econometric model for performing analysis and substantiate the choice.
5. To conduct analysis and discover which properties selected cryptocurrencies demonstrate with respect to selected equity indices.
6. To demonstrate how adding cryptocurrency to an investor portfolio mimicking each stock market index affects risk-adjusted performance.
7. To explain the academic and practical implications of obtained results to underline the usefulness of research for its audience.
Main results:
• Bitcoin, Ethereum, and BNB can serve as diversifiers to the portfolio mimicking MSCI Developed Markets Index
• Bitcoin, Ethereum, and BNB can serve as weak hedges to the portfolio mimicking MSCI Emerging Markets Index
• Ethereum can serve as a diversifier to the portfolio mimicking MSCI Russia Index</td></tr>
</table>

	• Bitcoin and BNB can serve as weak hedges to the portfolio mimicking MSCI Russia Index Moreover, to get an understanding of how adding each cryptocurrency to investor portfolio represented by each stock market index affects risk-adjusted performance, portfolios combined with a cryptocurrency and each stock market index were constructed and analyzed. In brief, risk-adjusted performance of portfolios mimicking the MSCI Developed Markets Index, the MSCI Emerging Markets Index, and the MSCI Russia Index was improved by adding any of the studied cryptocurrencies, but portfolios with BNB demonstrated the best risk-adjusted performance.
Keywords	Cryptocurrency, Bitcoin, Ethereum, BNB, diversifier, weak hedge, strong hedge, MSCI stock market indices

Table of Contents

Introduction

This work is devoted to the cryptocurrencies and studying prospects of their applicability for hedging and diversification of investment portfolio. Cryptocurrency is a digital currency, for which the encryption techniques are used to control the emission of new currency units and which transactions are verified, and records maintained by a decentralized system using cryptography, rather than by a centralized authority. (Schueffel, Groeneweg, & Baldegger, 2019) In simple words, decentralized system is a network of myriad of computers, running separate copies of the same program.[1]

The cryptocurrencies market is on rise, as can be confirmed either by high growth of total market capitalization of cryptocurrencies (CAGR equal to ~29.5% for a period from 1 January 2018 till 25 February 2022) market and by wide coverage in the news. On the moment of writing this paper, total market capitalization of cryptocurrencies amounts to $1.72 trillion USD consisting of 15,617 crypto tokens traded on 446 exchanges worldwide.[2] Furthermore, the rapid growth of cryptocurrency owners says that there are more and more potential cryptocurrency investors coming, thus underlining the importance and actuality of studying cryptocurrencies. Moreover, if the current growth rate is extrapolated in 2022, the global number of crypto users can reach even a figure of 1 billion by the end of 2022. (Hon, Wang, Bolger, Wu, & Zhou, 2022)

While other financial assets properties are widely studied, the cryptocurrencies, as a new financial instrument provides a lot of ground for research, being the source of disrupt in modern financial industry. Cryptocurrencies are different from stock indices and commodities in terms of higher volatility and high tail risks (Feng, Wang, & Zhang, 2018). High volatility leads to higher uncertainty about future prices of cryptocurrencies, making them quite a risky financial instrument for investors. In context of raising interest in cryptocurrencies and active growth of cryptocurrency wallets' holders it becomes more and more important to provide more ground for decisions concerning adding cryptocurrencies to investor portfolio. This research is aimed to study the association between Bitcoin, Ethereum and BNB cryptocurrencies' returns and external variables in the role market indices returns to understand whether each analyzed cryptocurrency has diversifier or weak/strong hedge property. In this field of research, the number of works is even smaller, emphasizing the research gap.

Research question of this paper is: "Do selected cryptocurrencies have diversifier, weak hedge or strong hedge properties for world equity indices?". Research goal is formulated as follows: "To

[1] https://www.wsj.com/articles/what-is-cryptocurrency-how-does-it-work-11638386626
[2] https://coinmarketcap.com/charts/

identify whether the selected cryptocurrencies have diversifier, weak hedge or strong hedge properties for selected stock market indices". The formulated research objectives are as follows:

1. To get an understanding of current state of research in the field by reading and analyzing existing academic papers.
2. To define the set of cryptocurrencies and equity indices for analysis and to set a timeframe for a dataset.
3. To collect data and form a dataset for analysis.
4. To choose the econometric model for performing analysis and substantiate the choice.
5. To conduct an analysis and discover which properties selected cryptocurrencies demonstrate with respect to selected equity indices.
6. To demonstrate how adding cryptocurrency to an investor portfolio mimicking each stock market index affects risk-adjusted performance.
7. To explain the academic and practical implications of obtained results to underline the usefulness of research for its audience.

Considering the applicability of results obtained in this paper, the potential investor should gain deeper understanding of the effects of including studied cryptocurrencies in investment portfolios.

The novelty of work is supported by including not only Bitcoin and Ethereum, which mostly were the focus of previous studies, but also BNB (Binance cryptocurrency), and also adding the MSCI Russia index returns as independent variable (which will be especially interesting for investors in Russian stock market) besides updating the set of generally used indices with the new ones: MSCI World Index (devoted to developed markets) and MSCI Emerging markets index (devoted to emerging markets) returns. Adding these indices provides more detailed view on studied properties of cryptocurrencies separately for developed, emerging markets, and for Russian market. Finally, the more recent data is used (also covering the COVID-19 pandemic period), making this work more up to date.

Chapter 1. Theoretical review

1.1 About studied cryptocurrencies

<u>Bitcoin (BTC)</u>

Market snapshot on 03.04.2022[3]:

- Rank according to market capitalization: 1
- Price: $46,453.57
- Market capitalization: $882,703,992,270.52
- Circulating supply: 19,001,856 BTC

Bitcoin was the emerged in 2009 by Satoshi Nakamoto (Nakamoto, 2008), which is an anonymous developer of even a group of developers. Bitcoin is a cryptocurrency, or virtual currency, that acting as money and a payment method independent of any person, organization, or entity, hence eliminating the need for involving any third-party in financial transactions. (Frankenfield & Mansa, 2022)

Bitcoin network relies on block chain (blockchain), which is a publicly shared ledger. This ledger accumulates information on all confirmed transactions in the network. (Bitcoin.org, 2022) Information in the blockchain is secured by exploiting encryption, represented by SHA-256 hashing algorithm. The transaction in Bitcoin Network can be described as follows: information flows from previous block to the new one, then it is encrypted, and transaction is finally validated by so called miners. (Frankenfield & Mansa, 2022) Bitcoin is given to blockchain miners in exchange for their efforts in verifying transactions and can be bought and sold on numerous platforms. Transactions validation in Bitcoin network is based on consensus protocol named Proof of Work protocol. Proof of Work protocol assumes that miners, participating in transaction validation, compete between each other to be the first who solves the math problem. Winner of such competition gets reward in form of Bitcoin (Coinbase, 2022)

Main usage cases of Bitcoin are payments and investing. If a user has a cryptocurrency wallet, he or she can use it as a payment for goods and services. By the way, it is accepted as a mean of payment by many organizations like IT-companies, Telecom, restaurants, airlines and even more. Examples of large companies who accept Bitcoin are Wikipedia, AT&T, Microsoft, Burger King, Pizza Hut, Virgin Galactic, Norwegian Air, and the list is even longer. (Beigel, 2022) Nevertheless, the Bitcoin as a mean of payment is not adopted worldwide and is not accepted in many countries. For example, in case of Burger King only Venezuela and German branches accept Bitcoin. Bitcoin

[3] https://coinmarketcap.com/historical/20220403/

also can be traded on cryptocurrency exchanges. For instance, Bitcoin can be bought and sold on such exchanges like Binance, Coinbase, Kraken, etc. (Hayes & Brown, 2022)

Ethereum (ETH)

Market snapshot on 03.04.2022[4]:

- Rank according to market capitalization: 2
- Price: $3,522.83
- Market capitalization: $423,557,081,705.00
- Circulating supply: 120,231,936 ETH

Ethereum was introduced by Vitalik Buterin in his whitepaper in 2014. (Buterin, 2014) Ethereum is actually a decentralized software platform. It has its own cryptocurrency named Ether (ETH), which can be used in its network.

As a Bitcoin, it also relies on blockchain technology. The principle of transaction mechanics in Ethereum is the same as in Bitcoin network. Ethereum also applies Proof of Work consensus protocol, where network participants compete for transaction validation, which essence is solving the math puzzle. The first miner who solved the math problem correct takes the reward in form of Ether (ETH). Nevertheless, in the close future (around Q3 or Q4 of 2022) Ethereum will switch to Proof of Stake consensus protocol (Ethereum.org, 2022). This consensus protocol work in a different way: owners of ETH stake ether in a pool for getting a chance to validate a transaction and ultimately earn a reward. Here participants do not compete to solve a math problem first – the network conducts a selection of validator based on amount of staked cryptocurrency in a pool and time the crypto was kept in a pool. (Coinbase, 2022)

As opposed to Bitcoin', Ethereum blockchain is created not only for support of its cryptocurrency. Ethereum is a platform for myriad of DApps (decentralized applications), which have a lot in common with traditional apps used by many people today. (Ethereum.org, 2022; Frankenfield & Anderson, Ethereum, 2022) DApps differ by absence of intermediaries.[5] So, use cases of Ethereum are a bit wider: besides payments with ETH[6] and investing in ETH, Ethereum is a place for non-fungible tokens (NFT), which result from tokenization of art and DeFi (decentralized finance) applications based on Ethereum, which can be exploited to borrowing, sending and receiving funds, and earning interest.[7]

[4] https://coinmarketcap.com/historical/20220403/
[5] https://www.coindesk.com/learn/how-to-use-ethereum/
[6] https://cryptonews.com/guides/who-accepts-ethereum.htm
[7] https://ethereum.org/en/

BNB (BNB)

Market snapshot on 03.04.2022[8]:

- Rank according to market capitalization: 4
- Price: $450.35
- Market capitalization: $74,360,146,489.04
- Circulating supply: 165,116,761 BNB

BNB is the cryptocurrency issued by Binance exchange, which was launched in the course of Initial Coin Offering[9] (ICO) in July 2017.

Firstly, it was launched on Ethereum blockchain but later it was transferred to Binance chain – blockchain of Binance, becoming native asset of Binance chain. Considering the consensus protocol, Binance Chain applies Tendermint BFT consensus, where initial validators are chosen from among trustworthy Binance community members. Later, selection of validators will be transferred to more individuals as the Binance blockchain and ecosystem grow. (Binance, 2022)

The main use of BNB is paying for trading and transaction fees on Binance exchange with a discount. (Cointelegraph, 2022) Nevertheless, as Binance now is not only exchange platform – it's more about ecosystem, BNB use cases are much more wider. For instance: trading, investment, entertainment, booking hotels and flights, etc. Broader view on BNB application cases can be obtained from the figure below:

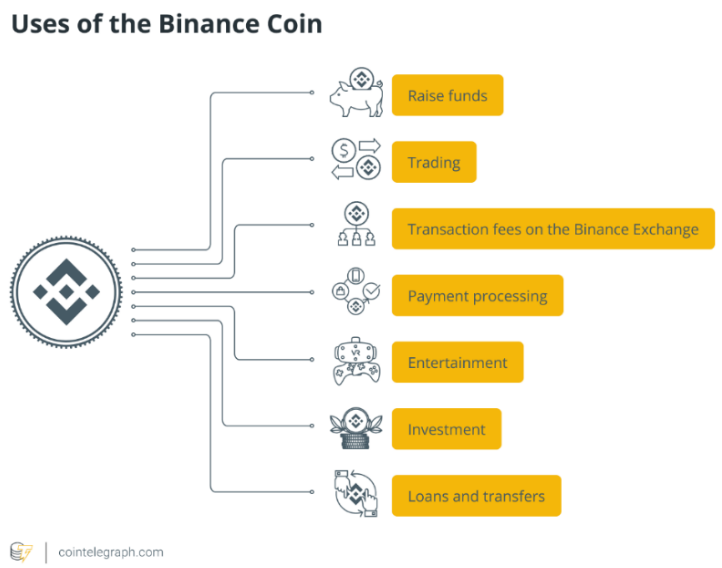

Figure 1 BNB application cases. Retrieved from (Cointelegraph, 2022)

[8] https://coinmarketcap.com/historical/20220403/
[9] Cryptocurrency equivalent to IPO. More: https://www.investopedia.com/terms/i/initial-coin-offering-ico.asp

1.2 Definitions of diversifier, weak hedge, and strong hedge

In “Research problem, goal, objectives, and hypotheses” section definitions of diversifier, weak hedge and strong hedge were mentioned. This section aims to elaborate on these asset characteristics.

Baur and Lucey were the first who introduced definitions of diversifier and hedge for the assets in a testable manner. (Baur & Lucey, 2010) However, the important differentiation between weak hedge and strong hedge was provided in the work of Baur and McDermott (Baur & McDermott, 2010), which makes an analysis more precise. This extension is important, as there is a difference in nature of how weak hedge asset or strong hedge asset function. If an asset demonstrates strong hedge properties (it is negatively correlated with other asset), it can provide to investor a positive return when other (hedged) asset experiences negative return. The situation is different in case of application of weak hedge asset (it is not correlated with another asset). (Baur & McDermott, 2010)

In general terms, returns co-movement were studied. In their works authors concluded on diversifier properties of a gold for stock index in case the beta coefficient for stock index logarithmic return in mean equation of the model was positive and significant, meaning that there is a positive association between gold and stock market index returns on average. In case the beta coefficient for stock index logarithmic return in mean equation of the model was non-significant – they concluded that gold has weak hedge properties for stock index, meaning that there is no association between gold and stock market index returns on average. In case the beta coefficient for stock index logarithmic return in mean equation of the model was negative and significant – they concluded that gold has strong hedge properties for stock index, meaning that there is a negative association between gold and stock market index returns on average.

This classification was often used in other papers in the field studying cryptocurrencies by such authors like (Dyhrberg, 2016; Stensås, Nygaard, & Treepongkaruna, 2019; Chan, Le, & Wu, 2019; Abdul-Rahim & Soon, 2019;Wang, Ma, & Wu, 2020; Bouri, Lucey, & Roubaud, 2020) Hence, this paper will also be based on this classification.

1.3 Previous studies in the field

As it was mentioned in the introduction section, the field is not widely studied yet. However, some researchers attempted to study the cryptocurrencies in terms of their diversifier and hedge (weak/strong if researcher decided to use the extended classification as in this working paper) properties.

Anne Haubo Dyhrberg in her paper "Hedging capabilities of bitcoin. Is it the virtual gold?" attempts to study the bitcoin hedging properties against FTSE Index, dollar-sterling and also dollar -euro. Author applied asymmetric GARCH model in combination with ARMA. Results are as follows: Bitcoin returns are not correlated with FTSE Index returns on average, which makes it possible to hedge some of the risk of FTSE. Considering the other results, it was discovered, that Bitcoin return has low positive correlation with US Dollar. However, author claims that as correlations are quite low and their significance can be questioned, hedging is possible in short term. Finally, author concludes that Bitcoin can be added to the list of instruments lowering the risk. (Dyhrberg, 2016)

Ruzita Abdul-Rahim and Ling Pick Soon in their work "Diversifier, Hedge & Safe Heaven Properties of Cryptocurrencies: The Case Against Asian Fiat Currencies" study the safe haven and hedge properties of the set of cryptocurrencies against Asian region ten currencies. Authors apply MGARCH dynamic conditional correlation model on daily returns of studied instruments. Timeframe of data is December 2013 – June 2019. Results of this work are the following: Bitcoin can serve as a weak hedge for 3 conventional currencies and can serve as a strong hedge for 2 of them: Taiwan Dollar and Hong Kong Dollar. However, considering the safe haven properties, Bitcoin is a safe haven for all studied currencies. Altcoins (which are the cryptocurrencies other than Bitcoin[10]) are also considered in this work and results show that, for instance, Ripple demonstrates better perspectives for using it as a hedge by proving to be a weak hedge for 8 conventional currencies of 10 and proving to be a strong hedge for 7 of them. It also can function as a safe haven for all studied traditional currencies. Ethereum serves as a weak hedge for 5 of 10 traditional currencies, being a strong hedge only for 4 of them. Moreover, Ethereum serves as safe haven for 9 of 10 conventional currencies. Litecoin serves as a weak hedge for 3 of 10 traditional currencies, being a strong hedge only for 2 of them. Moreover, Litecoin serves as safe haven for all 10 conventional currencies. Monero serves as a weak hedge for 7 of 10 traditional currencies, being a strong hedge only for 4 of them. Additionally, Monero serves as safe haven for 8 of 10 conventional currencies. Finally, Stellar serves as a weak hedge and strong hedge for 6 of 10 traditional currencies. Moreover, Stellar serves as safe haven for all of 10 conventional currencies. (Abdul-Rahim & Soon, 2019)

Anders Stensås, Khine Kyaw, Magnus Frostholm Nygaard & Sirimon Treepongkaruna in their work "Can Bitcoin be a diversifier, hedge or safe haven tool?" attempt to investigate whether Bitcoin possesses hedge, diversification or safe haven properties. This research paper exploits GARCH DCC (dynamic conditional correlation) for performing the econometric analysis on daily

---

[10] https://www.investopedia.com/terms/a/altcoin.asp

returns. Considering the sample, this work is focused on several developed and developing countries and takes into account ten commodities and also 5 regional indices. The timeframe of sample is from September 2011 to January 2018. The results of this research are the following: Bitcoin is not a hedge for countries from developed markets (United States, Canada, United Kingdom, Germany, Italy, France and Japan) and can be regarded only as a diversifier. Nevertheless, Bitcoin acts as a strong hedge in case of countries from developing countries (these are India, South Korea and Russia), and also acts as a weak hedge for Brazil. Considering the safe haven properties, Bitcoin acts as a strong save haven only in case of United States, Zimbabwe and India. Moreover, when it comes to regional stock market indices (World, Europe, Asia, Pacific, BRIC) and commodities, Bitcoin serves only as a diversifier against all of them. Finally, considering the safe haven properties, Bitcoin acts as a strong save haven for World index, Pacific index, BRIC index and Europe index. As of commodities, Bitcoin functions as a safe haven only for gold, All wheat and World commodity index. (Stensås, Nygaard, & Treepongkaruna, 2019)

Wing Hong Chan, Yan Wendy Wu and Minh Le in their research paper "Holding Bitcoin longer: The dynamic hedging abilities of Bitcoin" examine whether the Bitcoin demonstrates hedging or diversification properties against the set of selected stock market indices: S&P 500, Nikkei, Euro STOXX, TSX and Shanghai A-Share. The timeframe of sample is from October 2010 till October 2017. Daily, weekly, and monthly returns are used for analysis. Simple ARMA-GARCH and Constant Conditional Correlation models are applied in this work. As of results obtained from the ARMA-GARCH model for daily returns, it can be observed that Bitcoin has weak hedge properties against studied stock market indices. In case of weekly returns the situation is pretty the same and Bitcoin also demonstrated weak hedge properties for this data frequency. However, in case of monthly data, Bitcoin returns demonstrate significant negative association with all the studied indices, leading to a conclusion that Bitcoin acts as a strong hedge against these indices. As of results obtained from the Constant Conditional Correlation model, these are similar to the results obtained from ARMA-GARCH model and can be summarized as follows: Bitcoin acts as a weak hedge against studied indices for daily and weekly data and acts as a strong hedge against studied stock market indices for monthly data. (Chan, Le, & Wu, 2019)

The work "Cryptocurrencies and Investment Diversification: Empirical Evidence from Seven Largest Cryptocurrencies" by Nguyen Phuc Canh, Su Dinh Thanh, Nguyen Quang Binh, is aimed to examine diversification properties of 7 largest cryptocurrencies (Bitcoin, Ripple, Litecoin, Monero, Stellar, Bytecoin and Dash) against a set of economic factors represented by gold price, USD index, LIBOR, WTI oil price and S&P 500 stock market index. The timeframe of sample is from August 2014 till June 2018. Weekly data is analyzed. Simple ARMA-GARCH and Dynamic

Conditional Correlation Multivariate GARCH models are exploited for the analysis. Results of this paper are the following: BTC demonstrated the negative significant correlations with Oil Price, S&P 500 Index and LIBOR economic factors. These results can infer that Bitcoin is a good tool for hedging fluctuations in these economic factors. Nevertheless, Bitcoin is not a hedge for gold and USD index. Considering the XRP, it demonstrates significant negative association with oil price. Dash demonstrates significant positive association with LIBOR, serving only as diversifier there. Moreover, it has significant negative association with USD index, serving as a hedge tool. Stellar experiences significant positive correlation with the S&P 500 Index, serving only as diversifier against it. Monero serves as a diversifier for LIBOR fluctuations, demonstrating significant positive fluctuations. (Canh, Binh, & Thanh, 2019)

Gang-Jin Wang, Hao-yu Wu and Xin-yu Ma in their work "Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests?" make a step aside and focus on stablecoins, and specifically which properties stablecoins possess. Selected stablecoins can be divided into two groups: USD-pegged and gold-pegged. USD pegged are Tether, NuBits and BitUSD. The study tries to examine whether these stablecoins can serve as hedge or diversifier of safe haven against Bitcoin, Litecoin and XRP. Sample timeframe for USD-pegged cryptocurrencies is from March 2015 till March 2019. Gold-pegged stablecoins are XAUR, HGT and DGD. Sample timeframe for Gold-pegged cryptocurrencies is from October 2017 till March 2019. In this work ARMA-GARCH Dynamic Conditional correlation model was applied for analysis of daily returns. Obtained results are as follows: Tether returns demonstrate significant negative correlations with selected cryptocurrencies returns. Hence, it can serve as a hedge against Bitcoin, Litecoin and XRP. BitUSD returns demonstrate significant positive association with all selected cryptocurrencies returns. It can be inferred that BitUSD acts as a diversifier against Bitcoin, Litecoin and XRP. NuBits returns also experience significant positive association with all selected cryptocurrencies returns as in case with BitUSD. It can be inferred that NuBits acts as a diversifier against Bitcoin, Litecoin and XRP. Considering the gold-pegged stablecoins, the overall result for them is positive significant association of their returns with cryptocurrencies returns. It leads to a conclusion that gold-pegged stablecoins act as diversifiers against Bitcoin, Litecoin and XRP. (Wang, Ma, & Wu, 2020)

Lanouar Charfeddine, Youcef Maouchi, Noureddine Benlagha in their work "Investigating the dynamic relationship between cryptocurrencies and conventional assets: Implications for financial investors" attempt to explore diversification potential of Bitcoin and Ethereum against gold, crude oil and S&P 500 stock market index. Logarithmic returns series are applied for analysis. For Bitcoin the sample period is set from July 2010 to October 2018 and for Ethereum it is from

September 2015 till October 2018. Authors apply the set of instruments, including ARFIMA-FIAPARCH model, time-varying copula techniques, structural changes tests and the set of multivariate GARCH models. Coming to results, Bitcoin demonstrates weak negative association with S&P 500 and Ethereum experiences weak positive association with S&P 500 on average. Considering gold, the association between both cryptocurrencies and gold is weak positive on average. Furthermore, the association between both cryptocurrencies and crude oil is weak negatives on average. (Charfeddine, Benlagha, & Maouchi, 2020)

Elie Bouria, Brian Lucey and David Roubaud in their work "Cryptocurrencies and the downside risk in equity investments" attempt to classify the set of cryptocurrencies as a diversifier, weak or strong hedge and weak or strong safe haven again stock market indices represented by MSCI USA, MSCI Europe, MSCI Asia-Pacific and MSCI Japan. The selected cryptocurrencies are the Bitcoin, Ripple, Stellar, Litecoin and Ethereum. Daily logarithmic returns are applied for conduction of analysis. The sample timeframe is from August 2015 to July 2018. Authors apply dynamic conditional correlation GARCH model. Coming to the results, Bitcoin is regarded as a strong hedge against MSCI USA, MSCI Asia-Pacific and MSCI Japan and as a diversifier against MSCI Europe index. Considering Ethereum, it acts as a diversifier against MSCI USA and MSCI Europe and as a strong hedge against MSCI Asia-Pacific and MSCI Japan. Ripple is a diversifier for USA, Europe and Asia-Pacific, but is a strong hedge against Japan stock market. Litecoin is a weak hedge for USA, a diversifier for Europe and is a strong hedge against Asia-Pacific and Japan. Finally, Stellar is only a diversifier against all the selected MSCI indices. In portfolio analysis section, authors inferred that Bitcoin and Ethereum are the best options to include in the portfolios represented by MSCI Asia-Pacific and MSCI Japan according to Sharpe Ratio improvement. (Bouri, Lucey, & Roubaud, 2020)

In closing, it can be concluded that there is still a lot of space for research, as cited works vary from one to another in terms of cryptocurrencies studied, independent variables chosen, sample periods and even in terms of obtained results. For example, (Chan, Le, & Wu, 2019) claim that Bitcoin serves as a weak hedge for S&P 500, while according to results of (Canh, Binh, & Thanh, 2019) Bitcoin has significant negative association with S&P 500 returns, serving as a strong hedge.

1.4 Research gap and hypotheses

There were several recent studies, as can be observed from previous chapter, which attempted to discover the characteristics of cryptocurrencies in terms of their relationship to different economic variables like stock market indices, conventional currencies, commodities and to examine cryptocurrencies diversification/hedging abilities against mentioned variables. One work also attempted to study diversification/hedging abilities of stablecoins against other cryptocurrencies. Nevertheless, the research a gap exists: field is not widely studied yet, as there are still few works investigating cryptocurrencies diversification/hedging properties and results of these works have contradictions; different approaches in terms of choice of the model are applied; set of studied cryptocurrencies varies; sample time period also varies from one work to another; different independent variable choices are made. All the listed concerns are reasons for adding new results and experience in the field and hence, to write this paper.

Furthermore, after studying the existing classification of assets in terms of extent to which these assets reduce portfolio risk the basis for setting the hypotheses and for making a conclusion on cryptocurrency property is obtained. To answer the research question and to accomplish the goal of this work of getting the understanding of cryptocurrencies' properties, 3 hypotheses are stated. Each of selected cryptocurrencies will be analyzed through the perspective of the following hypotheses for each selected stock market index:

H1. The selected cryptocurrency demonstrates diversification properties.

H2. The selected cryptocurrency demonstrates weak hedge properties.

H3. The selected cryptocurrency demonstrates strong hedge properties.

For making conclusions on hypotheses, the decision criterions introduced in works of (Baur & Lucey, 2010) and (Baur & McDermott, 2010) of whether a cryptocurrency is diversifier, weak hedge or strong hedge are applied. Decision criterions can be summarized as follows:

Coefficient before stock index returns in mean equation	Meaning	Conclusion
Positive and significant	Returns of cryptocurrency and equity index co-move on average	Diversifier
Not significant	Returns of cryptocurrency and equity index do not co-move on average	Weak hedge
Negative and significant	Returns of cryptocurrency and equity index move in opposite directions on average	Strong hedge

Table 1 Decision criterions on cryptocurrencies' properties

Chapter 2. Methodology

2.1 Data

For conducting the research, the data on daily returns of selected cryptocurrencies and equity indices is obtained from Bloomberg Terminal. The timeframe is set from January 2018 until 25 of February 2022. The choice of starting point of timeframe start is based on the fact of worldwide cryptocurrency popularization in the end of 2017 and active rally of cryptocurrencies' prices (especially the unprecedented boom on cryptocurrency market December 2017) followed by what is named as "Bitcoin Crash"[11] or "Great crypto crash"[12] in January 2018 with around 80% dramatic fall of MVIS CryptoCompare Digital Assets 10 Index[13] (based on performance of 10 largest and the most liquid cryptocurrencies). Please, refer to Figure 4 for graphical representation of cryptocurrency market capitalization for the timeframe starting period (the "Great crypto crash" is pointed with the red circle on the chart). The end point choice is explained by the suspension of trading on the Moscow Stock Exchange since 28th of February (thus, last available data is from 25.02).[14]

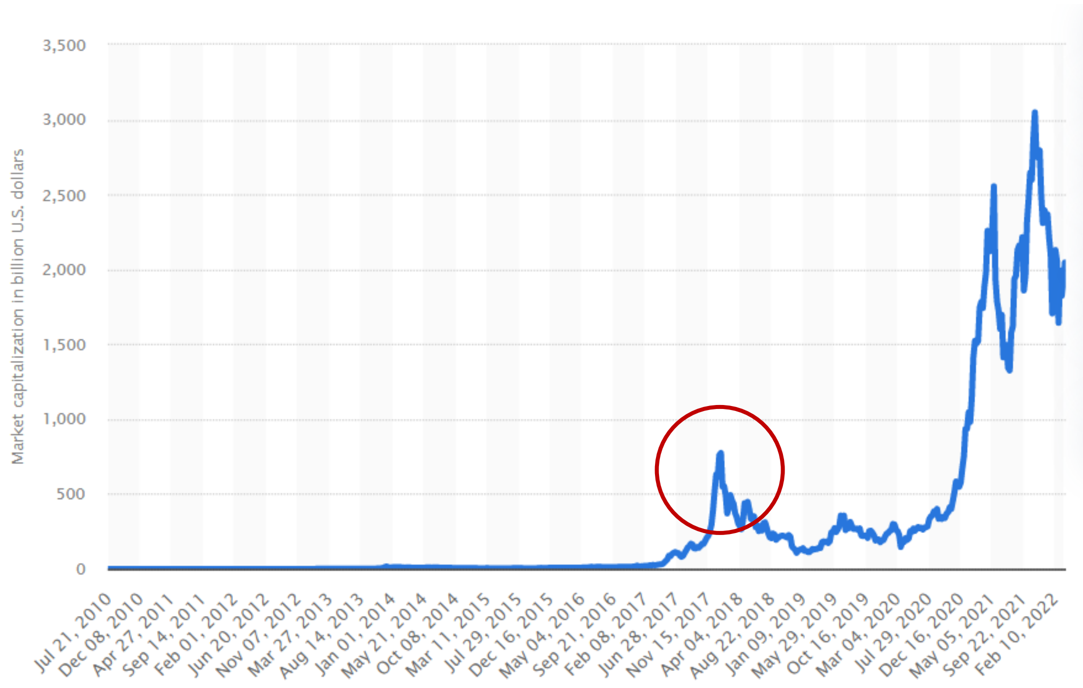

Figure 2 Overall cryptocurrency market capitalization per week from July 2010 to March 2022 in bln USD (Statista.com)

Thus, as there are returns distributed over a time period, the time series data is faced.

[11] https://money.cnn.com/2018/09/11/investing/bitcoin-crash-victim/index.html
[12] https://www.bloomberg.com/news/articles/2018-09-12/crypto-s-crash-just-surpassed-dot-com-levels-as-losses-reach-80
[13] https://www.mvis-indices.com/indices/digital-assets/mvis-cryptocompare-digital-assets-10
[14] https://www.vedomosti.ru/finance/news/2022/02/28/911248-o-priostanovke-torgov-tsennimi-bumagami-na-mosbirzhe

The chosen equity indices are MSCI World Index, MSCI Emerging Markets Index and MSCI Russia Index. The MSCI World Index is a broad global equity index that represents large and mid-cap equity performance across all 23 developed markets countries. It covers approximately 85% of the free float-adjusted market capitalization in each country.[15] MSCI Emerging Markets index covers more than 1400 large-cap and mid-cap securities form 24 countries across five regions. [16] MSCI Russia Index covers around 85% of the market capitalization in Russian market.[17] MSCI Russia in standalone index and is not included in MSCI Emerging Markets Index, allowing to capture it separately in analysis. The reason of choice of MSCI indices is their homogeneity, which makes the analysis more consistent. [18]

The following cryptocurrencies were selected, as these are the top 3 cryptocurrencies (excluding USDT, which is a stablecoin[19], serving as a U.S. Dollar equivalent) which have the highest market capitalization values on April 3, 2022[20]: Bitcoin (BTC), Ethereum (ETH), BNB (BNB). All variables' prices are denominated in U.S. Dollars.

Log returns were calculated on basis of USD prices for each variable. The formula of logarithmic return is as follows:

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

Where r_t is logarithmic return, P_t is the closing price of asset for a current period t and P_{t-1} is the closing price of asset for a previous period. The logarithmic returns are chosen due to several reasons: (1) Symmetric nature giving the equivalent multiple to increase and decrease, leaving them only sign difference; (2) Time series of logarithmic returns can be seen as stationary (which is crucial for usage of time-series models); (3) Interpretation purpose: if we have log-log model, we can interpret influence of independent variable on dependent variable in percentages.

[15] https://www.msci.com/our-solutions/indexes/developed-markets
[16] https://www.msci.com/our-solutions/indexes/emerging-markets
[17] https://www.msci.com/documents/10199/607bc974-36ce-4e56-a1a1-78c435a5f2ae
[18] https://www.refinitiv.com/en/financial-data/indices/equity-indices/third-party/msci
[19] https://www.coinbase.com/learn/crypto-basics/what-is-a-stablecoin
[20] https://coinmarketcap.com/historical/20220403/

2.2 Variables

The preliminary view on variables is the following:

- Dependent variable – cryptocurrency daily logarithmic return
- Independent variables:
  - Lagged cryptocurrency daily log-return and lagged error term (ARMA orders, finally included if they are significant)
  - MSCI World Index (developed markets) logarithmic return
  - MSCI Emerging Markets Index (emerging markets) logarithmic return
  - MSCI Russia Index logarithmic return

2.3 Model choice

As the data has the time-series nature, it is important to focus attention on time-series analysis models. In previous research in the same field GARCH family models were exploited: some of the authors used simple univariate GARCH(1,1) model and some used asymmetric models like T-GARCH or GJR-GARCH and some authors also used multivariate DCC-GARCH model.

Despite the fact that in the works of (Dyhrberg, 2016) and (Chan, Le, & Wu, 2019) there is no clear explanation why GARCH is used, it is important to know why this model should be used particularly in this work.

There are different models for workings with time-series. For example, there are autoregressive models for univariate time-series like AR (for stationary time-series), ARIMA (for time-series with a trend), SARIMA (for time-series with seasonal component). The main drawback of these types of models is the assumption of constant variance, which in practice is not always true. There are some time-series, in which variance is changing over time. In finance it is about periods of higher and lower volatility, forming volatility clusters ("large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes") (Mandelbrot, 1963). So, in this case changes in variance are correlated over time which leads to ARCH method for volatility modelling, which models the variance with lagged squared residual from mean process (difference between mean and realized return). Generalized ARCH or GARCH generalizes ARCH model allowing modelling variance not only with the lagged squared residuals, but also with lagged variance. In the ARCH process the conditional variance is specified as a linear function of past sample variances only, whereas the GARCH process allows lagged conditional variances to enter as well. This corresponds to some sort of adaptive learning mechanism.[21] In general, GARCH performs better and requires less parameters than ARCH. GARCH models can

[21] https://machinelearningmastery.com/develop-arch-and-garch-models-for-time-series-forecasting-in-python/

be used in the analysis of a number of different types of financial data, such as macroeconomic data[22].

For this work the GJR-GARCH model for modelling volatility will be exploited. It was developed by (Glosten, Jagannathan, & Runkle, 1993). This model has an advantage over simple GARCH(1,1). The main advantage is that GJR-GARCH accounts for asymmetry in volatility. It simply means that volatility reacts differently to positive and negative shocks of previous day. It makes sense because of existence of asymmetric volatility. This concept implies the negative correlation between returns and conditional variance of next period returns. It means that negative returns lead to higher volatility, while positive returns are more associated with lower volatility. (Wu, 2001) It is also called Asymmetric Volatility Phenomenon. The other explanation is that volatility has a tendency of being higher in falling markets than in markets in a period of rise. (Kenton, 2022) Hence, for capturing the volatility asymmetry the GJR-GARCH model is applied.

The GARCH model consists of 2 different equations: conditional mean and conditional variance. For comparison with GJR-GARCH there is a simple GARCH (1,1) model presented below.

Conditional mean equation:

$$R_t = \mu + \varepsilon_t$$

Conditional variance equation:

$$\boldsymbol{\sigma_t^2} = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

In order to understand the difference between simple GARCH(1,1) and GJR-GARCH(1,1) the conditional variance equation for GJR-GARCH is provided:

$$\boldsymbol{\sigma_t^2} = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}$$

Where I_{t-1} is a dummy variable:

$$I_{t-1} = \begin{cases} 1 \; if \; \varepsilon_{t-1} < 0 \\ 0 \; if \; \varepsilon_{t-1} \geq 0 \end{cases}$$

Dummy variable equals to 1 in case of negative previous shock, which makes GJR-GARCH able to capture asymmetric volatility effect.

Nevertheless, it will be important to not only capture the time varying volatility, the main focus of this work to analyze the conditional mean with inclusion of external regressors to understand the

[22] https://www.investopedia.com/terms/g/garch.asp

co-movements of equity indices' returns and selected cryptocurrencies returns. That's why the mean equation is modelled with ARMA approach with external regressors. Finally, in this work the combination of ARMA and GJR-GARCH will be applied, resulting in ARMA-GJR-GARCH final view of the model. The mean equation is modelled by ARMA model with external regressors, and volatility is modelled by GJR-GARCH model. The same approach of combining the ARMA with GARCH family model was applied in (Baur & Lucey, Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold, 2010), (Dyhrberg, 2016), (Cermak, 2017) , (Canh, Binh, & Thanh, 2019)and (Wang, Ma, & Wu, 2020).

2.4 Algorithm of analysis

2.4.1 Stationarity check

One of the preconditions for working with time-series is stationarity. In the finance literature the common assumption is that series of returns are weakly stationary. Weak stationarity implies constant variation around the constant mean. Weak stationarity is acceptable for making inferences about future observations of time series. (Tsay, 2010)

For detecting the stationarity in time series, the plots of series returns will be analyzed and a formal method - Augmented Dickey-Fuller test[23] - is applied. Augmented Dickey-Fuller test tests whether a unit-root is present is time series. The basic intuition is that this test determines to which extent a time series is defined by a trend. This test has the following hypotheses:

- Null hypothesis (H0): Unit root is present (non-stationarity of time-series)
- Alternative hypothesis (H1): Unit root is not present (stationarity of time-series)

We infer the conclusions by checking the p-value of the test result. Decision rules:

- We fail to reject the null hypothesis in case the p-value from the test result is higher than 0.05, concluding that our time-series data is non-stationary and unit root is present.
- Null hypothesis is rejected in case of resulting p-value from the test is equal to or lower than 0.05 and we can conclude that our time-series data is stationary.

2.4.2 Testing for ARCH effects

As this working paper is based on application of GJR-GARCH model, the test for ARCH effects should be performed to understand whether the GJR-GARCH model is suitable for the data we have.

[23] https://www.machinelearningplus.com/time-series/augmented-dickey-fuller-test/

The goal of ARCH test is to identify whether conditional heteroscedasticity is present in the series. Conditional heteroscedasticity refers to varying volatility which is dependent on prior period volatility.[24] It means that the time-series which exhibits the volatility conditional on the previous period volatility is considered to have ARCH effects.

In this work the ARCH-LM test is applied for identifying ARCH effects. Lagrange Multiplier test was introduced by R. Engle in 1982 (Engle R. F., 1982). The logic of this test is to understand whether the squared residuals of the mean equation can be explained by the previous periods squared residuals. In essence, this test is equivalent to F-test in linear regression where dependent variable is the squared residual for the current period and independent variables are squared residuals for the previous periods. (Tsay, 2010) Hence:

- Null hypothesis (H0): No ARCH effects in the time series (coefficients before squared residuals in regression all equal to zero)
- Alternative hypothesis (H1): ARCH effects are present in the time series (at least one coefficient is different from zero)

We infer the conclusions by checking the p-value of the test result. Decision rules:

- We fail to reject the null hypothesis in case the p-value from the test result is higher than 0.05, concluding that no ARCH effects are present in our time-series data.
- Null hypothesis is rejected in case of resulting p-value from the test is equal to or lower than 0.05 and we can conclude that ARCH effects are present in our time-series data.

2.4.3 Model construction and choice of the most suitable one

After checking for stationarity and ARCH effects of our time series, we proceed to model construction. As it was mentioned in the model choice, the ARMA-GJR-GARCH model will be exploited in this work. Hence, it should be identified which number of AR an MA orders should be used in ARMA in the mean equation. This can be performed by looking at PACF (for AR order) and ACF (for MA order) graphs.

Considering the GJR-GARCH(p,q), the number of orders is set to p=1 and q=1, resulting in GJR-GARCH(1,1) model. This number of orders is used by other researchers in most applications due to its simplicity and sufficiency in capturing movements of volatility. This point of view is also supported by research of Angabini & Wasiuzzaman, which concluded about no evidence of outperforming of models with higher number of orders for GARCH, EGARCH and GJR-GARCH

[24] https://www.investopedia.com/terms/h/heteroskedasticity.asp

(Angabini & Wasiuzzaman, 2011). One more reason for these orders choice is to follow (Baur & Lucey, Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold, 2010) approach.

Error term in the ARCH and GARCH models is often assumed to follow normal or Student-t distribution. (Tsay, 2010) In our case the models will be run for both distributions separately and the models which fits the best will be chosen as a final one. The choice will be made according to Quantile-Quantile plot for standardized residuals and histogram plot for standardized residuals.

Finally, the best model can be chosen according to Akaike Information Criterion. In scope of this work is the varying factors among models are the assumed distributions and order numbers for ARMA in mean equation. For calculation of AIC value the following formula is applied:

$$AIC = \frac{-2}{T} ln(L) + \frac{2}{T} k$$

where L is the maximum-likelihood estimate and T is the sample size. (Tsay, 2010)

The selection rule is straightforward: we should choose the model with the lowest AIC.

2.4.4 Model validity check

For checking the validity of the resulting model, the Ljung-Box test is performed for standardized residuals and standardized squared residuals of the model. For the standardized residuals the logic is the following: there should be no autocorrelation of standardized residuals if the ARMA in mean equation is specified adequately. For the squared standardized residuals, the logic is the following: there should be no autocorrelation of squared standardized residuals GARCH specification is adequate, and it explains volatility. (Tsay, 2010)

This test has the following hypotheses:

- Null hypothesis (H0): There is no autocorrelation in standardized (or squared standardized) residuals. It means that the autocorrelation between standardized (or squared standardized) residuals for a set of lags *k* equals to zero.
- Alternative hypothesis (H1): There is an autocorrelation in standardized (or squared standardized) residuals. It means that at least one autocorrelation is greater than zero for the set of lags *k*.

We infer the conclusions by checking the p-value of the test result. Decision rules:

- We fail to reject the null hypothesis in case the p-value from the test result is higher than 0.05, concluding that there is no autocorrelation of standardized (or squared standardized) residuals of the model. For standardized residuals it means that mean equation is adequate, and model explained autocorrelation of standardized residuals. For squared standardized residuals it means that variance equation (ARCH/GARCH) performed well and captured that autocorrelation of squared standardized residuals.

- Null hypothesis is rejected in case of resulting p-value from the test is equal to or lower than 0.05 and we can conclude that there is autocorrelation of standardized (or squared standardized) residuals of the model. For standardized residuals it means that mean equation is not adequate, and model did not capture autocorrelation of standardized residuals. For squared standardized residuals it means that variance equation (ARCH/GARCH) has not succeeded in explaining autocorrelation of squared standardized residuals.

The number of lags m for this test is chosen as follows: $m \approx ln(T)$, where T is the number of observations. The degrees of freedom equal to $m - p - q$, where p and q are orders of the ARMA or GARCH model (depending on which residuals are tested: standardized or standardized squared residuals). (Tsay, 2010)

Chapter 3. Results and discussion

In this chapter descriptive statistics are provided. Then, econometric models are presented and interpreted. Afterwards. portfolios are constructed and analyzed. Discussion of results closes the chapter.

3.1 Descriptive statistics

Descriptive statistics of daily returns for each variable are presented in the table below:

Variable	N	mean	median	sd	min	max	skewness	kurtosis
MSCI DM	1084	0.0004	0.0008	0.0109	-0.0992	0.0877	-1.0962	19.3293
MSCI EM	1084	0.0001	0.0005	0.0107	-0.0671	0.0573	-0.7244	5.8080
MSCI Russia	1084	0.0000	0.0008	0.0231	-0.3811	0.2646	-3.3799	86.7420
BTC	1084	0.0020	0.0011	0.0451	-0.2719	0.2500	-0.1025	4.1349
ETH	1084	0.0031	0.0011	0.0616	-0.4455	0.4297	0.0365	6.2108
BNB	1084	0.0060	0.0023	0.0716	-0.4396	0.6997	1.3460	16.5237

Table 2 Descriptive statistics (daily returns)

Generally, it can be observed from the table above, that cryptocurrencies (BTC, ETH, BNB) have higher daily mean and median returns than MSCI DM, MSCI EM and MSCI Russia indices, also demonstrating higher volatility. In further paragraphs other aspects like skewness and kurtosis will be discussed in the context of each variable.

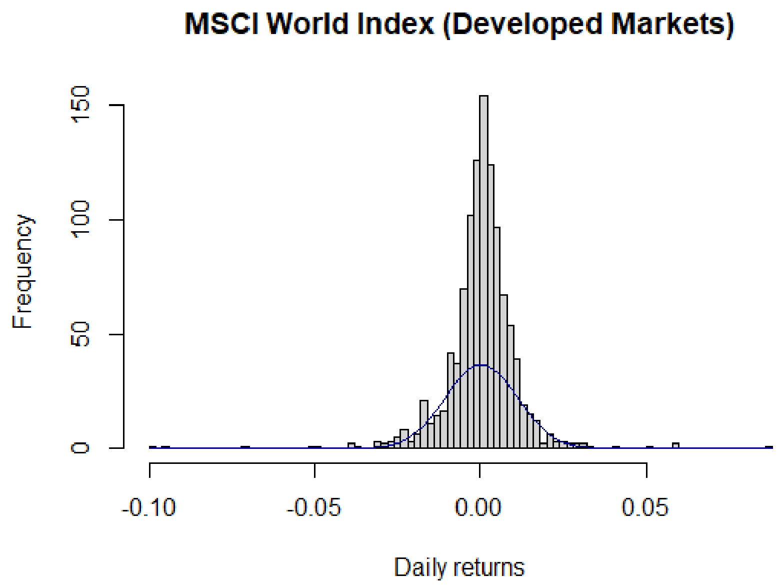

Figure 3 MSCI DM daily returns histogram
Dark blue line added for presentation of normal distribution.

Considering MSCI World Index, which is related to Developed Markets [25], the first thing which can be observed is the high kurtosis of 19.3293. As normal distribution demonstrates kurtosis equal to 3, the kurtosis value higher than 3 confirms that the distribution of MSCI Developed Markets Index is fat-tailed. Skewness equals to -1.0962 telling us that return distribution is negatively skewed (which is also confirmed by the median greater than mean), meaning that there are frequent small positive returns and few extreme negative returns (which can also be observed from the Figure 5).

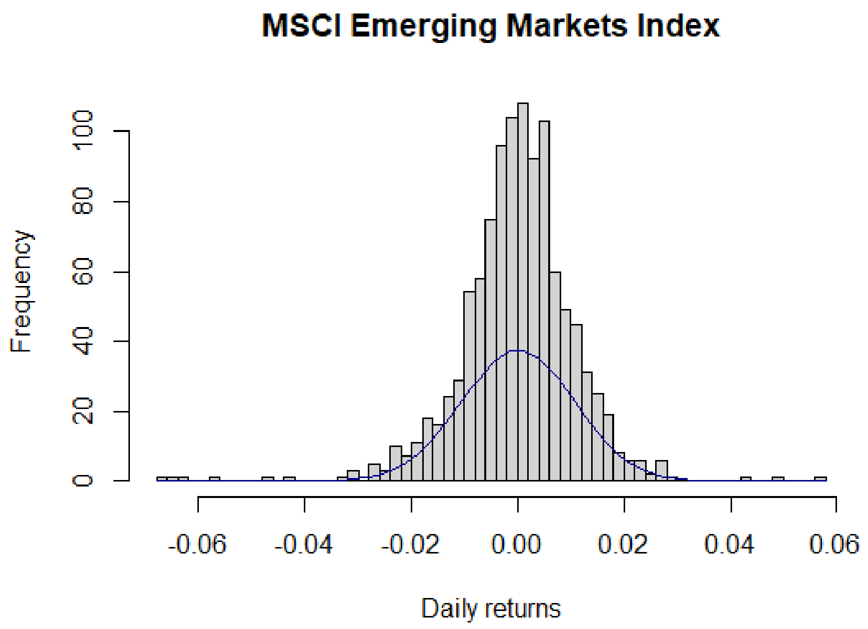

Figure 4MSCI EM daily returns histogram
Dark blue line added for presentation of normal distribution.

Considering MSCI Emerging Markets Index [26], the first thing which can be observed is the high kurtosis of 5.8080. As normal distribution demonstrates kurtosis equal to 3, the kurtosis value higher than 3 confirms that the distribution of MSCI Emerging Markets Index is fat-tailed. Skewness equals to -0.7244 and tells us that return distribution is negatively skewed (which is also confirmed by the median greater than mean), meaning that there are frequent small positive returns and few extreme negative returns (which can also be observed from the Figure 6).

[25]https://www.msci.com/our-solutions/indexes/developed-markets
[26]https://www.msci.com/our-solutions/indexes/emerging-markets

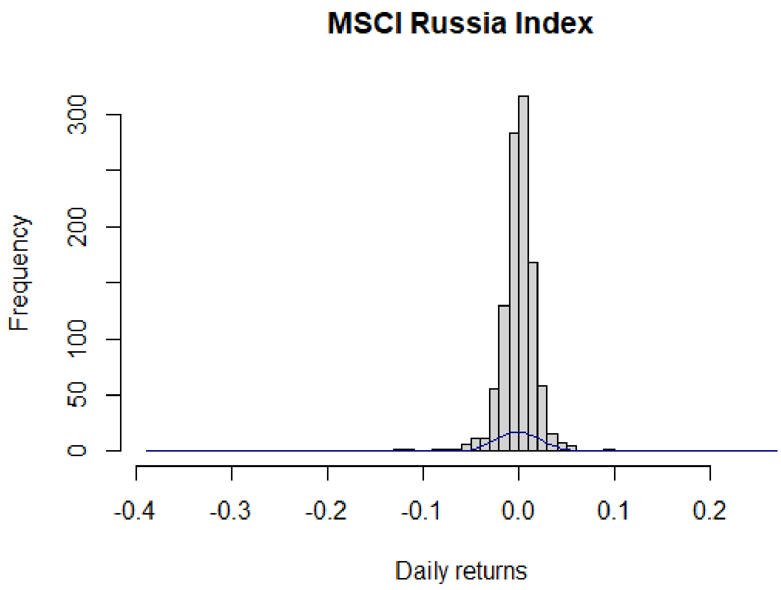

Figure 5 MSCI Russia daily returns histogram
Dark blue line added for presentation of normal distribution.

Next is MSCI Russia Index. Here the very high kurtosis of 86.7420 can be observed. The kurtosis value higher than 3 confirms that the distribution of MSCI Russia Index is fat-tailed. Skewness equals to -3.3799 and tells us that return distribution is negatively skewed (which is also confirmed by the median greater than mean), meaning that there are frequent small positive returns and few extreme negative returns (please, refer to Figure 7). The one more interesting point there is standard deviation which is 2x times higher than for Emerging Markets Index.

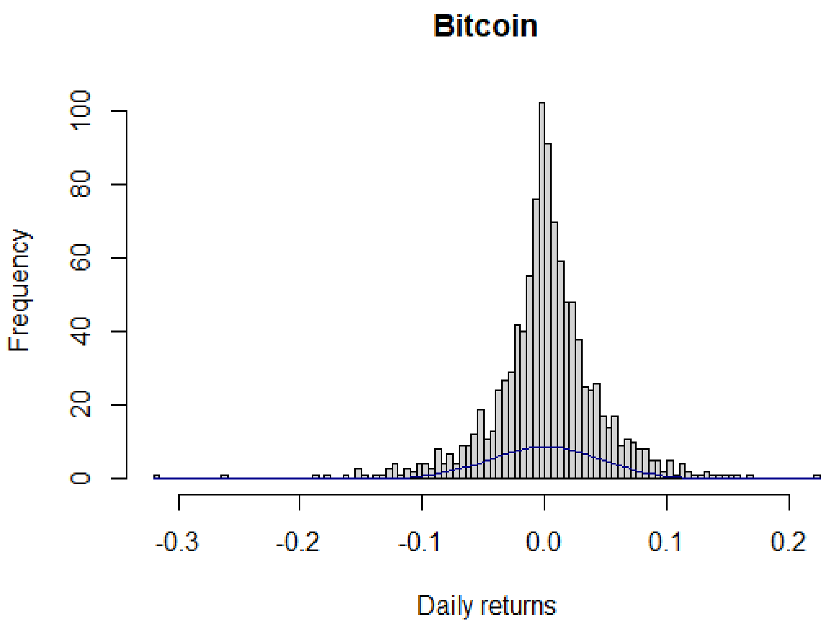

Figure 6 Bitcoin daily returns histogram
Dark blue line added for presentation of normal distribution.

Bitcoin has kurtosis of 4.1349. As normal distribution demonstrates kurtosis equal to 3, the kurtosis value higher than 3 confirms that the distribution of Bitcoin is fat-tailed. Skewness equals to -0.1025 tells us that return distribution is slightly negatively skewed meaning that there are frequent small positive returns and few extreme negative returns.

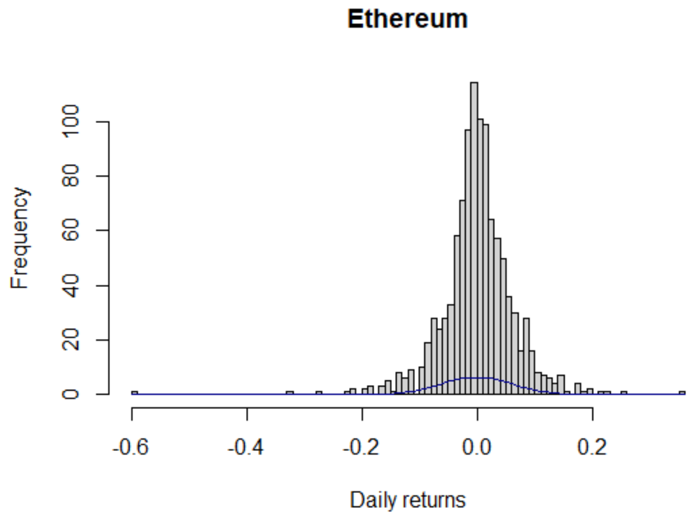

Figure 7 Ethereum daily returns histogram
Dark blue line added for presentation of normal distribution.

Ethereum has kurtosis of 6.4683. As normal distribution demonstrates kurtosis equal to 3, the kurtosis value higher than 3 confirms that the distribution of Bitcoin is fat-tailed. In contrast to other variables, skewness equals to 0.0685 tells us that return distribution is slightly positively skewed meaning that there are frequent small negative returns and few extreme positive returns.

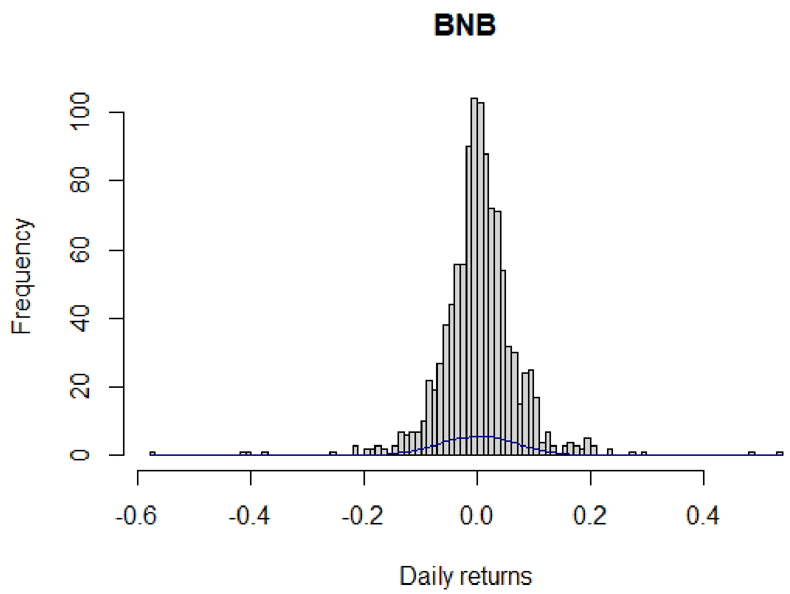

Figure 8 BNB daily returns histogram
Dark blue line added for presentation of normal distribution.

BNB has kurtosis of 16.5237. As normal distribution demonstrates kurtosis equal to 3, the kurtosis value higher than 3 confirms that the distribution of BNB is fat-tailed. Like in case of Ethereum, skewness is positive and equals to 1.3460. It tells us that return distribution is slightly positively skewed meaning that there are frequent small negative returns and few extreme positive returns.

3.2 Econometric models

3.2.1 Model for Bitcoin

According to methodology the first step is the check of stationarity of time series. Thus, Augmented Dickey-Fuller test is performed for daily logarithmic returns of series of returns for Bitcoin, MSCI World Index (Developed Markets), MSCI Emerging Markets and MSCI Russia. The table summarizing the results of Augmented Dickey-Fuller test is presented below:

Series	Test value	p-value
BTC	-9.756	0.01
MSCI Developed Markets	-9.286	0.01
MSCI Emerging Markets	-10.074	0.01
MSCI Russia Index	-7.925	0.01

Table 3 Augmented Dickey-Fuller test results

As p-value of each of logarithmic returns series is less than 0.05, we can conclude that the null hypothesis of unit root presence is rejected, and our series are stationary. This allows us to continue the analysis with application of time-series models.

Then, according to algorithm the presence of ARCH effects should be examined. First of all, let us observe the plot of logarithmic returns series of Bitcoin. Please, refer to the figure below:

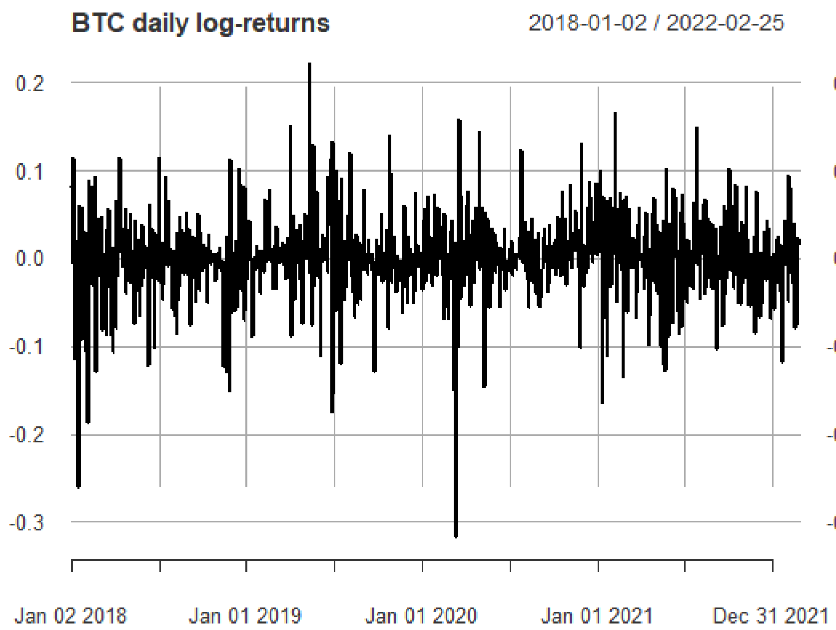

Figure 9 Bitcoin daily log-returns

From the picture above it can be observed that log returns mostly constantly vary around the mean of zero, demonstrating high volatility spikes in some periods like the beginning of 2018 (which coincides with «Great Crypto Crash» [27] described in Data chapter) or in the end of first quarter of 2020 (which coincides with a turmoil caused by Covid-19). Moreover, we can observe that volatility clusters are present as there is some inertia in volatilities in different periods of time. While visual test is useful, the formal test should be applied in order to derive a credible conclusion on presence of ARCH effects. That is why the ARCH-LM test is applied. The results are as follows:

Series	Chi-squared	p-value
BTC	41.995	0.00

Table 4 Results of ARCH-LM test

Null hypothesis of absence of ARCH effects is rejected at 1% significance level as p-value of ARCH-LM test result is lower than 0.01. This lets us conclude that ARCH effects are present, and the volatility of Bitcoin is conditional on the previous period volatility. Hence, it is reasonable to apply GARCH for modelling volatility.

Next step is choice of the most suitable model. For choosing the AR and MA orders for mean equation we should check PACF and ACF graphs.

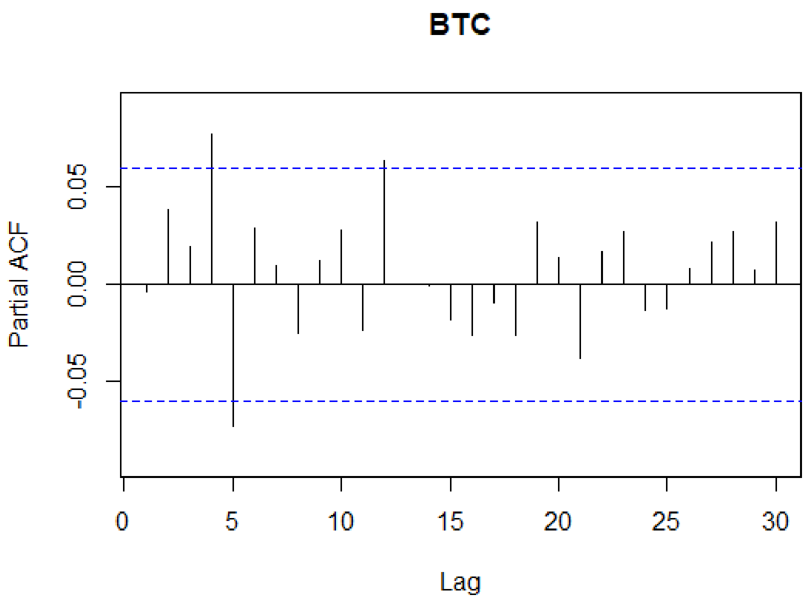

Figure 10 Partial ACF graph for BTC log-return series

According to PACF graph on Figure 12 it makes sense to consider AR orders till the 5^{th} one as orders 4 and 5 demonstrate the partial autocorrelation significantly different from zero. There is no need to consider more lags as it can lead to unnecessary overfitting of the model.

[27] https://www.bloomberg.com/news/articles/2018-09-12/crypto-s-crash-just-surpassed-dot-com-levels-as-losses-reach-80

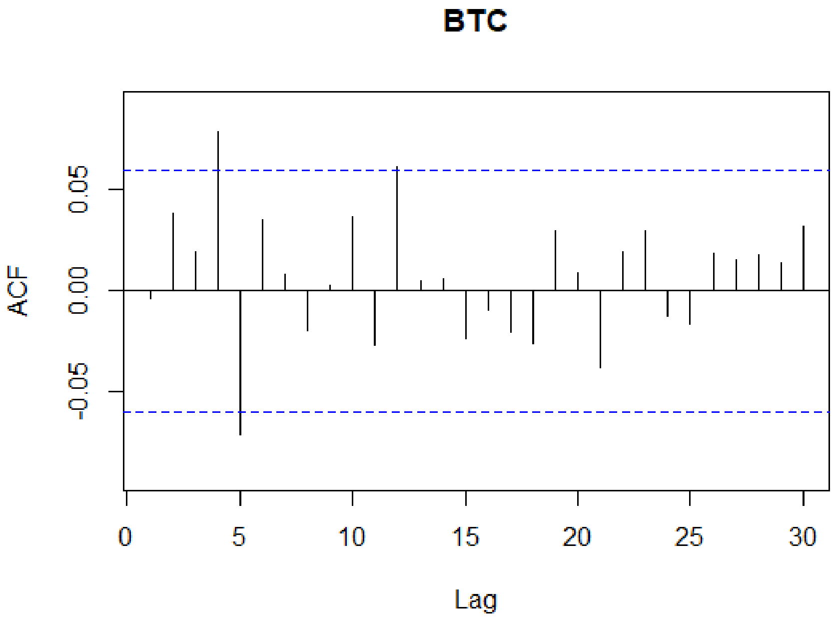

Figure 11 ACF graph for BTC log-return series

By observing ACF graph for Bitcoin log-return series we should also consider MA orders till the 5th one. The logic of number of order choice is the same as in AR case above.

Finally, the model ARMA(1,1)-GJR-GARCH(1,1) with external regressors and assumed Student-t distribution is chosen according to the lowest AIC. The model mean equation and variance equation are as follows.

Mean equation:

$$BTClogret_t = \mu + \beta_1 * BTClogret_{t-1} + \beta_2 * \varepsilon_{t-1} + \varphi_1 DMlogret_t + \varphi_2 EMlogret_t + \varphi_3 RUSlogret_t + \varepsilon_t$$

where $BTClogret_t$ – logarithmic return of Bitcoin for current period, $BTClogret_{t-1}$ – logarithmic return of Bitcoin of previous period (AR(1) order), ε_{t-1} – previous period error term (MA(1) order), $DMlogret_t$ – logarithmic return of MSCI Developed Markets Index (called World Index) for current period, $EMlogret_t$ - logarithmic return of MSCI Emerging Markets Index, $RUSlogret_t$ - logarithmic return of MSCI Russia Index and ε_t is current period error term.

Variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}$$

where ω is the unconditional variance, α is ARCH term showing the sensitivity of today's volatility to previous period shocks, β is the GARCH term, which shows the persistence of the volatility, γ is the so-called leverage effect, which shows how much higher is impact of negative shocks in previous period than that of positive shocks, capturing the asymmetric volatility effect. *I* is the dummy variable, which equals to 0 in case of positive shock in previous period and 1 in case of negative shock (the more detailed description is in model choice chapter).

Considering the choice of distribution, we can also check Quantile-Quantile plots of standardized residuals for normal and Student-t distributions:

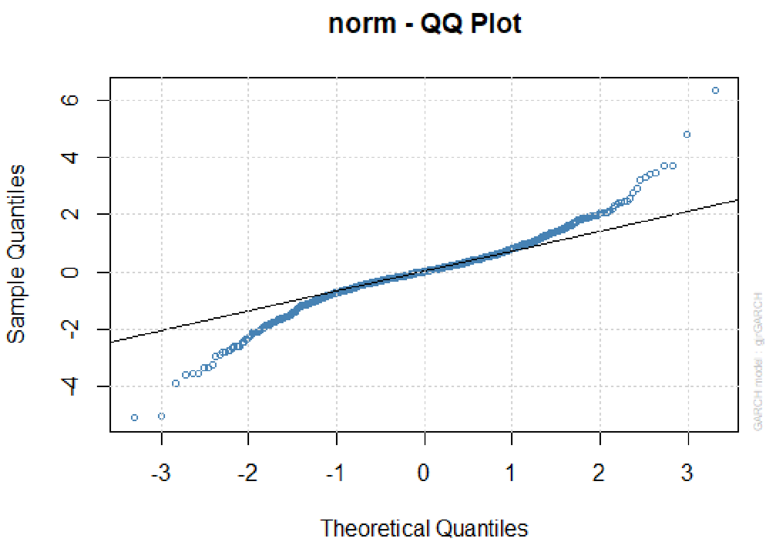

Figure 12 QQ-Plot of Standardized Residuals for model with normal distribution

We can see there that tails significantly deviate from the line representing normal distribution.

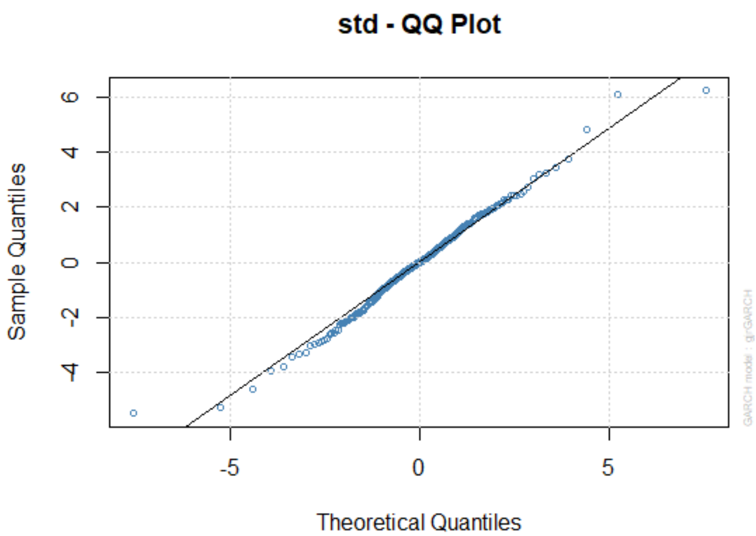

Figure 13 QQ-Plot of Standardized Residuals for model with Student-t distribution

However, in case of Student-t distribution we can see that standardized residuals mostly align the line representing Student-t distribution, leading to conclusion of better fit of model with Student-t distribution.

Model results					
Dependent variable:	Bitcoin log-returns		N obs:	1084	
Coefficient	Estimate	Std. Error	t-value	p-value	
Mean equation					
μ	0.00	0.00	0.85	0.40	
AR 1	0.98	0.01	143.69	0.00	**
MA 1	-0.96	0.00	-283.89	0.00	**
DM	0.72	0.12	6.18	0.00	**
EM	-0.07	0.12	-0.60	0.55	
RUS	0.02	0.05	0.45	0.65	
Variance equation					
ω	0.00	0.00	1.61	0.11	
α	0.08	0.02	3.38	0.00	**
β	0.91	0.02	47.29	0.00	**
γ	0.02	0.03	0.56	0.57	
shape	3.02	0.25	12.01	0.00	**

Table 5 Bitcoin ARMA(1,1)-GJR-GARCH(1,1) model results
**, ** correspond to 0.05 and 0.01 significance levels, respectively*

Firstly, the mean equation will be interpreted. Primarily, it is important that coefficients of AR and MA are significant at 1% level. It means that that today's logarithmic return value of Bitcoin is dependent on its lagged value from previous period and past period error term. The next part of interpretation is focused of DM, EM and RUS. Again, DM is the logarithmic return of MSCI Developed Markets Index. The coefficient before DM is positive and statistically significant at 1% level. According to the established criterion for conclusion on hypothesis, the Bitcoin can serve as a diversifier to the portfolio mimicking MSCI Developed Markets Index. EM is the logarithmic return of MSCI Emerging Markets Index. The coefficient before EM is slightly negative but not significant. According to the established criterion for conclusion on hypothesis, the Bitcoin can serve as a weak hedge to the portfolio mimicking MSCI Emerging Markets Index. Finally, RUS is the logarithmic return of MSCI Russia Index. The coefficient before RUS is positive, but not significant. Here, the conclusion is the same as for MSCI Emerging Markets Index - the Bitcoin can serve as a weak hedge to the portfolio mimicking MSCI Russia Index.

Now, the variance equation will be interpreted. What is the most important is that α and β coefficients are significant at 1%, which means that GARCH is appropriate for modelling volatility. Again, α shows the sensitivity of today's volatility to previous period shocks and β shows the persistence of the volatility. According to book of (Alexander, 2008), α usually varies in range from 0.05 for relatively stable market to 0.10 for more "jumpy" market. The typical range for β is from 0.85 to 0.98 and the higher the α, the lower the β. It is stated that relatively high α and relatively low β means that volatility is more bursting comparing with the opposite positioning of α and β. We can conclude there that Bitcoin volatility with α =0.08 and being close to 0.10 is spiky. The γ shows how much higher is impact of negative shocks in previous period than that of positive shocks, capturing the asymmetric volatility effect. As it is shown in the Table 5, the γ is not significant and, hence, is not significantly different from zero, leading to the conclusion of no leverage effect presence in Bitcoin volatility. The shape equal to 3 shows the number of degrees of freedom of Student distribution for standardized errors.

The last step there is to conduct model validity check with Ljung-Box test of standardized residuals and standardized squared residuals.

Chi-squared	p-value
6.5684	0.25

Table 6 Ljung-Box test for standardized residuals

As p-value of Ljung-Box test of standardized residuals is greater than 0.05, we fail to reject the null hypothesis, concluding that there is no autocorrelation of standardized residuals of the model. It means that mean equation is adequate, and model explained autocorrelation of standardized residuals.

Chi-squared	p-value
1.951	0.85

Table 7 Ljung-Box test for standardized squared residuals

As p-value of Ljung-Box test of standardized residuals is greater than 0.05, we fail to reject the null hypothesis, concluding that there is no autocorrelation of standardized squared residuals of the model. For squared standardized residuals it means that variance equation performed well and captured that autocorrelation of standardized squared residuals.

3.2.2 Model for Ethereum

Firstly, we check the stationarity of time series. Augmented Dickey-Fuller test is performed for daily logarithmic returns of series of returns for Ethereum, MSCI World Index (Developed Markets), MSCI Emerging Markets and MSCI Russia. The table summarizing the results of Augmented Dickey-Fuller test is presented below:

Series	Test value	p-value
ETH	-9.319	0.01
MSCI Developed Markets	-9.275	0.01
MSCI Emerging Markets	-10.067	0.01
MSCI Russia Index	-7.885	0.01

Table 8 Augmented Dickey-Fuller test results

As p-value of each of logarithmic returns series is less than 0.05, we can conclude that the null hypothesis of unit root presence is rejected, and our series are stationary. This allows us to continue the analysis with application of time-series models.

Then, according to algorithm the presence of ARCH effects should be examined. First of all, let us observe the plot of logarithmic returns series of Ethereum. Please, refer to the figure below:

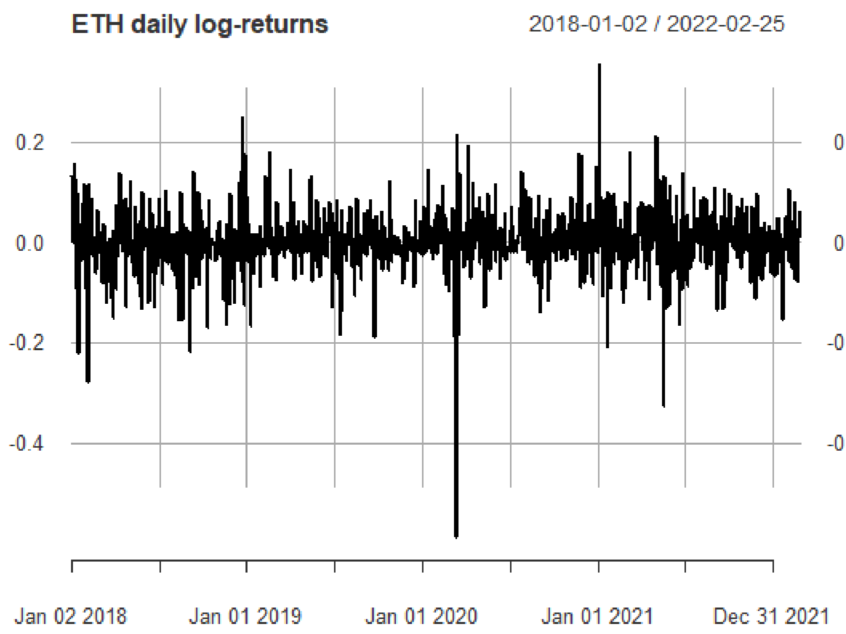

Figure 14 Ethereum daily log-returns

From the picture above it can be observed that log returns mostly constantly vary around the mean of zero, demonstrating high volatility spikes in some periods. The strongest spike is in the end of first quarter of 2020 (which coincides with a turmoil caused by Covid-19). Comparing to Bitcoin, Ethereum returns are even more negative, being even more than -40%, while Bitcoin highest loss is around -30%. Moreover, we can observe that volatility clusters are present as there is some inertia in volatilities in different periods of time. While visual test is useful, the formal test should be applied in order to derive a credible conclusion on presence of ARCH effects. That is why the ARCH-LM test is applied. The results are as follows:

Series	Chi-squared	p-value
ETH	24.983	0.01

Table 9 Results of ARCH-LM test

Null hypothesis of absence of ARCH effects is rejected at 1% significance level as p-value of ARCH-LM test result is equal to 0.01. This lets us conclude that ARCH effects are present, and the volatility of Ethereum is conditional on the previous period volatility. Hence, it is reasonable to apply GARCH for modelling volatility.

Next step is choice of the most suitable model. For choosing the AR and MA orders for mean equation we should check PACF and ACF graphs.

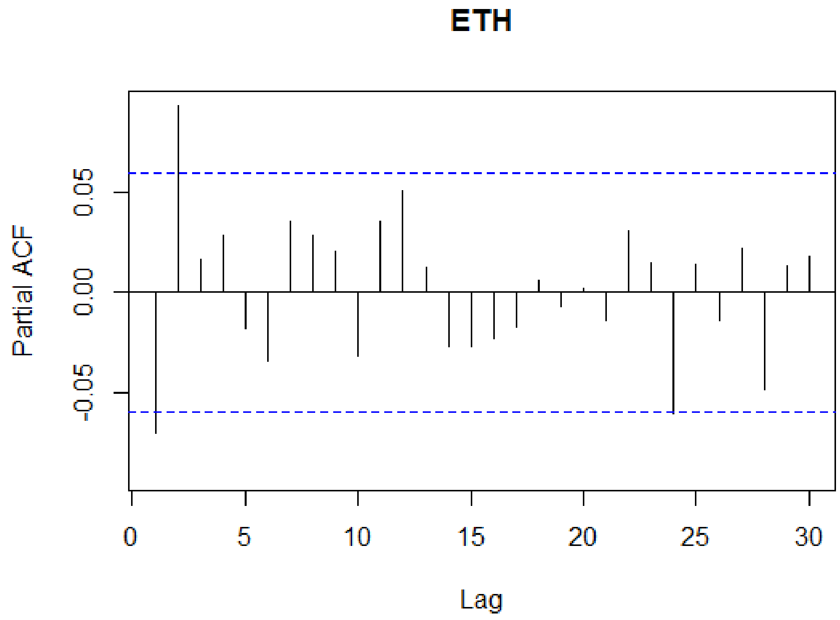

Figure 15 Partial ACF graph for ETH log-return series

According to PACF graph on Figure 17 it makes sense to consider AR orders till the 2nd one as orders 1 and 2 demonstrate the partial autocorrelation significantly different from zero.

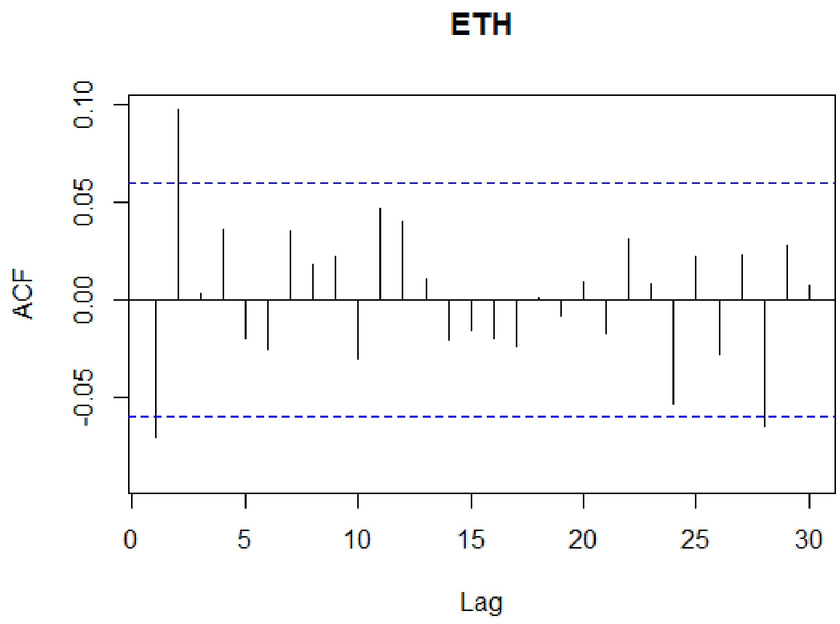

Figure 16 ACF graph for ETH log-return series

By observing ACF graph for Ethereum log-return series we should also consider MA orders till the 2nd one. The logic of number of order choice is the same as in AR case above.

Finally, the model ARMA(1,1)-GJR-GARCH(1,1) with external regressors and assumed Student-t distribution is chosen according to the lowest AIC. The model mean equation and variance equation are as follows.

Mean equation:

$$ETHlogret_t = \mu + \beta_1 * ETHlogret_{t-1} + \beta_2 * \varepsilon_{t-1} + \varphi_1 DMlogret_t + \varphi_2 EMlogret_t + \varphi_3 RUSlogret_t + \varepsilon_t$$

where $ETHlogret_t$ – logarithmic return of Ethereum for current period, $ETHlogret_{t-1}$ – logarithmic returns of Ethereum of a previous period (AR(1) order), ε_{t-1} – previous period error term (MA(1) order), $DMlogret_t$ – logarithmic return of MSCI Developed Markets Index (called World Index) for current period, $EMlogret_t$ - logarithmic return of MSCI Emerging Markets Index, $RUSlogret_t$ - logarithmic return of MSCI Russia Index and ε_t is current period error term.

Variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}$$

where ω is the unconditional variance, α is ARCH, β is the GARCH term, γ is the leverage effect, *I* is the dummy variable, which equals to 0 in case of positive shock in previous period and 1 in case of negative shock (the more detailed description is in model choice chapter).

Considering the choice of distribution, we again check Quantile-Quantile plots of standardized residuals for normal and Student-t distributions (please, refer to Figures 19 and 20). We can see there that tails significantly deviate from the line representing normal distribution. However, in case of Student-t distribution we can’t say it is a perfect fit, but there the standardized residuals still align the line representing Student-t distribution better, than that of normal distribution, leading to conclusion of better fit of model with Student-t distribution.

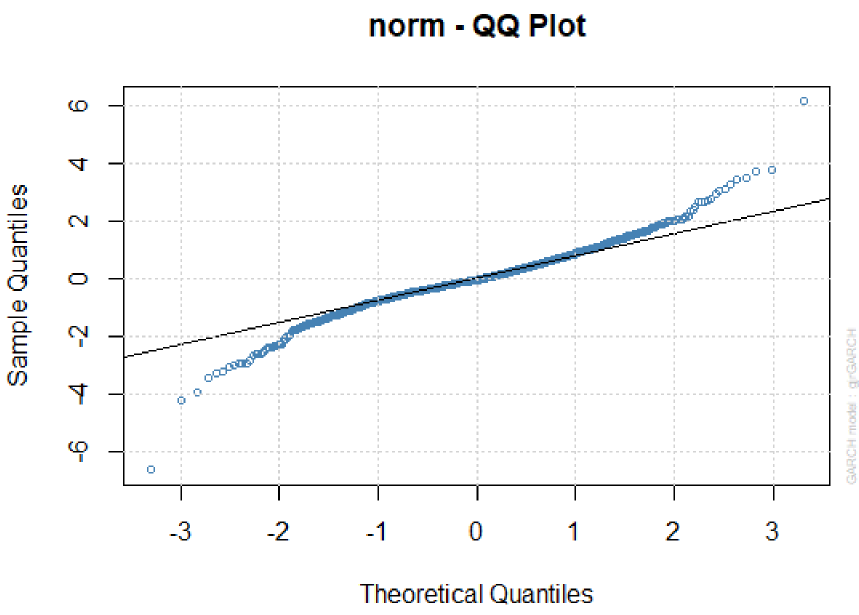

Figure 17 QQ-Plot of Standardized Residuals for model with normal distribution

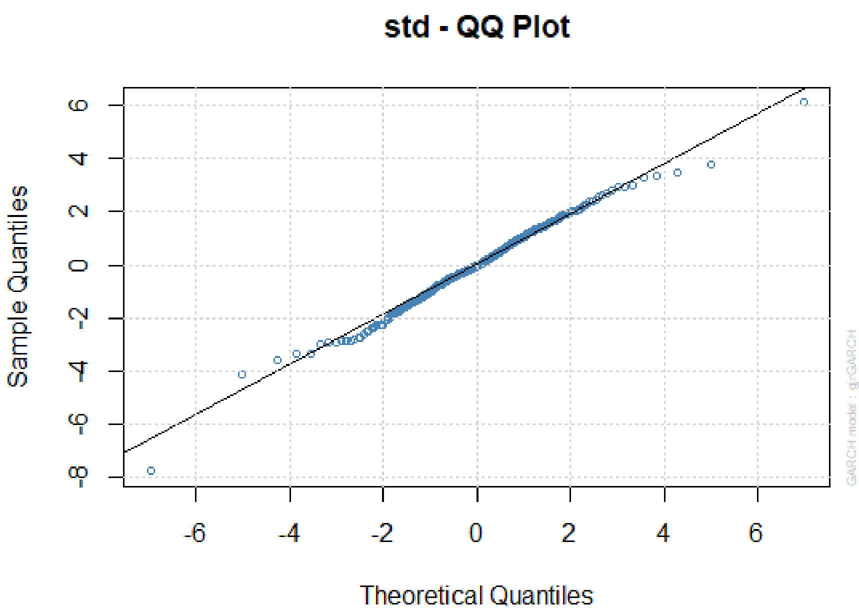

Figure 18 QQ-Plot of Standardized Residuals for model with Student-t distribution

Model results					
Dependent variable:	Ethereum log-returns		N obs:	1084	
Coefficient	Estimate	Std. Error	t-value	p-value	
Mean equation					
μ	0.00	0.00	0.42	0.68	
AR 1	-0.60	0.23	-2.60	0.01	**
MA 1	0.53	0.24	2.21	0.03	*
DM	1.06	0.20	5.37	0.00	**
EM	-0.33	0.19	-1.71	0.09	
Russia	0.18	0.09	1.98	0.05	*
Variance equation					
ω	0.00	0.00	1.86	0.06	
α	0.09	0.03	2.48	0.01	**
β	0.85	0.06	15.49	0.00	**
γ	0.00	0.04	-0.09	0.93	
shape	3.41	0.41	8.29	0.00	**

Table 10 Ethereum ARMA(1,1)-GJR-GARCH(1,1) model results
, * *correspond to 0.05 and 0.01 significance levels, respectively*

Firstly, the mean equation will be interpreted. Primarily, it is important that coefficients of AR and MA for are significant at 1% and at 5% level, respectively. It means that that today’s logarithmic return value of Ethereum is dependent on its lagged value from previous period and past period error term.

Results of Ethereum model are a bit different for Russia, comparing to Bitcoin model. The coefficient before DM is positive and statistically significant at 1% level. According to the established criterion for conclusion on hypothesis, the Ethereum can serve as a diversifier to the portfolio mimicking MSCI Developed Markets Index. The coefficient before EM is negative but is not statistically significant. According to the established criterion for conclusion on hypothesis, the Ethereum can serve as a weak hedge to the portfolio mimicking MSCI Emerging Markets Index. The coefficient before RUS is positive and statistically significant at 5% level. Here, the conclusion is the same as for MSCI Developed Markets Index - the Ethereum can serve as a diversifier to the portfolio mimicking MSCI Russia Index.

Now, the variance equation will be interpreted. Coefficients α and β are both significant at 1%, which means that GARCH is appropriate for modelling volatility. Again, α shows the sensitivity of today’s volatility to previous period shocks and β shows the persistence of the volatility. In line with discussion of results for Bitcoin we can conclude there that Ethereum volatility with α =0.09

and being close to 0.10 is spiky. As it is shown in the Table 10, the γ is not significant and, hence, is not significantly different from zero, leading to the conclusion of no leverage effect presence in Ethereum volatility. The shape equal to 3.41 shows the number of degrees of freedom of Student distribution for standardized errors.

The last step there is to conduct model validity check with Ljung-Box test of standardized residuals and standardized squared residuals.

Chi-squared	p-value
5.2494	0.38

Table 11 Ljung-Box test for standardized residuals

As p-value of Ljung-Box test of standardized residuals is greater than 0.05, we fail to reject the null hypothesis, concluding that there is no autocorrelation of standardized residuals of the model. It means that mean equation is adequate, and model explained autocorrelation of standardized residuals.

Chi-squared	p-value
2.9475	0.71

Table 12 Ljung-Box test for standardized squared residuals

As p-value of Ljung-Box test of standardized residuals is greater than 0.05, we fail to reject the null hypothesis, concluding that there is no autocorrelation of standardized squared residuals of the model. For squared standardized residuals it means that variance equation performed well and captured that autocorrelation of standardized squared residuals.

3.2.3 Model for BNB

AS in previous sections, firstly, we check the stationarity of time series. Augmented Dickey-Fuller test is performed for daily logarithmic returns of series of returns for BNB, MSCI World Index (Developed Markets), MSCI Emerging Markets and MSCI Russia. The table summarizing the results of Augmented Dickey-Fuller test is presented below:

Series	Test value	p-value
BNB	-9.171	0.01
MSCI Developed Markets	-9.275	0.01
MSCI Emerging Markets	-10.067	0.01
MSCI Russia Index	-7.885	0.01

Table 13 Augmented Dickey-Fuller test results

As p-value of each of logarithmic returns series is less than 0.05, we can conclude that the null hypothesis of unit root presence is rejected, and our series are stationary. This allows us to continue the analysis with application of time-series models.

Then, according to algorithm the presence of ARCH effects should be examined. First of all, let us observe the plot of logarithmic returns series of BNB. Please, refer to the figure below:

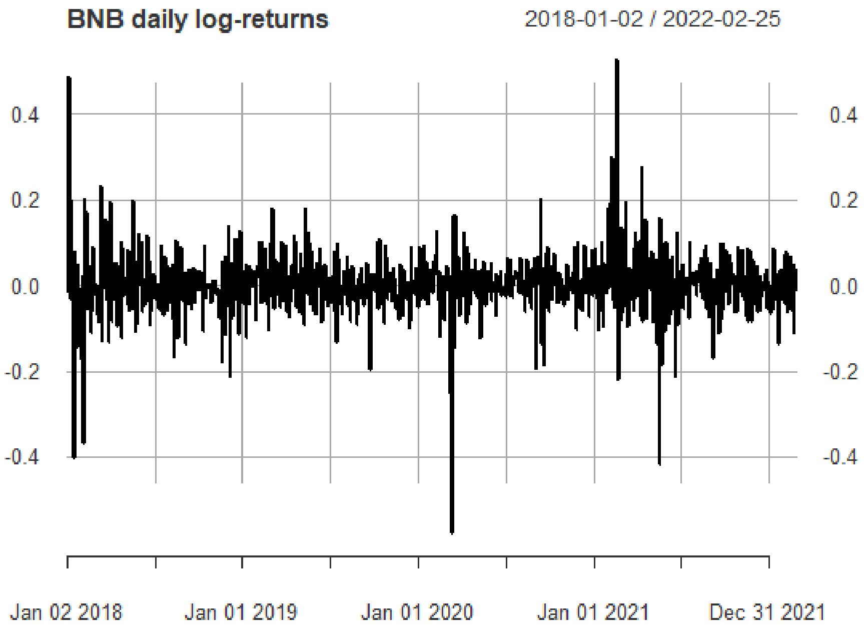

Figure 19 BNB daily log-returns

From the picture above it can be observed that log returns mostly constantly vary around the mean of zero, demonstrating high volatility spikes in some periods like the beginning of 2018 (like in case of Bitcoin), in the end of first quarter of 2020 (which coincides with a turmoil caused by Covid-19) and in the first quarter of 2021. Moreover, we can observe that volatility clusters are present as there is some inertia in volatilities in different periods of time. While visual test is useful, the formal test should be applied in order to derive a credible conclusion on presence of ARCH effects. That is why the ARCH-LM test is applied. The results are as follows:

Series	Chi-squared	p-value
BNB	48.633	0.00

Table 14 Results of ARCH-LM test

Null hypothesis of absence of ARCH effects is rejected at 1% significance level as p-value of ARCH-LM test result is lower than 0.01. This lets us to conclude that ARCH effects are present, and the volatility of BNB is conditional on the previous period volatility. Hence, it is reasonable to apply GARCH for modelling volatility.

Next step is choice of the most suitable model. For choosing the AR and MA orders for mean equation we should check PACF and ACF graphs.

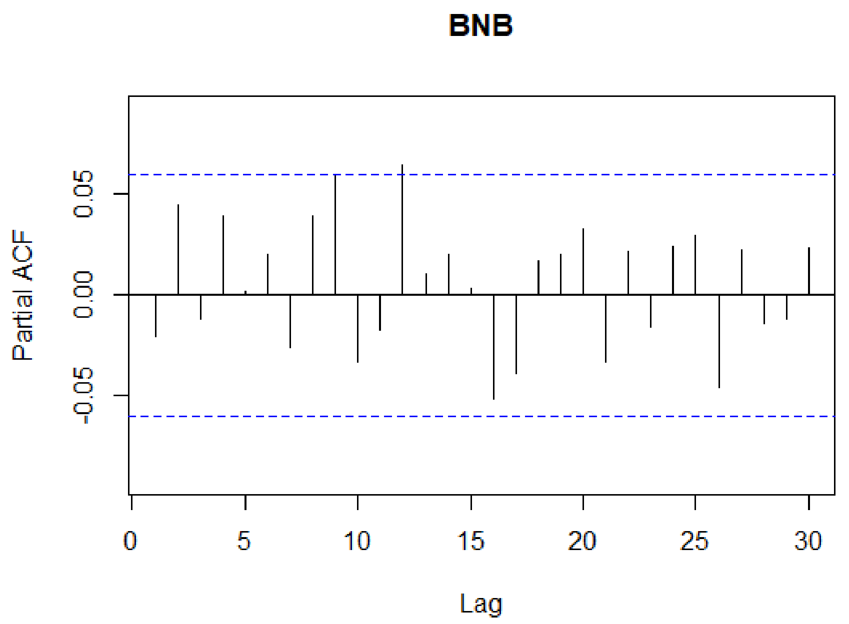

Figure 20 Partial ACF graph for BNB log-return series

According to PACF graph, the situation is vague. We can observe partial autocorrelation at lag 12 on the figure above, however, it makes sense not to consider very high AR orders for avoiding the overfitting of the model. Final number of lags will be defined according to AIC of constructed model.

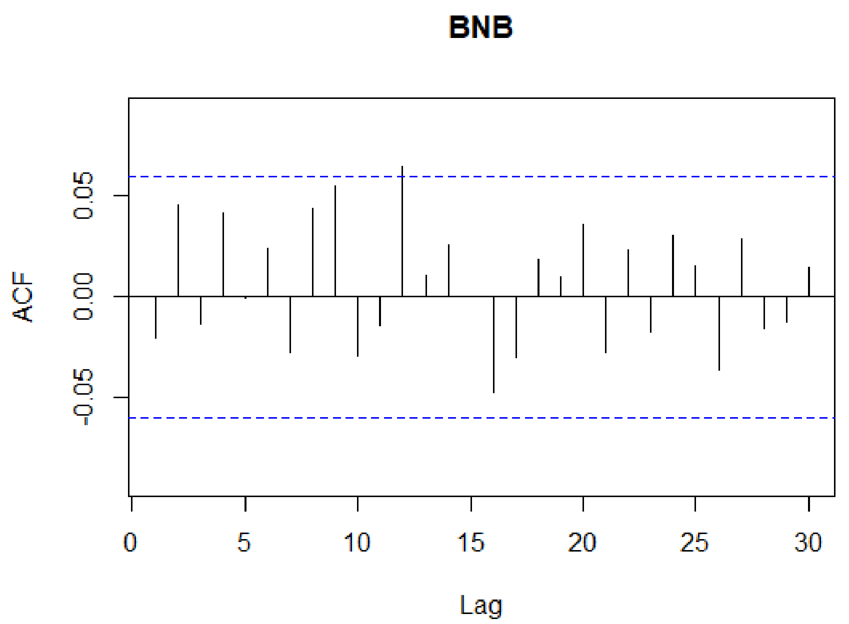

Figure 21 ACF graph for BNB log-return series

According to ACF graph, the situation is quite the same as with PACF graph. Final number of lags will be also defined according to AIC of constructed model.

Finally, the model ARMA(1,1)-GJR-GARCH(1,1) with external regressors and assumed Student-t distribution is chosen according to the lowest AIC. The model mean equation and variance equation are as follows.

Mean equation:

$$BNBlogret_t = \mu + \beta_1 * BNBlogret_{t-1} + \beta_2 * \varepsilon_{t-1} + \varphi_1 DMlogret_t + \varphi_2 EMlogret_t + \varphi_3 RUSlogret_t + \varepsilon_t$$

where $BNBlogret_t$ – logarithmic return of BNB for a current period, $BNBlogret_{t-1}$ – logarithmic returns of BNB of a previous period, ε_{t-1} – previous period error term, $DMlogret_t$ – logarithmic return of MSCI Developed Markets Index (called World Index) for current period, $EMlogret_t$ - logarithmic return of MSCI Emerging Markets Index, $RUSlogret_t$ - logarithmic return of MSCI Russia Index and ε_t is current period error term.

Variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}$$

where ω is the unconditional variance, α is ARCH, β is the GARCH term, γ is the leverage effect, *I* is the dummy variable, which equals to 0 in case of positive shock in previous period and 1 in case of negative shock (the more detailed description is in model choice chapter).

Considering the choice of distribution, we again check Quantile-Quantile plots of standardized residuals for normal and Student-t distributions (please, refer to Figures 24 and 25). We can see there that tails significantly deviate from the line representing normal distribution. However, in case of Student-t distribution the standardized residuals align the line representing Student-t distribution better, than that of normal distribution, leading to conclusion of better fit of model with Student-t distribution.

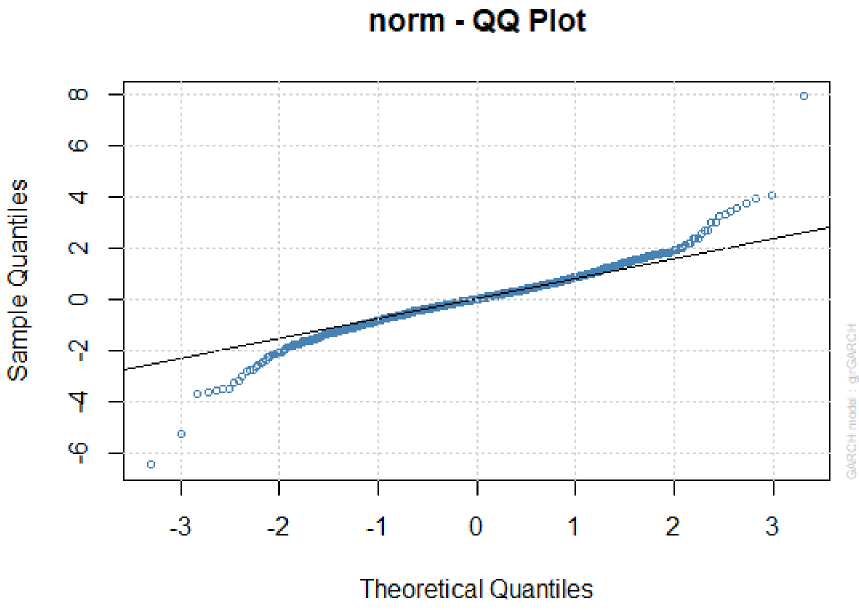

Figure 22 QQ-Plot of Standardized Residuals for model with normal distribution

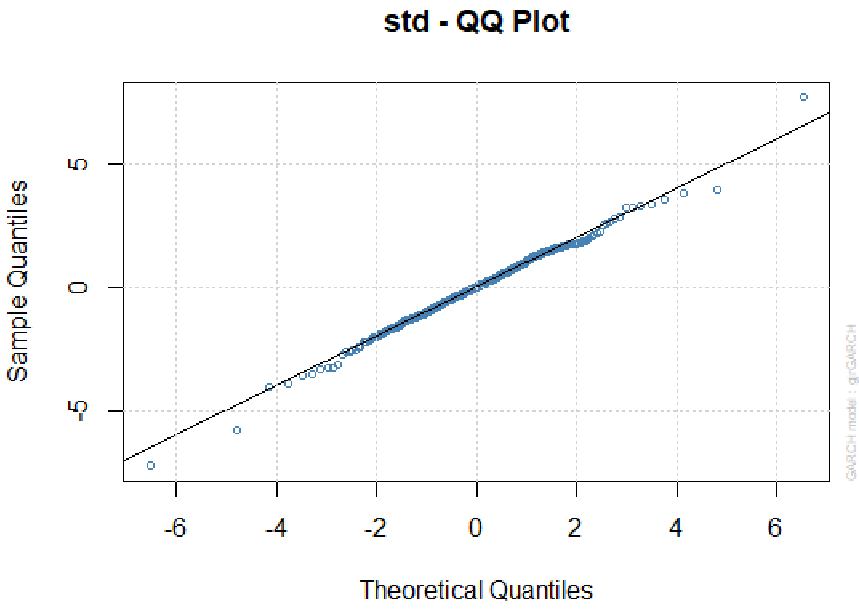

Figure 23 QQ-Plot of Standardized Residuals for model with Student-t distribution

The BNB model results are as follows:

Model results					
Dependent variable:	BNB log-returns		N obs:	1084	
Coefficient	Estimate	Std. Error	t-value	p-value	
Mean equation					
μ	0.00	0.00	1.51	0.13	
AR 1	0.58	0.18	3.31	0.00	**
MA 1	-0.63	0.17	-3.82	0.00	**
DM	0.97	0.18	5.28	0.00	**
EM	-0.26	0.19	-1.40	0.16	
Russia	0.10	0.06	1.68	0.09	
Variance equation					
ω	0.00	0.00	1.94	0.05	*
α	0.16	0.06	2.45	0.01	**
β	0.82	0.07	11.52	0.00	**
γ	-0.07	0.05	-1.50	0.13	
shape	3.72	0.46	8.13	0.00	**

Table 15 BNB ARMA(1,1)-GJR-GARCH(1,1) model results
**, ** correspond to 0.05 and 0.01 significance levels, respectively*

Firstly, the mean equation will be interpreted. Coefficients of AR and MA for are both significant at 1% level. It means that that today's logarithmic return value of BNB is dependent on its lagged value from previous period and past period error term.

Results of BNB model generally are in line with Bitcoin model. The coefficient before DM is positive and statistically significant at 1% level. Hence, the BNB can serve as a diversifier to the portfolio mimicking MSCI Developed Markets Index. The coefficient before EM is negative but is not statistically significant. According to the established criterion for conclusion on hypothesis, the Ethereum can serve as a weak hedge to the portfolio mimicking MSCI Emerging Markets Index. The coefficient before RUS is positive and is not statistically significant. Here, the conclusion is the same as for MSCI Emerging Markets Index - the BNB can serve as a weak hedge to the portfolio mimicking MSCI Russia Index.

Now, the variance equation will be interpreted. Coefficients α and β are both significant at 1%, which means that GARCH is appropriate for modelling volatility. Again, α shows the sensitivity of today's volatility to previous period shocks and β shows the persistence of the volatility. Comparing with Bitcoin and Ethereum, we can conclude there that BNB volatility with α =0.16 is even more spiky. As it is shown in the Table 15, the γ is not significant and, hence, is not significantly different from zero, leading to the conclusion of no leverage effect presence in BNB volatility. The shape equal to 3.72 shows the number of degrees of freedom of Student distribution for standardized errors.

The last step there is to conduct model validity check with Ljung-Box test of standardized residuals and standardized squared residuals.

Chi-squared	p-value
8.8105	0.12

Table 16 Ljung-Box test for standardized residuals

As p-value of Ljung-Box test of standardized residuals is greater than 0.05, we fail to reject the null hypothesis, concluding that there is no autocorrelation of standardized residuals of the model. It means that mean equation is adequate, and model explained autocorrelation of standardized residuals.

Chi-squared	p-value
1.4817	0.91

Table 17 Ljung-Box test for standardized squared residuals

As p-value of Ljung-Box test of standardized residuals is greater than 0.05, we fail to reject the null hypothesis, concluding that there is no autocorrelation of standardized squared residuals of the model. For squared standardized residuals it means that variance equation performed well and captured that autocorrelation of standardized squared residuals.

3.3 Portfolios construction and analysis

Econometric models provided a perspective on co-movements of cryptocurrencies and stock market indices returns. To add a more practical view, this section is aimed to understand how combining a cryptocurrency with each stock market index in a portfolio affects risk-adjusted performance, represented by Sharpe ratio. Sharpe ratio shows how much excess return (of portfolio over risk-free rate) is received for a unit of risk.[28] Sharpe ratio is calculated as follows:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

Where R_p is the annualized return of portfolio (calculated as a weighted average of returns of the assets in portfolio), R_f is risk-free rate and σ_p is an annualized standard deviation of portfolio. Standard deviation of portfolio for 2 assets (in our case the first is represented by MSCI index and the second is the cryptocurrency) is calculated by using the following formula:

$$\sigma_p = \sqrt{w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2Cov_{1,2}}$$

[28] https://www.investopedia.com/articles/07/sharpe_ratio.asp

Where W_1 and W_2 are weights of the assets in the portfolio, σ_1^2 and σ_2^2 are variances of assets 1 and 2, and $Cov_{1,2}$ is the covariance between 1 and 2 assets.

For example, in the work of (Bouri, Lucey, & Roubaud, 2020) it was revealed that adding Bitcoin and Ethereum to Asia Pacific and Japan equity indices portfolios leads to significant improvement of Sharpe Ratio.

Bouri, Lucey, & Roubaud approach will be followed, and for each stock market index a portfolio with 30% share (these weights were used by Bouri, Lucey, & Roubaud) of cryptocurrency will be constructed. Shorting is not considered in portfolio constructions, as in approaches of (Brière, 2015; Bouri, Lucey, & Roubaud, 2020). The timeframe is a period from the January 1, 2018 till February 25, 2022. In Sharpe ratio calculations the risk-free rate used equals to 2.1156%, which is the fitted yield on a U.S. Treasury 4 Year Zero Coupon Bond[29] on January 2, 2018 to approximately fit the timeframe of data used for portfolios construction.

3.3.1 Portfolios with MSCI World (Developed Markets) Index

From the table below portfolios combining MSCI World Index and BTC, ETH, BNB can be observed.

	Without crypto	*With BTC*	*With ETH*	*With BNB*
Annualized return	0.084	0.142	0.165	0.484
Annualized volatility	0.174	0.270	0.346	0.387
Sharpe ratio	0.364	0.448	0.416	1.194

Table 18 Portfolios constructed with MSCI World Index

Adding 30% Bitcoin to 70% of MSCI World Index results in increase of annualized return from 8.4% to 14.2% and in increase of annualized volatility from 17.4% to 27%. Sharpe ratio increases from 0.364 to 0.448, demonstrating better risk-adjusted performance.

Adding 30% Ethereum to 70% of MSCI World Index results in increase of annualized return from 8.4% to 16.5% and in increase of annualized volatility from 17.4% to 34.6%. Sharpe ratio increases from 0.364 to 0.416, demonstrating better risk-adjusted performance. However, Bitcoin-MSCI World Index portfolio still demonstrates better risk-adjusted performance.

Finally, adding 30% BNB to 70% of MSCI World Index results in increase of annualized return from 8.4% to 48.4% and in increase of annualized volatility from 17.4% to 38.7%. Sharpe ratio

[29] https://fred.stlouisfed.org/series/THREEFY4

increases from 0.364 to 1.194, demonstrating the best risk-adjusted performance among presented portfolios.

Generally, adding a cryptocurrency to a portfolio, represented by MSCI World (Developed Markets) Index with weights of 30% and 70%, respectively, tends to improve risk-adjusted performance for all presented cryptocurrencies. Nevertheless, BNB demonstrates the best risk-adjusted performance represented by the highest Sharpe ratio for defined weightings.

3.3.2 Portfolios with MSCI Emerging Markets Index

From the table below portfolios combining MSCI Emerging Markets Index and BTC, ETH, BNB can be observed.

	Without crypto	*With BTC*	*With ETH*	*With BNB*
Annualized return	0.003	0.085	0.108	0.427
Annualized volatility	0.169	0.256	0.333	0.376
Sharpe ratio	-0.108	0.250	0.261	1.079

Table 19 Portfolios constructed with MSCI Emerging Markets Index

Adding 30% Bitcoin to 70% of MSCI Emerging Markets Index results in increase of annualized return from 0.3% to 8.5% and in increase of annualized volatility from 16.9% to 25.6%. Sharpe ratio increases from -0.108 to 0.250, demonstrating a switch from a position of annualized return lower than risk-free rate to that of return higher than risk-free rate and better risk-adjusted performance.

Adding 30% Ethereum to 70% of MSCI Emerging Markets Index results in increase of annualized return from 0.3% to 10.8% and in increase of annualized volatility from 16.9% to 33.3%. Sharpe ratio increases from -0.108 to 0.261, demonstrating better risk-adjusted performance.

Finally, adding 30% BNB to 70% of MSCI Emerging Markets Index results in increase of annualized return from 0.3% to 42.7% and in increase of annualized volatility from 16.9% to 37.6%. Sharpe ratio increases from -0.108 to 1.079, demonstrating the best risk-adjusted performance among presented portfolios.

Generally, adding a cryptocurrency to a portfolio, represented by MSCI Emerging Markets Index with weights of 30% and 70%, respectively, tends to improve risk-adjusted performance for all presented cryptocurrencies. Nevertheless, as in previous case of MSCI World Index, BNB demonstrates the best risk-adjusted performance represented by the highest Sharpe ratio for defined weightings.

3.3.3 Portfolios with MSCI Russia Index

From the table below portfolios combining MSCI Russia Index and BTC, ETH, BNB can be observed.

	Without crypto	*With BTC*	*With ETH*	*With BNB*
Annualized return	-0.068	0.036	0.059	0.377
Annualized volatility	0.366	0.357	0.422	0.451
Sharpe ratio	-0.242	0.041	0.089	0.789

Table 20 Portfolios constructed with MSCI Russia Index

Adding 30% Bitcoin to 70% of MSCI Russia Index increases the annualized return from -6.8% to 3.6% and, actually, decreases the annualized volatility from 36.6% to 35.7%. Sharpe ratio increases from -0.242 to 0.041, demonstrating a switch from a position of annualized return lower than risk-free rate to that of return higher than risk-free rate and better risk-adjusted performance.

Adding 30% Ethereum to 70% of MSCI Russia Index results in increase of annualized return from -6.8% to 5.9% and in increase of annualized volatility from 36.6% to 42.2%. Sharpe ratio increases from -0.242 to 0.089, demonstrating better risk-adjusted performance.

Finally, adding 30% BNB to 70% of MSCI Russia Index results in increase of annualized return from -6.8% to 37.7% and in increase of annualized volatility from 36.6% to 45.1%. Sharpe ratio increases from -0.242 to 0.789, demonstrating the best risk-adjusted performance among presented portfolios.

Generally, adding a cryptocurrency to a portfolio, represented by MSCI Russia Index with weights of 30% and 70%, respectively, tends to improve risk-adjusted performance for all presented cryptocurrencies. Nevertheless, as in previous cases of MSCI World Index and MSCI Emerging Markets indices, BNB demonstrates the best risk-adjusted performance represented by the highest Sharpe ratio for defined weightings.

3.4 Discussion

This part of work is dedicated to summarizing the results and to explanations concerning academic and practical implications of this study.

3.4.1 Summary of results

Research question for this paper is: “Do selected cryptocurrencies have diversifier, weak hedge or strong hedge properties for world equity indices?” To sum up, three cryptocurrencies (Bitcoin, Ethereum and BNB) were analyzed through the perspective of hypotheses stated in “Research problem, goal, objectives, and hypotheses” section in this working paper and the answer to the research question for each studied cryptocurrency was obtained. The summary of the properties of each of them follows in the table below:

Property / **Equity Index**	**Diversifier**	**Weak hedge**
MSCI Developed Markets	BTC, ETH, BNB	—
MSCI Emerging Markets	—	BTC, ETH, BNB
MSCI Russia Index	ETH	BTC, BNB

Table 21

None of the studied cryptocurrencies has strong hedge properties for portfolios mimicking MSCI Developed Markets Index, MSCI Emerging Markets Index and MSCI Russia Index.

Portfolios combined of a cryptocurrency with each stock market index were constructed to get the understanding of how adding each cryptocurrency to each stock market index affects risk-adjusted performance, represented by the Sharpe ratio. Overall, risk-adjusted performance of portfolios mimicking MSCI Developed Markets Index, MSCI Emerging Markets Index and MSCI Russia Index was improved by adding any of studied cryptocurrencies: Bitcoin, Ethereum and BNB. Nevertheless, portfolios with BNB demonstrated the best risk-adjusted performance, showing the highest Sharpe ratios comparing to portfolios with Bitcoin or Ethereum.

3.4.2 Academic implications

Academic implications are fulfilling the research gap (especially in terms of usage the MSCI Russia Index and mix of cryptocurrencies instead of only Bitcoin) and adding new experience and results into emerging field of research of cryptocurrencies and their possible application as an investment tool, which again underlines the actuality of such a work for today.

Potential beneficiaries of this work are researchers, who already studied the same field, and future researchers in this field (including students).

3.4.3 Practical implications

Results on the classification of cryptocurrencies as a diversifier or a weak hedge, obtained from econometric models, give to investors more understanding of how cryptocurrencies' returns are associated with global stock market indices represented by the MSCI Developed Markets Index and MSCI Emerging Markets Index and Russian stock market index represented by MSCI Russia index. Hence, a potential investor has more ground on making investment decisions related to mixing cryptocurrencies with stock market indices in their portfolios: for example, if an investor with high exposure to emerging stock market index wants to invest in Bitcoin, she knows that its returns do not co-move on average with emerging stock market index returns and it can add possible diversification benefits.

Moreover, the "Portfolios construction and analysis" section provides an understanding of how adding each cryptocurrency to portfolios mimicking the MSCI Developed Markets Index, MSCI Emerging Markets Index and MSCI Russia Index affects risk-adjusted performance by practical examples of the construction of portfolios combining cryptocurrencies and stock market indices. Therefore, the potential investor gains an even more complete view of the effects of including studied cryptocurrencies in the investment portfolio. For example, an investor holding a portfolio mimicking MSCI World (Developed Markets) Index can improve the risk-adjusted performance of his/her portfolio by adding BNB to it. However, the risk tolerance of an investor should always be considered, as cryptocurrencies are far more volatile comparing to the studied stock market indices.

Potential beneficiaries of this work are private investors, investment fund and investment banks.

3.4.4 Limitations and further research directions

This section is dedicated to discussion of limitations of this paper and suggestion of further research directions.

As for limitations, first one is timeframe of sample: it covers a period from January 2018 to February 2022 as cryptocurrencies are still emerging field of potential investments and have a short story of worldwide spreading (choice of timeframe was discussed in "Data" section). This timeframe is quite short for reflecting long-term performance of stock market indices. Therefore, it would be useful to extend the timeframe in future research. Second limitation is observations frequency: analysis is performed on daily returns. It would be beneficial to add a perspective on weekly or even monthly returns in future research (especially when longer timeframe of data will be available). In this paper only MSCI World Index (Developed Markets), MSCI Emerging Markets and MSCI Russia indices are studied. One of further research directions to study other MSCI indices or even to study not MSCI Indices, but to consider national equity indices (e.g., RTSI for Russia, CSI300 for China, FTSE 100 for United Kingdom, etc.). Finally, only Bitcoin, Ethereum and BNB were studied, which is a limitation opening wide set of future directions of research considering the choice of studied cryptocurrencies.

Conclusion

In closing, this research paper is aimed at identification whether the studied cryptocurrencies (Bitcoin, Ethereum, BNB) have diversifier, weak hedge or strong hedge properties for selected stock market indices: MSCI Developed Markets Index, MSCI Emerging Markets Index and MSCI Russia Index. Bitcoin, Ethereum and BNB were analyzed through the perspective of hypotheses stated in "Research problem, goal, objectives, and hypotheses" section paper and the answer to the research question for each studied cryptocurrency was obtained. In brief:

- Bitcoin can serve as a diversifier to the portfolio mimicking MSCI Developed Markets Index, as a weak hedge to the portfolio mimicking MSCI Emerging Markets Index and as a weak hedge to the portfolio mimicking MSCI Russia Index.
- Ethereum can serve as a diversifier to the portfolio mimicking MSCI Developed Markets Index, as a weak hedge to the portfolio mimicking MSCI Emerging Markets Index. Ethereum also can serve as a diversifier to the portfolio mimicking MSCI Russia Index.
- BNB can serve as a diversifier to the portfolio mimicking MSCI Developed Markets Index, as a weak hedge to the portfolio mimicking MSCI Emerging Markets Index and as a weak hedge to the portfolio mimicking MSCI Russia Index.

Moreover, to get the understanding of how adding each cryptocurrency to investor portfolio represented by each stock market index affects risk-adjusted performance, portfolios combined of a cryptocurrency with each stock market index were constructed and analyzed. In brief, risk-adjusted performance of portfolios mimicking MSCI Developed Markets Index, MSCI Emerging Markets Index and MSCI Russia Index was improved by adding any of studied cryptocurrencies, but portfolios with BNB demonstrated the best risk-adjusted performance.

The novelty of work is supported by including BNB cryptocurrency. Novelty of this work also lies in using MSCI World, MSCI Emerging Markets and MSCI Russia indices as independent variables in applied model, which ultimately provides a detailed view on studied properties of cryptocurrencies separately for developed, emerging markets, and for Russian market. Finally, the more recent data is used which covers pandemic period.

From an academic viewpoint, this paper fulfills the research gap and adds new experience and results into emerging field of research of cryptocurrencies and their possible application as an investment tool. From a practical viewpoint, results on the classification of cryptocurrencies as a diversifier or a weak hedge provide to investors more understanding of how cryptocurrencies' returns are associated with studied stock market indices returns. Portfolios construction and analysis provides an extended view on how adding each cryptocurrency to portfolios mimicking the studied stock market indices affects risk-adjusted performance. Therefore, the potential investor gains an even more complete picture of the effects of including studied cryptocurrencies in the investment portfolio.

As for further research directions, there are several recommendations. It would be useful to consider extended timeframe. It would be also beneficial to add a perspective on weekly or even monthly returns in future research (especially when longer timeframe of data will be available). One of further research directions is to exploit other MSCI indices or even to apply not MSCI Indices, but national equity indices (e.g., RTSI for Russia, CSI300 for China, FTSE 100 for United Kingdom, etc.) for studying the diversification or weak/strong hedging properties of cryptocurrencies against those indices. In conclusion, only Bitcoin, Ethereum and BNB were studied, which provides wide set of future directions of research in terms of the choice of studied cryptocurrencies.

References

Abdul-Rahim, R., & Soon, L. P. (2019). Diversifier, Hedge & Safe Heaven Properties of Cryptocurrencies: The Case Against Asian Fiat Currencies. *Finance, Property, Technology, and the Economy Conference.* Adelaide, Australia: CFA Institute Asia-Pacific Research Exchange.

Alexander, C. (2008). *Market Risk Analysis: Pricing, Hedging and Trading Financial Instruments.* Chichester, West Sussex: John Wiley & Sons Ltd.

Angabini, A., & Wasiuzzaman, S. (2011). GARCH Models and the Financial Crisis-A Study of the Malaysian Stock Market. *The International Journal of Applied Economics and Finance*, 226-236.

Baur, D. G., & Lucey, B. M. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *The Financial Review 45*, 217–229.

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance 34*, 1886–1898.

Beigel, O. (2022). *Who Accepts Bitcoin as Payment?* Retrieved from 99 Bitcoins: https://99bitcoins.com/bitcoin/who-accepts/

Binance. (2022). *The Binance Chain Blockchain*. Retrieved from Binance Chain Docs: https://docs.binance.org/blockchain.html

Bitcoin.org. (2022). *How does Bitcoin work?* Retrieved from bitcoin.org: https://bitcoin.org/en/how-it-works

Bouri, E., Lucey, B., & Roubaud, D. (2020). Cryptocurrencies and the downside risk in equity investments. *Finance Research Letters 33*, 101211.

Brière, M. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management Vol.16, 6*, 365–373.

Buterin, V. (2014). *Ethereum: A Next-Generation Smart Contract and Decentralized Application Platform.* Retrieved from ethereum.org: https://ethereum.org/669c9e2e2027310b6b3cdce6e1c52962/Ethereum_Whitepaper_-_Buterin_2014.pdf

Canh, N. P., Binh, N. Q., & Thanh, S. D. (2019). Cryptocurrencies and Investment Diversification: Empirical Evidence from Seven Largest Cryptocurrencies. *Theoretical Economics Letters, 9*, 431-452.

Cermak, V. (2017). *Can Bitcoin Become a Viable Alternative to Fiat Currencies? An Empirical Analysis of Bitcoin's Volatility Based on a GARCH Model*. Retrieved from SSRN: https://dx.doi.org/10.2139/ssrn.2961405

Chan, W. H., Le, M., & Wu, Y. W. (2019). Holding Bitcoin longer: The dynamic hedging abilities of Bitcoin. *The Quarterly Review of Economics and Finance 71*, 107-113.

Charfeddine, L., Benlagha, N., & Maouchi, Y. (2020). Investigating the dynamic relationship between cryptocurrencies and conventional assets: Implications for financial investors. *Economic Modelling 85*, 198–217.

Ciaian, P., Rajcaniova, M., & Kancs, d. (2016). The economics of BitCoin price formation. *Applied Economics, 48(19)*, 1799–1815.

Ciaian, P., Rajcaniova, M., & Kancs, d. (2018). Virtual relationships: Short- and long-run evidence from BitCoin and Altcoin markets. *Journal of International Financial Markets, Institutions and Money, 52*, 173-195.

Coinbase. (2022). *What is "proof of work" or "proof of stake"?* Retrieved from Coinbase: https://www.coinbase.com/learn/crypto-basics/what-is-proof-of-work-or-proof-of-stake

Cointelegraph. (2022). *What is Binance Coin (BNB), and how does it work?* Retrieved from Cointelegraph: https://cointelegraph.com/altcoins-for-beginners/what-is-binance-coin-bnb-and-how-does-it-work

Corbet, S., Lucey, B., & Yarovya, L. (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters Vol. 26*, 81-88.

Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters 16*, 139-144.

Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *Journal of economic perspectives, 15(4)*, 157-168.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica Vol.50, No.4*, 987-1007.

Ethereum.org. (2022). *Ethereum-powered tools and services*. Retrieved from Ethereum.org: https://ethereum.org/en/dapps/

Ethereum.org. (2022). *The Merge*. Retrieved from Ethereum.org: https://ethereum.org/en/upgrades/merge/

Feng, W., Wang, Y., & Zhang, Z. (2018). Can cryptocurrencies be a safe haven: a tail risk perspective analysis. *Applied Economics Vol. 50*, 4745-4762.

Frankenfield, J., & Anderson, S. G. (2022). *Ethereum*. Retrieved from Investopedia: https://www.investopedia.com/terms/e/ethereum.asp

Frankenfield, J., & Mansa, J. (2022). *Bitcoin (BTC)*. Retrieved from Investopedia: https://www.investopedia.com/terms/b/bitcoin.asp

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance 48*, 1779-1801.

Hayes, A., & Brown, J. R. (2022). *How to Buy Bitcoin*. Retrieved from Investopedia: https://www.investopedia.com/articles/investing/082914/basics-buying-and-investing-bitcoin.asp

Hon, H., Wang, K., Bolger, M., Wu, W., & Zhou, J. (2022). *Crypto Market Sizing.* Crypto.com.

Hong, K. (2017). Bitcoin as an alternative investment vehicle. *Information Technology and Management 18 (4)*, 265-275.

Kenton, W. (2022). *Asymmetric Volatility Phenomenon (AVP)*. Retrieved from Investopedia: https://www.investopedia.com/terms/a/assymetricvolatility.asp#:~:text=The%20asymmet ric%20volatility%20phenomenon%20(AVP)%20is%20the%20observed%20tendency%20of,than%20given%20a%2010%25%20gain.

Mandelbrot, B. B. (1963). The Variation of Certain Speculative Prices. *The Journal of Business 36, No. 4,* 394-419.

Nakamoto, S. (2008). *Bitcoin: A Peer-to-Peer Electronic Cash System.* Retrieved from bitcoin.org: https://bitcoin.org/bitcoin.pdf

Ratner, M., & Chiu, J. (2013). Hedging stock sector risk with credit default swaps. *International Review of Financial Analysis, 30*, 18-25.

Schueffel, P., Groeneweg, N., & Baldegger, R. (2019). *The Crypto Encyclopedia.* Fribourg, Switzerland: School of Management Fribourg (HEG-FR), Institute of Finance.

Stensås, A., Nygaard, M. F., & Treepongkaruna, K. K. (2019). Can Bitcoin be a diversifier, hedge or safe haven tool? *Cogent Economics & Finance 7*.

Tsay, R. S. (2010). *Analysis of Financial Time Series Third Edition.* Chicago, IL: A John Wiley & Sons, Inc.

Wang, G.-J., Ma, X.-y., & Wu, H.-y. (2020). Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests? *Research in International Business and Finance 54*.

Wu, G. (2001). The Determinants of Asymmetric Volatility. *The Review of Financial Studies, Vol.14*, 837-859.