COPENHAGEN BUSINESS SCHOOL
HANDELSHØJSKOLEN

# BITCOIN AMID THE COVID-19 PANDEMIC: REVISITING BITCOIN'S SAFE HAVEN AND PORTFOLIO PERFORMANCE-ENHANCING PROPERTIES

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Abstract

Against a backdrop of the COVID-19 pandemic, investors fear an impending global financial crisis as uncertainty about the future economic outlook prevails. In pursuit of limiting financial losses, investors seek out assets, which carry value amid financial stress. Since the inception of Bitcoin, its high returns, volatility, as well as independence of government and monetary policy have led academics and practitioners to inconclusively associate Bitcoin with the search for safe haven and portfolio performance-enhancing assets during financial distress. The purpose of this thesis is to revisit Bitcoin's investment properties by testing its safe haven ability and performance-enhancing properties to a diversified portfolio during the hitherto COVID-19 pandemic - the first instance of severe global financial market stress since Bitcoin's inception. As part of a threefold approach using data from October 2013 through August 2020 as well as several shorter sub-periods within that timeframe, this thesis firstly identifies Bitcoin's time-limited and varying safe haven properties during COVID-19 for two of the 23 examined asset indices by regressing DCC GARCH estimated time-varying correlations between Bitcoin and each index. Secondly, in line with the compulsory liquidity requirement for safe havens, this thesis finds that Bitcoin's bid-ask spread and transaction costs remained relatively low compared to previous periods and other assets, thus supporting Bitcoin's modest safe haven properties amid COVID-19. Thirdly, the construction of 96 mean-variance and mean-CVaR optimized portfolios consisting of test (including Bitcoin) and benchmark (excluding Bitcoin) diversified tangency and global-minimum-variance portfolios adverts to Bitcoin's minor role in portfolio optimization. Moreover, the study discloses that Bitcoin has the potential to increase the Sharpe Ratio of the portfolios but proves less suitable and consistent for investors seeking to reduce their portfolios' modified VaR and CVaR or increase the Sortino and Adjusted Sharpe Ratio. While this study contributes with a comprehensive examination of Bitcoin amid COVID-19, it is questionable whether the pandemic has caused sufficient global financial distress to draw generalizable inferences about Bitcoin's investment properties during crises.

**Keywords** Bitcoin, COVID-19, Crisis, Cryptocurrencies, Investment, Portfolio Performance, Safe Haven

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## List of Abbreviations[1]

| | |
|---|---|
| ADF | Augmented Dickey-Fuller |
| ARCH | Auto Regressive Conditional Heteroscedasticity |
| ASR | Adjusted Sharpe Ratio |
| CVaR | Conditional-Value-at-Risk |
| DCC | Dynamic Conditional Correlation |
| DCC GARCH | Dynamic Conditional Correlation Generalized Auto Regressive Conditional Heteroscedasticity |
| E.g. | Exempli gratia: For example |
| ETF | Exchange-Traded Fund |
| GARCH | Generalized Auto Regressive Conditional Heteroscedasticity |
| GFSI | Global Financial Stress Index |
| GMVP | Global-Minimum-Variance Portfolio |
| I.a. | Inter altia: Among other things |
| I.e. | Id est: That is |
| MCVaR | Modified Conditional-Value-at-Risk |
| MPT | Modern Portfolio Theory |
| MVaR | Modified Value-at-Risk |
| RASR | Relative Adjusted Sharpe Ratio |
| RMCVaR | Relative Modified Conditional-Value-at-Risk |
| RMVaR | Relative Modified Value-at-Risk |
| RSoR | Relative Sortino Ratio |
| RSR | Relative Sharpe Ratio |
| SoR | Sortino Ratio |
| SR | Sharpe Ratio |
| STLFSI2 | St. Louis Fed Financial Stress Index |
| TP | Tangency Portfolio |
| VaR | Value-at-Risk |
| VIX | CBOE Volatility Index |
| WHO | World Health Organization |

[1] The list of abbreviations solely includes abbreviations used frequently throughout the thesis.

# Executive Summary

**Purpose** Against a backdrop of the COVID-19 pandemic, investors fear an impending global financial crisis as uncertainty about the future economic outlook prevails. In the attempt to limit their exposure to financial losses, investors seek out assets, which carry value amid financial market stress. Since the inception of Bitcoin, its high returns, volatility, as well as independence of government and monetary policy have attracted the attention of academics and practitioners towards Bitcoin's safe haven and portfolio performance-enhancing characteristics amid financial distress with, however, discrepant conclusions. Yet, significant research gaps endure, as no acute period of global financial stress, required to investigate Bitcoin's value to investors during financial crises, has occurred since Bitcoin began trading. Therefore, the purpose of this thesis is to test the viability of the preceding findings during the hitherto COVID-19 pandemic - the first instance of severe global financial market stress since Bitcoin's inception – by assessing Bitcoin's safe haven ability and performance-enhancing properties to a diversified portfolio.

**Methodology** From a positivist stance, the investigation of Bitcoin's investment properties pursues a three-fold methodological approach using data from October 2013 through August 2020 as well as several shorter sub-periods within that timeframe. First, Bitcoin's DCC GARCH estimated time-varying correlations with an international sample of asset indices are run through a regression analysis to determine whether and to which extent Bitcoin serves as a safe haven amid COVID-19. Second, to adhere to the compulsory liquidity requirement for safe havens, Bitcoin's liquidity during the pandemic is evaluated in terms of bid-ask spreads and transaction costs. Third, using a two-year rolling data window, Bitcoin's additive power to diversified portfolios is assessed on the basis of 96 mean-variance and mean-CVaR optimized portfolios consisting of test (including Bitcoin) and benchmark (excluding Bitcoin) tangency and global-minimum-variance portfolios. This allows for the identification of whether Bitcoin ought to be included in the portfolios and appends positive risk and return effects during COVID-19.

**Findings** This thesis finds that Bitcoin only carries safe haven properties for a short time horizon against two out of the 23 examined asset indices, alluding to Bitcoin's limited as well as time- and geography-varying safe haven property. Nonetheless, Bitcoin's bid-ask spread and transaction costs amid the pandemic remained relatively low compared to previous periods and other assets, which speaks in favor of Bitcoin's modest safe haven property. Moreover, the optimized test portfolios reported an average weight allocation to Bitcoin of no more than 0.715%, which adverts to Bitcoin's minor role in portfolio optimization amid COVID-19. While the inclusion of Bitcoin has the potential to increase the Sharpe Ratio of the portfolios, it generally proved less suitable and consistent for investors seeking to reduce downside risk, measured by modified VaR and modified CVaR, or increase the Sortino and Adjusted Sharpe Ratios during the pandemic.

**Contribution** To the best of the authors' knowledge, this study was the first of its kind to disclose a comprehensive examination of Bitcoin's investment properties during Bitcoin's first encounter with severe global financial market stress. It is, however, questionable whether global financial markets have encountered sufficient instances of severe stress to designate the COVID-19 crisis a global financial crisis and thus to draw accurate and generalizable inferences about Bitcoin's investment properties during crises in general. Nonetheless, Bitcoin proved to be of pertinence to short-term, high-frequency, and speculative retail investors as well as investors in pursuit of portfolio diversification and certain risk-return tradeoffs during the hitherto COVID-19 pandemic.

# 1. Introduction

Since its first occurrence in the Chinese city Wuhan in December 2019, COVID-19, an infectious disease caused by the new type of coronavirus SARS-CoV-2, has developed into a global crisis. Declared a pandemic by the World Health Organization (WHO) on March 11$^{th}$, 2020, COVID-19 represents a prime example of the interconnectedness and fragility of our globalized world (World Health Organization, 2020). At the time of writing, the duration, scope, and death toll of the ongoing COVID-19 pandemic remain uncertain, and so do its economic consequences. However, what is clear, is that the pandemic has turned into a severe global health crisis, which has vastly impacted real economic activity and created financial volatility and market stress across the globe (Goodell and Goutte, 2020). While the former is reflected in the forecasted average year-on-year decline in world Gross Domestic Product (GDP) of - 4.5% in 2020 (Amaro, 2020), the latter is exemplified by financial stress indicators reaching peaks unparalleled since the financial crisis of more than a decade ago (Wagner, 2020) As the human and economic costs of the COVID-19 pandemic loomed in March 2020, investors became spooked by fears of an impending global recession. The S&P 500 recorded its largest quarterly decline since 2008, the Dow Jones Industrial Average posted its worst showing since 1987, and the UK equity market reported its most substantial quarterly drop for more than three decades, which was an image mirrored by the European, Asian and emerging equity markets (Invesco, 2020).

Against a backdrop of a looming financial crisis, as feared in March 2020, investors typically seek out asset investments, which are perceived to help limit their exposure to losses, stabilize their portfolios and potentially even generate positive returns during a period of prolonged market distress. The motivation behind investing in such assets derives from the concept of loss aversion, which stipulates that investors hold greater sensitivity to acute losses than gains (Tversky and Kahneman, 1991). This loss aversion prompts investors to search for so-called safe haven assets, which remain or increase in value during times of heightened financial market stress. Given that financial market performance is found to increase in the long run, safe haven assets primarily appeal to investors seeking protection against crisis-induced inflation as well as short-term investors focusing on minimizing losses from market fluctuations, e.g., retail investors close to retirement. So, which assets carry these proclaimed safe haven characteristics? Commonly, experts have established liquid assets such as gold (i.a., Baur and Lucey, 2010; Baur and McDermott, 2010; Bredin, Conlon and Potì, 2017; Conlon, Lucey and Uddin, 2018), currencies (i.a., Ranaldo and Söderlind, 2010; Choudhury, 2020), commodities (i.a., Henriksen, 2018; Shahzad *et al.*, 2019), and long-dated Treasury bonds (i.a., Flavin, Morley and Panopoulou, 2014; Sekera, 2020) to be traditional safe havens. Of late, a new narrative, centering around the applicability of adding Bitcoin to the list of potential safe haven investments, has emerged (i.a., Bouri *et al.*, 2017; Shahzad *et al.*, 2019; Smales, 2019).

The public emergence of cryptocurrencies commenced in 2008 when an unknown inventor published a white paper presenting the first application of cryptography into a decentralized digital currency. The new virtual currency, named Bitcoin and backed by blockchain technology, was intended to serve as a peer-to-peer electronic cash system, which allows online payments to be sent directly from one party to another without the need for financial intermediaries (Nakamoto, 2008). Hence, unlike most other financial assets, Bitcoin is not based on any tangible asset, has no association with any government or monetary authorities and no physical representation. Along with Bitcoin's rapid growth and wide mainstream media coverage came a debate about whether Bitcoin should be seen as an alternative currency, used as a medium of exchange, or as an investment asset. An analysis of Bitcoin's public ledger revealed that a dominant share of Bitcoin is held by investors, whereas only a minority of Bitcoin holders appear to use the cryptocurrency purely as a medium of exchange (Baur, Hong and Lee, 2018). Importantly, the launch of Bitcoin futures contracts in late 2017 further enhanced the legitimacy of Bitcoin as an investment asset and moved it closer to the center of the financial world (Shahzad *et al.*, 2019).

Spurred by Bitcoin's high returns and volatility as well as its independence of government and monetary policy, academicians and practitioners began investigating Bitcoin's investment properties. As a result of Bitcoin's rising prices during the European Sovereign Debt Crisis from 2010 to 2013 as well as during the Cypriot Banking Crisis from 2012 to 2013, a narrative around Bitcoin's safe haven potential during times of crises began arising. Against this background, numerous studies, utilizing various methodologies, investigated the diversification, hedging, and safe haven properties of Bitcoin on average and during times of market stress with, however, discrepant findings. Several articles highlight the weak correlation between Bitcoin and other assets, showing that the inclusion of Bitcoin into a diversified portfolio can improve the risk-return efficiency (Brière, Oosterlinck and Szafarz, 2015; Dyhrberg, 2016; Bouri, Molnár, *et al.*, 2017; Baur, Hong and Lee, 2018; Guesmi *et al.*, 2019). Others even stress that Bitcoin investments can act as a hedge and safe haven due to its negative correlations with other assets (Luther and Salter, 2017; Urquhart and Zhang, 2019). On the contrary, Bouri *et al.* (2017), Klein, Pham Thu and Walther (2018), and Tiwari, Raheem and Kang

(2019) indicate that cryptocurrencies are a poor hedge and safe haven for most situations and may be suitable only for limited diversification benefits. Additionally, Smales (2019) stresses there to be a liquidity requirement inherent in the definition of a safe haven, why the high volatility and low liquidity of cryptocurrencies eliminate Bitcoin as a safe haven asset.

While the results of the young but expanding literature are decidedly mixed on Bitcoin's potential to be of value to investors during times of crises, it is questionable whether global markets have encountered sufficient cases of severe financial market stress since the inception of Bitcoin to enable adequate studies to be performed and accurate conclusions to be drawn. According to the CBOE Volatility Index (VIX), the Global Financial Stress Index (GFSI), and the St. Louis Fed Financial Stress Index (STLFSI2), no cases of acute stress have occurred since the global financial crisis up until the start of the COVID-19 pandemic. Thus, the ongoing COVID-19 pandemic - the first global market crisis since Bitcoin began actively trading - presents a strong motivation to test the viability of Bitcoin as both a safe haven against individual assets and a performance-enhancing addition to a diversified portfolio during bearish market conditions. Hypothesizing on the findings of the existing literature, this thesis pursues to find evidence for or against the following main hypothesis:

*(HI) Bitcoin acts as a safe haven against an international sample of asset indices and serves as a performance-enhancing addition to a diversified portfolio during the COVID-19 pandemic.*

To the best of the authors' knowledge, this thesis is the first academic work to test the existing literatures' conclusions on Bitcoin's value to investors during crises through a three-fold analytical approach. First, it is examined whether Bitcoin holds negative correlations with an international sample of asset indices under the COVID-19 pandemic, which would suggest Bitcoin to be a safe haven (see definition in section 1.2.). Second, Bitcoin's liquidity during the pandemic is tested to assess whether Bitcoin fulfills the crucial liquidity requirement for safe havens. Third, to extend the perspective to a portfolio setting, Bitcoin's additive value to a diversified portfolio during COVID-19 is evaluated. This three-fold approach is supported by three sub-hypotheses, which are developed in section 4.

Accordingly, the purpose of this thesis is to revisit Bitcoin's safe haven ability and performance-enhancing properties to a diversified portfolio by testing these during the hitherto COVID-19 pandemic - the first instance of severe global financial market stress since Bitcoin's inception. Besides contributing to the academic sphere on Bitcoin and safe havens, this thesis aims to provide valuable knowledge for market participants seeking to manage risks through crisis periods. Moreover, the aim is to present further evidence to support or reject the validity of considering Bitcoin within mainstream portfolio design research.

## 1.1. Delimitations

In acknowledgement of the vastness of the field, the scope of this thesis is delimited to ensure an in-depth analysis of the subject matter. First, this paper delimits itself to examining only one cryptocurrency, namely Bitcoin. It is, however, acknowledged that an ecosystem of more than 2,000 different cryptocurrencies has emerged since the inception of Bitcoin, why it could have been of interest to examine the value potential of various cryptocurrencies and indices to investors amid crises. Given that the market capitalization of Bitcoin constitutes approximately 66 percent of the total of all cryptocurrencies in 2020 (Statista, 2020), this thesis limits its focus to Bitcoin. Second, given Bitcoin's primary use for investment purposes, Bitcoin is treated as an investment asset throughout this thesis. Third, due to the recent launch of Bitcoin Futures and thus limited data availability, this thesis solely focuses on investing in actual Bitcoins rather than in Bitcoin futures. Fourth, this thesis delimits itself to the definitions of a safe haven, hedge, and diversifier outlined in the subsequent section 1.2. Fifth, this paper focuses on Bitcoin's short-term safe haven potential against fluctuations in asset indices under the COVID-19 crisis. It is acknowledged that studying Bitcoin's long-term safe haven potential against, for example, possible future inflation induced by the unprecedented COVID-19 related liquidity measures of central banks and governments might be of high relevance. Due to a lack of available data, this remains out of scope. Lastly, this study's methodological choices are based upon their relevance to retail investors. This delimitation is chosen in light of Bitcoin being a proclaimed retail driven phenomenon (Bhutoria, 2020). While the institutional adoption of Bitcoin is rising, the limited number of available Bitcoins as well as regulatory uncertainties render Bitcoin to be most spread among retail investor (Ibid).

## 1.2. Definitions

To ensure a uniform terminology and understanding throughout this thesis, the key concepts of safe haven, hedge, and diversifier assets are defined, and the terms used to describe financial distress are named. The academically related literature widely follows the investment property definitions established by the extensively cited Baur and Lucey (2010), who define a *safe haven* asset as "an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil" (p. 219), thereby "compensating the investor for losses since the price of the haven asset rises when the price of the other asset or portfolio falls" (p. 219). On a similar note, Baur and Lucey define an asset to be a *hedge* when it carries a negative correlation to another asset on average. Moreover, they refer to an asset as a *diversifier* if the correlation between two assets is not perfectly correlated, but positive on average. These distinctions and definitions have been applied repeatedly within empirical studies on safe havens of various kinds (i.a., Ratner and Chiu, 2013; Bouri, Gupta, *et al.*, 2017; Klein, Pham Thu and Walther, 2018; Shahzad *et al.*, 2019; Smales, 2019; Stensås *et al.*, 2019; Kang *et al.*, 2020). Building on the definition of Baur and Lucey (2010), Smales (2019) and Wang *et al.* (2019) highlight the utter importance of including liquidity in the definition of a safe haven asset. Smales (2019) advocates that "for an asset to truly act as a safe haven, it must be liquid such that investors can buy and sell the asset quickly at a relatively low cost" (p. 386). Given their prevalence in theoretically related literature, the aforementioned safe haven, hedge and diversifier definitions are followed throughout this thesis. Furthermore, for the proceedings of this thesis, the terms stress, turmoil, market crisis, bearish market conditions, turbulence, and distress are applied interchangeably to denote periods of financial market downturn.

## 1.3. Research Structure

After having set the stage for this study in introductory Chapter 1, contextual background knowledge of Bitcoin and the COVID-19 pandemic is provided in Chapter 2. Thereafter, Chapter 3 presents the existing literature on Bitcoin's investment characteristics across three identified lines of research and dwells upon the theories underlying the literature. After having outlined the shortcomings of the reviewed literature, Chapter 4 builds on the findings of existing studies and theories to logically develop the main research hypothesis as well as three sub-hypotheses. Thereupon, Chapter 5 elaborates upon the chosen scientific stance and the three-fold methodological approach taken to operationalize the three sub-hypotheses. Additionally, the utilized data is introduced and the research quality is dwelled upon. In accordance with the three-step methodological approach, Chapter 6 reports the empirical findings of each of the three performed analyses. Subsequently, in Chapter 7, the obtained findings are critically interpreted, discussed, and placed in context of the existing literature and theory. Since an ancillary objective of this paper is to present valuable insights for market participants, the final part of Chapter 7 discusses the implications of the results. Lastly, Chapter 8 concludes with a summary of the study, comments on whether the hypotheses can be supported or rejected, and dwells upon further research topics.

# 2. Background

## 2.1. Bitcoin

This section provides contextual knowledge of Bitcoin. Firstly, Bitcoin's founding, value proposition, and technical characteristics are described. Secondly, two prevalent views on the properties of Bitcoin are depicted. Lastly, Bitcoin's historical development is outlined.

### 2.1.1. Bitcoin – An Introduction

In October of 2008, a whitepaper with the title "Bitcoin: A Peer-to-Peer Electronic Cash System," written by the still unknown person or group called Satoshi Nakamoto, was published on an obscure email list dedicated to cryptographers. The whitepaper proposed a solution to overcome the inherent weaknesses of the digital financial system, which had come to primarily rely on banks as a trusted and centralized third party to process, verify and ensure the value and integrity of electronic payments between two counterparties. The weaknesses of this trust-based model count a certain percentage of unavoidable fraud, transaction costs related to mediation, and at times a minimum transaction size, which cuts off the possibility for small casual transactions (Nakamoto, 2008). While these challenges could be overcome by transacting in person using physical currencies, our globalized world, and the fact that financial transactions often cross borders render this physically impossible. Consequently, Nakamoto's whitepaper introduced a revolutionized and digital peer-to-peer payment system, which uses cryptographic proof as the basis of trust. By allowing transactions only to involve a payer and receiver, the system aims to offer a solution to the above-stated challenges but also to the problem of double-spending, which entails the possibility of counterfeiting payments. Thus, a transaction would no longer be dependent upon a facilitating and centralized third party (Ibid).

Similar to countries using fiat currencies, the peer-to-peer electronic cash system proposed Bitcoins as the medium of exchange. Rather than physical coins that can be carried around, Bitcoin is a virtual currency stored as a computer code in a virtual wallet that can be accessed through the internet (Wolla, 2018). Whereas fiat currencies are backed and verified by the respective countries' centralized governments, trust in Bitcoin is accomplished by distributing the power to a large blockchain network and establishing mass collaboration. Consequently, Bitcoin is rendered independent of monetary policy, which prevents governments from controlling the economy in case Bitcoin attains significant prominence as a medium of exchange in the future (Fama, Fumagalli and Lucarelli, 2019; Van Alstyne, 2014).

In technical terms, the mechanisms underlying the proposed digital payment system rely on blockchain technology and the process of mining to verify Bitcoin's use and overcome the problem of double-spending. Blockchain technology can be interpreted as a bookkeeping software that runs simultaneously on multiple computers, thereby representing a constantly growing chain of blocks, referred to as the decentralized general ledger. The blocks are identifiable by a timestamp and consist of a collection of stored transactions. Each block contains a link to the chain of previous blocks (Extance, 2015). The general ledger is updated with a new block of transactions through the decentralized process of mining. Mining is carried out by miners, who use their computer's processing power to try to solve a numerical equation in the fastest possible way to be allowed to update the ledger with a new block of transactions (Nakamoto, 2008). If a miner succeeds in solving the equation before other miners, he/she is allowed to update the ledger with an additional block of transactions, which is then broadcasted to all nodes, i.e., computers, in the network. The nodes verify the block based on a long list of criteria and express their acceptance of the block by creating a new block, which includes the timestamp of the previously reviewed and verified block. However, the system is only deemed secure as long as attacker nodes, which are defined as computers or devices that connect to the Bitcoin interface and try to modify history or transmit untruthful messages, control fewer units of central processing than honest nodes (Nakamoto, 2008).

To ensure an effective and consistent verification process, miners are incentivized by being rewarded with Bitcoins if they establish a new block (Ibid). The Bitcoins used for awarding the miners are new Bitcoins, why the process is called mining. The process of mining suggests that the number of Bitcoins will continue to grow; however, as set forth in the source code, Bitcoin's protocol stipulates a limited and finite supply of 21 million Bitcoins (Ibid). The reason for selecting a limited amount was for Bitcoin to resemble the value of other currencies, even though this was merely an educated guess, depending on whether Bitcoin remained a small niche or became a widely used medium of exchange (Pygas, 2020). After every 210,000 mined blocks, corresponding to approximately four years, the miner rewards per processed block are cut in half. Hence, the rate at which new Bitcoins are released into circulation is halved, which is Bitcoin's form of controlling inflation (Conway, 2020).

### 2.1.2. Bitcoin – Currency or Investment Asset

Although Nakamoto intended for Bitcoin to be a digital currency, which serves as an alternative for national (fiat) currencies, academic literature reports two conflicting perspectives on Bitcoin's nature. On one end of the spectrum, investment professionals such as Jim Breyer (Wingfield, 2013), Mick Novogratz (Schatzker, 2018), and Rogojanu and Badea (2014) argue that Bitcoin is a digital currency, which, in accordance with Nakomoto's initial propositions, is applicable as a medium of exchange. On the other end of the spectrum, significantly more proponents argue against Bitcoin's primary purpose as a currency and in favor of Bitcoin as an investment asset. As a consequence of Bitcoin's distinctive return properties, high volatility, still limited acceptance as a medium of exchange, and security issues, the second camp finds Bitcoin not to fulfill the three functions of money in an economy: medium of exchange, store of value, and unit of account (Glaser *et al.*, 2014; Bariviera *et al.*, 2017; Baur, Dimpfl and Kuck, 2018; Baur, Hong and Lee, 2018). Instead, and supported by an analysis of Bitcoin's public ledger, a dominant share of Bitcoin is claimed to be held for investment purposes (Baur, Hong and Lee, 2018). Some academic papers even suggest that Bitcoin should be viewed as a speculative investment, as it endures high expectations from investors due to its innovative technology and bursting bubble patterns (Yermack, 2013; Bouoiyour and Selmi, 2015; Baur, Hong and Lee, 2018). Refraining from the distinction between a speculative investment or merely an investment asset, Bitcoin is considered an investment asset in the proceedings of this thesis, as also stated in the delimitation section 1.1.

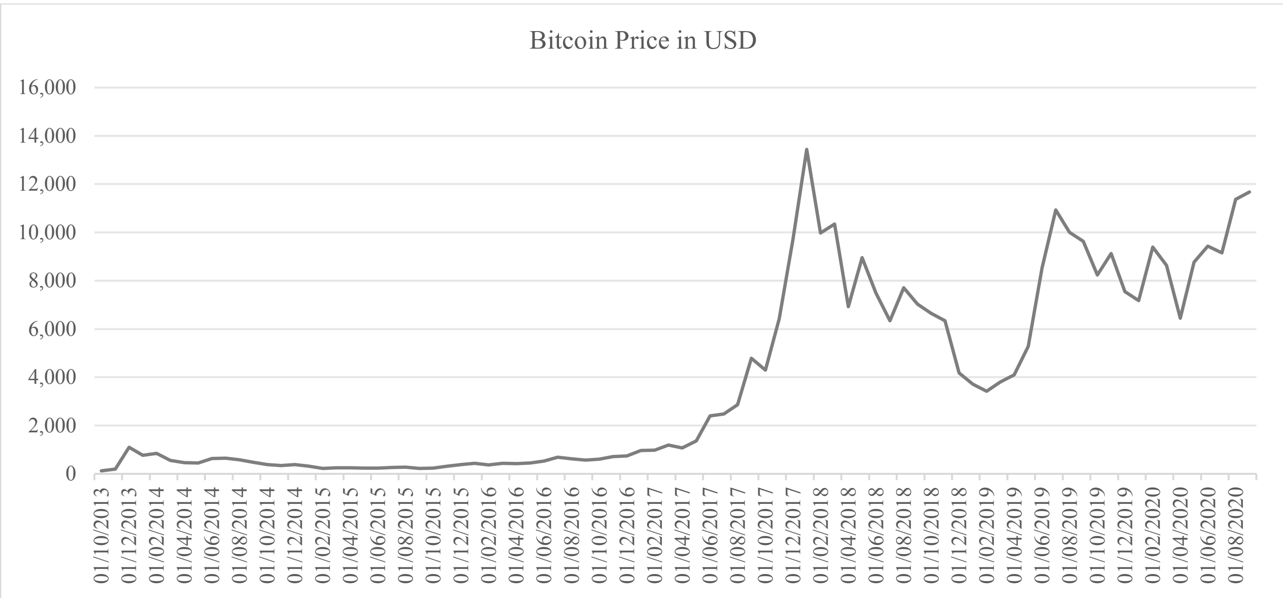
### 2.1.3. Bitcoin – Historical Development

After its introduction in 2008, Bitcoin was launched in January 2009 when the first block was mined. After a year of only being traded internally between miners, the first economic transaction with Bitcoin took place in 2010, when a man in Florida negotiated to purchase two pizzas for 10,000 Bitcoins. Today, that same transaction would have been worth 148 million USD. When the first Bitcoin exchange emerged in 2010, it became easier to trade Bitcoins and the market reached consensus for a price per Bitcoin, which did not exceed one USD for an extensive period of time. In line with Bitcoin exchanges opening around the world, Bitcoin's price started growing astronomically, punctuated by a few severe declines (Edwards, 2020). Given Bitcoin's increasing prices to an, at that point, all-time high of 200 USD in April 2013 and 1,000 USD in November 2013, a narrative surrounding Bitcoin's value to investors during the European Sovereign Debt Crisis from

2010 to 2013 and the Cypriot Banking Crisis from 2012 to 2013 began emerging (Bouri, Jalkh, *et al.*, 2017; Luther and Salter, 2017).

Subsequently, Bitcoin gained prominence as an investment asset due to its remarkable surge in price, which began in the second half of 2016 and continued throughout 2017. Specifically, the value of Bitcoin increased by 1,270% from January through December 2017, reaching a, to date, record high of close to 20,000 USD. The run-up in price was partly construed as excitement over the launch of Bitcoin futures at the Chicago Board Options Exchange and Chicago Mercantile Exchange in December 2017, which were seen as enhancing the legitimacy of Bitcoin as an investment asset and moving it closer to the center of the financial world (Shahzad *et al.*, 2019). More recently, a study found that Bitcoin's price surge in 2017 was predominantly manipulated by large volume trades of one cryptocurrency investor, which drove the price up (Cuthbertson, 2019). The enormous upsurge instigated great attention towards Bitcoin among mainstream media, regulators, the public, and financial markets, such that some call this period Bitcoin's 'IPO moment' (Damti, 2017; Kjærland *et al.*, 2018). However, Bitcoin's value declined drastically throughout 2018 as governments, regulators, policymakers, and practitioners raised serious issues regarding Bitcoin's legal status, illicit usage for payments, tax treatment, environmental unfriendly energy consumption, fraudulent schemes, exchange hacks, thefts, and scams (de Vries, 2018; Bedi and Nashier, 2020; Kethineni and Cao, 2020). Since then, the price of Bitcoin has fluctuated considerably and can be designated as extremely volatile (see Figure 1).

**Figure 1:** Bitcoin Price in USD




**Source:** CoinDesk (2020b)

Today, Bitcoin is traded at every hour of the day at multiple exchanges worldwide, with the largest being Bitfinex, Bitstamp, Coinbase, and Kraken. At the moment of writing, Bitcoin's circulating supply has reached 18.5 million Bitcoins out of a maximum supply of 21 million Bitcoins. Moreover, Bitcoin currently registers a market capitalization of 275.42 billion USD, which is almost six times as large as Ethereum, which holds the second place in the market for cryptocurrencies (CoinMarketCap, 2020).

## 2.2. COVID-19 Pandemic

Since its first occurrence in the Chinese city Wuhan in December 2019, COVID-19, an infectious disease caused by the new type of coronavirus SARS-CoV-2, has spread rapidly throughout the entire world. In the early months of 2020, the virus proved present on all continents, why the WHO declared the virus a global pandemic on March 11th, 2020 (World Health Organization, 2020). Thereupon, governments all around the world began to announce countrywide lockdowns and severe restrictions to reduce the spread of the virus, so that the vast majority of countries prohibited citizens from, for example, going to work and school, attending social events, or gathering with others by the end of March (Dunford *et al.*, 2020). While one share of the triggered policy responses was directed towards minimizing the virus spread, another significant share attempted to limit the economic and social fallouts from the pandemic. Against a backdrop of lockdowns, countries reported rapid declines in private sector demand, why governments and central banks put utter effort into providing public support in the form of monetary and fiscal stimulus to deter an economic collapse. With an extraordinary amount of money pumped into the economy, governments are left with record debt burdens and major fiscal challenges going forward (United Nations, 2020b). Despite the stimulus, the pandemic has caused severe declines in economic activity, as exemplified by a reportedly 14% reduction in working hours during the second quarter of 2020 - equivalent to the loss of 400 million full-time jobs on a global scale (United Nations, 2020a). Moreover, the Organization for Economic Co-operation and Development (OECD) recently adjusted its economic outlook prediction to an expected contraction of the world economy of 4.5% in 2020 (Amaro, 2020). While the virus did not limit itself to geographic regions, distinct building blocks and economic foundations have led countries around the world to experience the crisis at different levels of severity. Spain, for example, is forecasted to experience a contraction of 18.5% in 2020, whereas various forecasts predict the Swedish economy to only shrink by circa 5% this year (BBC, 2020).

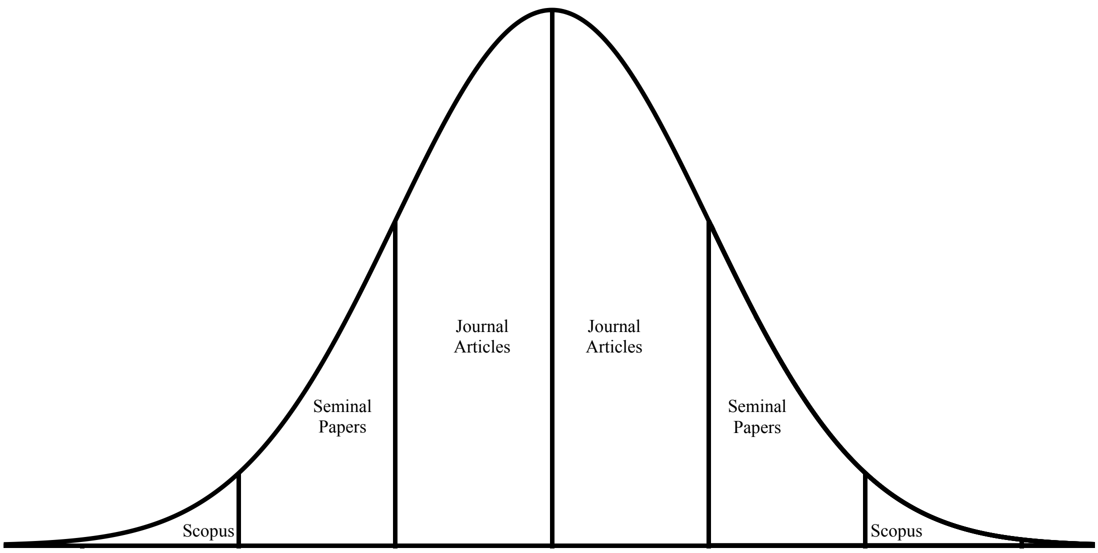
As the human and economic costs of the COVID-19 pandemic loomed in March 2020, investors became spooked by fears of an impending global recession. Accordingly, financial market stress indicators began reporting spikes unparalleled since the financial crisis of more than a decade ago (Wagner, 2020). Stock declines of greater magnitude than under the financial crisis of 2008 were noted, yields on even the most secure government bonds rose, and the most uncertain parts of the credit market, used for company financing, appeared close to freezing as market participants sought out cash. While the financial stress market indicators continued to report increased stress levels from the end of February to the end of the observation period of this study in August 2020 (CBOE, 2020), the volatile financial markets appeared to revive fairly quickly, reaching pre-COVID-19 levels in the late summer months (Praefke, 2020). Nonetheless, the OECD stressed that the economic impact of COVID-19 had heightened market risk aversion in ways not seen since the global financial crisis (OECD, 2020), leading a vast number of investors to react by changing their portfolios (Dyson, 2020). Surprisingly, however, Schroders' Global Investor Study across 32 worldwide locations between April 30th and June 15th, 2020, found that a third of investors took the opportunity to raise their exposure to higher-risk investments. Rupert Rucker, Schroders' Head of Income, comments on the finding by stating that "instinct tells us to take cover after a big shock", which most investors did, "and so it is not surprising to see that some investors were selling in the wake of Covid-19. But it's noteworthy such a large group took the opposite action and added to their risk" (Ibid, p.1). Thus, investors evidently responded to the volatile financial markets caused by the COVID-19 pandemic, despite different risk aversion levels (Dyson, 2020; OECD, 2020; Ortmann, Pelster and Wengerek, 2020).

At the time of writing, the duration, scope, and death toll of the ongoing COVID-19 pandemic remain uncertain, as a second wave of COVID-19 cases is a fact and a potential COVID-19 virus mutation stemming from minks could jeopardize future vaccines (Kevany, 2020). This mirrors in deep uncertainties for the real economy and financial markets.

# 3. Literature Review

The field of Bitcoin and its capability to provide value to investors during market stress comprises a relatively new area of academic enquiry, which has led to considerable interest by academics around the world. The ultimate aim of this thesis is to contribute to the academic knowledge on the topic, why it is essential to understand how this thesis will stand in relation to any existing research. To gain this understanding, the literature has been reviewed in an exploratory manner. The identified literature invites for a division into three structured lines of research, which revolve around the investment properties of Bitcoin during I) times with little or no financial stress (hereafter on average), II) periods of market turmoil, III) during COVID-19 representing the first global crisis since Bitcoin began trading. Line I explores the general investment properties of Bitcoin and its additive power in relation to portfolio optimization. Line II focuses on Bitcoin's potential to serve as a safe haven during times of market turmoil. Lastly, Line III comprises literature assessing Bitcoin's potential value to investors during the ongoing COVID-19 crisis. Not only does this literature review serve as a source of information on research already performed by others, it also is a source of methodological and theoretical ideas for this thesis (Veal and Darcy, 2014).

**Figure 2:** Literature Review Approach




**Source:** Authors' own illustration

To review the literature in a systematic manner, the following steps were undertaken (see Figure 2). First, an overall search on general keywords and for literature reviews on the topic was performed to identify the journals central to this field. Consequently, the journals were ranked according to their Academic Journal Guide Ranking (Chartered Association of Business Schools, 2018). To ensure credibility, only journals with a ranking higher than 2 on a scale from 1 to 4* are considered (see Appendix 1). A vast number of articles published in the highest ranked journals were identified and thereafter reviewed. Second, and on the basis of the journal articles reviewed in the first step, seminal papers on the topic were identified and reviewed. The first two steps led to the identification of central and specific keywords (see Appendix 2), which could thirdly be combined in a focused search for articles in the Scopus database. By doing so, a wide range of literature could be covered in an efficient and structured manner. This resulted in the review of 43 peer reviewed articles.

## 3.1. Literature Review Line I – Bitcoin during times of limited market stress

The first line of reviewed literature explores existing research on Bitcoin's investment characteristics and ability to provide benefits in a portfolio investment context. The research within this area centers around theories of portfolio optimization and diversification, which depart from the Modern Portfolio Theory (MPT) developed by the Nobel Prize winners Harry Markowitz and William Sharpe (Markowitz, 1952; Sharpe, Gordon and Bailey, 1985; Bodie, Kane and Marcus, 2018). Their insights prompt investors to construct portfolios of assets that achieve minimum risk for a given level of return, and maximum return for a given level of risk. They suggest that investors are able to diversify risk away from individual assets by constructing portfolios that contain a wide range of assets (Markowitz, 1952). This is most effectively achieved by including assets that respond differently to macroeconomic trends and thus have imperfect correlations (Ibid).

Through time, several different assets and asset classes have been studied in relation to optimizing portfolios. As new investment assets evolve and popularize, they often become subject to such an investigation. In line with the rise of the technological and digital age, Bitcoin, and cryptocurrencies in general, have been no exception (Ma *et al.*, 2020). While the literature on this topic is still in its infancy, various studies investigating especially Bitcoin's investment properties in a portfolio context have been published in recent years. In spite of employing a diverse range of research methodologies, all studies share the somewhat common understanding that Bitcoin can provide performance-enhancing benefits in the process of portfolio construction.

First and foremost, a plethora of the selected studies emphasize Bitcoin's exceptionally high returns and volatility. The authors explain that these characteristics sparked their interest to investigate Bitcoin's fluctuations in relation to other investment assets, as this would allow for an understanding of its potential diversification benefits (Brière, Oosterlinck and Szafarz, 2015; Henriques and

Sadorsky, 2018; Platanakis, Sutcliffe and Urquhart, 2018; Kajtazi and Moro, 2019; Symitsi and Chalvatzis, 2019; Bedi and Nashier, 2020; Platanakis and Urquhart, 2020). The first authors to present a study on the effect of adding Bitcoin to a diversified portfolio are widely regarded to be Brière, Oosterlinck and Szafarz (2015). To test Bitcoin's additive power, the three authors take a US investor perspective and construct several diversified portfolios, which partly include and partly exclude an investment in Bitcoin. More specifically, the authors use weekly return data between 2010 and 2013 and a mean-variance and statistical approach to create optimal tangency, global-minimum-variance as well as equally weighted portfolios. The study finds that Bitcoin exhibits a remarkably low correlation with the stock, bond, currency, commodity, hedge fund and real estate indices included in the diversified portfolio, thereby concluding that Bitcoin offers significant diversification benefits. Based on some of the estimated negative correlations, the authors even advocate that Bitcoin could be regarded as a hedge or safe haven. However, Brière, Oosterlinck and Szafarz highlight that numerous examples of assets exist, which initially presented safe haven capabilities but did not provide such characteristics when the first period of market turmoil occurred. Furthermore, the study discloses that including a small proportion of Bitcoin drastically improves the risk-return trade-off of the well-diversified portfolios. The researchers, however, emphasize that results should be interpreted cautiously, as the data reflects Bitcoin's early-stage price behavior. Despite the imperative implications of Bitcoin being at an infant state and the methodological impediments, the study recommends financial analysts and researchers to take virtual currencies seriously.

Building on this recommendation, several studies on Bitcoin's performance-enhancing capabilities followed and added to Brière, Oosterlinck and Szafarz' proposed methodological approach and results. In 2018, Platanakis, Sutcliffe and Urquhart contributed to the literature by investigating mean-variance and naïve optimized portfolios including weekly data from 2014 to 2018. On the basis of the Sharpe Ratio (SR) and Omega Ratio, the study finds portfolios including an investment in Bitcoin to show higher performance and diversification benefits as compared to a benchmark. In 2020, Platanakis and Urquhart confirmed their previous conclusion with an updated study including weekly data from 2011 to 2018 as well as several additional portfolio optimization methods. By means of the Markowitz' mean-variance optimization, Bayes-Stein Shrinkage Portfolio Approach[2], Black-

[2] For an introduction to this approach, the authors refer to Jorion, P. (1986). Bayes-Stein Estimation for Portfolio Analysis. *The Journal of Financial and Quantitative Analysis, 21*(3), 279-292.

Litterman portfolio construction mode[3], and naïve optimization, the test portfolios including an investment in Bitcoin were found to carry diversification benefits and a higher SR, Sortino Ratio (SoR) and Omega Ratio as compared to a benchmark portfolio of stocks and bonds.

To contribute to the existing discussion, Henriques and Sadorsky (2018) compare the investment properties of Bitcoin and gold. Their findings propose that higher risk-adjusted returns for an investment portfolio can be achieved when replacing an investment in gold with one in Bitcoin. By basing their study on several GARCH models[4] to forecast each portfolio's returns, the authors find their conclusion to hold even when transaction costs are taken into account. Further establishing a positive relationship between Bitcoin and portfolio performance, Kajtazi and Moro (2019) introduce the mean-Conditional-Value-at-Risk[4] (mean-CVaR) approach to explore the effect of adding Bitcoin to three portfolios representing US, European and Chinese asset classes. By relying on daily data between 2012 and 2017 and comparing the performance metrics of the SoRs and Omega Ratios, their results reveal that the portfolio improvement caused by Bitcoin is a result of an increase in returns rather than a reduction in volatility. Nonetheless, Symitsi and Chalvatzis (2019) advocate that Bitcoin, despite its high volatility, can also be of interest to risk-averse investors, as they uncovered Bitcoin to provide diversification benefits for a minimum-variance portfolio between 2011 and 2017. They arrive at this conclusion by studying the economic gains of adding Bitcoin to a global-minimum-variance and an equally weighted portfolio net of transaction costs. As transaction costs significantly shrink portfolio gains, Symitsi and Chalvatzis allude to the importance of accounting for transaction costs.

The most recent study on the topic was prepared by Bedi and Nashier (2020), who investigate Bitcoin's value in the context of a portfolio's currency denomination using monthly returns from 2010 to 2018. Their findings suggest that an optimized diversified portfolio denominated in Japanese Yen, Chinese Yuan and US Dollar exhibits an improved risk-adjusted return when adding an investment in Bitcoin. Bedi and Nashier derive their results by optimizing the Adjusted Sharpe Ratio (ASR), which uses the modified Conditional-Value-at-Risk (MCVaR) as the risk measure. Even though their findings are significant, Bedi and Nashier advocate that additional studies must be carried out to

[3] For an introduction to this approach, the authors refer to Cheung, W. (2010) The Black–Litterman Model Explained. *Journal of Asset Management,* 11(3), 229-43.
[4] For an introduction to this approach, the authors refer to this study's methodological section.

ascertain the investment capabilities of Bitcoin in a time-varying framework across different economic conditions and regional financial markets.

Despite the use of different methodologies and data periods, all of the above-reviewed articles reach consensus on the substantial diversification and portfolio performance-enhancing benefits of Bitcoin. Based on Bitcoin's correlations with other investment assets, the studies presented by Brière, Oosterlinck and Szafarz (2015), Bedi and Nashier (2020), and Urquhart and Platanakis (2020) even suggest the possibility of Bitcoin to exhibit safe haven capabilities. This is the primary focus of a plethora of research, which is extensively reviewed in the second line of literature.

## 3.2. Literature Review Line II – Bitcoin during market turmoil

The second line of reviewed literature centers around Bitcoin's potential to serve as a safe haven during times of crises. This area of research derives from theories of investor behavior and in particular of investor's loss aversion, which is captured by Kahneman and Tversky's (1979) formulated prospect theory. In their widely cited paper, Kahneman and Tversky establish that individuals, who consider the implications of making decisions under uncertainty, tend to think in terms of gains and losses instead of considering their final, absolute level of wealth. In extension, they find individuals to be loss averse as they hold greater sensitivity to acute losses than gains (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991). This loss aversion might motivate investors to hold a diversified portfolio by consciously combining assets with varying risk-return characteristics to reduce the overall portfolio risk of losses. However, it has been shown that the risk-return characteristics of assets generally become more aligned during periods of high market volatility, which is a phenomenon defined as financial contagion across markets (Baig and Goldfajn, 1999; Forbes and Rigobon, 1999; Campbell, Koedijk and Kofman, 2002). Since the decrease in diversification benefits often occurs at times when the risk of losses is at its highest, risk-averse investors embark on a so-called flight-to-safety, which leads them to invest in safe haven assets (Bernanke, Gertler and Gilchrist, 1996; Kindleberger, Aliber and Solow, 2005; Baur and Lucey, 2009; Conlon and Mcgee, 2020). By investing in safe haven assets which remain or increase in value during times of market stress, investors can compensate for assets bearing high risk of capital loss during these periods. Thereby, they can reduce the overall risk of losses while not necessarily optimizing their final level of wealth (Ibid).

Over the years, multiple assets have been found to carry safe haven properties at short to medium horizons, including gold (Baur and Lucey, 2010; Bredin, Conlon and Potì, 2017), currencies (Ranaldo and Söderlind, 2010), commodities (Henriksen, 2018), and long-dated Treasury bonds (Flavin, Morley and Panopoulou, 2014). Of late, Bitcoin's high returns and volatility, independence of government and monetary policy, and mining constraints, have led a strand of research to investigate whether Bitcoin can be added to the list of potential safe haven investments. Adopting multiple approaches and varying methodologies, the empirical findings generated by the young but increasingly proliferating literature present an inconclusive image of Bitcoin's safe haven potential. *One strand of literature* approaches the topic by assessing Bitcoin's characteristics during several types of market turbulence (see 3.2.1.). The overall consensus of these articles is that Bitcoin's value remains or increases during times of turmoil, thereby suggesting its potential to serve as a safe haven. While the first body of literature focuses on Bitcoin and market uncertainty in isolation, *a second strand of literature* assesses Bitcoin' safe haven potential by evaluating its correlation with a variety of traditional and international assets during times of market turbulence (see 3.2.2.). On the basis of econometric, graphical and regression modelling, many studies find evidence supporting the hypothesis that Bitcoin can, to some extent, serve as a safe haven asset during times of market turmoil. The articles indicate that Bitcoin's safe haven potential can vary across asset classes, geographies and time. *A third strand of literature* evaluates Bitcoin's safe haven potential and effectiveness by directly comparing it to the traditional safe haven assets gold and the US dollar (see 3.2.3.). While early research highlights the similarities between Bitcoin and gold as well as the US Dollar, more recent studies report contradictory findings by underlining that Bitcoin might carry some, but inferior safe haven potential to especially gold. In the following, the three strands are elaborated upon.

### 3.2.1. Bitcoin's safe haven potential amid uncertainty

Since a safe haven asset is expected to retain or increase in value during times of market turbulence, *the first strand of research* examines Bitcoin's safe haven potential by assessing its characteristics during times of uncertainty. Bouri, Gupta, *et al.* (2017) employ a quantile regression approach to determine whether Bitcoin can hedge global uncertainty, proxied by the VIX index of several developed and developing equity markets. They find that Bitcoin reacts positively to uncertainty at both higher quantiles and shorter frequency return movements in the period between 2011 and 2016. Consequently, they conclude that Bitcoin qualifies as a short-term hedge against uncertainty. Extending upon these findings, Bouri *et al.* (2018) explore the dependence between the GFSI and Bitcoin's returns in the period 2010 to 2017. Their findings indicate that Bitcoin is a safe haven asset for financially turbulent conditions in the short run. To assess Bitcoin's reaction to global geopolitical risk, Aysan *et al.* (2019) investigate the predictive power of the global geopolitical risk (GPR) index on Bitcoin's daily returns between 2010 and 2018. On the basis of a Bayesian Graphical Structural Vector Autoregressive technique[5], their results propose that negative changes in GPR lead to greater Bitcoin returns. In line with this, Wang *et al.* (2020) use a Dynamic Conditional Correlation GARCH[6] (DCC GARCH) model to show that Bitcoin's returns are significantly greater around days with high economic policy uncertainty. Similarly, Corbet *et al.* (2020) highlight that an increase in the percentage of negative macroeconomic news surrounding unemployment or durable goods is linked to an increase in Bitcoin's returns. Conversely, an increase in the percentage of positive news surrounding these announcements results in a decrease in Bitcoin returns. The consensus of the above-mentioned articles appears in favor of Bitcoin as a safe haven tool during times of uncertainty.

### 3.2.2. Bitcoin's safe haven potential on a global scale

Since uncertainty can be region-specific and affect different assets in varying ways, the first body of research sparks motivation to study Bitcoin's safe haven properties internationally and against various traditional assets. Therefore, a *second, and very substantial strand of research* examines Bitcoin's safe haven potential in an international context by assessing its correlation with a variety of traditional assets during times of market turbulence. Bouri, Molnár, *et al.* (2017) are among the first to investigate whether Bitcoin can act as a safe haven for major world stock, bond, oil, gold, commodity and US dollar indices. Using daily and weekly return data from 2011 to 2015, the authors apply a DCC GARCH model to reveal that Bitcoin can only serve as a strong safe haven against weekly extreme down movements in Asian stocks. For all other assets, their widely cited study finds that Bitcoin is suitable for diversification purposes only. This article provided further reasons to believe that Bitcoin's safe haven properties vary internationally, which inspired various other research. Urquhart and Zhang (2019) for example, assess Bitcoin's hedging and safe haven potential against a range of international currencies by employing GARCH models with hourly intraday data from 2014 to 2017. They present Bitcoin as an intraday hedge for the CHF, EUR and GBP, but as a diversifier for the AUD, CAD and JPY. Moreover, they conclude in favor of Bitcoin as a safe haven against the CAD, CHF and GBP. Kliber *et al.* (2019) use daily data for the period 2014 to 2017 to estimate the

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[5] For an introduction to this approach, the authors refer to Ahelegbey, D.F., Billio, M. and Casarin, R. (2016). Bayesian Graphical Models for Structural Vector Autoregressive Processes. *Journal of Applied Econometrics*, 31(2), 357-86.
[6] For an introduction to this approach, the authors refer to this study's methodological section.

dynamic conditional correlations (DCCs) between various global stock markets and Bitcoin denoted in the respective local currency, as well as between the various global stock markets and Bitcoin denoted in USD. They conclude that the USD denoted Bitcoin serves as a weak hedge in all markets, and that Bitcoin denoted in the respective local currency is only a safe haven for the Venezuelan stock market. Chan, Le and Wu (2019) use a GARCH model and monthly returns between 2010 and 2017 to provide evidence that Bitcoin can be used as a strong hedge against the Euro-Index, Shanghai A-Share, S&P 500, Nikkei, and the TSX Index. Further underlining regional differences in Bitcoin's safe haven potential, Stensås *et al.* (2019) use a DCC GARCH model to suggest that Bitcoin can be an effective hedge for developing countries. In contrast, Wang *et al.* (2019) find Bitcoin's safe haven property to be more pronounced in developed markets. Employing a quantile-on-quantile regression[7] model for daily data between 2011 to 2017, Selmi *et al.* (2018) show that Bitcoin can serve as a safe haven against extreme global oil price movements. Moreover, their empirical findings suggest that including Bitcoin in an oil portfolio significantly reduces downside risk as compared to holding an oil-only portfolio.

The above articles suggest that Bitcoin's safe haven potential varies for geographies as well as assets. On top of that, researchers highlight Bitcoin's ability to serve as a safe haven to be time-varying. On the basis of a DCC GARCH model and daily data from 2010 to 2015, Bouri, Molnár, *et al.* (2017) support this conclusion by finding that Bitcoin served as a strong safe haven against energy commodities before 2013, whereas, after Bitcoin's price crash in 2013, Bitcoin merely served as a diversifier. In a similar fashion and considering daily data between 2010 and 2016, Kang *et al.* (2020) use a GARCH model to reveal the time-varying safe haven potential of Bitcoin against the S&P 500, US dollar, Treasury bonds and gold futures. The authors highlight that the negative correlation was particularly high during the European Sovereign Debt Crisis between 2010 and 2013, suggesting that investors should frequently modify their portfolio structure and that findings on Bitcoin's safe haven potential should be reexamined frequently.

### 3.2.3. Bitcoin's safe haven potential compared to other safe havens

*A third strand of literature* assesses Bitcoin's safe haven potential and effectiveness by comparing it to traditional safe haven assets such as gold and the US dollar. Dyhrberg (2016a) uses a GARCH

[7] For an introduction to this approach, the authors refer to this study's methodological section.

framework to compare several aspects of the price volatility of Bitcoin, gold and the US dollar. For the period from 2010 to 2015, the author situates Bitcoin's hedging and safe haven capability in between the capability of gold, carrying store of value benefits, and the capability of the US dollar, providing medium of exchange advantages. These findings suggest that Bitcoin combines some of the advantages of commodities and currencies and is thus a useful tool in portfolio management. Complementing her own findings and using the same time frame, Dyhrberg (2016b) moreover finds Bitcoin to be a useful safe haven for the UK stock market and short-term hedge against the US dollar, concluding that Bitcoin, therefore, carries similar safe haven characteristics to gold. Bouri *et al.* (2020) compare the safe haven properties of Bitcoin, gold, and a commodity index against world, developed, emerging, US, and Chinese stock market indices between 2010 and 2018. Estimating the dependence, the authors highlight Bitcoin as the least dependent and thus most promising safe haven asset, followed by gold and then the commodity index. Contrary to these findings, Klein, Pham Thu and Walther (2018) dismiss any similarities between gold and Bitcoin. The authors use daily data between 2011 and 2017 to implement a GARCH model, which reveals that Bitcoin, contrary to gold, correlates positively with downward moves in developed markets, thereby ruling out any safe haven potential. In line with these findings, Baur, Hong and Lee (2018) find Bitcoin to exhibit distinctive return, volatility, and correlation characteristics compared to other assets, including gold and the US dollar. Bouri *et al.* (2020) use GARCH modelling to compare the safe haven and hedging role of gold and Bitcoin for the G7 stock markets on the basis of daily data from 2010 to 2018. While they reveal that Bitcoin can serve as a weak safe haven for Canada and France, the authors underline gold to be superior since it forms an undisputable safe haven for several G7 stock indices. Similarly, Naeem *et al.* (2020) compare the hedging and safe haven potential of Bitcoin and gold for different industry portfolios in the US between 2013 and 2019. They conclude that gold's safe haven and hedging potential for US industry portfolios by far outnumbers that of Bitcoin, thereby suggesting that Bitcoin is an inferior safe haven tool. Lastly, Smales (2019) considers Bitcoin data from 2011 to 2018 and concludes that Bitcoin should be ruled out as a safe haven asset because it is characterized by higher volatility, less liquidity and higher transaction costs than other assets such as gold.

While the findings generated by the young but increasingly expanding literature are decidedly mixed about Bitcoin's characteristics during times of market stress, many studies find evidence supporting the hypothesis that Bitcoin can, to some extent, serve as a safe haven amid market turmoil. However, various authors stress that it is questionable whether global markets have encountered sufficient instances of acute market stress since the inception of Bitcoin to enable adequate conclusions to be drawn (Smales, 2019; Chen, Liu and Zhao, 2020; Conlon and Mcgee, 2020; Dutta *et al.*, 2020). This is the point of departure for a very recent, third line of literature, which is reviewed in the following section.

## 3.3. Literature Review Line III – Bitcoin amid the COVID-19 pandemic

The third and last line of reviewed literature considers articles assessing Bitcoin's potential to serve as a safe haven during the ongoing COVID-19 crisis. While various of the previously reviewed articles expound Bitcoin's safe haven and value potential during market stress, their empirical research has been devoid of periods showing significant market turmoil on a global scale. As a consequence of the current global pandemic, the world is experiencing the first widespread bear market conditions since Bitcoin began actively trading. Subsequently, a few recently published studies have already provided a first reassessment of the propositions brought forward by prior literature on Bitcoin's investment properties during crises.

To investigate Bitcoin's price dynamics in the wake of the COVID-19 crisis, Chen, Liu and Zhao (2020) analyze the relationship between coronavirus fear sentiment, measured by hourly COVID-19 related Google search queries, and Bitcoin's price and trading volume. Their findings show that increasing fear of the coronavirus in the period January 2020 to April 2020 led to negative Bitcoin returns and high trading volume, thus indicating that Bitcoin deviates from traditional safe haven asset behavior. On the contrary, Goodell and Goutte (2020) show that Bitcoin's prices, especially for the period post April 5th, positively correlate with the number of COVID-19 related fatalities. Applying wavelet methods[8] to daily data of COVID-19 world deaths and Bitcoin prices between December 31st, 2019 and April 29th, 2020, the authors thus find evidence in favor of Bitcoin's safe haven potential.

Conlon, Corbet, and Mcgee (2020) test Bitcoin's international safe haven properties by adopting the perspective of an international index investor and examining the downside risk effect of pairing six equity index investments with a portfolio allocation to Bitcoin. On the basis of daily return data from April 2010 to April 2020, portfolios consisting of only equity investments as well as portfolios with varying weight allocations to Bitcoin and the respective equity index are created. Measuring downside risk by the portfolio's modified Value-at-Risk (MVaR) and MCVaR, Conlon, Corbet, and

[8] For an introduction to this approach, the authors refer to Fryzlewicz, P. (2010) Wavelet Methods. *Wiley Interdisciplinary Reviews: Computational Statistics,* 2(6), 654-67.

Mcgee find that Bitcoin does not carry safe haven properties for the majority of international equity indices and weight allocations. Rather, they find evidence of increased downside risk for portfolios holding an allocation to Bitcoin. An exception is the Chinese CSI 300 index, where Bitcoin allocations of up to 16% realized modest downside risk benefits. Employing a similar methodology for daily data in the period March 21$^{st}$, 2019 through March 20$^{th}$, 2020, Conlon and Mcgee (2020) highlight that Bitcoin decreases in price lockstep with the S&P 500 as the COVID-19 crisis developed. Moreover, they show that even a small allocation to Bitcoin substantially increases the downside risk of a portfolio holding an investment in the S&P 500 and Bitcoin. Dutta *et al.* (2020) revisit the safe haven property of Bitcoin and gold for the global oil market downturn following the COVID-19 outbreak. The results of the time-varying correlations estimated with a DCC GARCH model suggest that gold is a safe haven asset for the global oil markets in the period between December 2014 and March 2020. Bitcoin, on the contrary, only acts as a diversifier for oil in the entire period and especially amid the COVID-19 outbreak.

On a concluding note, the few recently published studies provide an initial reassessment of Bitcoin's investment characteristics during periods of market stress. The articles shed mixed yet rather negative light on Bitcoin's ability to be of value to investors at the start of the COVID-19 pandemic.

# 4. Hypotheses Development

The following section delineates the logical development of the research hypotheses. The section begins with a presentation of the potential shortcomings of the reviewed academic literature. Thereafter, literature-based predictions about Bitcoin's value to investors under the COVID-19 crisis are generated, which subsequently lead to the formulation of this study’s research hypotheses. Finally, the way in which the proposed hypotheses address the shortcomings of the existing research and contribute to the field is established.

## 4.1. Shortcomings of Academic Literature

The 43 articles addressed in the literature review provide information on Bitcoin's investment characteristics on average (Line I), during times of market turmoil (Line II) as well as during the current COVID-19 pandemic (Line III). Since this thesis aims to shed light on Bitcoin's value to investors under the COVID-19 crisis only literature shortcomings in relation to understanding Bitcoin's characteristics during times of crises are addressed.

The significant second line of literature focuses on examining Bitcoin's safe haven potential during times of pre-COVID-19 market stress. Based on a comprehensive range of methodologies, the reviewed studies arrive at decidedly mixed conclusions. While some authors cast doubt on Bitcoin's value for investors, many find evidence supporting the claim that Bitcoin can, to some extent, serve as a safe haven asset. The emerging take-away across the articles is that Bitcoin's safe haven potential can vary across asset classes, geographies and time. However, various authors question the accuracy of these conclusions by stressing that it is debatable whether global markets have encountered sufficient instances of acute market stress since the inception of Bitcoin to enable these articles to perform adequate analyses (i.a., Smales, 2019; Chen, Liu and Zhao, 2020; Conlon and Mcgee, 2020; Dutta *et al.*, 2020). According to the VIX, GFSI and STLFSI2, no cases of acute stress have occurred since the global financial crisis and until the start of the COVID-19 crisis (see section 2.2.). Therefore, the absence of a global bear market during the investigated sample period marks a potential shortcoming of the existing Line II literature and invites for a reexamination of the proposed conclusions during a period of global financial distress. Moreover, several authors acknowledge the time-variability of Bitcoin's safe haven potential (Bouri, Molnár, *et al.*, 2017; Kang *et al.*, 2020), thereby further underlining that the findings of the existing literature should be reassessed.

The third line of identified literature provides a first reassessment of the propositions brought forward by Line II and examines Bitcoin's investment value potential at the start of the COVID-19 pandemic - the first acute global market crisis since Bitcoin began actively trading (Chen, Liu and Zhao, 2020; Conlon and Mcgee, 2020; Dutta *et al.*, 2020; Federal Reserve Bank of St. Louis, 2020b). Chen, Liu and Zhao (2020), as well as Goodell and Goutte (2020), evaluate Bitcoin's safe haven potential by assessing Bitcoin's price dynamics against, respectively, hourly COVID-19 related Google search queries and the number of COVID-19 related fatalities. While Conlon, Corbet and Mcgee (2020) and Conlon and McGee (2020) draw conclusions on Bitcoin's safe haven potential by analyzing its additive power to an equity portfolio during COVID-19, Dutta *et al.* (2020) assess Bitcoin's correlation against the global oil market following the pandemic outbreak. Although these articles provide an initial assessment of Bitcoin's value to investors amid the first acute global crisis, they, unlike Line II literature, leave room for several methodological research gaps to be filled. First, the studies only focus on examining Bitcoin as a safe haven against a limited number of asset categories and countries. Since Line II suggested that Bitcoin's safe haven ability varies between asset classes and geographies, an extensive correlation analysis between Bitcoin and a wide range of international asset categories is deemed insightful. Second, the data range covered by the published articles ranges up until April 2020, thereby not covering the course of the ongoing COVID-19 pandemic. Given that previous research found Bitcoin's safe haven potential to be time-varying, an examination of Bitcoin's behavior over a longer COVID-19 period might show perceptive insights. Third, the use of GARCH models to assess time-varying correlations is widely established in the overall field of safe haven research (Baur and McDermott, 2010; Bouri, Molnár, *et al.*, 2017), why the lack of this methodological approach in all but one of the Line III articles forms another potential gap in the literature. Lastly, the existing Line III studies do not assess Bitcoin's safe haven potential following the full definition of a safe haven and do thereby not investigate Bitcoin's liquidity amid COVID-19.

While a significant number of articles in Line I shed light on Bitcoin's substantial performance-enhancing benefits for a portfolio during periods with no acute market stress, only a few published articles across Line II and III focus on Bitcoin's additive power to a portfolio during times of market turmoil. Selmi *et al.* (2018) are among the few researchers who have done so by defining turmoil through extreme global oil price movements and by focusing on a portfolio consisting of oil and Bitcoin. Furthermore, Conlon, Corbet and Mcgee (2020) and Conlon and McGee (2020) investigated the benefits of including Bitcoin in an equity portfolio at the beginning of the ongoing COVID-19 pandemic. While the three aforementioned articles shed light on Bitcoin's additive power to a portfolio during different types of market stress, they investigate the effect on a portfolio consisting of only one other asset class. However, in line with traditional portfolio theory, a retail investor is suggested to hold a portfolio consisting of an international sample of asset classes to optimally benefit from risk-return tradeoffs (i.a., Solnik, 1995; Anand, 2006; Bodie, Kane and Marcus, 2018; Dalio, 2020). Therefore, it can be of practical value to retail investors to understand Bitcoin's value for a diversified portfolio consisting of more than just oil or equity investments. Consequently, the lack of research on the effects of including Bitcoin into a diversified portfolio during times of global market stress has been identified as the last potential shortcoming of the existing literature.

## 4.2. Research Hypotheses

In line with the positivist philosophy of science adopted in this thesis, the research hypothesis is developed in a deductive manner. This involves the logical generation of literature- and theory-informed predictions concerning a particular phenomenon, which are subsequently captured in an empirically testable hypothesis.

This thesis seeks to investigate a phenomenon, which takes point of departure in both the current global COVID-19 pandemic as well as in the ongoing narrative surrounding Bitcoin's potential to be of value to investors during times of crises. The phenomenon sets these two factors in relation to each other in order to understand Bitcoin's potential to protect investors against COVID-19 related financial losses. When looking for guidance on this matter in the existing literature, an inconclusive image on Bitcoin’s properties during crises appears. Nonetheless, the existing studies allow for the generation of predictions regarding Bitcoin's potential to serve as a safe haven and valuable addition to a diversified portfolio amid COVID-19.

First, several academics conclude in favor of Bitcoin as a safe haven against increases in the VIX, GFSI, GPR and EPU index as well as against negative macroeconomic news surrounding unemployment and durable goods (Bouri, Gupta, *et al.*, 2017; Bouri *et al.*, 2018; Aysan *et al.*, 2019; Corbet *et al.*, 2020; Wang *et al.*, 2020). As delineated in section 2.2., the COVID-19 pandemic caused, and continues to cause, spikes in both the VIX and GFSI as well as significant political and economic policy uncertainty related to the measures undertaken to combat the virus. In addition, the pandemic has vastly impacted real economic activity, thereby provoking negative macroeconomic news about, amongst other, rising unemployment numbers. Consequently, the prediction that Bitcoin can be a safe haven against the turmoil created by the COVID-19 pandemic is inferred.

Second, a vast body of existing literature comes to varying conclusions regarding Bitcoin's safe haven potential, thereby underlining that this characteristic can differ across asset classes, geographies and time. This conclusion is reached by examining the correlation between Bitcoin and various assets of international character during the different assets' lowest return quantiles. Since the empirical research of these articles has arguably been devoid of periods showing significant global market turmoil, the uncertainty factor causing the different assets' lowest return quantiles as well as their duration and severity might differ from region to region as well as from asset class to asset class. According to Baur and McDermott (2012), different uncertainty factors invoke different types of investor and flight-to-safety behavior. In consequence, the conclusion that Bitcoin's safe haven potential varies between asset classes, geographies and time might partly be explainable by the fact that the investigated sample period included various types of uncertainty factors. While the severity of the impact of the current COVID-19 crisis differs between countries and asset classes, the pandemic is of global nature and causes similar uncertainty factors in all markets (see section 2.2.). Hence, the prediction that Bitcoin can be a safe haven against an international sample of asset classes amid the global COVID-19 pandemic is established. The focus thus lies on whether Bitcoin can be a safe haven during a global crisis. Thereby, this thesis refrains from using the inconclusive findings, generated by arguably incomplete empirical research, to assume that Bitcoin has varying safe haven capabilities across geographies and asset classes.

Third, and based on Bitcoin's low correlation with other assets, the reviewed literature presents Bitcoin as a performance-enhancing addition to a diversified portfolio during times of no acute market stress. While it has been shown that the correlations of assets generally become more aligned during periods of high market volatility (Campbell, Koedijk and Kofman, 2002), this thesis predicts Bitcoin to maintain its performance-enhancing capability for a diversified portfolio amid the COVID-19 crisis. This grounds in the fact that Bitcoin is, as captured by the previous two predictions, said to react positively to uncertainty and to correlate inversely with many traditional asset classes during times of market stress.

Based on these three predictions, the thesis sets out to empirically test the following research hypothesis:

*(HI) Bitcoin acts as a safe haven against an international sample of asset indices and serves as a performance-enhancing addition to a diversified portfolio during the COVID-19 pandemic.*

To test and operationalize the main research hypothesis in a structured manner, three sub-hypotheses are proposed. The first sub-hypothesis tests whether Bitcoin can be regarded as a safe haven asset against a sample of asset indices by assessing the time-varying correlation between Bitcoin and the respective index. This widely established method in the overall field of safe haven research (i.a., Baur and McDermott, 2010; Bouri, Molnár, *et al.*, 2017) allows for the identification of a safe haven if the time-varying correlation between Bitcoin and the respective index is negative (see section 1.2.). The first sub-hypothesis thus builds on the aforementioned prediction that Bitcoin serves as a safe haven against an international sample of asset indices under the COVID-19 crisis and is formulated as follows:

*(SHI) Bitcoin's time-varying correlation with an international sample of asset indices is negative during the COVID-19 pandemic.*

To comprehensively test Bitcoin's potential to serve as a safe haven under the COVID-19 crisis, the second sub-hypothesis investigates the extent to which Bitcoin is fulfilling the liquidity requirement inherent in the definition of a safe haven (see section 1.2.). This definition proposes that an asset can only truly act as a safe haven when investors can buy and sell the asset quickly, and with relatively low transaction costs. While Bitcoin has been criticized for its lack of liquidity (Smales, 2019; Schmitz and Hoffmann, 2020), the theory stipulates the following hypothesis to hold if Bitcoin were to be a safe haven asset under the COVID-19 crisis:

*(SHII) Investors can buy and sell Bitcoin relatively quickly and at relatively low transaction costs during the COVID-19 pandemic.*

Extending the perspective from looking at the investment properties of Bitcoin against each asset index in isolation, the third sub-hypothesis focuses specifically on the effects of including Bitcoin into a diversified portfolio under the COVID-19 crisis. In line with portfolio theory, a retail investor is suggested to hold a portfolio consisting of an international sample of asset classes to reduce risk and optimally benefit from risk-return tradeoffs (i.a., Solnik, 1995; Anand, 2006; Bodie, Kane and Marcus, 2018; Dalio, 2020). Therefore, if Bitcoin is to be of value to portfolio investors during a crisis, Bitcoin should add value to a diversified portfolio under COVID-19 related market stress. Given that the risk of losses increases during times of crises, Bitcoin would add value to a portfolio by reducing the portfolio's downside risk. Despite the importance of downside risk reduction, investors are unlikely to consider an investment in Bitcoin for tail risk purposes in isolation. Instead, their allocation decisions will also consider the tradeoff between risk and return (Sharpe, Gordon and Bailey, 1985), why Bitcoin is also expected to increase the risk-return characteristics of the diversified portfolio under the COVID-19 crisis. The following sub-hypothesis is formulated:

*(SHIII) An investment allocation to Bitcoin enhances the risk-return characteristics and downside-risk reduction performance of a diversified portfolio during the COVID-19 pandemic.*

In line with the existing literature on the topic, the presented hypotheses thereby rely on MPT, prospect theory as well as flight-to-safety theory, which have been elaborated in the literature review and are further expanded upon in the methodology section.

## 4.3. Contribution to Academic Literature

Investigating the proposed research hypotheses contributes to the existing academic literature in numerous ways. Most importantly, this thesis addresses the shortcoming that so far, no extensive investigation of Bitcoin's investment properties has been performed during a period of acute global market stress. To the best of the authors' knowledge, this thesis is the first study to test the viability of the existing literatures' conclusions on Bitcoin's value to investors during crises through an investigation of I) its correlation with a sample of assets, II) its liquidity, III) its additive value to diversified portfolios during the first period of acute global market stress since Bitcoin began actively trading. In comparison to existing articles on Bitcoin amid COVID-19, the aforementioned three-fold approach is the first of its kind and allows for a more comprehensive analysis of the topic. Moreover, this study is the first to include data from a longer COVID-19 period, thereby allowing for a more representative analysis of Bitcoin under the persisting COVID-19 crisis. Lastly, the proposed hypotheses also address the shortcoming that so far, no study has specifically investigated Bitcoin's performance-enhancing properties as part of a diversified portfolio during a period of market stress.

The subsequent sections will explore the methodological approach towards operationalizing and testing the proposed hypotheses.

# 5. Methodology

This thesis aims to shed light on whether and to what extent Bitcoin acts as a safe haven against an international sample of asset class indices and serves as a performance-enhancing addition to a diversified portfolio amid COVID-19. The following sections outline the methodological approach and considerations taken to investigate the research hypothesis. The section commences with a description of the scientific stance adopted in this research. This is followed by a presentation of the methodological approach applied to investigate the research hypotheses at hand. Thereafter, the dataset composition, as well as the data collection process, are delineated. Lastly, the quality of the research is dwelled upon in line with the criteria set forth by the chosen scientific stance.

## 5.1. Scientific Stance

To fully comprehend the methodological approach as well as data selection and collection techniques of this research project, it is critical to commence with a description of its underpinning philosophical assumptions (Saunders, Lewis and Thornhill, 2016). This thesis studies the research hypotheses on the philosophical basis of positivism. Adopting this stance, this research takes point of departure in the ontological assumption that a singular, verifiable reality exists independently of human knowledge and experience (Patton, 2002). Hence, this thesis assumes there to be one real truth around Bitcoin's potential to serve as a safe haven and performance-enhancing addition to a diversified portfolio during the COVID-19 period, which can be studied when gaining access to relevant data and facts (Veal and Darcy, 2014).

The positivist ontology further translates into an epistemological position, which studies knowledge on the basis of objectivism and considers observable and measurable facts about the true reality to constitute acceptable, valid, and legitimate knowledge (Burrell and Morgan, 1982; Crotty, 1998). Following this epistemology, the methodology of this thesis relies on a quantitative study to gain objective knowledge from observable, factual numbers stemming from public databases. Furthermore, the thesis is of multiple-method nature by investigating the topic through three different analytical methods, which are outlined in section 5.2. The combination of these allows for a rich and objective investigation of the reality around Bitcoin's investment characteristics (Saunders, Lewis and Thornhill, 2016).

Considered typical for positivism, this research roots in the deductive approach to theory development. This involves the logical generation of literature- and theory-based predictions concerning a particular phenomenon, in this case, Bitcoin's value to investors during the COVID-19 crisis, and advances by capturing the predictions in hypotheses (Cohen, Manion and Morris, 2011). Subsequently, the proposed hypotheses are empirically tested on the basis of the collected quantitative data, using the multiple analytical methods touched upon above.

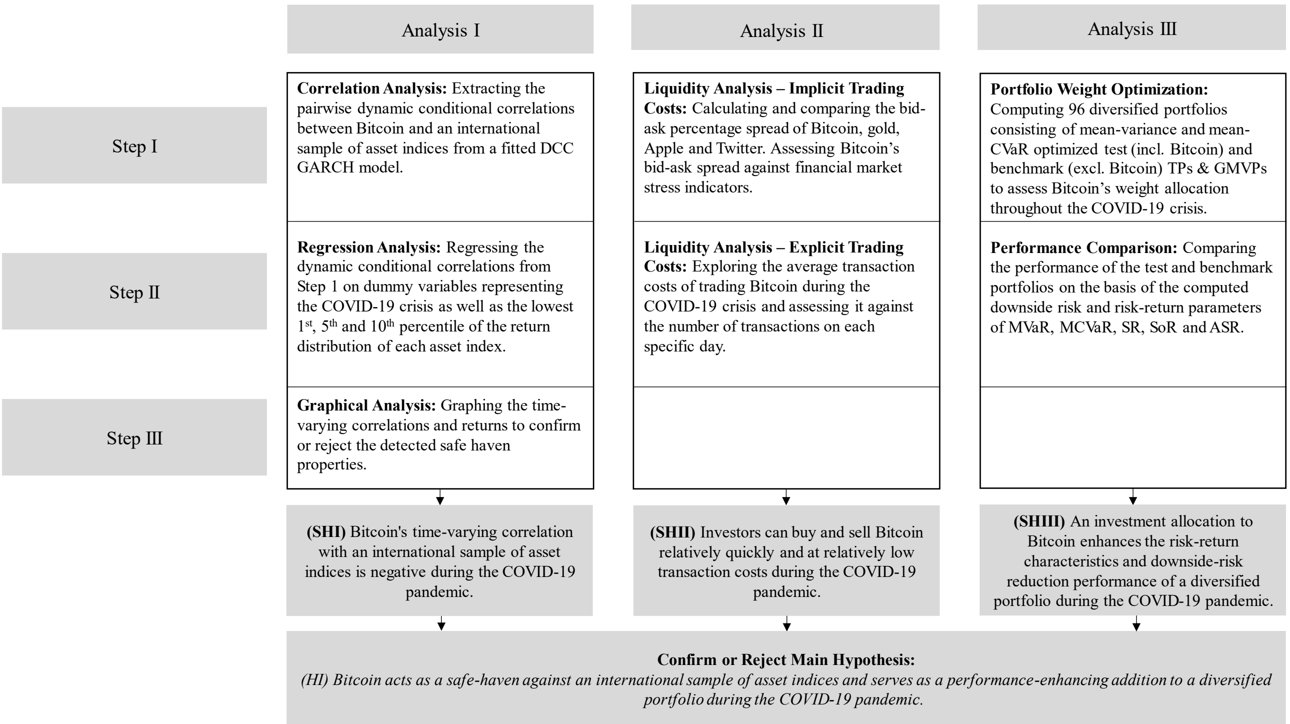
Of critical importance to the deductive and positivist approach is the ability to test the proposed hypotheses accurately. To allow for a quantitative and factual measurement, the concepts constituting the hypothesis need to be operationalized (Saunders, Lewis and Thornhill, 2016). For this thesis, it is essential to operationalize the measurement of when an asset counts as a safe haven or performance-enhancing addition to a diversified portfolio, why these definitions are thoroughly delineated in the introduction. The operationalization of further concepts is outlined in the methodological sections dedicated to the approaches used for testing each sub-hypothesis.

To adhere to the positivist research paradigm, it is essential to reflect upon the research quality criteria of positivism: 1) internal validity, 2) external validity, 3) reliability, and 4) objectivity (Guba & Lincoln, 1994). These are discussed in section 5.4. After having introduced the scientific and philosophical assumptions underpinning this study, the subsequent sections explore the methodological approach as well as data selection and collection.

## 5.2. Methodological Approach

In the following section, the methodological approach to this project's empirical analysis is presented. The empirical analysis seeks to answer the overall research hypothesis and the three sub-hypotheses across three levels, as illustrated by Figure 3.

**Figure 3:** Methodological Approach




**Source:** Authors' own illustration

Analysis I seeks to assess Bitcoin's time-varying correlation with a sample of international asset indices to determine whether and to which extent Bitcoin serves as a safe haven during the persisting COVID-19 crisis. First, this entails the estimation of the pairwise DCCs between Bitcoin and each selected asset index by means of the econometric DCC GARCH model. In a second step, the generated correlations form the input for a regression analysis exploring the safe haven, hedge, and diversification properties of Bitcoin against each asset both on average as well as during the COVID-19 pandemic. Third, the correlation and return data are graphed throughout the COVID-19 pandemic to substantiate the regression analysis. This leads to the confirmation or rejection of sub-hypothesis I.

Analysis II completes the examination of Bitcoin's potential to serve as a safe haven by investigating the extent to which Bitcoin is fulfilling the liquidity requirement inherent in the definition of a safe haven. In the first step, the bid-ask percentage spread of Bitcoin is compared to other assets and assessed against stress indicators to understand the implicit costs of trading Bitcoin during the COVID-19 crisis. In a second step, the average transaction costs of trading Bitcoin are assessed over time and against the number of transactions on that specific day to assess the explicit costs of trading Bitcoin. Analysis II thus addresses sub-hypothesis II.

Analysis III extends the perspective of Analysis I and II from looking at the investment properties of Bitcoin against each selected asset in isolation, to investigate the risk and return effects of including Bitcoin in a diversified portfolio through time to resemble a real-life investment case. Therethrough, investors will obtain a more comprehensive and practical insight for future investment strategies with Bitcoin during crises. Analysis III centers around portfolio optimization and can be divided into two steps. First, it is investigated if and to which extent Bitcoin should be included in a portfolio over time and under the COVID-19 crisis. Second, the analysis moves on to evaluate whether including Bitcoin in the investment set leads to higher portfolio performance as compared to not holding an investment in Bitcoin. Again, the performance is assessed over time and under the COVID-19 crisis. Consequently, these three analyses provide investors with a comprehensive understanding of the investment properties of Bitcoin during the COVID-19 pandemic.

### 5.2.1. Methodological Approach – Analysis I

This section outlines the methodological approach and limitations of Analysis I. The ultimate aim of Analysis I is to examine whether Bitcoin acts as a safe haven against an international sample of assets during the COVID-19 pandemic. The chosen assets are delineated in data section 5.3.1. Following Baur and Lucey's (2010) correlation-based distinction between a safe haven, hedge, and diversifier (see definition in section 1.2.), the first step of Analysis I computes the pairwise time-varying return correlations between Bitcoin and each one of the selected assets. This is done using the econometric modeling procedure given by the DCC GARCH model. The generated correlations then form the input for a regression analysis assessing the safe haven, hedge, and diversification properties of Bitcoin during the COVID-19 pandemic in the second step of Analysis I. As the last step, a graphical analysis of the time-varying correlations and returns of Bitcoin and each asset index is performed to finally confirm or reject the findings from the regression analysis. To convey the reasoning behind choosing an econometric model, more specifically, the DCC GARCH model, for the computation of correlations, it is deemed necessary to commence with a subsection describing the theoretic context of the DCC GARCH model. Subsequently, the applied DCC GARCH model, the regression analyses, as well as the graphical analyses, are presented. Lastly, the limitations of the chosen Analysis I methods are outlined.

### *5.2.1.1. Contextual Information: DCC GARCH*

Financially speaking, a correlation is a statistic, which measures the degree to which two assets move in relation to each other. The correlation coefficient can take a value from –1, equal to being perfectly unassociated, to +1, equivalent to being perfectly associated (Bodie, Kane and Marcus, 2018). Mathematically, the correlation between two assets is a function of the covariance of the assets' returns, divided by the product of the volatility of each asset's return. The DCC GARCH model is a financial model that enables the estimation of correlations while recognizing their time-varying nature and offering computational advantages. To understand the underlying assumptions, it is necessary to comprehend the model generating the correlations.

It all started with the lack of adequate models to forecast returns and measure volatility while accounting for the heteroscedasticity of the error term, which means that the variance of the error term varies over time and is generally not constant. This led Engle (1982) to develop the Auto Regressive Conditional Heteroscedasticity (ARCH) model, which was further developed into the improved generalized ARCH (GARCH) model by Bollerslev in 1986. The model captures the conditional variance of financial data by taking the weighted average of past squared residuals, with declining weights that never go completely to zero, thereby constructing models that are parsimonious, easy to estimate, and even in their simplest form have proven successful in predicting conditional variances (Engle, 2001). These initial ARCH and GARCH models were of univariate nature, which means that the time-varying volatility of one asset was independent of the movements of other assets. However, a plethora of applications in financial management require information on the co-movement between asset returns. Consequently, the univariate GARCH model was extended into the multivariate GARCH (MGARCH) model to account for and estimate the interaction effect between the volatility of different assets (Orskaug, 2009).

Since the general MGARCH is regarded as highly flexible but too complex for most purposes, several restricted MGARCH models, which each have a different approach to estimating the covariance matrix between assets, exist. Each of these approaches aims at finding a valuable tradeoff between flexibility and parsimony. One of the many approaches has been to decompose the conditional covariance matrix into conditional correlations and conditional standard deviations. The first model utilizing this approach was the Constant Conditional Correlation GARCH model (CCC GARCH), which assumed the conditional standard deviation to be time-varying and the conditional correlation to be constant over time (Bollerslev, 1990). Aiming to create a model that would capture both conditional correlations and conditional standard deviations as time-varying, the DCC GARCH model was proposed by Engle and Shepphard (2001) as an extension to the CCC GARCH. Given that it provides a superior estimate of time-varying correlations, this thesis makes use of the DCC GARCH model, which has moreover been gaining prominence as an advanced model that carries computational advantages over other MGARCH models (Cho and Parhizgari, 2008). Furthermore, the model is popular in the literature surrounding safe haven investments as it allows for the extraction of the time-varying correlations needed to establish a regression model that can investigate assets' safe haven, hedge and diversification properties (Baur and Lucey, 2010; Ratner and Chiu, 2013; Bouri, Molnár, *et al.*, 2017).

#### *5.2.1.2. DCC GARCH Model*

After having set the context and reasoned for the choice of model, this section describes the technical notes of the DCC GARCH model. The model parameterizes the DCCs in two steps. The first step estimates the univariate GARCH (1,1) model. This is followed by the second step, which estimates the time-varying conditional correlations using the standardized residuals generated from the first step.

The model is defined as (Engle, 2002; Orskaug, 2009):

$$r_t = \mu_t + a_t \qquad (1)$$

$$a_t = H_t^{\frac{1}{2}} z_t \qquad (2)$$

$$H_t = D_t R_t D_t \qquad (3)$$

The following notations apply:

$r_t$: $n \times 1$ vector of log returns of $n$ assets at time $t$

$a_t$: $n \times 1$ vector of mean $-$ corrected returns of $n$ assets at time $t$

$\mu_t$: $n \times$ vector of the expected value of the conditional $r_t$

$H_t$: $n \times n$ matrix of conditional variances of $a_t$at time $t$

$H_t^{\frac{1}{2}}$: Any $n \times n$ matrix at time $t$ such that $H_t$ is the conditional variance matrix of $a_t$.

$D_t$: $n \times n$, diagonal matrix of conditional standard deviations of $a_t$ at time $t$
$R_t$: $n \times n$ conditional correlation matrix of $a_t$ at time $t$
$z_t$: $n \times 1$ vector of iid errors such that $\mathrm{E}[z_t] = 0$ *and* $\mathrm{E}[z_t z_t^T] = I$

The DCC equation is given by:

$$Q_t = (1 - \phi - \gamma)\bar{Q} + \gamma Q_{t-1} + \phi z_{i,t-1} z_{j,t-1} \qquad (4)$$

Where $Q_t$ is the time-varying unconditional correlation matrix of $z$, which are the standardized residuals obtained in the estimation of step one. $\phi$ and $\gamma$ are parameters that represent the effects of former shocks and previous DCCs on current DCCs. Following from this, the DCC between asset *i* and *j* is estimated by:

$$\rho_{ij,t} = \frac{(1 - \phi - \gamma)\bar{Q}_{ij} + \gamma Q_{ij,t-1} + \phi z_{i,t-1} z_{j,t-1}}{\left[(1 - \phi - \gamma)\bar{Q}_{ii} + \phi z_{i,t-1}^2 + \gamma Q_{ii,t-1}\right]^{\frac{1}{2}} \left[(1 - \phi - \gamma)\bar{Q}_{jj} + \phi z_{j,t-1}^2 + \gamma Q_{jj,t-1}\right]^{\frac{1}{2}}} \qquad (5)$$

The calculations are performed in Stata/SE 16.0 using the built-in 'mgarch dcc' function. To ensure that the DCC GARCH model is well-fitted to provide the most accurate correlations matrix, several diagnostics tests are performed. Before the model is run, the commonly used Augmented Dickey-Fuller (ADF) test is performed to test for stationarity of each dataset in isolation (Cromwell, Labys and Terraza, 1994). Covariance-stationarity, in its simplest form, asserts that the probability distribution of the time series does not change over time, so that the series' mean, variance, and autocorrelation structure prevail constant over time (Enders, 2004). The importance of stationarity is proclaimed, as non-stationary time series can lead to spurious regressions, whereby two series are perceived to be correlated with one another, despite being fictitious (Stock and Watson, 2015). Testing for stationarity is testing for unit roots, which comprises assessing whether a unit root specification provides a reasonable approximation for the variable of interest (Becketti, 2020).

To determine the best-fitted model, the likelihood value generated by each model should be maximized. This is achieved by finding each model's optimal combination of the likelihood function and distribution specification for the standardized residuals. First, to detect which likelihood function should be maximized, a trial-and-error process is performed when, as was the case in this thesis, the default function is unable to fit a model. The likelihood function can be specified by four different functions, which thereupon can be set to change after differing numbers of iterations when running the model. This renders the process of finding the most well-fitted model vastly complex. This thesis refers to Stata's manual 'Maximize — Details of iterative maximization' for an in-depth explanation of the specifications. Second, and in addition to the above, the three distributions under consideration, namely the multivariate Gaussian (normal) distribution, the multivariate Student's t-distribution, and the multivariate skew Student's t-distribution, are tested to determine which combination of distribution and likelihood functions provides the best-fitted model for each pair. Consequently, a vast bulk of models was run for each pair to detect the best-fitted model, which was evaluated based on the maximum likelihood values of each model given by the Akaike Information Criterion and the Schwarz's Bayesian Information Criterion. Each criterion presents slightly different tradeoffs between goodness of fit and model complexity and enables the comparison and determination of the best-fitted model as indicated by the model that provides the lowest criterion measures (Williams, 2015; Becketti, 2020; Stock and Watson, 2020). When the most suitable model specification is determined for each pair, the models are well-fitted. Thus, it can be assumed that the DCC GARCH estimates are reliable and accurate. The best-fitted model specifications are presented in Appendix 3.

#### *5.2.1.3. Regression Analyses*

In line with the methods employed by various theoretically related articles on safe havens (i.a., Ratner and Chiu, 2013; Bouri *et al.*, 2017; Urquhart and Zhang, 2019), this thesis utilizes a regression analysis to assess the extent to which Bitcoin can be considered a diversifier, hedge or safe haven against various assets during the COVID-19 period.

Following the DCC GARCH estimations, the DCCs between Bitcoin and each of the respective asset indices are extracted from *equation (5)* into separate time series of weekly intervals *t* for the period from October 2013 through August 2020. To assess whether Bitcoin can be considered a safe haven, diversifier, or hedge, this thesis regresses the extracted correlations through three regression models with differing dummy variables in Stata. The first regression model is given by *equation (6)* and specifies the dummy variable to contain observations from February 28$^{th}$, 2020, through August 2020, representing the COVID-19 period. The second regression model is delineated in *equation (7)* and applies a dummy variable representing a shorter COVID-19 period. A look at financial stress indicators (see Appendix 4) shows that financial markets experienced the most severe levels of COVID-19 related financial stress in the period February 28$^{th}$ to April 10$^{th}$, 2020, why this specific period was chosen for the second COVID-19 regression model. The last regression model (see *equation (8)*) regresses the correlations from October 2013 through August 2020 upon three dummy variables, $c_1, c_2$ and $c_3$, which represent observations for the lowest 1%, 5%, and 10% quantiles of the return distribution of each index. The latter is performed as a mere robustness check and necessary for two reasons. First, Bitcoin can only be regarded as a safe haven if the return of Bitcoin increases, while the return of the other asset decreases during a period of financial market stress. If the empirical results estimated in the COVID-19 regression analyses reveal that Bitcoin and the different indices are negatively correlated during the COVID-19 periods, this could, in fact, also be the result of a decrease in the value of Bitcoin and an increase in the value of the respective asset. Since the quantile regression reports the correlation for the lowest return quantile observations of the respective asset, a negative correlation result automatically means that Bitcoin's value increased while the asset's value was at its lowest. Since many of the assets' minimum returns over the entire sample period are registered amid the pandemic (see section 6.1.1.), more evidence is provided in favor of Bitcoin serving as a safe haven against the respective asset during the COVID-19 crisis when both the COVID-19 and quantile regression report negative correlation estimates. To finally confirm Bitcoin's safe haven potential against the respective asset, the returns of both assets need to be graphed against each other to detect whether Bitcoin's return increases while the assets' return decreases. Second, the quantile regression serves as a confirmation of whether the observations from the COVID-19 regressions also hold during a wider period of data.

Consequently, the regression models are outlined below, where $c_0$ denotes the average correlation between Bitcoin and the respective asset during all the weeks not captured by the dummy variables, whereas the coefficients $c_1, c_2, and\ c_3$ are marginal effects on the correlations during the period represented by the dummy variables. The regression equations are given by:

$$DCC_t = c_0 + c_1 D(COVID - 19) \qquad (6)$$

$$DCC_t = c_0 + c_1 D(COVID - 19_{short}) \qquad (7)$$

$$DCC_t = c_0 + c_1 D(r_{asset} q_1) + c_2 D(r_{asset} q_5) + \ c_3 D(r_{asset} q_{10}) \qquad (8)$$

*D* will be equal to one during the specific COVID-19 periods in *equation (6)* and *(7),* as well as when the returns of the respective indices exceed the given quantile thresholds in *equation (8)*. These regression models propose that Bitcoin is a diversifier against movements in the selected assets on average if $c_0$ is significantly positive. Moreover, Bitcoin is a hedge against movements in the selected assets on average if $c_0$ is significantly negative.

During the COVID-19 period, Bitcoin acts as a safe haven against movements in the specific asset if the sum of $c_0$ and $c_1$ are significantly negative. To verify the detected results, the sum of $c_0$ and $c_1, c_2, and\ c_3$ must also be significantly negative for Bitcoin to provide safe haven capabilities. An example of the precise interpretation of each regression model is provided in section 6.1.2.1. alongside the interpretation of the regression results. Finally, all coefficients are tested for significance at a 1%, 5%, and 10% level to validate the findings.

#### *5.2.1.4. Graphical Analyses*

Lastly, a graphical approach is embraced to substantiate the findings from the regression analyses. First, the time-varying correlations between Bitcoin and each of the considered asset indices are extracted from the DCC GARCH model and graphed over the course of a one-year period from September 2019 through August 2020. This allows for an understanding of whether the estimates provided by the regression analyses prevail for the entire COVID-19 period. If the former step highlights Bitcoin as a safe haven against certain assets, an assessment of the specific weeks as well as the time horizon for which Bitcoin carries the potential safe haven property is performed. Second and finally, the returns of Bitcoin and the asset indices for which the regression analyses and previous steps determined Bitcoin to be a safe haven are graphed against each other. This allows for identifying whether it is the increasing return of Bitcoin during a downturn of the other asset's return that causes the negative correlation, and not vice versa. Only then, Bitcoin's safe haven properties can be finally confirmed or rejected.

#### *5.2.1.5. Methodological Limitations I*

At this stage, it is worth noting that the primary aim of this thesis is not to provide insights into econometric time-series or DCC modeling. Instead, this model is used as a tool to gain accurate and superior correlation input for the regression analyses, which allows for an answer to the overall research hypothesis. Consequently, the description of the econometric theory and methodology, as well as a detailed discussion of the DCC GARCH model's limitations, are kept brief. For a detailed introduction to the models, their specifications and limitations, this thesis refers to the work of Bollerslev, Engle and Wooldrige (1988), Bollerslev (1990), Engle, Ng and Rothshild (1990), Kroner and Claessens (1991), Bollerslev, Chao and Kroner (1992), Engle and Mezrich (1996), and Ding and Engle (2001). Nevertheless, the main point of criticism of the DCC GARCH model, namely its lack of a rigorous derivation with explicit details regarding the existence of moments and testability of the stationarity conditions, should not go unacknowledged (Caporin and McAleer, 2013). Therefore, Caporin and McAleer suggest that the model should only be used with care to forecast returns but serves well as a means to extract the DCCs. This is in line with how this thesis utilizes the DCC GARCH model.

With respect to the regression model, it is noteworthy that the extracted DCCs are, in fact, predicted correlations generated by the DCC GARCH forecast model, which is based on the inserted historical data. Consequently, an element of uncertainty in the estimated DCCs used for the regression analysis is present, despite being predicted from the DCC GARCH model with a high degree of accuracy. Moreover, it would be negligent not to point to the critique of the quantile regression analysis provided by Reboredo (2013), who advocates that the model is insufficient in describing the dependence structure, as the marginal effects do not fully account for the joint extreme market movements. However, this is accommodated by substantiating the regression with a graphical analysis of the returns of the asset pairs that present negative correlations to detect the precise reason for the correlations over time. Lastly, it is recognized that amid the considered COVID-19 period, several other factors, i.a., the US presidential election and Brexit disputes, have affected financial markets, why it cannot be refuted that these have impacted the marginal effects of the COVID-19 dummy variables.

### 5.2.2. Methodological Approach – Analysis II

After having assessed Bitcoin's pairwise correlation behavior in Analysis I, Analysis II completes the examination of Bitcoin's safe haven properties by investigating the extent to which Bitcoin is fulfilling the liquidity requirement inherent in the definition of a safe haven (see section 1.2.). In this context, an asset is defined as more liquid than another if it can be converted into cash quickly and at a low cost, thus "if it is more certainly realizable at short notice without loss" (Keynes, 1930, p. 69). In line with Smales (2019), Marshall, Nguyen and Visaltanachoti (2018), and Schmitz and Hoffmann (2020), this thesis explores Bitcoin's relative liquidity by means of the bid-ask spreads, as implicit costs of trading, as well as transactions fees, as explicit costs of trading. The chosen measures thereby provide an understanding of the degree to which Bitcoin can be quickly bought or sold on a marketplace at stable prices and low costs (Amihud, 2002).

#### 5.2.2.1. Implicit Costs of Trading

The daily bid-ask percentage spreads from Bitcoin's bid and ask prices for the period from October 2013 through August 2020 are generated. In addition, the bid-ask percentage spreads of gold, Apple Inc (hereafter Apple), and Twitter Inc (hereafter Twitter) are computed for comparative reasons. The choice of these three assets is reasoned for in data section 5.3.2. This allows for the comparison of Bitcoin with gold, which has already been established to present safe haven capabilities in the existing literature, as well as one relatively volatile stock, Twitter, and one relatively less volatile stock, Apple. The bid-ask percentage spread is calculated as follows:

$$Bid - ask\ spread\ (\%) = \frac{(ask\ price - bid\ price)}{ask\ price} \times 100 \qquad (9)$$

Organizing the spreads in a graph over the entire time period as well as during a shorter and more recent time frame from September 2019 through August 2020 enables a comparative trend analysis of Bitcoin's liquidity characteristics with respect to gold, Apple, and Twitter. To allow for a more precise comparison of the liquidity characteristics of Bitcoin, gold, Apple, and Twitter, the mean of each asset's bid-ask spreads for 1) the entire sample ranging from October 2013 through August 2020, 2) the more recent sub-period ranging from September 2019 through August 2020, 3) a sub-period ranging from February 24$^{th}$, 2020 to April 10$^{th}$, 2020 - the same period of high COVID-19 related market stress as utilized in Analysis I - are computed. To test whether the differences in means between the assets during the three periods are significantly different from zero, Welch's mean-comparison two-sample t-tests with unequal variances are run (Agresti and Franklin, 2014; Stata, 2020). This test is performed in Stata (see Appendix 5) and evaluated on the basis of the p-value, which is the probability summary of the evidence against the null hypothesis that the difference of the means is zero. The smaller the p-value, the stronger the evidence that the null hypothesis can be rejected. This thesis follows the academically accepted 5% significance level (Agresti & Franklin, 2014). Furthermore, the bid-ask percentage spread of Bitcoin is graphed against two financial stress indices from September 2019 through August 2020 to examine Bitcoin's liquidity development during COVID-19.

#### 5.2.2.2. Explicit Costs of Trading

As outlined in section 2.1.1., every Bitcoin transaction must be added to the blockchain, the official public ledger of all Bitcoin transactions, in order for the transaction to be successfully completed and valid. Bitcoins cannot exist or be held independently of the blockchain. The validation of all transactions occurs through the process of mining, which takes care of including transactions in the limited space of a 1 MB block. When a block is filled up with transactions, it is added to the blockchain, which occurs circa every 10 minutes. Transaction fees are charged for this process, which make up the most substantial share of the overall fees charged when trading Bitcoins on exchanges. While smaller, additional fees might be charged by the exchanges at which Bitcoins are bought and sold, this analysis solely focuses on the transaction costs of using the Bitcoin network and disregards the additional fees applied by exchanges, which differ across exchanges (CoinDesk, 2020a). The explicit transaction cost characteristics of trading Bitcoins are explored by computing the mean and maximum of the average transaction fees per day during the same (sub-)periods as for the bid-ask spread analysis. Moreover, daily median transaction fee data is graphed against the number of daily transactions from October 1st, 2013 to August 31st, 2020, to assess the relation between investment demand and transaction costs. Since investors flee to safe haven assets during crises, demand often rises, why it is essential to know if the transaction fees increase when safe havens are needed the most (Schmitz & Hoffmann, 2020).

#### *5.2.2.3. Methodological Limitations II*

The methodological approach chosen to analyze Bitcoin's liquidity is subject to criticism. Commencing with the implicit costs, it is acknowledged that the significance test of the differences in means of the bid-ask spreads can be impaired due to possible Type I or Type II errors. Whereas Type I errors imply the rejection of the null hypothesis, i.e., that the difference in means is zero, when it, in fact, cannot be rejected, Type II errors imply that the null hypothesis is not rejected even when it, in fact, should be. This study minimizes Type I errors by applying the academically accepted 5% significance level. Type II errors are reduced by utilizing large samples of 1,805 observations for the whole period, 261 observations for sub-period 1, and 35 observations for sub-period 2 (Agresti and Franklin, 2014). Moreover, it is acknowledged that the statistical significance of the results does not necessarily mean practical significance (Ibid).

Turning to the explicit costs, it is important to note that the approach only provides evidence for Bitcoin's transaction fees related to mining, which does not allow for a comparison to the transaction costs of other assets. The latter is also a consequence of difficulties associated with measuring the transaction costs of traded assets, as these consist of several components of which especially the variable component consisting of commissions charged by brokers, taxes, and transfer fees are hard to measure (Collins and Fabozzi, 1991; Lv, Liu and Wang, 2012). Hence, this has been omitted due to the scope of the thesis and the difficulty related to arriving at comparable measures.

Moreover, it is acknowledged that liquidity is not only associated with bid-ask spreads and transaction costs but also concerns the market depth of assets. The latter refers to the ability of the market to sustain relatively large market orders without impacting the price of an asset. However, Scharnowski (2020) argues that "while bid-ask spreads typically matter most for retail investors, institutional investors are more concerned about their price impact" (p. 2). Consequently, as this thesis is delimited to primarily provide practical implications for retail investors (see section 1.1.), it is not of utmost importance to investigate market depth, why it has been disregarded in this thesis.

### 5.2.3. Methodological Approach – Analysis III

To complete the comprehensive analysis of Bitcoin's investment characteristics, Analysis III investigates the risk and return effects of including Bitcoin in a diversified portfolio amid the COVID-19 pandemic. The analysis centers around portfolio optimization and is divided into two steps. First, it is investigated if and to which extent Bitcoin should be included in the diversified portfolio of an investor. Second, the analysis moves on to evaluate whether including Bitcoin in the investment set leads to higher portfolio performance as compared to not holding an investment in Bitcoin. Both analytical steps are performed and assessed throughout COVID-19. The following sections operationalize Analysis III and present the methodological approach taken. Thereby, the section starts by explaining how the optimal portfolios, used to assess Bitcoin's weight allocation and performance-enhancing value to a portfolio, are computed. Subsequently, the performance metrics, used to evaluate the additive value of Bitcoin to a diversified portfolio, are introduced. This is followed by a presentation of the method employed to explore the development of Bitcoin's weights and performance throughout the COVID-19 pandemic. At last, the methodological limitations of Analysis III are outlined.

#### *5.2.3.1. Portfolio Computation*

As a first step, test portfolios, which are optimized with the possibility to invest in Bitcoin, and benchmark portfolios, which are optimized without the possibility to invest in Bitcoin, are computed. At this point, it is important to stress that Analysis III is operationalized by delimiting the scope of the analysis to focus on diversified portfolios of US investors, thereby allowing for an in-depth study. This entails that the assets included in the diversified portfolios are denoted in their base currency, which in this case, is the USD. To, however, keep the implications of the Analysis III findings as generalizable as possible, the selected portfolio assets reflect a US investor who seeks to diversify broadly, globally, and across asset classes, thereby showing limited home-country bias. Here, home-country bias is defined as the tendency for investors to favor assets from their own countries over those from other countries, even though this can cause diversification disadvantages (Bodie, Kane and Marcus, 2018). Thus, the investment universe for the benchmark portfolios includes one world equity index, one world bond index, one world commodity index, one currency index, and one world real estate index. On top of these assets, the test portfolios can also invest in Bitcoin. It is assumed that investors use exchange-traded funds (ETFs) or certificates to conveniently trace the development of the selected indices without the need to buy all the index constituents as individual direct investments. The indices are further described under data composition and collection in section 5.3.3.

The diversified benchmark and test portfolios are computed based on two optimization frameworks: Markowitz's (1952) mean-variance and Rockafellar and Uryasev's (2000) mean-CVaR optimization. Hence, this study refrains from constructing equally- or capitalization-weighted portfolios or using naïve optimization, as this would inhibit the investigation of to which optimal extent Bitcoin should be included in a portfolio when considering its correlation as well as risk-return characteristics. Given that most of the methodologically related research papers analyze performance-enhancing effects using Markowitz' traditional mean-variance framework (i.a., Platanakis, Sutcliffe and Urquhart, 2018; Borri, 2019; Brauneis and Mestel, 2019; Liu, 2019; Symitsi and Chalvatzis, 2019; Platanakis and Urquhart, 2020), this thesis conforms to the same approach to properly evaluate whether the conclusions generated by previous research hold true during times of financial market turmoil. Nonetheless, the limiting assumptions of mean-variance optimization should not go unacknowledged. Most notably, Markowitz's estimate of risk by variance assumes that returns are normally distributed, and investors exhibit quadratic preferences. However, it has been heavily documented that the returns of financial assets follow a non-normal distribution and, at times, even witness zero-probability tail events (i.a., Pagan, 1996; Cont, 2001; Rangvid, 2020). This holds particularly well for Bitcoin, which has been shown to be characterized by extreme price movements, clustering, and bubble-like dynamics (Corbet et al., 2019; 2018a; Urquhart, 2017). Appendix 6 further supports this stance by visually displaying the non-normality of the return data of all assets included in this study's optimized portfolios, thereby questioning the accuracy of solely using mean-variance optimization. Therefore, and in line with academically related research (i.a., Gasser, Eisl and Weinmayer, 2015; Kajtazi and Moro, 2019; Bedi and Nashier, 2020), this thesis also makes use of mean-CVaR optimization, which was proposed by Rockafellar and Uryasev (2000, 2002) and allows for non-normality in portfolio optimization. According to Rockafellar and Uryasev (2000) and Krokhmal, Palmquist, and Uryasev (2001), a comparison of mean-variance and mean-CVaR optimized, efficient portfolios leads to similar results when returns are normally distributed. However, significant differences become apparent as soon as normality does not hold (Ibid). Therefore, it is deemed relevant to compute portfolios based on both the widely used mean-variance and mean-CVaR optimization to ensure robustness in the empirical findings when assessing Bitcoin's optimal weight allocation and additive value to a diversified portfolio. It is important to note that this thesis uses the optimization frameworks as a tool to enable this study's analytical steps, why this thesis refers to the works of Rockafellar and Uryasev (2000, 2002) and Cornuejols and Tütüncü (2006) for a detailed introduction to the frameworks and their differences as well as limitations. It is, moreover, acknowledged that a variety of other and more advanced optimization frameworks could have been chosen. However, this study's choice bases itself on DeMiguel, Garlappi, and Uppal (2007), who argue against the consistent effectiveness and superiority of sophisticated optimization models.

##### 5.2.3.1.1. Mean-Variance Optimization Framework

The mean-variance optimization framework weighs risk, expressed as variance, against expected return, and stems from MPT pioneered by US economist Harry Markowitz in 1952. The key insight of MPT is that, when selecting a portfolio of assets, the investor's main concern is to achieve minimum risk for a given level of return and maximum return for a given level of risk. Given an opportunity set of risky assets, the portfolio combinations satisfying these investors' criteria are termed efficient. The spectrum of efficient risk-return portfolio combinations can be graphed as a curve called the efficient frontier of risky assets. Among these efficient portfolios, the portfolio displaying the lowest variance is titled the global-minimum-variance portfolio (GMVP). If a risk-free asset yielding a sure return $rf$, is also available for investment, a new efficient frontier starting from the risk-free return and tangent to the efficient frontier of risky assets can be created. This new efficient line is commonly known as the Capital Allocation Line (CAL). The portfolio on the tangency point between the CAL and the efficient frontier of risky assets is known as the tangency portfolio (TP), which maximizes the reward-to-volatility ratio for the investor, also known as the SR (Sharpe, 1966, 1994). While the TP is the optimal risky portfolio for all investors, the overall optimal portfolio allocation for an individual investor, who invests in a combination of the TP and a risk-free asset, depends on the individual's risk preferences. Therefore, Tobin's separation property specifies that portfolio choices can be divided into the two independent tasks of 1) determining the optimal risky

TP and 2) finding the personal, ideal mix of the optimal risky TP and the risk-free asset (Markowitz, 1952, 1959; Bodie, Kane and Marcus, 2018). This thesis focuses on task one and computes the optimal risky benchmark and test TP. To appeal to the risk-averse nature of many investors during especially times of crises, the GMVPs are calculated in addition to the TPs.

Following Bodie, Kane, and Marcus (2018), a portfolio optimization problem starts with defining the risk-return characteristics of the risky assets in the asset universe. To perform the mean-variance optimization, the return $r$ of each considered asset at T data points, the mean return $r_m$ of each asset's returns throughout the T data points, and the respective covariance matrix need to be estimated (Markowitz, 1952, 1959). The covariance of two assets $i$ and $j$ is calculated as:

$$cov_{i,j} = \frac{1}{T-1}\sum\nolimits_{t=1}^{T}(r_{i,t} - r_{m,i}) * (r_{j,t} - r_{m,j}) \qquad (10)$$

The expected return of the portfolio is calculated by multiplying the average return $r_m$ of each asset included in the portfolio with the weights assigned to each asset $w$ as follows:

$$\mu_p = r_{m,i} * w_i + r_{m,j} * w_j + \ldots + r_{m,z} * w_z \qquad (11)$$

The portfolio variance can then be computed using the following formula:

$$Var(r_p) = \sum_{i=1}^{N}(x_i)^2 Var(r_i) + 2\sum_{i=1}^{N}\sum_{j=1+1}^{N} x_i x_j \, Cov(r_i, r_j) \qquad (12)$$

Taking departure in the above input, the weights for the GMVPs and TPs are computed in excel on the mathematical basis of the following (Munk, 2013). Note that $\mu$ forms the vector of the expected rates of return, $\underline{\sum}$ = (Σij) is the variance-covariance matrix of the rates of return, and $r_f$ is the risk-free rate. However, in line with, Brauneis and Mestel (2019) and Schmitz and Hoffmann (2020), the risk-free weekly rate is assumed to be zero throughout all calculations in Analysis III. This assumption is deemed reasonable because of the very low-interest environment in the considered observation period (Federal Reserve Bank of St. Louis, 2020a; Redder, 2020). Moreover, the portfolio weight vector must satisfy $\pi * 1 = \pi_1 + \pi_2 + \cdots + \pi_i = 1$, and a long-only constraint is introduced. The deviation from Markowitz's traditional unconstrained mean-variance optimization is motivated by the assumption that Bitcoin could serve as a potential safe haven, why one would not consider going short in Bitcoin or any of the other assets.

Thereupon, the equation for the GMVP is given by:

$$\pi_{min} = \frac{1}{C} * \underline{\Sigma}^{-1}1 = \frac{1}{1 * \underline{\Sigma}^{-1}1}\underline{\Sigma}^{-1}1 \qquad (13)$$

where the auxiliary constants are given by (14):

$$A = \mu^T \underline{\Sigma}^{-1} \mu = \mu \underline{\Sigma}^{-1} \mu$$
$$B = \mu^T \underline{\Sigma}^{-1} 1 = \mu \underline{\Sigma}^{-1} 1 = 1^T \underline{\Sigma}^{-1} \mu = 1 * \underline{\Sigma}^{-1} \mu$$
$$C = 1^T \underline{\Sigma}^{-1} 1 = 1 * \underline{\Sigma}^{-1} 1$$
$$D = AC - B^2$$

Supposing that $B \neq C\, r_f$, the calculations of the weights for the optimal risky TP are defined as follows:

$$\pi_{tan} = \frac{\underline{\Sigma}^{-1}(\mu - r_f 1)}{1 * \underline{\Sigma}^{-1}(\mu - r_f 1)} = \frac{1}{B - C\, r_f} \underline{\sum}^{-1} (\mu - r_f 1) \qquad (15)$$

#### 5.2.3.1.2. Mean-CVaR Optimization Framework

The mean-CVaR framework works with the same return proxies as the mean-variance optimization but uses the Conditional-Value-at-Risk (CVaR) of portfolio returns as the risk proxy instead of variance. Given that Value-at-Risk (VaR) is defined as measuring the predicted maximum loss at a specified probability level over a certain period of time, the CVaR at a chosen confidence level is the expected loss given that the loss is greater than the VaR at that level (Rockafellar and Uryasev, 2000, 2002). Hence, while mean-variance optimization uses a risk proxy, which incorporates information from both the loss and gain end of the distribution tail, mean-CVaR's risk proxy solely focuses on losses inherent in the extreme tail of the distribution. In line with the presented research and theories on safe havens, investors are particularly worried about the downside risk captured by the latter optimization framework (Ibid). Following Rockafellar and Uryasev, portfolio CVaR for a portfolio *pf* is calculated as:

$$CVaR_\alpha(pf) = \frac{1}{1-\alpha} \int_{f(pf,y) \geq VaR_\alpha(pf)} f(pf,y)p(y)dy \qquad (16)$$

where $\alpha$ is a probability level with a value between 0 and 1, $f(pf, y)$ is the loss function for a portfolio *pf* and a portfolio return $y$, $p(y)$ is the probability density function for a portfolio return $y$ and

$VaR_\alpha(pf)$ is the VaR at probability level $\alpha$. Throughout this thesis, the common confidence level of 95% is employed. The VaR is defined as:

$$VaR_\alpha(pf) = \min\{y : \Pr[f(pf, Y) \leq y] \geq \alpha\} \qquad (17)$$

To describe the probability distribution of returns, the mean-CVaR optimization takes a finite sample of return scenarios $y_s$ with $s = 1, 2 \ldots, S$. Each $y_s$ is an $n$ vector that contains the returns for each of the $n$ assets under scenario $s$. The sample of $S$ scenarios is stored as a scenario matrix of size $S$-by-$n$. The loss function $f(pf, y) = -{y_s}^T pf$ is the portfolio loss under scenario $s$. Consequently, the portfolio risk proxy for the mean-CVaR optimization is given by:

$$CVaR_\alpha(pf) = VaR_\alpha(pf) + \frac{1}{(1-\alpha)\,\mathrm{S}} \sum_{s=1}^{S} max\{0, -{y_s}^T pf - VaR_\alpha(pf)\} \qquad (18)$$

On the theoretical basis of the aforementioned, the mean-CVaR optimized portfolios are computed with the 'PortfolioCVaR' object in the Financial Toolbox of the software MATLAB. Asset scenarios are generated to simulate a distribution that tries to mimic the inserted empirical return data of each stock. Following the optimal portfolio selection of Campbell, Huisman, and Koedijk (2001) and Gasser, Eisl, and Weinmayer (2015), the weights for the mean-CVaR GMVPs are obtained by firstly generating the respective efficient frontier and secondly extracting the portfolio weights for the portfolio with the lowest CVaR located at the lower end of the efficient frontier.

The weights for the mean-CVaR TPs are optimized in a similar fashion as the mean-variance TPs by maximizing a modified version of the SR, defined as follows:

$$MSR = \frac{E_{rpf} - r_f}{CVaR_\alpha(pf)} \qquad (19)$$

Equal to the mean-variance optimization, a long-only restriction is introduced. The authors refer to Appendix 7 for the script of the utilized codes and mathworks.com for detailed specifications of the codes.

#### 5.2.3.1.3. Portfolio Details

The two portfolio optimization frameworks are used to create several test and benchmark TPs and GMVPs. Optimal portfolios are computed once every month from September 2019 through August 2020, which results in a total of 12 optimizations. At the end of each of the 12 months, the portfolios are optimized based on two full years of historical weekly return data counting backward from the date of optimization. Thus, the portfolio optimization considers a rolling window of a consistent amount of data, which allows for an analysis of how Bitcoin's optimal portfolio weight allocation and additive value develop over time. More specifically, it provides an understanding of how Bitcoin's weight allocation and additive value change as the optimization rolls into the months including COVID-19 related global financial market stress. Given that this study optimizes based on two optimization frameworks and computes test and benchmark TPs and GMVPs, a total of 96 portfolios are generated. Namely, 12 test TPs, 12 benchmark TPs, 12 test GMVPs, and 12 benchmark GMVPs per optimization framework. Each portfolio is named after the month at which end it is optimized, so the portfolios named 'July 2020', for example, include the mean-variance and mean-CVaR optimized test and benchmark TPs and GMVPs, which are optimized on the basis of data from the start of August 2018 to the end of July 2020.

### *5.2.3.2. Portfolio Performance Comparison*

As a second step, the computed test and benchmark portfolios are compared on the basis of various portfolio performance metrics, which measure the average weekly performance throughout the two-year data window of each portfolio. This allows for an analysis of whether a portfolio including an investment in Bitcoin would have rendered a higher performance during a period including COVID-19 related financial stress compared to not investing in Bitcoin. The chosen metrics include the downside risk measures of MVaR and MCVaR, as well as the risk-return metrics of SR, SoR, and ASR. These are introduced in the following sections.

#### 5.2.3.2.1. Modified Value-at-risk and Conditional-Value-at-Risk

As depicted in the literature review, the risk of losses increases during times of market turmoil, why one of the performance metrics used to compare the test portfolio to the benchmark portfolio is each portfolio's downside risk. This allows for insights into whether including Bitcoin into a portfolio can mitigate such tail risk. In this thesis, downside risk is determined by the two prominent measures: VaR, defined as the loss level during a time period of length $T$ that with $X$% certainty will not be exceeded, and CVaR, which is defined as the loss expectation conditional on the loss being larger than VaR (Hull, 2018). For a portfolio with normally distributed returns, a two-moment VaR and CVaR would be an adequate measure of tail risk. However, as outlined earlier, it has been heavily documented that the returns of financial assets follow a non-normal distribution and even witness zero-probability tail events (i.a., Pagan, 1996; Cont, 2001; Rangvid, 2020). This makes it likely that a two-moment VaR and CVaR cannot accurately capture the risk of potentially large non-normal returns. For that reason, the four-moment MVaR and MCVaR, derived from the Cornish-Fisher Expansion, are employed to account for the skewness and kurtosis of the empirical distribution when assessing downside risk (Favre and Galeano, 2002). Given that most academically related research analyzes Bitcoin's downside risk reduction ability based on MVaR and MCVaR (i.a., Gasser, Eisl and Weinmayer, 2015; Kajtazi and Moro, 2019; Bedi and Nashier, 2020; Conlon and Mcgee, 2020), this thesis follows suit to properly evaluate whether the conclusions generated by previous research hold true during times of acute financial market stress. Moreover, the choice of MVaR and MCVaR are motivated by the aspiration to display a similar downside risk measure as used for the mean-CVaR optimization.

In the Cornish-Fisher expansion, the quantile of the distribution is approximated in the following manner (Hull, 2018):

$$Z\left(\alpha, S_p, K_p\right) = z(\alpha) + \frac{1}{6}(z(\alpha)^2 - 1)S_p + \frac{1}{24}(z(\alpha)^3 - 3z(\alpha))K_p - \frac{1}{36}\left(2z(\alpha)^3 - 5z(\alpha)\right){S^2}_p \qquad (20)$$

where $\mu_p$, $\sigma_p$, $S_p$, and $K_p$ are the mean, standard deviation, skewness, and excess kurtosis of the portfolio returns. z(α) is the α quantile of the standard normal distribution. As touched upon earlier, the chosen confidence interval α is set to 95% throughout this thesis. Having calculated the Cornish-Fisher expansion, the four-moment MVaR is then computed as:

$$MVaR_p(\alpha) = -(\mu_p + \sigma_p Z\left(\alpha, S_p, K_p\right)) \qquad (21)$$

After having calculated MVaR, the MCVaR can be defined as the expected average loss during time T conditional on the loss being greater than $MVaR_p$ :

$$MCVaR_p(X,T) = E\left(R_p | R_p > MVaR_p\right) \quad (22) \quad \text{if } R_p \text{ is a loss.}$$

$MCVaR_p$ can be calculated as (Doug and Arora, 2015):

$$MCVaR_p = -\left(\mu - \frac{\sigma}{\alpha} * \emptyset\left(Z\left(\alpha, S_p, K_p\right)\right) * (1 + \frac{1}{6} Z\left(\alpha, S_p, K_p\right)^3 * S_p + \frac{1}{72} * \left(Z\left(\alpha, S_p, K_p\right)^6 - 9 * Z\left(\alpha, S_p, K_p\right)^4 + 9 * Z\left(\alpha, S_p, K_p\right)^2 + 3\right) * S_p{}^2 + \frac{1}{24} * \left(Z\left(\alpha, S_p, K_p\right)^4 - 2 * Z\left(\alpha, S_p, K_p\right)^2 - 1\right) * K_p\right) \quad (23)$$

where $\emptyset$ is the standard normal density function of the $\left(Z\left(\alpha, S_p, K_p\right)\right)$. Since the goal of estimating the four-moment MVaR and MCVaR is to quantify Bitcoin's potential to reduce downside risk, the relative MVaR (RMVaR) and MCVaR (RMCVaR) are calculated as:

$$RMVaR = \frac{MVaR_{Test}(1 - \alpha)}{MVaR_{Benchmark}(1 - \alpha)} \quad (24)$$

$$RMCVaR = \frac{MCVaR_{Test}(1 - \alpha)}{MCVaR_{Benchmark}(1 - \alpha)} \quad (25)$$

Thereby, RMVaR and RMCVaR calculate the proportion of the benchmark portfolio's MVaR and MCVaR that remains after including Bitcoin into the investment mix. Consequently, small values of RMVaR and RMCVaR indicate that Bitcoin carries a large downside risk reduction benefit, and vice versa. As the last step, a frequency count is conducted to establish the number of times the test portfolios realize a lower MVaR and MCVaR than the benchmark portfolios.

##### 5.2.3.2.2. Sharpe Ratio, Sortino Ratio, and Adjusted Sharpe Ratio

Despite the importance of downside risk reduction during crises, investors are unlikely to consider an investment in Bitcoin for MVaR and MCVaR purposes in isolation. Instead, their allocation decisions will consider the tradeoff between risk (or downside risk) and return. For that reason, the SR, SoR, and ASR are computed and compared for the test and benchmark portfolios.

The SR measures excess return on variance and was maximized for the creation of the mean-variance TPs (Sharpe, 1966; Sharpe, Gordon and Bailey, 1985). While the SR is widely used as a performance indicator, Israelsen (2005) found that the reliability of the classical SR as a ranking indicator between portfolios decreased as soon as the excess return adopted a negative value. To circumvent this shortcoming and ensure that portfolios can be ranked "according to residual return over residual risk, whether or not the excess return is positive or negative" (Israelsen, 2005: 427), Israelsen proposed a slight modification to the SR, which is given by:

$$SR = \frac{\mu_p - r_f}{\sigma_p^{\left(\frac{\mu_p - r_f}{Abs(\mu_p - r_f)}\right)}} \qquad (26)$$

where $\mu_p$ is the average weekly return of the portfolio and $r_f$ is the risk-free rate, which throughout this thesis is assumed to be zero as previously outlined. The denominator is the standard deviation of the portfolio, which is calculated as the square root of *equation (12)* taken to the power of the excess return divided by the absolute value of the excess return. The classical SR and Israelsen's modified version are identical when the excess return is positive but differ when the excess return is negative. Given that this thesis uses the risk-return performance metrics as ranking criteria for the test and benchmark portfolios, Israelsen's modified SR is applied and hereafter referred to as SR.

Arguably, an investor is more occupied with a portfolio's risk-adjusted returns for downside rather than upside volatility (Kajtazi & Moro, 2019), why the SoR is estimated as an additional performance metric. The SoR, pioneered by Sortino and Van der Meer (1991), considers the excess return divided by the standard deviation of only the downside returns of the portfolio, defined as:

$$SoR = \frac{\mu_p - r_f}{\sigma_{DownsidePortfolio}} \qquad (27)$$

Here, the standard deviation of the downside returns of the portfolio is defined as the standard deviation of all the negative weekly portfolio returns.

The final risk-return metric applied is the ASR, which measures excess return on MCVaR. This is a commonly used metric to capture the return over extreme losses inherent in the tail of the return distributions (Campbell, Huisman and Koedijk, 2001; Bedi and Nashier, 2020). While the ASR is theoretically equal to the measure MATLAB maximizes for the mean-CVaR optimization of the TPs, the ASR is computed based on excess return over the MCVaR computed in section 5.2.3.2.1. rather than the estimated CVaR in MATLAB. This choice is justified by the aspiration to properly evaluate whether the conclusions generated by the vast amount of academically related earlier literature, measuring the ASR as this thesis does, hold true during times of acute financial market stress (i.a., Kajtazi and Moro, 2019; Bedi and Nashier, 2020; Conlon and Mcgee, 2020; Conlon, Corbet and Mcgee, 2020).

The ASR is given by: $$ASR = \frac{\mu_p - r_f}{MCVaR_p} \qquad (28)$$

Similar to the RMVaR and RMCVaR, the relative SR (RSR), relative SoR (RSoR), and relative ASR (RASR) are then calculated as:

$$RSR = \frac{SR_{Test}}{SR_{Benchmark}} \qquad (29)$$

$$RSoR = \frac{SoR_{Test}}{SoR_{Benchmark}} \qquad (30)$$

$$RASR = \frac{ASR_{Test}}{ASR_{Benchmark}} \qquad (31)$$

These measures detail the improvement or worsening in risk-adjusted returns following the addition of Bitcoin to a diversified portfolio. A value greater than one indicates an increase in the risk-adjusted return compared to the benchmark portfolio and vice versa. As a final step, a frequency evaluation of the RSR, RSoR, and RASR results is performed to understand how often the three measures are greater than one.

#### *5.2.3.3. Time Horizon Analysis*

Throughout Analysis III, a time horizon analysis is conducted to highlight the changes in weights allocated to Bitcoin as well as the realized performance of the test portfolio compared to the benchmark portfolio over time. More specifically, it is investigated how the weight allocation to Bitcoin and relative performance of the test portfolios prove during the months showing the highest COVID-19 related market stress as indicated by the VIX, GFSI, as well as the STLFSI2, described in section 5.3.4.

#### *5.2.3.4. Methodological Limitations III*

In this section, the methodological limitations of Analysis III are portrayed. Firstly, this thesis refers to section 5.2.3.1. for the limiting factors of the chosen portfolio optimization frameworks and the approach employed to overcome these weaknesses. Secondly, this study limits itself by assuming there to be no transaction costs and illiquidity issues in the portfolio optimization problem. While it is acknowledged that these factors might impact the optimal weight allocation to Bitcoin and are relevant for future research, this thesis directs interested readers to Analysis II for insights into Bitcoin’s liquidity. Moreover, this study refers to research by Schmitz and Hoffmann (2020), who find that the introduction of transaction cost budgets does not necessarily reduce the attractiveness of cryptocurrencies in diversified portfolios. Thirdly, it is worth noting that the optimal weights generated in the portfolio computation step depend on the selected portfolio asset universe. This thesis considers well-known benchmarks for a diverse range of asset classes (see section 5.3.3.), but it is important to note that a different selection of assets might have yielded varying results. Fourthly, a critical issue in portfolio optimization can be the limited availability of the assets required for the optimal portfolio weight allocation. For high portfolio weights of an asset or very large investment amounts, it is possible that the optimization model suggests buying more of the asset than currently offered on the market (Trimborn, Li and Hardle, 2018). For example, approximately 88% of the limited supply of Bitcoins, which are restricted to never exceed more than 21 million Bitcoins, is currently already circulating on the market (CoinDesk, 2020b). While Bitcoins can also be traded on secondary markets, the limited market supply might be an issue for large institutional investors, for whom the market might not be large enough (Pechman, 2020). Fifthly, it is important to point out that the analysis of Bitcoin's optimized weight development throughout the COVID-19 period is the result of the inclusion of one (more) month of weekly return data from under the COVID-19 crisis, but also the exclusion of one month of weekly return data from the beginning of the two-year rolling window of data. While this allows the portfolio optimization to include a consistent number of observations, inferences about the impact of COVID-19 on the weight development should be drawn mindfully. Sixthly, this thesis acknowledges that the choice of MVaR and MCVaR as downside risk measures bears certain limitations including the high variability of MVaR and MCVaR due to their dependence on mean, standard deviation, skewness, and kurtosis estimators (Doug and Arora, 2015). Nevertheless, the use of these measures is deemed appropriate because 1) this thesis takes a backward-looking perspective and does not forecast future risk, 2) this study solely uses the MVaR and MCVaR measures to evaluate whether the test portfolio outperformed the benchmark, and 3) the measures are widely established in academically related research. Curious readers are guided to the papers of Koliai (2016) and Doug and Arora (2015) for further critique of the assumptions underlying (M)VaR and (M)CVaR as well as other downside risk measure suggestions. Lastly, to allow for a more in-depth study, the focus of Analysis III was confined by optimizing the portfolio for a US investor, who invests broadly and globally, thereby experiencing only limited home-country bias. While the absence of home-country bias takes point of departure in an ideal investor and ensures a certain degree of generalizability to investors from other nationalities, it is questionable whether this is a realistic assumption to make (Bodie, Kane and Marcus, 2018).

## 5.3. Data composition & collection

The following section outlines the data collection process, the data composition, and its relevance of use. Table 1 introduces the indices selected for the three analyses. All data, except Bitcoin, are extracted from Bloomberg in each asset's local currency using the PX_Last function. An adjustment for capital actions, such as dividends and stock splits, is not required since Bloomberg's price information accounts for this.

**Table 1:** Data Overview

| Asset Name | Bloomberg Ticker | Country/ Region | Currency Denomination | Asset Class/Category | Analysis Use |
|---|---|---|---|---|---|
| CoinDesk Bitcoin Price Index | | | USD | Cryptocurrency | Analysis 1, 2, & 3 |
| MSCI ACWI | MXWD | World | USD | Equity | Analysis 1 & 3 |
| MSCI World | MXWO | Developed | USD | Equity | Analysis 1 |
| MSCI Emerging Markets | MXEF | Emerging | USD | Equity | Analysis 1 |
| S&P 500 | SPX | United States | USD | Equity | Analysis 1 |
| Shanghai Stock Exchange Composite | SHCOMP | China | CNY | Equity | Analysis 1 |
| NIKKEI 225 | NKY | Japan | JPY | Equity | Analysis 1 |
| Hang Seng Index | HSI | Hong Kong | HKD | Equity | Analysis 1 |
| FTSE 100 | UKX | United Kingdom | GBP | Equity | Analysis 1 |
| CAC 40 | CAC | France | EUR | Equity | Analysis 1 |
| DAX | DAX | Germany | EUR | Equity | Analysis 1 |
| S&P BSE 500 | BSE500 | India | INR | Equity | Analysis 1 |
| Bloomberg Barclays Global Aggregate Index | LEGATRUU | World | USD | Bond | Analysis 1 & 3 |
| FTSE World Government Bond Index | SBWGU | World | USD | Bond | Analysis 1 |
| Bloomberg Barclays Global Aggregate Corporate Index | LGCPTRUU | World | USD | Bond | Analysis 1 |
| J.P. Morgan Emerging Market Bond Index | EMB US | Emerging | USD | Bond | Analysis 1 |
| Bloomberg Barclays US Aggregate Bond Index | LBUSTRUU | United States | USD | Bond | Analysis 1 |
| Gold Spot $/Oz | XAUCurncy | | USD | Commodity | Analysis 1 & 2 |
| US Crude Oil WTI Cushing OK Spot | USCRWTIC | | USD | Commodity | Analysis 1 |
| S&P Goldman Sachs Commodity Index | SPGSCI | World | USD | Commodity | Analysis 1 & 3 |
| Deutsche Bank Long USD Currency Portfolio Index Excess Return | DBUSDLE | | USD | FX market | Analysis 1 & 3 |
| MSCI ACWI Real Estate Index | MXWD0RE | World | USD | Real Estate | Analysis 1 & 3 |
| MSCI World Real Estate Index | MXWO0RE | Developed | USD | Real Estate | Analysis 1 |
| Dow Jones US Real Estate Index | DJUSRE | United States | USD | Real Estate | Analysis 1 |
| CBOE Volatility Index | VIX | United States | | Stress Indicator | Analysis 1, 2, & 3 |
| Global Financial Stress Index | GFSI | World | | Stress Indicator | Analysis 1, 2, & 3 |
| St. Louis Fed Financial Stress Index | SLFXSI2 | United States | | Stress Indicator | Analysis 1, 2, & 3 |
| Apple Inc | AAPL | | USD | Equity | Analysis 2 |
| Twitter Inc | TWTR | | USD | Equity | Analysis 2 |

### 5.3.1. Data – Analysis I

For Analysis I, return data is required to explore Bitcoin's safe haven potential by analyzing the time-varying correlations between Bitcoin and an international sample of asset indices. A plethora of studies have shown that substantial advantages in risk reduction can be attained through diversification into both a variety of asset classes as well as international holdings (i.a., Solnik, 1995; Anand, 2006; Bodie, Kane and Marcus, 2018; Dalio, 2020). For that reason, the data sample under investigation consists of equity, bond, commodity, currency, and real estate indices from and covering several geographies. Indices are chosen to represent the different asset classes because they provide guidance on the performance of the respective asset class' overall market (Bodie, Kane and Marcus, 2018).

The overall chosen dataset covers a period from October 1st, 2013 to August 31st, 2020, which was determined by the availability of Bitcoin prices. The approximate seven-year time frame allows for the inclusion of different economic and business cycles. As shown by the GFSI, this period includes times of relatively calm markets in 2013 and 2014, slightly more stressful periods in 2015 and late 2018 (Elliott, 2018), as well as COVID-19, US presidential election and BREXIT dispute related high-stress periods in 2020 (Darbyshire, 2020). For all indices, weekly closing prices are extracted from Bloomberg. According to Box and Tiao (1975) and Rasmussen and Harberg (2019), a minimum of 100 observations is required to properly perform a time series regression as in Analysis I. With weekly data, a total of 361 observations are considered, and thus the required threshold is fulfilled. Furthermore, the inclusion of a weekly data frequency allows for the exclusion of noisy weekday effects. As outlined in the methodological approach of Analysis I, two sub-samples of the entire data sample are utilized to focus on the period surrounding the COVID-19 crisis. From the end-of-week closing prices for all assets, weekly logarithmic rates of returns are computed, such that:

$$r_t = \left[\ln \frac{P_t}{P_{t-1}}\right] * 100 \qquad (32)$$

#### *5.3.1.1. Bitcoin Index*

Bitcoin price data, denoted in USD, is collected from CoinDesk (2020b). The CoinDesk Bitcoin Price Index, launched in September 2013, represents an average of Bitcoin prices against the USD from leading global Bitcoin exchanges and is widely used when researching Bitcoin's return data (Ma and Tanizaki, 2019; Shahzad *et al.*, 2019; Bedi and Nashier, 2020). Unlike all other assets included in the dataset, Bitcoin is also traded on weekends, why only Bitcoin's weekday prices are considered to synchronize the data. Studies by Baur and McDermott (2010), Bedi and Nashier (2020) and Kliber *et al.* (2019) showed that a common currency denomination of all assets in USD can significantly change the safe haven, hedging, and diversifying capabilities of an asset. Therefore, each asset index included in this study is denominated in its local currency, and the Bitcoin price is converted to the respective currency using historical exchange rates obtained from Bloomberg. In consequence, the disparity in Bitcoin's diversification, hedging, and safe haven capabilities for investors dealing in different national currencies is captured. While most of the chosen assets' base denomination is the USD, this exercise results in the use of Bitcoin price data in USD, CNY, JPY, HKD, GBP, EUR, and INR.

#### *5.3.1.2. Equity Indices*

To mirror an international equity investment universe, this thesis considers all developed and emerging equity markets, which account for greater than 2.5% of world stock market capitalization. Consequently, this includes the United States (40.6%), China (13.3%), Japan (7.9%), Hong Kong (5.2%), United Kingdom (4.4%), France (3.4%), Germany (2.8%), and India (2.5%), which are represented by the S&P 500, Shanghai Stock Exchange Composite, NIKKEI 225, Hang Seng Index, FTSE 100, CAC 40, DAX and S&P BSE 500, respectively (Bodie, Kane and Marcus, 2018, pp. 854-862). Following MSCI (2020), who base the classification of an emerging and developed market on an assessment of the respective country's economic development, size and liquidity of the equity market, and accessibility for foreign investors, this dataset includes six developed countries (US, Japan, Hong Kong, UK, France, Germany) and two emerging markets (China, India). Moreover, as an overall proxy for the world, developed, and emerging equity markets, the MSCI ACWI, MSCI Emerging Markets, and MSCI World index are selected (Ibid).

#### *5.3.1.3. Bond Indices*

In order to represent the global bond market, five well-known bond indices are included in the dataset. First, to provide a broad overview of various bond categories in both developed and emerging markets, the Bloomberg Barclays Global Aggregate Index is considered. The index measures the performance of global investment grade debt from 24 local currency markets, including treasury, government-related, corporate, and securitized fixed-rate bonds (Bloomberg, 2020a). Second, to allow for a more narrow analysis of the correlation between Bitcoin and the respective bond category, one global government bond index and one corporate bond index are considered. Consequently, the FTSE World Government Bond Index is included, which measures the performance of fixed-rate, local currency, investment-grade sovereign bonds from 20 countries (London Stock Exchange Group plc, 2020). Representing the corporate bond category, the Bloomberg Barclays Global Aggregate Corporate Index is selected, which measures global investment-grade, fixed-rate corporate debt in both developed and emerging markets (Bloomberg, 2020a). Lastly, to assess the correlation between Bitcoin and the bond performance in certain geographical regions, an emerging market and US bond index are examined. Representing government and corporate bonds issued by emerging markets, the J.P. Morgan Emerging Market Bond Index, which is represented by the iShares JP Morgan USD Emerging Markets Bond ETF tracking this index, is included in the dataset (JP Morgan Chase & Co, 2020). The US bond market is represented by the Bloomberg Barclays US Aggregate Bond Index, which is a benchmark for treasuries, government-related and corporate securities, MBS, ABS, and CMBS (Bloomberg, 2020b).

#### *5.3.1.4. Commodity Indices*

Numerous publications have stressed the attractiveness of investing in commodity futures because of their potential to offer diversification benefits, exposure to growing demand following world economic growth, as well as protection against rising inflation, with commodities being one of the few assets that tend to rise in price with inflation (Gorton and Rouwenhorst, 2006; Kung, Chepolis and Diorio, 2010; Bhardwaj, Gorton and Rouwenhorst, 2015; Bodie, Kane and Marcus, 2018). As outlined in the literature review, some commodities, especially gold, are even highlighted to carry safe haven properties by being negatively correlated with other assets during periods of market stress (Baur and Lucey, 2010; Baur and McDermott, 2010; Areal, Oliveira and Sampaio, 2015; Bredin, Conlon and Potì, 2017; Conlon, Lucey and Uddin, 2018).

In consequence, Bitcoin's correlations with both gold and crude oil, as well as with an overall commodity index are analyzed. Bloomberg's Gold Spot price (hereafter gold), measured as USD per troy ounce of gold, is widely used as a benchmark for the global gold market and therefore included in this dataset (World Gold Council, 2020). Similarly, the US Crude Oil WTI Cushing OK Spot is widely referred to as the benchmark for the crude oil market and serves as a proxy for this commodity in the dataset (Klein, Pham Thu and Walther, 2018; Corbet, Larkin and Lucey, 2020). Lastly, the S&P Goldman Sachs Commodity Index is used as a broad-based and production weighted benchmark for the performance of the global commodity market. The S&P Goldman Sachs Commodity Index commenced in 1991 and represents an unleveraged, long-only investment in commodity futures spanning the commodity sectors of energy, industrial metals, precious metals, agriculture, and livestock (Bodie, Kane and Marcus, 2018; Goldman Sachs, 2020).

#### *5.3.1.5. Currency Index*

Since Bitcoin's intended purpose is to serve as a currency (Nakamoto, 2008), it is deemed insightful to examine the correlation of Bitcoin with that of a traditional currency index. The relevance of including a currency index into the dataset is further amplified by the fact that the foreign exchange market is the world's largest financial market, with more than 5 trillion USD in daily trading volume (Weil, 2019). Moreover, various studies have pointed out that the foreign-exchange market generally does not trade in sync with stocks and bonds, thereby offering diversification, sometimes even proclaimed safe haven benefits, when included in an investment portfolio (Ranaldo and Söderlind, 2010; Weil, 2019).

Since the analysis assumes that investors use ETFs to trace the development of the selected indices, the traditional currency index for this dataset is chosen based on it being the index traced by the well-known and largest currency ETF - the Invesco DB US Dollar Index Bullish Fund (Fabian, 2017; Jaiswal, 2019). The ETF follows the Deutsche Bank Long USD Currency Portfolio Index Excess Return (hereafter USD Currency Portfolio), which tracks the performance of the US dollar relative to a basket of the six major world currencies: the Euro, Japanese Yen, British Pound, Canadian Dollar, Swedish Krona and Swiss Franc (Bloomberg, 2020c).

#### *5.3.1.6. Real Estate Indices*

Investments in real estate are regarded as a valuable source of diversification because real estate values tend to move slowly and are of relatively stable nature (Bodie, Kane and Marcus, 2018; Swehla, 2020). Accordingly, a real estate index is included in the dataset, which is selected to be the MSCI ACWI Real Estate Index. The MSCI ACWI Real Estate Index is a market capitalization index, which consists of large and mid-cap equity in the real estate sector across 23 developed and 26 emerging countries and which is chosen because of its global orientation (MSCI Inc., 2020). To isolate the correlation between Bitcoin and developed countries, the MSCI World Real Estate Index representing 23 developed markets is chosen. The MSCI Emerging Markets Real Estate Index, accounting for 26 emerging markets, was not available on Bloomberg and Thomson Reuters and, therefore, not included in the dataset (Ibid). Additionally, to isolate the correlation between the US real estate market and Bitcoin, the Dow Jones US Real Estate Index is considered. The Dow Jones

US Real Estate Index tracks the performance of real estate investment trusts and other companies that invest directly or indirectly in real estate (S&P Dow Jones Indices, 2020).

### 5.3.2. Data – Analysis II

In Analysis Level II, the bid-ask spreads of Bitcoin are assessed in comparison to the traditional safe haven asset gold as well as two stocks. Following Smales (2019) and due to Bitcoin's base in blockchain technology, the two chosen stocks are those of technology companies Apple and Twitter. This allows for the comparison of Bitcoin with one relatively volatile stock, Twitter, and one relatively less volatile stock, Apple (Yahoo! Finance, 2020). For gold as well as both stocks, the daily bid-ask spread for the period October 2013 through August 2020 is extracted by the use of Bloomberg's bid-ask spread function. The daily bid-ask spread for Bitcoin in the same period is obtained from data.bitcoinity.org (2020), which provides USD denoted liquidity data for cryptocurrencies traded on the four largest global exchanges Bitfinex, Bitstamp, Coinbase, and Kraken. Moreover, Bitcoin's daily median transaction fee in USD is extracted from blockchain.com (2020). The number of daily transactions is downloaded from charts.bitcoin.com (2020).

### 5.3.3. Data – Analysis III

For Analysis III, weekly return data is needed for the 12 optimizations of diversified test and benchmark portfolios. Given that the portfolios are optimized at the end of each month in the period September 2019 through August 2020 and include two years of rolling data counting from the date at which they are optimized, the entire considered sample period reaches from October 2017 to August 2020. To mimic a US investor who seeks to diversify broadly, globally, and across asset classes, the assets eligible for inclusion into the benchmark portfolio are one world equity, bond, commodity, currency, and real estate index. The respective indices are chosen to be the USD denoted MSCI ACWI Real Estate Index, Bloomberg Barclays Global Aggregate Index, S&P Goldman Sachs Commodity Index, USD Currency Portfolio, and MSCI ACWI Real Estate Index. On top of these assets, the test portfolios also contain the USD denoted Bitcoin in their investment universe. Given that the aforementioned asset indices are also included in Analysis I, this study refers to section 5.3.1. for an introduction to the chosen indices as well as the steps undertaken to transfer the price data into return data.

### 5.3.4. Data – Financial Market Stress Indicators

The financial market stress indicators are used throughout all analyses to provide a meaningful assessment of Bitcoin's characteristics during COVID-19 related financial market stress. The most widely applied index measuring stress in the financial sector is the VIX (Reuters, 2010), which tracks the expected volatility of the S&P 500 Index as a proxy for financial stress. In addition, the STLFSI2 is considered, which measures the degree of financial stress in the US markets on the basis of seven interest rates, six yield spreads, and five other indicators (Federal Reserve Bank of St. Louis, 2020b). However, since the VIX and STLFSI2 are primarily focused on the US, this thesis also includes the GFSI. The GFSI aggregates 23 financial stress measures covering financial risk, hedging demand, and investor appetite for risk across various asset classes (credit, equity, interest rates, forex, and commodity markets) and geographies. Hence, the GFSI covers more aspects of financial markets than the VIX and STLFSI2 do (Reuters, 2010). As a rule of thumb, a VIX level below 12 is generally considered to represent low levels of financial stress, a level above 20 to be high, and a level in between to be normal (Edwards and Preston, 2017). The STLFSI2 reports values below zero in case of below-average financial stress and values above zero during periods of above-average financial stress (Federal Reserve Bank of St. Louis, 2020b). For the GFSI, values greater than zero indicate heightened financial market stress, and vice-versa (Reuters, 2010).

### 5.3.5. Data Limitations

The following depicts the potential limitations and delimitations of the collected data as well as the data collection process. While the above sections have aimed to explain the reasoning behind the choice of data, it is acknowledged that the data, through having been selected by the authors of this thesis, is subject to some degree of researcher bias. It is also worth noting that the chosen asset datasets are by no means an exhaustive list and that a certain degree of overlap between some of the asset indices used for Analysis I exists. As touched upon earlier, the time period chosen for the dataset is naturally limited by the availability of Bitcoin data. While the collected data covers a period of seven years, the accuracy of the dataset could be enhanced by including a longer time period so that the weighting of each individual observation impacting the results is reduced. Consequently, it is recommended that the findings presented in this thesis should be reviewed as soon as a longer return time series of Bitcoin is available. On a general note, it is to be noted that this thesis uses historical data, which according to the efficient market hypothesis should not be an indicator of future performance. Thus, this could pose a limit to the lessons that can be taken from the data analyses and applied in the future. Finally, it is acknowledged that the financial stress indicators chosen to allow for an assessment of Bitcoin's investment characteristics under COVID-19 related financial stress in 2020 are most likely also impacted by financial stress stemming from final BREXIT deal disputes and the upcoming US presidential election (Darbyshire, 2020).

## 5.4. Research Quality

Lastly, it is essential to reflect upon the research quality criteria of positivism: 1) internal validity, 2) external validity, 3) reliability, and 4) objectivity (Guba and Lincoln, 1994). Internal validity in studies of causal relationships refers to proving that it is the independent variable, in this case, Bitcoin, that had an effect on the dependent variable, in this case, the safe haven property against other assets or higher portfolio performance. This thesis limits the effects of external variables on the investigated relationship by 1) graphically examining whether it indeed was Bitcoin's return that increased while the other asset's return decreased during times of market turmoil before concluding on Bitcoin's safe haven ability, 2) comparing the effect of including Bitcoin in a portfolio to a benchmark portfolio which does not include an investment in Bitcoin. By selecting a large sample of well-known indices representing different asset classes and geographies as the data input, a certain level of generalizability, also defined as external validity, is established. Also, given that the market capitalization of Bitcoin constitutes approximately 66 percent of the total of all cryptocurrencies in 2020, the findings can, to some extent, be generalized to the wider cryptocurrency market. However, this thesis acknowledges that further research on similarities between Bitcoin and other virtual currencies is needed to support this claim. A degree of reliability is ensured by utilizing publicly available data and meticulously following and describing the applied theories and models, which ensure that the results are replicable by other authors using the same data sample and time period. However, given that Bitcoin's investment characteristics during crises are largely dependent on investor behavior, the reliability of the results decreases as results may vary between different points in time. Lastly, the use of publicly available data, the thorough description of the methods employed, the presence of two researchers conducting the study, as well as the application of multiple analytical methods enhance the objectivity of this thesis.

# 6. Empirical Results

Section 6 reports the empirical results generated by Analysis I, II, and III. Following the methodological approach displayed in Figure 3, the results are systematically presented for each analysis. The results of Analysis I display Bitcoin's time-varying correlation with a sample of asset indices. In line with the definitions outlined in section 1.2., this allows for an assessment of whether and to which extent Bitcoin serves as a safe haven during the persisting COVID-19 pandemic. The results of Analysis II complete the examination of Bitcoin's potential to serve as a safe haven by investigating the extent to which Bitcoin is fulfilling the liquidity requirement inherent in the definition of a safe haven. Finally, the results of Analysis III shed light on Bitcoin's ability to be of additive value to a diversified portfolio during COVID-19.

## 6.1. Empirical Results – Analysis I

The following sections present the empirical findings of Analysis I, which explore Bitcoin's correlation with a sample of asset indices during the persisting COVID-19 crisis. First, the stylized facts of the returns of the assets included in the correlation analysis are summarized to provide a general overview of the data. Second, the results of the regression analyses on the DCCs extracted from the DCC GARCH model are presented. These allow for the classification of Bitcoin as a safe haven, hedge, or diversifier. Third, a graphical approach is embraced to visualize the time-varying returns and correlations of Bitcoin and those asset indices for which the regression analyses determined Bitcoin to be a safe haven. This allows for the final confirmation or rejection of Bitcoin's safe haven properties. Moreover, it allows for an assessment of the time horizon for which Bitcoin carries this potential property.

### 6.1.1. Stylized Facts

Table 2 displays the stylized facts of the weekly asset return data for the period from October 2013 through August 2020. The assets considered for this analysis are delineated in data section 5.3.1. and have been organized according to their asset classes. The table reports the number of observations, means, standard deviations, maximum values, minimum values, the 1%, 5%, and 10% lowest quantiles, the kurtosis and skewness, as well as the ADF of the return data.

**Table 2:** Stylized Facts – Weekly Return Data

Stylized Facts Regression Analysis — Oct 2013 - Aug 2020

| | Observations | Mean | St.Dev. | Min | Max | Q1 | Q5 | Q10 | Skewness | Kurtosis | ADF (P-value) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ***Bitcoin Index*** | | | | | | | | | | | |
| Bitcoin USD | 360 | 1.2657% | 10.8955% | -44.8024% | 52.4735% | -27.3683% | -14.9729% | -10.7178% | 0.5380 | 7.0893 | 0.0000 |
| Bitcoin EUR | 360 | 1.3017% | 10.8674% | -43.2127% | 53.4911% | -26.8611% | -14.7871% | -10.4298% | 0.5706 | 7.0375 | 0.0000 |
| Bitcoin GDP | 360 | 1.3162% | 10.8814% | -38.6900% | 53.1719% | -27.6945% | -14.4268% | -10.8747% | 0.5775 | 6.7524 | 0.0000 |
| Bitcoin CNY | 360 | 1.2975% | 10.8913% | -43.6948% | 52.5430% | -27.3815% | -14.7399% | -10.7174% | 0.5478 | 7.0171 | 0.0000 |
| Bitcoin JPY | 360 | 1.2873% | 10.9238% | -42.7085% | 53.6347% | -26.4810% | -15.2648% | -11.3680% | 0.6041 | 7.0867 | 0.0000 |
| Bitcoin HDK | 360 | 1.2655% | 10.8956% | -44.7380% | 52.3877% | -27.3592% | -14.9441% | -10.7655% | 0.5391 | 7.0755 | 0.0000 |
| Bitcoin INR | 360 | 1.3151% | 10.9048% | -44.6450% | 52.4639% | -27.1159% | -14.8580% | -10.5265% | 0.5332 | 7.0560 | 0.0000 |
| ***Equity Indices*** | | | | | | | | | | | |
| MSCI ACWI (World) | 360 | 0.1178% | 2.1515% | -13.2267% | 9.9544% | -6.3629% | -2.9194% | -1.9976% | -1.3756 | 13.5642 | 0.0000 |
| MSCI World (Developed) | 360 | 0.1284% | 2.1820% | -13.2994% | 10.4180% | -6.2869% | -2.9637% | -2.0925% | -1.3687 | 14.2028 | 0.0000 |
| MSCI Emerging Markets (Emerging) | 360 | 0.0297% | 2.4125% | -12.7205% | 7.4841% | -7.4172% | -3.7645% | -1.3356% | -0.6680 | 6.1321 | 0.0000 |
| S&P 500 (US) | 360 | 0.2028% | 2.2829% | -16.2279% | 1.1424% | -7.3122% | -3.3249% | -2.0808% | -1.4706 | 15.0403 | 0.0000 |
| Shanghai Stock Exchange Composite (China) | 360 | 0.1245% | 3.0430% | -14.2909% | 9.0735% | -10.5386% | -5.0022% | -3.1413% | -0.9346 | 6.7077 | 0.0000 |
| NIKKEI 225 (Japan) | 360 | 0.1360% | 2.9832% | -17.4281% | 15.8171% | -8.4781% | -4.9618% | -3.0664% | -0.5469 | 8.9880 | 0.0000 |
| Hang Seng Index (Hong Kong) | 360 | 0.0261% | 2.4320% | -9.9725% | 7.6034% | -6.8190% | -4.0725% | -3.0306% | -0.3206 | 4.0336 | 0.0000 |
| FTSE 100 (UK) | 360 | -0.0220% | 2.2373% | -18.5921% | 7.5921% | -6.0246% | -3.1362% | -2.4317% | -1.9361 | 17.9191 | 0.0000 |
| CAC 40 (France) | 360 | 0.0510% | 2.7464% | -22.1425% | 10.1642% | -7.1472% | -3.9300% | -3.0231% | -1.7057 | 15.7004 | 0.0000 |
| DAX (Germany) | 360 | 0.1147% | 2.8965% | -22.3297% | 10.3521% | -8.1583% | -4.2532% | -3.2300% | 1.4961 | 14.0046 | 0.0000 |
| S&P BSE 500 (India) | 360 | 0.2064% | 2.3319% | -13.0411% | 11.4555% | -7.2111% | -3.6781% | -2.3513% | -0.6426 | 8.3631 | 0.0000 |
| ***Bond Indices*** | | | | | | | | | | | |
| Bloomberg Barclays Global Aggregate Index (World) | 360 | 0.0471% | 0.7436% | -3.9076% | 3.1242% | -2.2459% | -1.1032% | -0.7707% | -0.7892 | 7.8150 | 0.0000 |
| FTSE World Government Bond Index (World) | 360 | 0.0073% | 0.8532% | -3.8116% | 3.2416% | -2.5038% | -1.3488% | -0.9320% | -0.0344 | 5.3577 | 0.0000 |
| Bloomberg Barclays Global Aggregate Corporate Index (World) | 360 | 0.0745% | 0.8620% | -8.3576% | 4.6423% | -1.9519% | -0.9445% | -0.6173% | -3.5536 | 39.5995 | 0.0000 |
| J.P. Morgan Emerging Market Bond Index (Emerging) | 360 | 0.0122% | 1.3765% | -14.1767% | 6.8517% | -3.8236% | -1.6567% | -1.1423% | -3.5573 | 41.3808 | 0.0000 |
| Bloomberg Barclays US Aggregate Bond Index (US) | 360 | 0.0753% | 0.5086% | -3.2179% | 2.6203% | -1.4918% | -0.7578% | -0.5050% | -0.9622 | 10.4924 | 0.0000 |
| ***Commodity Indices*** | | | | | | | | | | | |
| US Crude Oil WTI Cushing OK Spot | 360 | -0.2451% | 5.8941% | -34.6863% | 27.5756% | -21.9270% | -8.7499% | -6.5604% | -0.5393 | 9.4649 | 0.0000 |
| S&P Goldman Sachs Commodity Index (World) | 360 | -0.1587% | 2.8371% | -14.5503% | 8.0998% | -11.1030% | -4.7368% | -3.4460% | -0.9419 | 6.4191 | 0.0000 |
| Gold Spot US Dollar | 360 | 0.1124% | 1.9470% | -8.9958% | 8.2886% | -4.6883% | -3.0568% | -2.1309% | -0.0777 | 4.9432 | 0.0000 |
| ***Currency Index*** | | | | | | | | | | | |
| Deutsche Bank Long USD Currency Portfolio Index | 360 | 0.0471% | 0.9913% | -4.9160% | 4.5442% | -2.2134% | -1.5572% | -1.1254% | 0.0206 | 5.6023 | 0.0000 |
| ***Real Estate Indices*** | | | | | | | | | | | |
| MSCI ACWI Real Estate Index (World) | 360 | 0.0311% | 2.5274% | -22.7840% | 15.4623% | -6.7007% | -3.0731% | -2.0850% | 1.7614 | 27.8319 | 0.0000 |
| MSCI World Real Estate Index (Developed) | 360 | 0.0418% | 2.6111% | -23.8142% | 16.7570% | -7.1696% | -2.9104% | -2.0799% | -1.7184 | 29.6224 | 0.0000 |
| Dow Jones US Real Estate Index (US) | 360 | 0.0767% | 3.0422% | -28.3846% | 20.4030% | -9.1235% | -3.7192% | -2.6839% | -1.6565 | 31.4389 | 0.0000 |

The above table shows that Bitcoin, regardless of its currency denomination, provides the highest mean of weekly returns during the entire sample period. The mean of Bitcoin's weekly returns denominated in different currencies ranges from 1.2655% to 1.3151%. In line with previous literature, this data sample supports findings on Bitcoin's high price volatility as outlined by its standard deviation of 10 to 11% and wide minimum-maximum spread ranging from weekly returns of -44.8024% to 53.6347%. Thereby, Bitcoin denotes the by far largest deviations from the mean across all included assets and reports the lowest 1%, 5%, and 10% return percentiles. Despite its high observed negative returns, Bitcoin exhibits a positively skewed distribution with values circling between 0.5 and 0.6, which are only outperformed by the MSCI ACWI Real Estate Index and DAX. Lastly, all Bitcoin asset return series are found to be leptokurtic, meaning that kurtosis exceeds three, thereby presenting tails that are heavier than normal, i.e., more observations appear with extreme values. In fact, the leptokurtic characteristic holds for all the considered assets with the kurtosis parameters ranging from 4.0336 for the Hang Seng Index to 41.3808 for the J.P Morgan Emerging Market Bond Index. Moreover, all asset indices register skewness. Except for Bitcoin, the DAX, USD currency Portfolio, and MSCI ACWI Real Estate Index, the skewness of all asset indices is negative, indicating a skew to the left with more observations carrying values in the lower end of the spectrum. Hence, it can be concluded that the asset indices' returns follow a non-normal distribution.

Continuing in accordance with the layout of Table 2, all equity indices, besides FTSE 100 with a mean of -0.02195%, rendered positive weekly mean returns ranging from 0.0261% to 0.2064%. Relative to Bitcoin, the equity indices report low standard deviations between 2% and 3%. Contrary to Bitcoin, the equity indices do not demonstrate minimum and maximum values of equal latitude. The lowest minimum returns of approximately -22% are observed for the CAC 40 and DAX, while the highest maximum value of 15.8171% is rendered by Nikkei 225. Lastly, it can be inferred that the Shanghai Stock Exchange Composite has experienced the lowest 1% return quantile with -10.5386%.

The bond indices experienced mean weekly returns ranging from 0.0073% to 0.0753%. In comparison to Bitcoin, the standard deviations, measured between 0% and 1.5%, are very low, with the J.P Morgan Emerging Market Bond index being the most volatile. This is also indicated by the fact that it has the lowest minimum observed return of -14.5503%. For commodities, currencies, and real estate, a common pattern of relatively low standard deviations emerges. An exception to this pattern is driven by the crude oil index, which has experienced volatile weekly returns ranging from a minimum of -34.6863% to a maximum of 27.5756%. On the contrary, the USD Currency Portfolio has exhibited a very low standard deviation with a minimum return of -4.9160% and a maximum of 4.5442%.

For all asset indices, except the HSI Index, the minimum observed return value lies between March 13th and 27th, 2020, which, as outlined in the background section, covers the period in which the WHO declared COVID-19 a global pandemic and governments all around the world began announcing countrywide lockdowns. Interestingly, the maximum observed return values of all asset indices, but Bitcoin, HSI Index, and Shanghai Stock Exchange Composite Index, lie close to the minimum observed values, namely from March 20th and onwards. Consequently, this emphasizes that COVID-19 caused a period of extreme financial market distress characterized by high volatility. In addition, it appears to be the first such period experienced by Bitcoin. However, Bitcoin's maximum weekly return of 52.473% was observed at the beginning of December 2017. This peak has been construed as excitement over the start of Bitcoin Futures' trading at CBOE on December 10th, 2017, which some regarded as a prelude to wider acceptance of Bitcoin as a store of value (Sharma, 2017). Finally, it is essential to note that the ADF test reports p-values of 0.000 for all asset indices. For that reason, it can be inferred that the datasets do not contain unit roots but resemble random walks. This is imperative when using data for modeling and regression analyses since non-stationary time series can lead to spurious regressions.

### 6.1.2. Regression Analyses

The empirical results of the regression analyses on Bitcoin's safe haven capabilities under the COVID-19 crisis are presented in the following. First, the section dwells upon how the regression coefficients generated by the COVID-19 regressions, as well as the lowest return quantile regression, should be understood. Second, the DCC estimates (hereafter referred to as correlation) of the regression analyses are reported categorically by asset class.

#### *6.1.2.1. Regression Interpretation and Estimates*

Tables 3 and 4 summarize the estimation results on the safe haven, hedge, and diversification capabilities of Bitcoin during the COVID-19 crisis. Table 5 displays the results of the lowest return quantile regression for the entire data period, which, as outlined in the methodology section, is included for robustness purposes. The use of a robustness check is necessary for two reasons. First, Bitcoin can only be regarded as a safe haven if the return of Bitcoin increases, while the return of the other asset decreases during a period of financial market stress. Thus, if the empirical results estimated in the COVID-19 regression analyses (Table 3 & 4) reveal that Bitcoin and the different indices are negatively correlated during the COVID-19 periods, this could also be the result of a decrease in the value of Bitcoin and an increase in the value of the respective asset. Since the quantile regression only reports the correlation for the lowest return quantile observations of the respective asset, a negative correlation automatically means that Bitcoin's value increased while the asset's value was at its lowest. The stylized facts, described in section 6.1.1., showed that the minimum observed returns of all assets, except the HSI index, over the entire sample period, lie during the COVID-19 crisis. Hence, whenever the COVID-19 regressions suggest Bitcoin to serve as a safe haven, this finding is checked against the quantile regression results. If both the COVID-19 and quantile regression report negative correlation estimates, more evidence is provided in favor of Bitcoin serving as a safe haven against the respective asset during the COVID-19 crisis. To finally confirm Bitcoin's safe haven potential against the respective asset, the returns of both assets need to be graphed against each other to detect whether Bitcoin's return increases while the assets' return decreases. Second, the quantile regression serves as a confirmation of whether the observations from the COVID-19 regressions also hold during a wider period of data. For all three regressions, significantly negative coefficients in the

$c_0$ column indicate that Bitcoin is a hedge against the particular asset index on average during all the weeks not captured by the dummy variables. On the contrary, positive $c_0$ coefficients, which are different from one, indicate that Bitcoin carries diversification benefits against the specific asset index on average during all the weeks not captured by the dummy variables. To hereafter ease the description of the $c_0$ coefficients, this thesis refers to it as denoting Bitcoin's hedge or diversification capabilities on average. For Tables 3 and 4, the dummy coefficient $c_1$ reports the marginal effect of the specified COVID-19 periods on the average correlation between Bitcoin and the respective asset index. Similarly, for Table 5, the dummy coefficients $c_1, c_2, c_3$ are to be interpreted as the marginal effect of the 1, 5, and 10% lowest return quantiles of each asset index on the average correlation between Bitcoin and the respective asset index. Thereby, all dummy coefficients represent periods of market distress. To determine whether Bitcoin provides safe haven capabilities, the marginal effects should be seen in light of the overall regression that specifies the correlation and thereby as the sum of $c_0$ and the respective $c_1, c_2, or\ c_3$ coefficients.

**Table 3:** Regression Analysis – Long COVID-19 Period

| Regression Analysis COVID-19 Long Period — February 28th, 2020 – August 31st, 2020 | | |
|---|---|---|
| | $(c_0)$ | COVID-19 $(c_1)$ |
| ***Equity Indices*** | | |
| MSCI ACWI (World) | 0.0353975*** | 0.1856339*** |
| MSCI World (Developed) | 0.1095502*** | 0.0430227*** |
| MSCI Emerging Markets (Emerging) | 0.0562469*** | 0.0524859*** |
| S&P 500 (US) | 0.0562669*** | 0.1073324*** |
| Shanghai Stock Exchange Composite (China) | 0.0249235*** | 0.012817*** |
| NIKKEI 225 (Japan) | 0.1845769*** | 0.0284439*** |
| Hang Seng Index (Hong Kong) | 0.0293115*** | 0.0434229*** |
| FTSE 100 (UK) | 0.1079755*** | 0.0028325** |
| CAC 40 (France) | 0.0419373*** | 0.1539262*** |
| DAX (Germany) | 0.1609054*** | 0.0031541 |
| S&P BSE 500 (India) | -0.0294632*** | -0.0096454 |
| ***Bond Indices*** | | |
| Bloomberg Barclays Global Aggregate Index (World) | 0.0799029*** | 0.0014534 |
| FTSE World Government Bond Index (World) | 0.0213107*** | 0.1000574*** |
| Bloomberg Barclays Global Aggregate Corporate Index (World) | 0.0900762*** | 0.0035544** |
| J.P. Morgan Emerging Market Bond Index (Emerging) | 0.1144646*** | 0.0036707*** |
| Bloomberg Barclays US Aggregate Bond Index (US) | 0.0457501*** | 0.0028862*** |
| ***Commodity Indices*** | | |
| XAU Gold Price | 0.0593682*** | 0.0038897*** |
| US Crude Oil WTI Cushing OK Spot | -0.0133798*** | 0.2112646*** |
| S&P Goldman Sachs Commodity Index (World) | -0.0071101* | 0.2388982*** |
| ***Currency Index*** | | |
| Deutsche Bank Long USD Currency Portfolio Index Excess Return | -0.0630532*** | -0.0817844*** |
| ***Real Estate Indices*** | | |
| MSCI ACWI Real Estate Index (World) | 0.0309227*** | 0.0496954*** |
| MSCI World Real Estate Index (Developed) | -0.0136834*** | 0.1979154*** |
| Dow Jones US Real Estate Index (US) | 0.0123225*** | 0.0003689*** |

*Note:* This table presents the estimation results from *Equation (6)*
***, **, *indicate statistical significance at the 1%, 5% and 10% level

**Table 4:** Regression Analysis – Short COVID-19 Period

| Regression Analysis COVID-19 Short Period — February 28th, 2020 – April 10th, 2020 | | |
|---|---|---|
| | $(c_0)$ | COVID-19 $(c_1)$ |
| ***Equity Indices*** | | |
| MSCI ACWI (World) | 0.0463648*** | 0.1270288*** |
| MSCI World (Developed) | 0.1108176*** | 0.0947998*** |
| MSCI Emerging Markets (Emerging) | 0.0574514*** | 0.1331756*** |
| S&P 500 (US) | 0.0625578*** | 0.0760312*** |
| Shanghai Stock Exchange Composite (China) | 0.0253346*** | 0.0265207*** |
| NIKKEI 225 (Japan) | 0.1848302*** | 0.0926595*** |
| Hang Seng Index (Hong Kong) | 0.0302152*** | 0.1149401*** |
| FTSE 100 (UK) | 0.1080767*** | 0.0053292** |
| CAC 40 (France) | 0.0510408*** | 0.104848*** |
| DAX (Germany) | 0.1610637*** | 0.0035985 |
| S&P BSE 500 (India) | -0.0293685*** | -0.0406791*** |
| ***Bond Indices*** | | |
| Bloomberg Barclays Global Aggregate Index (World) | 0.0799029*** | 0.0014534 |
| FTSE World Government Bond Index (World) | 0.0274561*** | 0.0564711*** |
| Bloomberg Barclays Global Aggregate Corporate Index (World) | 0.0902248*** | 0.0055822** |
| J.P. Morgan Emerging Market Bond Index (Emerging) | 0.1145278*** | 0.0103944*** |
| Bloomberg Barclays US Aggregate Bond Index (US) | 0.004493*** | 0.0458715*** |
| ***Commodity Indices*** | | |
| XAU Gold Price | 0.0594487*** | 0.0103197*** |
| US Crude Oil WTI Cushing OK Spot | -0.0011559 | 0.157783*** |
| S&P Goldman Sachs Commodity Index (World) | 0.0066507 | 0.1816065 *** |
| ***Currency Index*** | | |
| Deutsche Bank Long USD Currency Portfolio Index Excess Return | -0.0673427*** | -0.0837836*** |
| ***Real Estate Indices*** | | |
| MSCI ACWI Real Estate Index (World) | 0.0326316*** | 0.0969452*** |
| MSCI World Real Estate Index (Developed) | -0.0021241 | 0.1422867*** |
| Dow Jones US Real Estate Index (US) | 0.0123313*** | 0.0009168*** |

*Note:* This table presents the estimation results from *Equation (7)*
***, **, *indicate statistical significance at the 1%, 5% and 10% level

For Tables 3 and 4, which report *COVID-19* $c_1$ coefficients, it follows that if these are negative, the correlation between Bitcoin and the analyzed asset index is decreasing during the COVID-19 crisis. To determine whether Bitcoin acts as a safe haven during these periods, three properties must be fulfilled. First, the *COVID-19* $c_1$coefficients must be significantly negative, as this provides evidence of a negative effect on the overall correlation within the period. Second, the sum of the regression, thereby $c_0$ and $c_1$, must also be negative to provide safe haven properties. In contrast, if the sum of $c_0$ and $c_1$ remains positive, Bitcoin only provides diversification benefits against the other assets. If $c_1$ then is positive (negative) Bitcoin becomes more (less) correlated with the asset index during the COVID-19 period, thereby providing a weaker (stronger) diversification benefit. Third, Bitcoin's value must go up, while the respective assets' value declines during the periods in which the regression claims the two to be negatively correlated. The latter analysis is performed by comparing the results to the quantile regression as well as by graphically visualizing the returns of Bitcoin and the assets, with which Bitcoin is negatively correlated.

**Table 5:** Regression Analysis – Quantiles

| Regression Analysis Lower Return Quantiles — Oct 2013 - Aug 2020 | | | | |
|---|---|---|---|---|
| | $(c_0)$ | 1% quantile $(c_1)$ | 5% quantile $(c_2)$ | 10% quantile $(c_3)$ |
| ***Equity Indices*** | | | | |
| MSCI ACWI (World) | 0.0450871*** | 0.0395976 | -0.0021301 | 0.0341073** |
| MSCI World (Developed) | 0.1106431*** | 0.0355772* | 0.0141263 | 0.0091572 |
| MSCI Emerging Markets (Emerging) | 0.0588427*** | 0.1190526*** | 0.0134536 | -0.0079341 |
| S&P 500 (US) | 0.0613525*** | 0.0409155* | 0.0124355 | 0.0160394 |
| Shanghai Stock Exchange Composite (China) | 0.0256268*** | -0.0170736* | 0.0077812 | 0.000249 |
| NIKKEI 225 (Japan) | 0.1861573*** | -0.0178573 | 0.041636 | -0.0140513** |
| Hang Seng Index (Hong Kong) | 0.0304036*** | -0.0038942 | 0.006122 | 0.0178421* |
| FTSE 100 (UK) | 0.1080416*** | -0.0007504 | 0.0008168 | 0.0010608 |
| CAC 40 (France) | 0.0520891*** | 0.0260565 | 0.011083 | 0.0014971 |
| DAX (Germany) | 0.1609162*** | -0.0000338 | 0.0009048 | 0.0017219 |
| S&P BSE 500 (India) | -0.030538*** | -0.0287632 | -0.0068031 | 0.0103549 |
| ***Bond Indices*** | | | | |
| Bloomberg Barclays Global Aggregate Index (World) | 0.0800304*** | 0.0001047 | 0.0027462 | -0.0016064 |
| FTSE World Government Bond Index (World) | 0.0302765*** | 0.01898 | 0.0037611 | -0.0211354* |
| Bloomberg Barclays Global Aggregate Corporate Index (World) | 0.0904608*** | 0.0026277 | 0.0049857** | -0.0040523** |
| J.P. Morgan Emerging Market Bond Index (Emerging) | 0.1146567*** | 0.0070104*** | 0.0027333 | -0.0014097 |
| Bloomberg Barclays US Aggregate Bond Index (US) | 0.0459533*** | 0.001888 | 0.001353 | -0.0008283 |
| ***Commodity Indices*** | | | | |
| XAU Gold Price | 0.0597*** | 0.0004007 | 0.0000409 | -0.0005814 |
| US Crude Oil WTI Cushing OK Spot | -0.0005181 | 0.1764032*** | 0.0016825 | 0.0038879 |
| S&P Goldman Sachs Commodity Index (World) | 0.0090764* | 0.2007879*** | -0.0423792 | 0.0100026 |
| ***Currency Index*** | | | | |
| Deutsche Bank Long USD Currency Portfolio Index Excess Return | -0.070628*** | -0.0329217 | 0.0237462 | 0.0082561 |
| ***Real Estate Indices*** | | | | |
| MSCI ACWI Real Estate Index (World) | 0.0329914*** | 0.0546656*** | 0.0224989** | -0.0020611 |
| MSCI World Real Estate Index (Developed) | -0.0028076 | 0.0942947** | 0.0302639 | 0.0088739 |
| Dow Jones US Real Estate Index (US) | 0.012335*** | 0.0009489*** | -0.00005 | 0.0000615 |

*Note:* This table presents the estimation results from *Equation (8)*
***, **, *indicate statistical significance at the 1%, 5% and 10% level

For Table 5 it follows that if the $c_1, c_2,$ or $c_3$ coefficients are negative, the correlation between Bitcoin and the analyzed assets indices are decreasing during the lowest return quantiles of the respective asset index. To determine whether Bitcoin acts as a safe haven during these periods, two properties must be fulfilled. First, the $c_1, c_2,$ and $c_3$ coefficients must be significantly negative. Second, the sum of the regression must also be negative for Bitcoin to provide safe haven properties. The overall effect for any quantile is given by the sum of all coefficient estimates down to the chosen quantile. Hence, Bitcoin is a safe haven in the period displaying the 1% lowest quantile of the asset returns, if $c_1$ is significantly negative and the sum of coefficients $c_0$, $c_1, c_2,$ and $c_3$ are negative.

### *6.1.2.2. Regression Results*

The presentation of the empirical results has been divided according to asset classes, as presented in the above tables. The three regression results displayed in Table 3, 4, and 5 are interpreted in comparison to each other. The primary focus is on the COVID-19 regressions as the quantile regression is applied for robustness and verification purposes.

#### 6.1.2.2.1. Equity Indices

The results displayed in Table 3, 4, and 5 provide evidence that the correlations between Bitcoin and all the equity indices on average, defined by $c_0$, are significantly positive at the 1% significance level. The only exception is the Indian S&P BSE 500 index. In addition to the positive correlation during normal times, the $c_1, c_2,$ and $c_3$ coefficients presented in all of the above tables are either insignificantly different from zero or significantly positive. In this case, the Japanese Nikkei 225 and the Shanghai Stock Exchange Composite Index form exceptions for respectively the 10% and 1% quantile. Consequently, Bitcoin is a mere diversifier for world, developing, and emerging market equity indices as well as the country-specific equity indices of the US, Hong Kong, UK, France, and Germany on average as well as during periods of market stress. Across the three tables, the positive $c_0$ coefficients thereby range from a minimum of 0.0256 for the Chinese equity index to a maximum of 0.1846 for the Japanese equity index. The low but positive correlation between Bitcoin and each of the equity indices suggests that Bitcoin can generally provide a substantial diversification benefit. The fact that the coefficients for the quantiles and COVID-19 periods are either significantly positive or insignificantly different from zero signifies that Bitcoin does not provide any additional diversification benefits during these periods of market turmoil. However, as delineated above, the $c_3$ coefficient of the Nikkei 225, representing its 10% lowest return quantile, as well as the $c_1$ coefficient of the Shanghai Stock Exchange Composite, denoting the 1% lowest quantile of its returns, display significant negative marginal effects. This indicates that the correlation between Bitcoin and the two respective indices decreases during market turmoil. Since the two dummy coefficients are not negative enough to let the sum of the remaining coefficients reach below zero, there is merely talk of an improvement of the diversification benefits. Consequently, Bitcoin does not stipulate any safe haven capabilities against the aforementioned equity indices.

On the contrary, the correlation between Bitcoin and the Indian S&P BSE 500 is significantly negative during normal times across all three tables, as proven by the negative $c_0$ coefficients. These range between -0.0305 and -0.0294, thereby highlighting a relatively small negative correlation at the 1% significance level. Considering the periods of market turmoil, the quantile coefficients $c_1, c_2,$ and $c_3$ of Table 5 as well as the entire COVID-19 period represented by $c_1$ in Table 3 exhibit negative marginal effects, which, however, prove insignificantly different from zero. Coefficient $c_1$ of Table 4, however, reports a negative marginal effect of the short COVID-19 sub-period measured at -0.0407 at a 1% significance level. Consequently, it can be inferred that Bitcoin potentially served as a safe haven against the Indian equity index during both COVID-19 periods and other times of Indian equity market stress.

#### 6.1.2.2.2. Bond Indices

A clear picture arises when interpreting the coefficients for the bond indices presented across the three tables. The positive $c_0$ coefficients show that Bitcoin can solely serve as a diversifier for the bond indices, regardless of their categorical as well as geographical nature. It is, however, noteworthy that Bitcoin takes the role of a relatively strong diversifier with low correlations ranging from 0.0045 between Bitcoin and the Bloomberg Barclays US Aggregate Bond Index (US) to 0.1147 between Bitcoin and the J.P. Morgan Emerging Market Bond Index (Emerging) in Table 5. All coefficients are significant at a 1% level. For both regressions employing COVID-19 dummy variables, the coefficients $c_1$ report positive marginal values, which are either significant or insignificantly different from zero (Table 3 & 4). This suggests that Bitcoin does not become a stronger diversifier for bond indices and instead becomes more correlated during the COVID-19 crisis. The sole exception is the Bloomberg Barclays Global Aggregate Index, for which the correlation with Bitcoin remains the same as on average.

To test the robustness of the above findings, Table 5 discloses that the marginal effects during the periods showing each bond's lowest return quantile were primarily insignificantly different from zero or slightly significantly positive. This resembles the findings from the COVID-19 regressions. However, the FTSE World Government Bond Index and Bloomberg Barclays Global Aggregate Corporate Index report that the correlation with Bitcoin respectively declined with -0.0211 and -0.0041 at a 10% and 5% significance level. Thereupon, it is acknowledged that the correlation between Bitcoin and the two aforementioned bond indices slightly decreases during times of turmoil.

#### 6.1.2.2.3. Commodity Indices

The results presented in Table 3, 4, and 5 coherently exhibit that the correlation between Bitcoin and gold is significantly positive on average with $c_0$ coefficients of 0.0594, 0.0594, and 0.0597. In addition, the marginal effects on the correlations during the COVID-19 periods are solely positive at a significance level of 1%, thereby indicating that the COVID-19 crisis only causes Bitcoin and gold to become more correlated. For the periods in which gold returns are at their lowest, as represented by the coefficients $c_1, c_2,$ and $c_3$ in Table 5, the marginal effects are insignificantly different from zero, suggesting that these periods have no additional effect on the correlation between Bitcoin and gold.

In contrast, the correlations between Bitcoin and crude oil take on negative values of -0.0134, -0.0012, and -0.0005 on average, as presented by the $c_0$ coefficients in Table 3, 4, and 5. However, only the $c_0$ coefficient from Table 3 is significant, while Table 4 and 5 report coefficients insignificantly different from zero. This suggests Bitcoin to be a modest hedge against crude oil on average. The marginal effects of both COVID-19 periods, as well as periods of extreme decline in oil returns, indicate that the two assets become more correlated during times of market turmoil. Hence, Bitcoin can only be an effective diversifier against crude oil during these times.

Lastly, for the S&P Goldman Sachs Commodity Index, the projected estimates are decidedly mixed as Table 3, 4, and 5 report $c_0$ coefficients of -0.0071, -0.0067, and 0.0091. Hence, it is suggested that Bitcoin is only an effective diversifier. This indecisive image continues for the marginal coefficients, which are either insignificantly different from zero or positive, revealing that these periods have no decreasing effect on the correlation between Bitcoin and the S&P Goldman Sachs Commodity Index.

#### 6.1.2.2.4. Currency Index

Similar to the findings for the Indian equity index, the correlation between Bitcoin and the USD Currency Portfolio is significantly negative on average, as reported by the $c_0$ coefficients in all three tables. Thus, it is established that Bitcoin can be a hedge against the USD Currency Portfolio, suggesting that Bitcoin can reduce the risk associated with adverse movements in the USD Currency Portfolio on average. Moreover, the marginal effects of both COVID-19 periods are significantly negative at the 1% level with $c_1$ coefficients reporting a value of -0.0818 for the long COVID-19 period and -0.0838 for the short COVID-19 period. This indicates that the overall correlation between Bitcoin and the USD Currency Portfolio for the long COVID-19 period is -0.1448 (the sum of $c_0$ and $c_1$), and -0.1511 for the short COVID-19 period. Thus, the results suggest that Bitcoin served as a safe haven during both periods and as a moderately stronger safe haven during the short COVID-19 period. It is, however, essential to note that the quantile regression does not explicitly support the safe haven findings, as $c_1, c_2,$ and $c_3$ are insignificantly different from zero. This suggests that periods of low negative returns in the USD Currency Portfolio do not further change the correlation between Bitcoin and the USD Currency Portfolio. However, since the correlation on average is negative, and the marginal effects are insignificantly different from zero, the correlation appears to remain negative during periods of market stress.

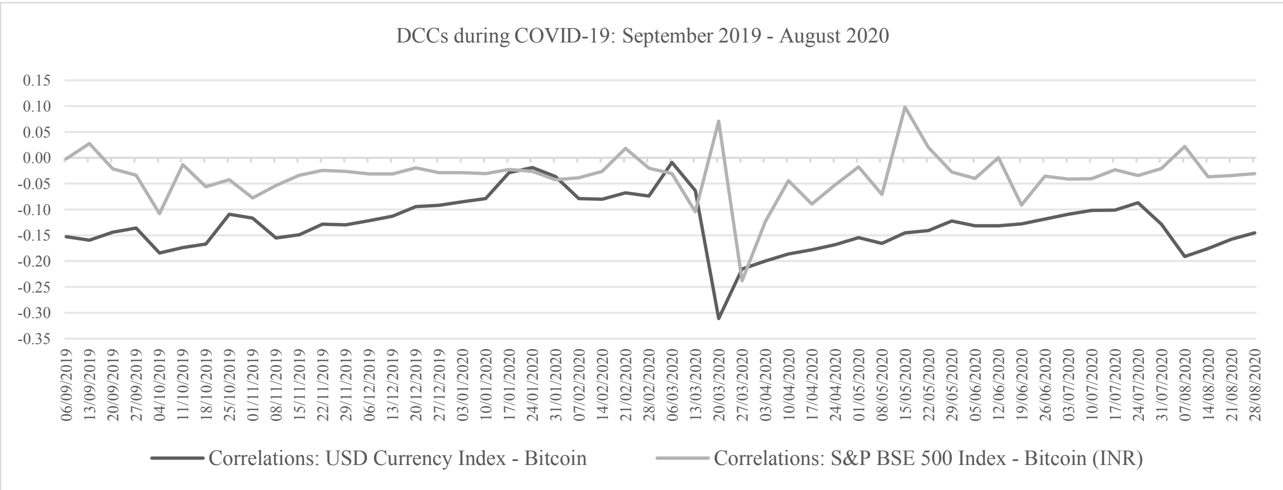
#### 6.1.2.2.5. Real Estate Indices

Finally, the correlations between Bitcoin and the three real estate indices, representing the world, developed countries, and the US, are on average either significantly positive or insignificantly different from zero. The MSCI World Real Estate Index in Table 3 poses an exception with a $c_0$ coefficient of -0.0137 at a 1% significance level. Thus, while Table 3 suggests Bitcoin to be a modest hedge for the MSCI World Real Estate Index on average, all other tables project Bitcoin to only be an effective diversifier. The marginal effects of both COVID-19 and extreme periods of decline are significantly positive or indifferent from zero, providing evidence of no supplementary diversifying effect of these periods on the correlations. On the contrary, both COVID-19 regressions imply that Bitcoin and the Real Estate indices become more correlated during the COVID-19 crisis.

### 6.1.3. Graphical Analyses

To substantiate the above findings and to understand whether the estimates provided by the regression analyses hold true throughout the entire investigated COVID-19 pandemic, the time-varying correlations between Bitcoin and each asset index are displayed graphically in Appendix 8 for a one-year period from September 2019 through August 2020. In accordance with the structure employed for analyzing the regression coefficients, the correlations are mapped for each of the five asset classes. This leads to the confirmation that the time-varying correlations did not go (significantly) below zero throughout the entire COVID-19 period, except for the correlations between Bitcoin and the S&P BSE 500 as well as the USD Currency Portfolio (see Figure 4). For the two latter, the regression analyses estimated significant negative coefficients, which indicated that Bitcoin could potentially be a safe haven during the COVID-19 crisis. However, to finally confirm this property, the graphed time-varying correlations between Bitcoin and the two assets are further investigated to understand whether the correlation remains negative for the entire period. Lastly, the returns of Bitcoin and the two indices are portrayed to evaluate whether it, in fact, is Bitcoin that serves as a safe haven against the two indices and not vice versa. All three figures enable an analysis of the time horizon throughout which Bitcoin or the indices provide potential safe haven capabilities.

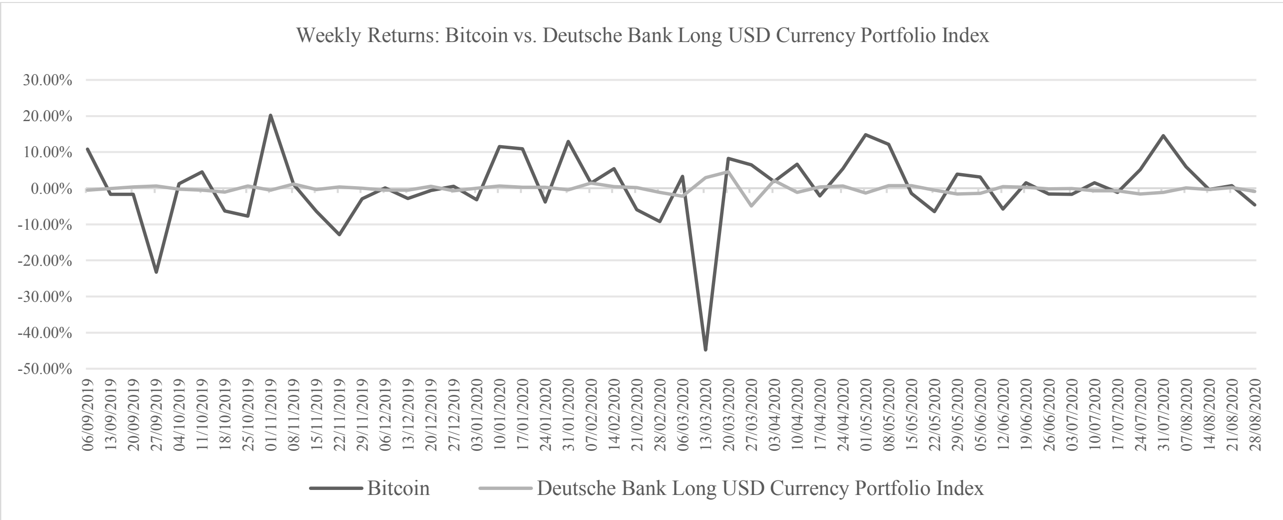
**Figure 4:** Dynamic Conditional Correlations – Potential Safe Havens




**Source:** Calculations DCC GARCH Model, Stata

Evidently, the above graph supports the regression analyses as the correlations between Bitcoin and both indices are primarily negative for the long COVID-19 period. As from when the WHO declared the COVID-19 virus a global pandemic, the correlation between both pairs took a steep dive towards the negative end of the spectrum. The correlations between Bitcoin and the USD Currency Portfolio remained negative until the end of the observation period. While the correlation between Bitcoin (INR) and S&P BSE 500 remained negative for most of the observation window, three positive correlation spikes occurred. Whereas the first appeared shortly after the steep correlation dive in March 2020, the second occurred in May 2020, and a very small and insignificant spike happened in August 2020. Nonetheless, the positive spikes remain rare. Hence, safe haven characteristics become apparent for both of the pairwise correlations during the entire COVID-19 period. However, to finally confirm if it, in fact, is Bitcoin that serves as the safe haven against downturns in the USD Currency Portfolio and the S&P BSE 500, it is necessary to identify the direction of the return relationship by displaying the returns of Bitcoin against each of the indices.

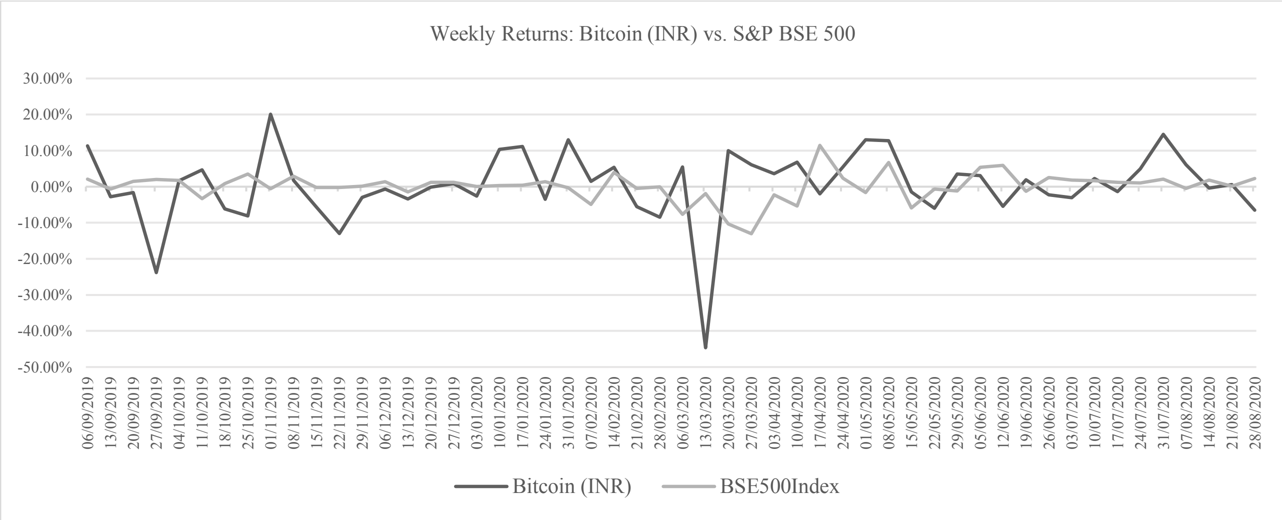
**Figure 5:** Weekly Returns – Bitcoin vs. Deutsche Bank Long USD Currency Portfolio Index




**Source:** Bloomberg Professional Services (2020) and CoinDesk (2020b)

Figures 5 and 6 show that Bitcoin's returns are of fluctuating nature during the COVID-19 crisis. Commencing with Figure 5 and the USD Currency Portfolio, Bitcoin's returns dropped low, whereas the returns of the USD Currency Portfolio remained relatively stable or slightly increased, at the very beginning of the COVID-19 crisis as well as in mid-May and mid-June. This suggests that the USD Currency Portfolio served as a safe haven against the decreases in the value of Bitcoin. Nonetheless, five occasions are observed where the return of the USD Currency Portfolio dropped slightly below zero, while Bitcoin's returns increased. This occurs at the end of March, the beginning of April, from the end of April to the beginning of May, at the beginning of June, and lastly, from the end of July to the beginning of August. Despite the fact that the returns of the USD Currency Portfolio only decrease slightly, Bitcoin could, to some extent, provide safe haven capabilities during these few periods amid the COVID-19 crisis.

**Figure 6:** Weekly Returns – Bitcoin (INR) vs. S&P BSE 500




**Source:** Bloomberg Professional Services (2020) and CoinDesk (2020b)

In contrast to the above findings, Figure 6 shows that Bitcoin (INR) only provides safe haven capabilities against the S&P BSE 500 during one occasion amid the COVID-19 period, namely at the beginning of the crisis between March 20th and April 10th. For the entire period, it becomes evident that the returns of both fluctuate below and above zero percent, mostly in line with each other and sometimes in contradiction to each other. Hence, no systematic pattern arises.

Lastly, it can be evoked that Bitcoin only provides safe haven capabilities for both indices in few periods and for short time horizons. Across both pairs, Bitcoin appears to provide the longest safe haven horizon for the S&P BSE 500 in the period from March 20th to April 10th. For the USD Currency Portfolio, Bitcoin only provides minor safe haven capabilities with no horizon lasting longer than approximately a week or two. However, in general it can be advocated that Bitcoin provides robust diversification benefits, as all coefficient estimates, regardless of asset class, lie particularly close to zero.

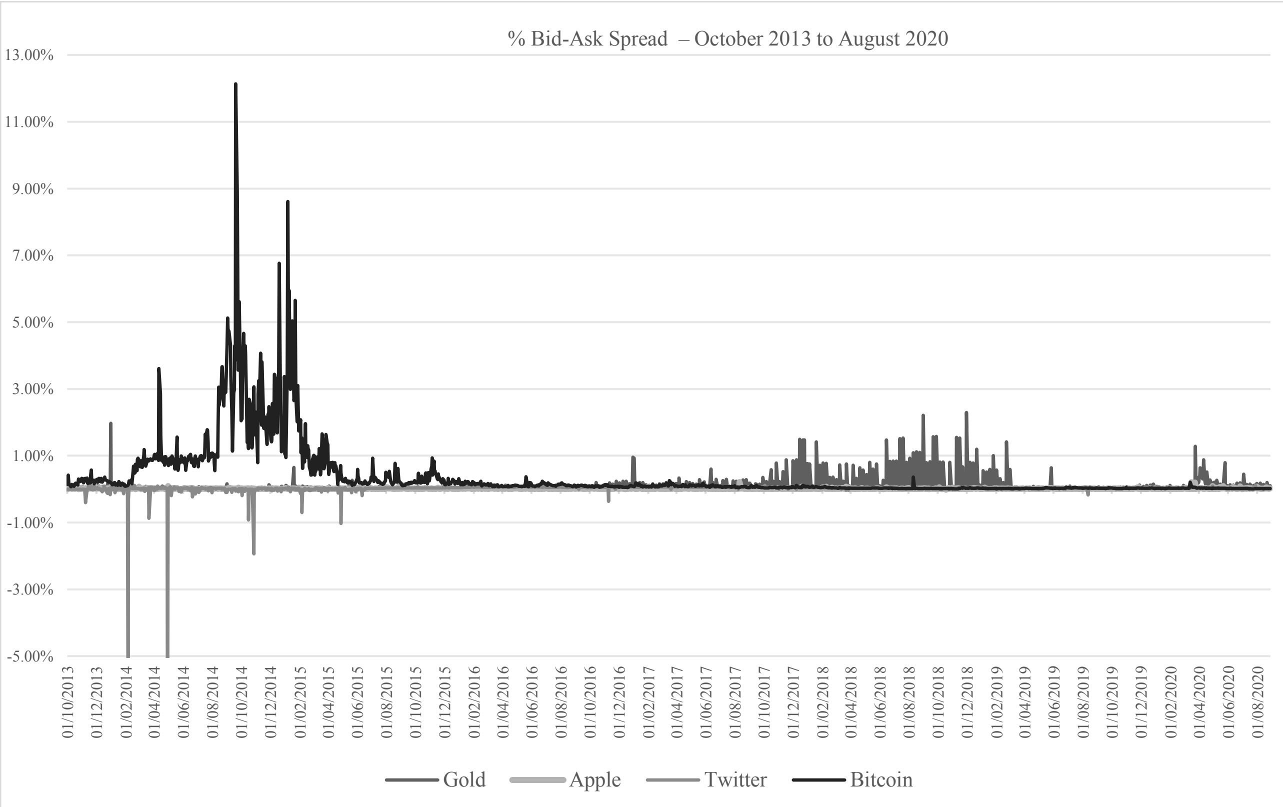
## 6.2. Empirical Results – Analysis II

The empirical results established by Analysis II complete the examination of Bitcoin's potential to serve as a safe haven by investigating the extent to which Bitcoin is fulfilling the liquidity requirement inherent in the definition of a safe haven (see section 1.2.). First, the implicit costs of trading Bitcoin are compared to other assets by means of the bid-ask spread to understand the degree to which Bitcoin can be bought or sold quickly at stable prices on a marketplace. Moreover, the bid-ask percentage spread of Bitcoin is briefly assessed against two financial stress indices to examine Bitcoin's liquidity development during times of market turmoil. Second, the explicit costs of trading are investigated by assessing the average transaction costs against the number of transactions for each specific day. Since investors flee to safe haven assets during crises, demand often rises, why it is important to know if the transaction fees increase when safe havens are needed the most.

### 6.2.1. Implicit Costs of Trading

Figure 7 and 8 depict the bid-ask percentage spreads of Bitcoin, gold, Apple, and Twitter in the period October 2013 through August 2020 (Figure 7) as well as for a more narrow and recent time frame from September 2019 through August 2020 (Figure 8).

**Figure 7:** Percentage Bid-Ask Spread 2013-2020 – Bitcoin, Gold, Apple, and Twitter

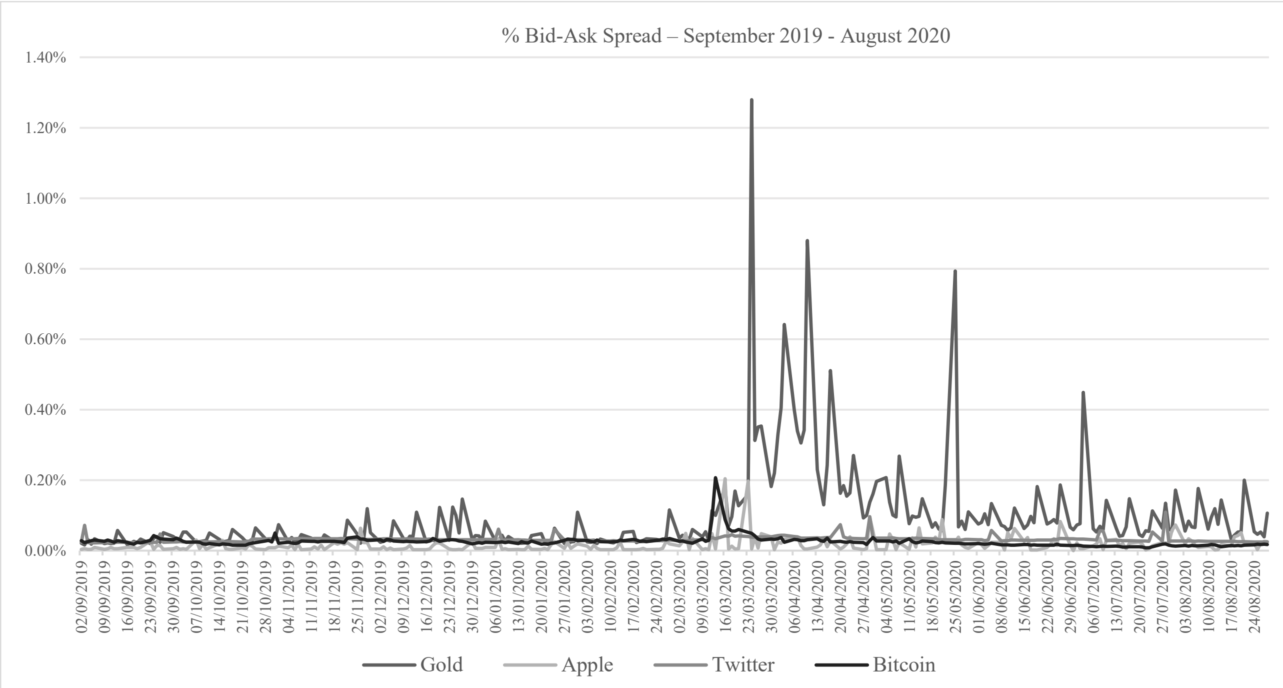



**Source:** Bloomberg Professional Services (2020) and data.bitcoinity.org (2020)

It becomes apparent that Bitcoin's average bid-ask spread has generally declined, thereby signaling an improvement in Bitcoin's liquidity over time. From October 2013 to October 2016, Bitcoin reported the relatively highest spread across the considered assets reaching a peak of 12.14% in September 2014. Thereafter, Bitcoin's spread decreased and stabilized to values close to zero percent with gold beginning to report larger bid-ask spreads than Bitcoin. This image is supported by Figure

8, which demonstrates that Bitcoin's bid-ask spread was lower than gold, at a similar level to the volatile stock Twitter, but higher than Apple in the period from September 2019 through August 2020. Moreover, Figure 8 shows that the spreads of all the considered assets became more volatile and started reporting peaks as COVID-19 began spreading globally in March 2020. Thus, the liquidity of all four assets decreased at the outset of the COVID-19 crisis. This finding is supported by the three graphs in Appendix 9, which portray Bitcoin's bid-ask spread alongside the VIX and GFSI over time. These show that spikes in Bitcoin's bid-ask spread seem to move in lockstep with the sharp increases of the two stress indicators in March 2020.

**Figure 8:** Percentage Bid-Ask Spread 2019-2020 – Bitcoin, Gold, Apple, and Twitter




**Source:** Bloomberg Professional Services (2020) and data.bitcoinity.org (2020)

To allow for a more precise comparison of the liquidity characteristics of Bitcoin, gold, Apple, and Twitter, Table 6 demonstrates the mean of each asset's bid-ask spreads for 1) the entire sample ranging from October 2013 through August 2020, 2) a more recent sub-period ranging from September 2019 through August 2020, 3) a sub-period ranging from February 24th, 2020 to April 10th, 2020, thereby reflecting the period of high COVID-19 related market stress previously utilized in Analysis I. To test whether the differences in means between the assets during the three periods are significantly different from zero, this thesis refers to the results of the statistical significance test reported in Table 6.

**Table 6:** Difference in Means – Test Statistics

| | Mean | t-statistic | p-value |
|---|---|---|---|
| ***Panel A: Entire sample period (01/10/2013 - 28/08/2020)*** | | | |
| Bitcoin | 0.3787% | | |
| Gold | 0.0819% | 13.6958 | 0.0000 |
| Apple | 0.0148% | 17.1988 | 0.0000 |
| Twitter | 0.0198% | 16.2480 | 0.0000 |
| ***Panel B: Sub-period 1 (02/09/19 – 28/08/20)*** | | | |
| Bitcoin | 0.0254% | | |
| Gold | 0.0932% | -8.1969 | 0.0000 |
| Apple | 0.0173% | 4.8123 | 0.0000 |
| Twitter | 0.0321% | -6.0223 | 0.0000 |
| ***Panel C: Sub-period 2 (24/02/20 – 10/04/20)*** | | | |
| Bitcoin | 0.0430% | | |
| Gold | 0.2266% | -4.0717 | 0.0003 |
| Apple | 0.0286% | 1.5082 | 0.1365 |
| Twitter | 0.0358% | 1.2650 | 0.2140 |

For the entire sample, Bitcoin's average bid-ask spread of 0.3787% is significantly higher than that of gold, Apple, and Twitter, thus indicating that Bitcoin has a low relative liquidity. As previously described and shown in Figure 7, this relatively high mean spread is, however, vastly influenced by Bitcoin's high spread in its early years from 2013 to 2016. Therefore, a look at the first sub-period provides a more current picture of Bitcoin's liquidity. The first sub-period shows that Bitcoin's mean spread of 0.0254% lies significantly below the bid-ask spread of gold and Twitter but above that of Apple. Hence, Bitcoin is relatively liquid when looking at a recent timeframe. When zooming in on the assets' liquidity during the second sub-period, which reports high COVID-19 related market stress, it becomes apparent that Bitcoin's mean spread of 0.043% is higher than its mean of 0.02454% during the first sub-period. This observation also holds for gold, Apple, and Twitter, which, in line with Figure 8 and Appendix 9, indicates that the liquidity of the four assets decreased during the period of high COVID-19 related market stress. Despite the decrease, Bitcoin's liquidity remains significantly better than that of the traditional safe haven gold. The results of the statistical significance test highlight that no significant inferences can be made about the difference in means between Bitcoin and Apple as well as Bitcoin and Twitter in the second sub-period. While Bitcoin's liquidity decreased under the high COVID-19 related financial market stress, Bitcoin appears to be more liquid than the traditional safe haven of gold and equally liquid as Apple and Twitter.

### 6.2.2. Explicit Costs of Trading

As outlined in section 2.1.1., every Bitcoin transaction must be added to the blockchain - the official public ledger of all Bitcoin transactions - in order for the transaction to be successfully completed and valid. Bitcoins cannot exist or be held independently of the blockchain. The validation of all transactions occurs through the process of mining, which takes care of including transactions in the limited space of a 1 MB block. When a block is filled up with transactions, it is added to the blockchain, which occurs circa every 10 minutes. Transaction fees are charged for this process, which make up the most substantial share of the overall fees charged when trading Bitcoins on exchanges. While smaller, additional fees might be charged by the exchanges at which Bitcoins are bought and sold, this analysis solely focuses on the transaction costs of using the Bitcoin network and disregards the additional fees applied by exchanges, which differ across exchanges (CoinDesk, 2020a).

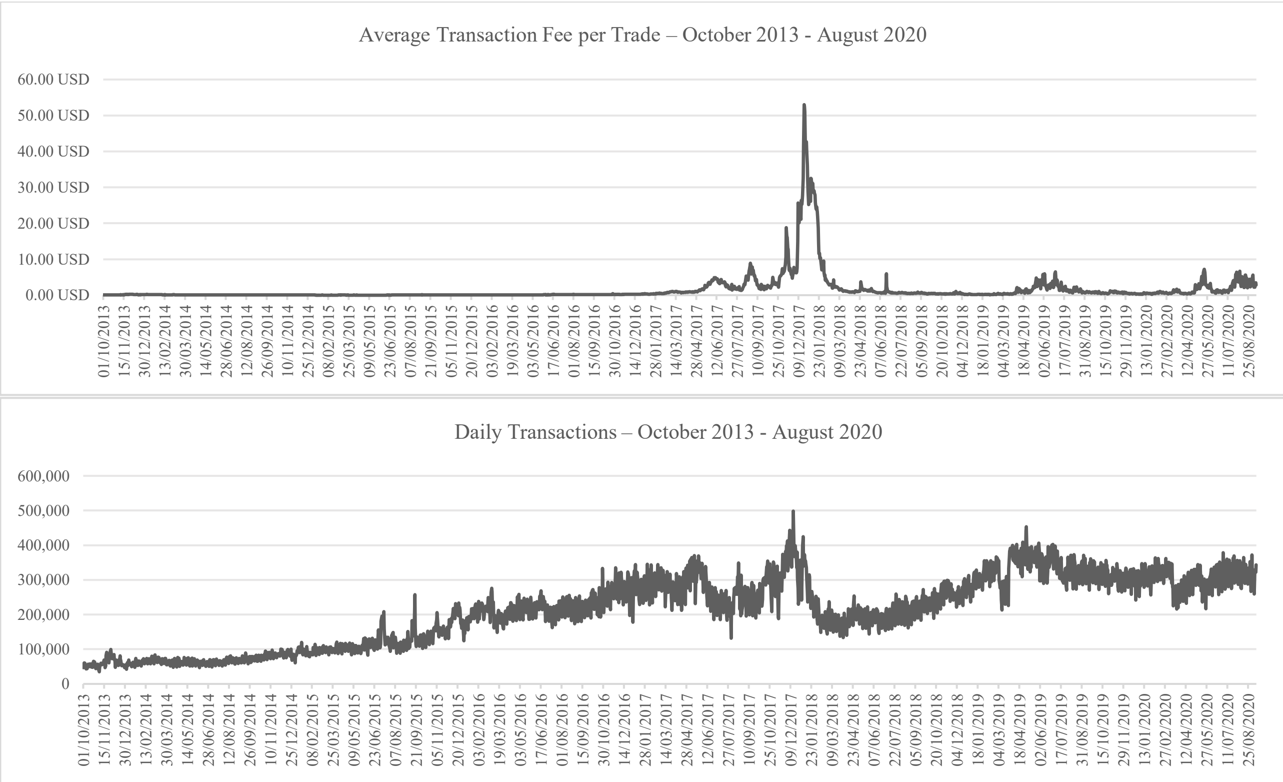
**Table 7:** Stylized Facts – Transactions Fees

| | Entire sample period (01/10/2013 – 28/08/2020) | Sub-period 1 (02/09/19 – 28/08/20) | Sub-period 2 (24/02/20 – 10/04/20) |
|---|---|---|---|
| Mean | 1.5246 | 1.4749 | 0.8094 |
| Max | 54.6380 | 6.4291 | 1.7856 |

**Source:** blockchain.com (2020)

Table 7 shows the mean and maximum of the average transaction fees per day during the same sub-periods, as outlined in the bid-ask spread section. While the mean of the average transaction fees for the entire period amounts to 1.5246 USD, the maximum observed average transaction fee totaled to 54.638 USD in December 2017. For sub-period 1, the average transaction fee was 1.4749 USD, with a maximum measured at 6.4291 USD at the end of July 2020. For sub-period 2, the mean and maximum of the average transaction fees amounted to 0.8094 and 1.7856 USD, respectively, thereby highlighting there to have been low transaction costs amid high COVID-19 related financial market stress.

**Figure 9:** Bitcoin – Average Transaction Fee per Trade vs. Daily Transactions




**Source:** blockchain.com (2020) and charts.bitcoin.com (2020)

Figure 9 portrays the average transaction fee per trade per day and the corresponding number of transactions on that specific day in the period October 2013 through August 2020. Comparing the two suggests there to be a positive relationship between transaction demand and transaction costs. For example, as the total number of daily transactions spiked in December 2017, so did the average transaction fee reaching the maximum value of 54.638 USD. While no later transactions reported similarly high fees, a relationship between increases in the number of transactions and the average fee can be observed at several points in time. During the ongoing COVID-19 period, the number of transactions, as well as average transaction fees, remained relatively stable with some spikes at the end of June as well as from the end of July to end of August. This suggests that Bitcoin was tradable at changing, but relatively low costs during the period with the highest COVID-19 related stress from February through April 2020, and at relatively higher costs during the summer months of 2020.

## 6.3. Empirical Results – Analysis III

The following sections present the empirical findings of Analysis III, which extend the perspective of Analysis I and II from looking at the investment properties of Bitcoin against each selected asset in isolation to investigating the risk and return effects of including Bitcoin in the diversified portfolio of a US investor. First, the stylized facts of the returns of the assets included in the computed test and benchmark portfolios are presented to provide a general overview. Second, the extent to which Bitcoin should be included in optimized portfolios during the COVID-19 crisis is highlighted. Third, the section reports whether including Bitcoin in the investment set leads to higher portfolio performance as compared to not holding an investment in Bitcoin by evaluating the downside risk metrics of MVaR and MCVaR as well as the risk-return metrics of SR, SoR, and ASR.

### 6.3.1. Stylized Facts

The stylized facts depicted in Table 8 cover the weekly returns of the six assets for the period of September 2017 through August 2020. Thereby, the period reflects the rolling two-year historical asset return data used for the optimization of all the test and benchmark TPs and GMVPs as well as for the performance evaluation. The mean and standard deviation, minimum and maximum observed value, the buy and hold return, as well as the kurtosis and skewness of the data, are discussed.

**Table 8:** Stylized Facts – Portfolio Assets

Stylized Facts Portfolio Assets — Sep 2017 to Aug 2020

| | Bitcoin | Equity | Bond | Commodity | FX | Real-estate |
|---|---|---|---|---|---|---|
| | CoinDesk Bitcoin Price Index | MSCI ACWI Index | Bloomberg Barclays Global Aggregate Index | S&P Goldman Sachs Commodity Index | DB Long USD Currency Portfolio Index Excess Return | MSCI ACWI Real Estate Index |
| Observations | 152 | 152 | 152 | 152 | 152 | 152 |
| Mean | 0.6732% | 0.1224% | 0.0803% | -0.0683% | 0.0238% | -0.0161% |
| St.Dev. | 11.0855% | 2.7751% | 0.7598% | 3.2477% | 0.9708% | 3.4005% |
| Max | 52.4735% | 9.9544% | 3.1242% | 8.0997% | 4.5442% | 15.4623% |
| Min | -44.8024% | -13.2267% | -3.9076% | -14.5503% | -4.9160% | -22.7840% |
| Skewness | 0.1621 | -1.4075 | -1.2892 | -1.4468 | -0.0949 | -1.6836 |
| Kurtosis | 4.3404 | 8.3833 | 10.1546 | 4.7242 | 6.5138 | 17.5348 |
| MVaR (95%) | 16.0735% | 4.9798% | 1.2684% | 6.3087% | 1.4714% | 5.8525% |
| MCVaR (95%) | 23.0144% | 11.6882% | 3.3022% | 11.0856% | 2.3996% | 17.5402% |
| B&H Return | 96.0524% | 17.7850% | 12.7112% | -8.4915% | 2.8089% | -3.1231% |

The mean weekly return in the period from September 2017 through August 2020 ranges from -0.0683% for the commodity index to 0.6732% for Bitcoin. This image is supported by the buy and hold return for the entire period, which registers Bitcoin to have the highest return, measured at 96.0524%, and the commodity index to report the lowest return of -8.4915%. Besides rendering the largest returns, Bitcoin also displays the largest minimum-maximum spread of the data sample with weekly returns ranging from a minimum of -44.8024% to a maximum of 52.4735%. The bond index demonstrates the lowest minimum-maximum spread with values from -3.9076% to 3.1242%. As already described in section 6.1.1., the minimum observed return value of all assets lies between March 9$^{th}$ and 27$^{th}$, 2020, which covers the period in which the WHO declared COVID-19 a global pandemic and governments all around the world began announcing countrywide lockdowns. Interestingly, the maximum observed return values for all assets, but Bitcoin, lie close to the minimum observed values, namely between March 16$^{th}$ and May 8$^{th}$, 2020. For context on Bitcoin's maximum weekly return of 52.473%, this thesis refers to section 6.1.1. Bitcoin's large minimum-maximum spread translates into the highest standard deviation of the data sample, measured at 11.0855%. The bond index reported the lowest standard deviation. The non-zero skewness and kurtosis parameters indicate that all the asset return series are non-normally distributed. Bitcoin is the asset with the lowest skewness as well as the only asset demonstrating positive skewness measured at 0.1621. All return series have excess kurtosis with parameters reaching from 4.7242 (commodity index) to 17.5348 (real estate index). The high kurtosis hints at a leptokurtic distribution. A look at the individual asset's MVaR and MCVaR shows that Bitcoin registers the highest downside risk with a weekly MVaR of 16.0735% and an expected average loss (MCVaR) of 23.0144% conditional upon the loss being larger than the MVaR. Across the assets, the bond index registers the lowest weekly MVaR of 1.2684%, and the FX index reports the lowest MCVaR of 2.3996%.

### 6.3.2. Portfolio Weight Allocation to Bitcoin

The following section presents the results of the portfolio weight optimization analysis of the test TPs and GMVPs across the two optimization frameworks. To begin with, a general overview of the weight allocation to the different assets is provided for all 12 TPs and 12 GMVPs and both optimization frameworks. Since the 12 TPs and GMVPs are optimized on the basis of a rolling window of data, the section continues by reporting how the weight allocation to Bitcoin develops in accordance with the emergence of COVID-19 related global financial stress.

Table 9 displays the mean, standard deviation, maximum, and minimum weight of the assets included in the 12 test TPs and 12 test GMVPs for both the mean-variance as well as mean-CVaR optimization framework. Across the two frameworks, the global bond index receives the highest mean weight allocation, followed by the USD Currency Portfolio, the world equity, commodity, Bitcoin, and real estate index. While the mean weight of Bitcoin is greater than zero for both the GMVPs and TPs of the two optimization frameworks, it becomes apparent that Bitcoin only plays a minor role in the optimal portfolios. The minimum reported portfolio weight for Bitcoin is measured at 0%, and the maximum computed weight lies at 0.715%. Bitcoin's low maximum-minimum weight spread translates into a low standard deviation, whereby the standard deviation of the TPs is larger than that of the GMVPs. This indicates that the weight allocation changes less across the optimized portfolios for the GMVPs than for the TPs. Moreover, it becomes evident that Bitcoin's relatively high volatility, as well as MCVaR in the period considered for portfolio optimization, is penalized in the GMVPs, resulting in smaller average weight allocations to Bitcoin than in the TPs.

**Table 9:** Stylized Facts – Optimized Weights

Stylized Facts of Optimized Weights Test Portfolio

Mean-Variance Optimization – Test Portfolio

| | TP | | | | GMVP | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | St.Dev. | Max | Min | Mean | St.Dev. | Max | Min |
| BTC | 0.1973% | 0.1546% | 0.5106% | 0.0000% | 0.0625% | 0.1286% | 0.3423% | 0.0000% |
| Equity | 3.3133% | 2.3017% | 6.3910% | 0.1006% | 3.6837% | 0.7427% | 4.8560% | 2.6561% |
| Bond | 53.4803% | 2.1100% | 57.0434% | 50.4128% | 52.8046% | 1.7712% | 55.7344% | 50.7015% |
| Commodity | 0.2931% | 0.5033% | 1.4307% | 0.0000% | 1.1391% | 1.1928% | 2.5441% | 0.0051% |
| FX | 42.7160% | 2.7939% | 48.2613% | 37.5549% | 42.3098% | 3.5785% | 46.1051% | 37.9628% |
| Real Estate | 0.0000% | 0.0000% | 0.0000% | 0.0000% | 0.0000% | 0.0000% | 0.0000% | 0.0000% |

Mean-CVaR Optimization – Test Portfolio

| | TP | | | | GMVP | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | St.Dev. | Max | Min | Mean | St.Dev. | Max | Min |
| BTC | 0.3499% | 0.2451% | 0.7150% | 0.0000% | 0.2265% | 0.1931% | 0.4737% | 0.0000% |
| Equity | 5.7034% | 2.9236% | 10.4230% | 0.0519% | 4.8726% | 1.2574% | 6.8504% | 3.5983% |
| Bond | 49.2913% | 2.2070% | 53.3520% | 46.2260% | 51.0768% | 2.3344% | 54.6990% | 48.3350% |
| Commodity | 0.2492% | 0.4548% | 1.2454% | 0.0000% | 1.1118% | 0.8647% | 2.1978% | 0.0000% |
| FX | 44.1125% | 3.7897% | 52.1010% | 38.4130% | 42.6612% | 2.0527% | 44.9430% | 39.5270% |
| Real Estate | 0.2261% | 0.5301% | 1.4637% | 0.0000% | 0.0515% | 0.1625% | 0.5654% | 0.0000% |

A comparison between the two optimization frameworks shows that the mean weight allocation to Bitcoin in both the TP and GMVP is slightly larger for the mean-CVaR optimization than for the mean-variance framework. Thus, small differences stemming from the optimization assumption are present, thereby justifying the use of both frameworks. These differences are visualized in Appendix 10, where the efficient frontier of the mean-variance optimized efficient test portfolios for each month are expressed in terms of CVaR and graphed next to the efficient frontier of the mean-CVaR optimized efficient test portfolios. This further manifests itself in the efficient portfolio weight maps shown in Appendix 11. These illustrate the differences between the mean-variance and mean-CVaR portfolio weight allocation for 10 test portfolios on the respective efficient frontier.

While Table 9 provides an overall image of Bitcoin's role in optimal portfolio construction, Table 10 allows for insights into how the weight allocation to Bitcoin changes over time. For an overview of the optimal weight development for all other assets included in the test portfolios, the authors refer to Appendix 12. As outlined in the methodology section, 12 test TPs and GMVPs are optimized on the basis of two years of weekly historical data, with each of the 12 portfolios being optimized at the end of a month in the period September 2019 through August 2020. Thereby, a rolling window of data is generated, which allows for an analysis of how Bitcoin's optimal portfolio weight allocation develops in accordance with the emergence of COVID-19 related global financial stress. Each TP and GMVP is named after the month at which end it is optimized, e.g., the row July 2020 includes the TPs and GMVPs which are optimized on the basis of data from the start of August 2018 to the end of July 2020.

**Table 10:** Bitcoin Weights vs. Financial Stress Indicators

| | Bitcoin Weights | | | | Financial Stress Indicators | | |
|---|---|---|---|---|---|---|---|
| | Mean-Variance Optimization | | Mean-CVaR Optimization | | VIX | GFSI | STLFSI2 |
| | TP | GMVP | TP | GMVP | | | |
| Sep/19 | 0.2351% | 0.0000% | 0.4836% | 0.0000% | 16.2400 | 0.1700 | -0.1120 |
| Oct/19 | 0.1435% | 0.0000% | 0.2041% | 0.0000% | 13.2200 | 0.0000 | -0.3590 |
| Nov/19 | 0.0000% | 0.0000% | 0.0000% | 0.0121% | 12.6200 | -0.1200 | -0.4220 |
| Dec/19 | 0.0000% | 0.0721% | 0.0000% | 0.0798% | 13.7800 | -0.2700 | -0.3990 |
| Jan/20 | 0.5106% | 0.3423% | 0.6600% | 0.4626% | 18.8400 | -0.0900 | -0.2610 |
| Feb/20 | 0.2552% | 0.3261% | 0.4289% | 0.4310% | 40.1100 | 0.5500 | 0.5450 |
| Mar/20 | 0.1622% | 0.0000% | 0.1567% | 0.3827% | 53.5400 | 1.7500 | 4.9810 |
| Apr/20 | 0.0272% | 0.0000% | 0.1439% | 0.4737% | 34.1500 | 0.9500 | 1.9570 |
| May/20 | 0.2351% | 0.0030% | 0.4945% | 0.3830% | 27.5100 | 0.5900 | -0.1260 |
| Jun/20 | 0.4047% | 0.0030% | 0.7150% | 0.2672% | 30.4300 | 0.4600 | 0.2510 |
| Jul/20 | 0.1479% | 0.0030% | 0.3615% | 0.1635% | 24.4600 | 0.3300 | -0.2930 |
| Aug/20 | 0.2459% | 0.0000% | 0.5507% | 0.0629% | 26.4100 | 0.2100 | -0.2470 |
| 12-m average | 0.1973% | 0.0625% | 0.3499% | 0.2265% | 25.9425 | 0.3775 | 0.4596 |

**Source:** Bloomberg Professional Services (2020)

A look at the color-coded global financial stress indices on the right-hand side of the table shows that market stress was reported to be average or below average from September 2019 through January 2020. At this point, this thesis refers to section 5.3.4. for assistance on how to interpret the stress indicators. As from February 2020, and as COVID-19 cases started spreading worldwide, financial stress indicators increased to a level above average. While the VIX and GFSI continue to report increased market turmoil for the entire period from February through August 2020, the STLSFI2 shows below average market stress during May, July, and August 2020. Across all stress indices, the highest stress levels were recorded from February through April 2020.

The TP weight allocation to Bitcoin under both the mean-variance and mean-CVaR optimization starts with a decrease from September 2019 to a weight of zero percent in November 2019 and December 2019. The TP weight of Bitcoin increases in January 2020 and then decreases again during the months of February, March, and April. Considering the spiking financial stress indicators during the months of February, March, and April 2020, it becomes apparent that the optimal TP includes a decreased, yet positive, investment in Bitcoin under the high COVID-19 related financial stress. Thereafter, Bitcoin's TP weights increased again in May and June. While these two months register less high-stress levels than the period February to April 2020, they are still affected by above-average market stress. The weight allocation to Bitcoin decreases again in July to finally increase in August. While the mean-CVaR optimized TP weights are higher than the mean-variance optimized weights during all but one month (March 2020), the changes in weight allocation to Bitcoin follow the same trend under both optimization frameworks.

Opposed to the aligned TPs, the optimal GMVP Bitcoin weight allocation follows a differing trend depending on the chosen optimization assumption. In line with the image created in Table 9, the mean-variance optimized GMVP weight of Bitcoin remains below the TP weight during all months besides December 2019 and February 2020. Moreover, the mean-variance optimized GMVP weights to Bitcoin are zero or close to zero percent in all months besides December to February 2020. Hence, Bitcoin receives limited attention during the months showing high COVID-19 related stress. On the contrary, the mean-CVaR optimized GMVP weights surmount the assigned TP weights during five of the 12 months, namely in November and December 2019, as well as between February and April 2020. This indicates that Bitcoin, despite its overall high volatility, was considered in minimum variance portfolios during the months reflecting the effects of the increased global market stress from

February to April 2020. While dropping below the TP weights again as from May 2020, the mean-CVaR optimized GMVPs continue to include an investment in Bitcoin from June to August 2020.

Having elaborated upon the minor, yet for many months positive, investment allocations to Bitcoin in test portfolios, the following section compares the performance of test TPs and GMVPs, which include the above-mentioned optimal Bitcoin weights, to benchmark portfolios, which are optimized without the possibility to invest in Bitcoin.

### 6.3.3. Portfolio Metrics Comparison

In this section, the results of the test and benchmark portfolio performance analysis are systematically presented. First, the test and benchmark portfolios' downside risk metrics of MVaR and MCVaR are reported and compared. Second, the comparative performance metric analysis turns to the risk-return measures of SR, SoR, and ASR. Thereby, each performance metric section begins with a comparison of the test and benchmark TPs for both optimization frameworks, followed by a comparison of the test and benchmark GMVPs across the two frameworks. Besides focusing on the average performance metric of the portfolios, the development of the performance is described to set the overall averages into perspective and avoid potential miss-interpretations caused by single extreme observations.

#### *6.3.3.1. Downside Risk Reduction Metric – MVaR*

As depicted in the literature review, the risk of losses increases during times of market turmoil, why one of the performance metrics used to compare the test portfolio to the benchmark portfolio is each portfolio's downside risk. Therefore, the test and benchmark portfolios' MVaR are compared to understand whether the inclusion of Bitcoin into a diversified portfolio can reduce the expected worst weekly loss level, which with 95% certainty will not be exceeded (see Table 11).

**Table 11:** Performance Metric: Modified Value-at-Risk

MVaR

Mean-Variance Optimization

| | TP-Test | TP-Benchmark | Relative | GMVP-Test | GMVP-Benchmark | Relative |
|---|---|---|---|---|---|---|
| Sep/19 | 0.3296% | 0.3181% | 1.0361 | 0.3207% | 0.3207% | 1.0000 |
| Oct/19 | 0.3581% | 0.3522% | 1.0168 | 0.3451% | 0.3451% | 1.0000 |
| Nov/19 | 0.3510% | 0.3510% | 1.0000 | 0.3456% | 0.3456% | 1.0000 |
| Dec/19 | 0.3405% | 0.3405% | 1.0000 | 0.3405% | 0.3386% | 1.0054 |
| Jan/20 | 0.3108% | 0.3100% | 1.0025 | 0.3047% | 0.3052% | 0.9985 |
| Feb/20 | 0.3235% | 0.3244% | 0.9974 | 0.3227% | 0.3220% | 1.0022 |
| Mar/20 | 0.4274% | 0.4228% | 1.0107 | 0.4185% | 0.4185% | 1.0000 |
| Apr/20 | 0.4160% | 0.4126% | 1.0082 | 0.4173% | 0.4173% | 1.0000 |
| May/20 | 0.4323% | 0.4258% | 1.0152 | 0.4234% | 0.4233% | 1.0002 |
| Jun/20 | 0.4544% | 0.4409% | 1.0306 | 0.4322% | 0.4321% | 1.0002 |
| Jul/20 | 0.4729% | 0.4690% | 1.0083 | 0.4344% | 0.4343% | 1.0002 |
| Aug/20 | 0.5035% | 0.4956% | 1.0158 | 0.4479% | 0.4479% | 1.0002 |
| Average | 0.3933% | 0.3886% | 1.0118 | 0.3794% | 0.3792% | 1.0006 |
| Frequency | | | 8.33% | | | 8.33% |

Mean-CVaR Optimization

| | TP-Test | TP-Benchmark | Relative | GMVP-Test | GMVP-Benchmark | Relative |
|---|---|---|---|---|---|---|
| Sep/19 | 0.3461% | 0.3268% | 1.0590 | 0.3193% | 0.3193% | 1.0000 |
| Oct/19 | 0.3605% | 0.3663% | 0.9841 | 0.3464% | 0.3464% | 1.0000 |
| Nov/19 | 0.3524% | 0.3524% | 1.0000 | 0.3445% | 0.3450% | 0.9986 |
| Dec/19 | 0.3407% | 0.3407% | 1.0000 | 0.3384% | 0.3405% | 0.9940 |
| Jan/20 | 0.3178% | 0.3131% | 1.0151 | 0.3047% | 0.3028% | 1.0065 |
| Feb/20 | 0.3346% | 0.3235% | 1.0342 | 0.3209% | 0.3208% | 1.0003 |
| Mar/20 | 0.4433% | 0.4285% | 1.0345 | 0.4724% | 0.4522% | 1.0446 |
| Apr/20 | 0.4399% | 0.4207% | 1.0456 | 0.4776% | 0.4548% | 1.0503 |
| May/20 | 0.5501% | 0.5596% | 0.9829 | 0.5108% | 0.5503% | 0.9281 |
| Jun/20 | 0.5967% | 0.6007% | 0.9933 | 0.5258% | 0.5022% | 1.0470 |
| Jul/20 | 0.6237% | 0.6626% | 0.9413 | 0.5157% | 0.5474% | 0.9420 |
| Aug/20 | 0.7386% | 0.6533% | 1.1305 | 0.5357% | 0.5289% | 1.0130 |
| Average | 0.4537% | 0.4457% | 1.0184 | 0.4177% | 0.4175% | 1.0020 |
| Frequency | | | 33.33% | | | 33.33% |

Across the 12 created portfolios, the mean-variance optimized test TPs realize an average weekly MVaR of 0.3933%, which is slightly higher than the TP benchmark portfolios rendering an average MVaR of 0.3886%. This is supported by the relative MVaR measure, which underlines that the inclusion of Bitcoin into a diversified portfolio only reduces portfolio downside risk for one of the 12 portfolios. The test portfolio thus only slightly outperforms the benchmark for the portfolios optimized at the end of February 2020, for which the weight allocation to Bitcoin is measured at 0.225%. Since the inclusion of Bitcoin in most portfolios optimized amid the COVID-19 crisis increases the MVaR, Bitcoin's potential to reduce tail risk appears limited.

The mean-CVaR optimized test TPs report an average MVaR of 0.4537%, which, similar to the above, is higher than the average of the benchmark TPs. However, this is not comprehensively supported by the relative measures, which exhibit that the test portfolio outperforms the benchmark portfolio in terms of MVaR in four of the 12 cases. While the first test portfolio with superior MVaR performance does not include return data from under the COVID-19 crisis, the three remaining portfolios are optimized at the end of May, June, and July 2020, thereby including data from months showing high COVID-19 related stress. This indicates that Bitcoin's inclusion into a diversified portfolio can, to some extent, reduce downside risk compared to the benchmark.

In line with the theory, the test and benchmark GMVPs showcase lower MVaR risk measures than the TPs across the two optimization frameworks. On average, the mean-variance optimized test GMVP has a MVaR of 0.3794%, which is only slightly larger than the benchmark GMVP's MVaR of 0.3792%. Similar to the mean-variance optimized TPs, the inclusion of Bitcoin into a diversified portfolio only results in a reduction of downside risk in one of the 12 cases, namely for the portfolio optimized at the end of January 2020, which includes a weight allocation to Bitcoin of 0.342%. For all other portfolios, especially those optimized during periods with high COVID-19 related financial stress, the inclusion of Bitcoin results in no reduction of downside risk.

Similarly, the average MVaR of the mean-CVaR optimized test GMVP is marginally higher than that of the benchmark with averages of 0.4177% and 0.4175%, respectively. Nonetheless, the test GMVPs outperform the benchmark in four of the 12 cases. Two of these superior portfolios are optimized amid the COVID-19 crisis in May and July 2020. Noticeably, the average MVaR of both the test and benchmark TPs and GMVPs appear to be higher under the mean-CVaR optimization than under the mean-variance approach.

### *6.3.3.2. Downside Risk Reduction Metric – MCVaR*

Whereas the former section outlined whether an investment in Bitcoin can reduce portfolio MVaR, Table 12 exhibits whether the MCVaR, defined as the average loss expectation conditional on the loss being larger than MVaR, is reduced upon including Bitcoin into a diversified portfolio.

**Table 12:** Performance Metric: Modified Conditional-Value-at-Risk

| MCVaR | | | | | | |
|---|---|---|---|---|---|---|
| Mean-Variance Optimization | | | | | | |
| | TP-Test | TP-Benchmark | Relative | GMVP-Test | GMVP-Benchmark | Relative |
| Sep/19 | 0.5091% | 0.4880% | 1.0434 | 0.5063% | 0.5063% | 1.0000 |
| Oct/19 | 0.5578% | 0.5483% | 1.0174 | 0.5285% | 0.5285% | 1.0000 |
| Nov/19 | 0.5166% | 0.5166% | 1.0000 | 0.5235% | 0.5235% | 1.0000 |
| Dec/19 | 0.5083% | 0.5083% | 1.0000 | 0.5259% | 0.5213% | 1.0089 |
| Jan/20 | 0.4609% | 0.4653% | 0.9904 | 0.4686% | 0.4702% | 0.9966 |
| Feb/20 | 0.4904% | 0.4920% | 0.9969 | 0.5045% | 0.5054% | 0.9983 |
| Mar/20 | 0.6084% | 0.5993% | 1.0152 | 0.6787% | 0.6787% | 1.0000 |
| Apr/20 | 0.6167% | 0.6182% | 0.9976 | 0.6880% | 0.6880% | 1.0000 |
| May/20 | 0.7184% | 0.6770% | 1.0611 | 0.7011% | 0.7005% | 1.0008 |
| Jun/20 | 0.8204% | 0.7346% | 1.1169 | 0.7189% | 0.7183% | 1.0008 |
| Jul/20 | 0.8810% | 0.8468% | 1.0404 | 0.7260% | 0.7254% | 1.0009 |
| Aug/20 | 0.9903% | 0.9257% | 1.0698 | 0.7228% | 0.7224% | 1.0007 |
| Average | 0.6399% | 0.6183% | 1.0291 | 0.6077% | 0.6074% | 1.0006 |
| Frequency | | | 25.00% | | | 16.67% |
| Mean-CVaR Optimization | | | | | | |
| | TP-Test | TP-Benchmark | Relative | GMVP-Test | GMVP-Benchmark | Relative |
| Sep/19 | 0.5269% | 0.5145% | 1.0241 | 0.4967% | 0.4967% | 1.0000 |
| Oct/19 | 0.5432% | 0.5809% | 0.9352 | 0.5299% | 0.5299% | 1.0000 |
| Nov/19 | 0.4905% | 0.4905% | 1.0000 | 0.5157% | 0.5113% | 1.0087 |
| Dec/19 | 0.4809% | 0.4809% | 1.0000 | 0.5128% | 0.5227% | 0.9810 |
| Jan/20 | 0.4484% | 0.4742% | 0.9455 | 0.4617% | 0.4570% | 1.0102 |
| Feb/20 | 0.4671% | 0.4862% | 0.9607 | 0.4871% | 0.4830% | 1.0085 |
| Mar/20 | 0.6331% | 0.6072% | 1.0427 | 1.0156% | 0.8748% | 1.1610 |
| Apr/20 | 0.7549% | 0.7044% | 1.0716 | 1.0273% | 0.8637% | 1.1895 |
| May/20 | 1.3484% | 1.2966% | 1.0400 | 1.1929% | 1.3271% | 0.8988 |
| Jun/20 | 1.5657% | 1.4477% | 1.0815 | 1.2329% | 1.1143% | 1.1064 |
| Jul/20 | 1.6283% | 1.6768% | 0.9710 | 1.1756% | 1.3252% | 0.8871 |
| Aug/20 | 1.9562% | 1.6236% | 1.2048 | 1.1885% | 1.1872% | 1.0010 |
| Average | 0.9036% | 0.8653% | 1.0231 | 0.8197% | 0.8077% | 1.0210 |
| Frequency | | | 33.33% | | | 25.00% |

Across the 12 mean-variance optimized TPs, the test portfolios have a slightly larger average MCVaR of 0.6399% compared to the benchmark reported at 0.6138%. Nonetheless, the inclusion of Bitcoin leads to a reduction of downside risk for three of the 12 optimized portfolios, namely for the portfolios optimized at the end of January, February, and April 2020. Bitcoin was represented in these three test portfolios with weights of respectively 0.5106%, 0.2552%, and 0.0272%. Interestingly, these three months include high COVID-19 related financial market stress. However, for all other portfolios, including those optimized during months with high market stress, the benchmark portfolio outperforms the test portfolio.

Considering the 12 mean-CVaR optimized TPs, the test portfolio continues to show larger average downside risk, measured at 0.9036%, compared to the benchmark's MCVaR of 0.8653%. The relative comparison shows that the test portfolio outperforms the benchmark in four of the 12 cases, namely for the portfolios optimized at the end of October 2019 as well as January, February, and July 2020. For all other optimizing months, including those with high COVID-19 related stress, the benchmark portfolio outperforms the test portfolio.

For both optimization frameworks, the GMVPs render lower average MCVaR values than the respective TPs. A look at the mean-variance optimized GMVPs shows that the average MCVaR of the test GMVP is measured at 0.6077% and lies slightly above the 0.6074% MCVaR of the benchmark. Similar to the mean-variance optimized test TPs, the test GMVPs only outperform the benchmark portfolios for the portfolios optimized at the end of January and February 2020. These two test portfolios include Bitcoin weights of 0.3423% and 0.3261%, respectively. Turning to the results of the mean-CVaR optimized GMVPs, it becomes apparent that the test portfolio shows a higher average downside risk than the benchmark with values of 0.8179% and 0.8077%, respectively. The test portfolio only outperforms the benchmark for the portfolios optimized at the end of December 2019, May 2020, and July 2020. Similar to the results of the MVaR analysis, the average MCVaR of both the test and benchmark TPs and GMVPs appear to be higher under the mean-CVaR optimization than under the mean-variance assumption. While the inclusion of Bitcoin into a diversified portfolio leads to a reduction of MVaR and MCVaR for some portfolios, the majority of the test portfolios underperform as a result of Bitcoin's relatively high individual MVaR and MCVaR (see Table 8).

### *6.3.3.3. Risk-Return Metric – Sharpe Ratio*

Despite the importance of downside risk reduction, investors are unlikely to consider an investment in Bitcoin for MVaR and MCVaR purposes in isolation. Instead, their allocation decisions will consider the tradeoff between risk and return. To ascertain any potential risk-return gains of an investment in Bitcoin, the SRs of the test and benchmark portfolios are compared. Table 13 summarizes the SRs calculated for each of the 12 optimized test and benchmark TPs and GMVPs.

**Table 13:** Performance Metric: Sharpe Ratio

| Sharpe Ratio | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean-Variance Optimization | | | | | | | | | | | | | | |
| | TP - Test | | | TP - Benchmark | | | Relative | GMVP - Test | | | GMVP - Benchmark | | | Relative |
| | Mean | St.Dev. | SR | Mean | St.Dev | SR | Relative | Mean | St.Dev. | SR | Mean | St.Dev. | SR | Relative |
| Sep/19 | 0.0750% | 0.2287% | 0.3278 | 0.0734% | 0.2254% | 0.3255 | 1.0069 | 0.0724% | 0.2240% | 0.3234 | 0.0724% | 0.2240% | 0.3234 | 1.0000 |
| Oct/19 | 0.0668% | 0.2345% | 0.2851 | 0.0663% | 0.2332% | 0.2844 | 1.0023 | 0.0652% | 0.2313% | 0.2821 | 0.0652% | 0.2313% | 0.2821 | 1.0000 |
| Nov/19 | 0.0683% | 0.2385% | 0.2863 | 0.0683% | 0.2385% | 0.2863 | 1.0000 | 0.0645% | 0.2317% | 0.2782 | 0.0645% | 0.2317% | 0.2782 | 1.0000 |
| Dec/19 | 0.0668% | 0.2333% | 0.2862 | 0.0668% | 0.2333% | 0.2862 | 1.0000 | 0.0637% | 0.2287% | 0.2787 | 0.0642% | 0.2288% | 0.2807 | 0.9930 |
| Jan/20 | 0.0858% | 0.2249% | 0.3814 | 0.0851% | 0.2281% | 0.3731 | 1.0221 | 0.0791% | 0.2176% | 0.3635 | 0.0782% | 0.2199% | 0.3555 | 1.0225 |
| Feb/20 | 0.0843% | 0.2311% | 0.3650 | 0.0849% | 0.2337% | 0.3632 | 1.0049 | 0.0766% | 0.2225% | 0.3444 | 0.0767% | 0.2244% | 0.3420 | 1.0071 |
| Mar/20 | 0.0766% | 0.2821% | 0.2714 | 0.0763% | 0.2815% | 0.2710 | 1.0014 | 0.0699% | 0.2698% | 0.2589 | 0.0699% | 0.2698% | 0.2589 | 1.0000 |
| Apr/20 | 0.0860% | 0.2830% | 0.3038 | 0.0854% | 0.2815% | 0.3035 | 1.0008 | 0.0831% | 0.2771% | 0.2999 | 0.0831% | 0.2771% | 0.2999 | 1.0000 |
| May/20 | 0.0785% | 0.2799% | 0.2806 | 0.0781% | 0.2791% | 0.2796 | 1.0035 | 0.0767% | 0.2767% | 0.2772 | 0.0767% | 0.2767% | 0.2771 | 1.0001 |
| Jun/20 | 0.0783% | 0.2853% | 0.2744 | 0.0768% | 0.2822% | 0.2721 | 1.0085 | 0.0753% | 0.2794% | 0.2694 | 0.0753% | 0.2794% | 0.2694 | 1.0002 |
| Jul/20 | 0.0791% | 0.2909% | 0.2719 | 0.0788% | 0.2902% | 0.2716 | 1.0010 | 0.0730% | 0.2793% | 0.2613 | 0.0730% | 0.2792% | 0.2613 | 1.0001 |
| Aug/20 | 0.0725% | 0.2979% | 0.2434 | 0.0717% | 0.2955% | 0.2428 | 1.0027 | 0.0655% | 0.2823% | 0.2319 | 0.0654% | 0.2823% | 0.2318 | 1.0001 |
| Average | 0.0765% | 0.2592% | 0.2981 | 0.0760% | 0.2585% | 0.2966 | 1.0045 | 0.0721% | 0.2517% | 0.2891 | 0.0721% | 0.2521% | 0.2884 | 1.0019 |
| Frequency | | | | | | | 83.33% | | | | | | | 50.00% |

Mean-CVaR Optimization

| | TP – Test | | | TP – Benchmark | | | Relative | GMVP – Test | | | GMVP – Benchmark | | | Relative |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | St.Dev. | SR | Mean | St.Dev | SR | Relative | Mean | St.Dev. | SR | Mean | St.Dev. | SR | Relative |
| Sep/19 | 0.0770% | 0.2373% | 0.3245 | 0.0732% | 0.2276% | 0.3216 | 1.0090 | 0.0729% | 0.2252% | 0.3237 | 0.0729% | 0.2252% | 0.3237 | 1.0000 |
| Oct/19 | 0.0667% | 0.2372% | 0.2814 | 0.0669% | 0.2385% | 0.2807 | 1.0027 | 0.0653% | 0.2327% | 0.2804 | 0.0653% | 0.2327% | 0.2804 | 1.0000 |
| Nov/19 | 0.0695% | 0.2461% | 0.2823 | 0.0695% | 0.2461% | 0.2823 | 1.0000 | 0.0654% | 0.2332% | 0.2803 | 0.0666% | 0.2351% | 0.2835 | 0.9887 |
| Dec/19 | 0.0677% | 0.2396% | 0.2825 | 0.0677% | 0.2396% | 0.2825 | 1.0000 | 0.0646% | 0.2304% | 0.2803 | 0.0650% | 0.2300% | 0.2827 | 0.9916 |
| Jan/20 | 0.0879% | 0.2336% | 0.3764 | 0.0852% | 0.2293% | 0.3718 | 1.0124 | 0.0820% | 0.2200% | 0.3728 | 0.0815% | 0.2229% | 0.3659 | 1.0190 |
| Feb/20 | 0.0872% | 0.2445% | 0.3566 | 0.0839% | 0.2324% | 0.3612 | 0.9873 | 0.0794% | 0.2252% | 0.3525 | 0.0792% | 0.2279% | 0.3475 | 1.0145 |
| Mar/20 | 0.0770% | 0.2955% | 0.2607 | 0.0771% | 0.2852% | 0.2705 | 0.9636 | 0.0646% | 0.2806% | 0.2303 | 0.0646% | 0.2755% | 0.2345 | 0.9816 |
| Apr/20 | 0.0818% | 0.2833% | 0.2889 | 0.0827% | 0.2780% | 0.2975 | 0.9710 | 0.0796% | 0.2914% | 0.2731 | 0.0795% | 0.2882% | 0.2759 | 0.9898 |
| May/20 | 0.0733% | 0.3187% | 0.2300 | 0.0766% | 0.3190% | 0.2401 | 0.9577 | 0.0725% | 0.3016% | 0.2404 | 0.0673% | 0.3107% | 0.2165 | 1.1106 |
| Jun/20 | 0.0751% | 0.3387% | 0.2216 | 0.0778% | 0.3380% | 0.2301 | 0.9632 | 0.0726% | 0.3079% | 0.2360 | 0.0673% | 0.2963% | 0.2272 | 1.0384 |
| Jul/20 | 0.0759% | 0.3504% | 0.2167 | 0.0850% | 0.3713% | 0.2290 | 0.9461 | 0.0706% | 0.3033% | 0.2329 | 0.0705% | 0.3108% | 0.2270 | 1.0261 |
| Aug/20 | 0.0757% | 0.4074% | 0.1858 | 0.0786% | 0.3634% | 0.2163 | 0.8588 | 0.0653% | 0.3104% | 0.2105 | 0.0682% | 0.3042% | 0.2242 | 0.9388 |
| Average | 0.0762% | 0.2860% | 0.2756 | 0.0770% | 0.2807% | 0.2820 | 0.9727 | 0.0712% | 0.2635% | 0.2761 | 0.0707% | 0.2633% | 0.2741 | 1.0082 |
| Frequency | | | | | | | 25.00% | | | | | | | 41.67% |

An obvious takeaway is the improvement of the SR upon the inclusion of Bitcoin for most of the TPs in the mean-variance optimization framework. More specifically, this holds for all portfolios except those optimized at the end of November and December 2019, which do not include any weight in Bitcoin and thus have equal SRs to the benchmark. Hence, the test portfolios were found to be largely favorable compared to the benchmark SRs during times of high COVID-19 related market stress. On average, across the 12 portfolios, the mean-variance optimized test TP exhibits the highest SR of 0.2981, followed by the benchmark with 0.2966. A different image emerges when turning to the mean-CvaR optimized TPs. In this case, the average SR is more favorable for the benchmark rather than the test portfolio, which is the result of the benchmark's slightly higher average return and slightly lower average standard deviation. Correspondingly, the inclusion of Bitcoin only leads to a higher risk-return for the portfolios optimized at the end of September 2019, October 2019, and January 2020. The test portfolios optimized with return data from under the COVID-19 crisis displayed lower SRs than the respective benchmark.

Turning to the GMVPs, it quickly becomes evident that Bitcoin is not included in five of the mean-variance optimized test portfolios, leading the test and benchmark portfolio to perform equally well for these portfolios. Six portfolios, however, proved to benefit from the inclusion of Bitcoin, leading the average SR of the test portfolio, reported at 0.2891, to be slightly higher than that of the benchmark, measured at 0.2884. Many of the portfolios outperforming the benchmark contained return data from under the COVID-19 related bear market, thereby indicating that the inclusion of Bitcoin was preferable during the COVID-19 crisis. The mean-CVaR optimized GMVPs provide an inconclusive image on the contribution of Bitcoin to SR performance. The test portfolios realize both a higher and lower SR than the benchmark for five portfolios each, showing no clear cohesion to the impact of COVID-19 related stress. The remaining two test portfolios do not include any weight in Bitcoin. Nonetheless, this results in a slightly higher average SR for the test portfolios of 0.2761 as compared to the benchmark SR of 0.2741.

#### *6.3.3.4. Risk-Return Metric – Sortino Ratio*

Since an investor is more occupied by a portfolio's risk-adjusted returns for downside rather than upside volatility, the following section reports the results of the SoR analysis displayed in Table 14.

**Table 14:** Performance Metric: Sortino Ratio

| Sortino Ratio | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean-Variance Optimization | | | | | | | | | | | | | | |
| | TP - Test | | | TP - Benchmark | | | Relative | GMVP - Test | | | GMVP - Benchmark | | | Relative |
| | Mean | St.Dev.D | SoR | Mean | St.Dev.D | SoR | Relative | Mean | St.Dev.D | SoR | Mean | St.Dev.D | SoR | Relative |
| Sep/19 | 0.0750% | 0.1624% | 0.4616 | 0.0734% | 0.1535% | 0.4780 | 0.9657 | 0.0724% | 0.1573% | 0.4606 | 0.0724% | 0.1573% | 0.4606 | 1.0000 |
| Oct/19 | 0.0668% | 0.1800% | 0.3715 | 0.0663% | 0.1740% | 0.3810 | 0.9749 | 0.0652% | 0.1653% | 0.3947 | 0.0652% | 0.1653% | 0.3947 | 1.0000 |
| Nov/19 | 0.0683% | 0.1663% | 0.4105 | 0.0683% | 0.1663% | 0.4105 | 1.0000 | 0.0645% | 0.1631% | 0.3952 | 0.0645% | 0.1631% | 0.3952 | 1.0000 |
| Dec/19 | 0.0668% | 0.1588% | 0.4206 | 0.0668% | 0.1588% | 0.4206 | 1.0000 | 0.0637% | 0.1631% | 0.3908 | 0.0642% | 0.1613% | 0.3981 | 0.9818 |
| Jan/20 | 0.0858% | 0.1472% | 0.5825 | 0.0851% | 0.1498% | 0.5681 | 1.0253 | 0.0791% | 0.1460% | 0.5421 | 0.0782% | 0.1424% | 0.5491 | 0.9873 |
| Feb/20 | 0.0843% | 0.1557% | 0.5415 | 0.0849% | 0.1569% | 0.5409 | 1.0011 | 0.0766% | 0.1605% | 0.4774 | 0.0767% | 0.1577% | 0.4867 | 0.9809 |
| Mar/20 | 0.0766% | 0.1987% | 0.3853 | 0.0763% | 0.1932% | 0.3947 | 0.9761 | 0.0699% | 0.2043% | 0.3419 | 0.0699% | 0.2043% | 0.3419 | 1.0000 |
| Apr/20 | 0.0860% | 0.2011% | 0.4276 | 0.0854% | 0.2002% | 0.4267 | 1.0021 | 0.0831% | 0.2105% | 0.3948 | 0.0831% | 0.2105% | 0.3948 | 1.0000 |
| May/20 | 0.0785% | 0.2172% | 0.3616 | 0.0781% | 0.2073% | 0.3766 | 0.9600 | 0.0767% | 0.2091% | 0.3669 | 0.0767% | 0.2090% | 0.3670 | 0.9996 |
| Jun/20 | 0.0783% | 0.2429% | 0.3222 | 0.0768% | 0.2245% | 0.3420 | 0.9420 | 0.0753% | 0.2149% | 0.3503 | 0.0753% | 0.2148% | 0.3504 | 0.9997 |
| Jul/20 | 0.0791% | 0.2602% | 0.3040 | 0.0788% | 0.2548% | 0.3093 | 0.9827 | 0.0730% | 0.2139% | 0.3411 | 0.0730% | 0.2138% | 0.3412 | 0.9996 |
| Aug/20 | 0.0725% | 0.2882% | 0.2516 | 0.0717% | 0.2767% | 0.2592 | 0.9705 | 0.0655% | 0.2139% | 0.3059 | 0.065% | 0.2139% | 0.3060 | 0.9997 |
| Average | 0.0765% | 0.1982% | 0.4034 | 0.0760% | 0.1930% | 0.4090 | 0.9834 | 0.0721% | 0.1852% | 0.3968 | 0.0721% | 0.1844% | 0.3988 | 0.9957 |
| Frequency | | | | | | | 25.00% | | | | | | | 0.00% |

Mean-CVaR Optimization

| | TP - Test | | | TP - Benchmark | | | Relative | GMVP - Test | | | GMVP - Benchmark | | | Relative |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | St.Dev.D | SoR | Mean | St.Dev.D | SoR | Relative | Mean | St.Dev.D | SoR | Mean | St.Dev.D | SoR | Relative |
| Sep/19 | 0.0770% | 0.1688% | 0.4560 | 0.0732% | 0.1646% | 0.4448 | 1.0253 | 0.0729% | 0.1550% | 0.4703 | 0.0729% | 0.1589% | 0.4586 | 1.0255 |
| Oct/19 | 0.0667% | 0.1781% | 0.3749 | 0.0669% | 0.1886% | 0.3549 | 1.0563 | 0.0653% | 0.1676% | 0.3894 | 0.0653% | 0.1721% | 0.3793 | 1.0266 |
| Nov/19 | 0.0695% | 0.1562% | 0.4449 | 0.0695% | 0.1704% | 0.4077 | 1.0914 | 0.0654% | 0.1622% | 0.4031 | 0.0666% | 0.1628% | 0.4094 | 0.9846 |
| Dec/19 | 0.0677% | 0.1513% | 0.4475 | 0.0677% | 0.1670% | 0.4053 | 1.1039 | 0.0646% | 0.1594% | 0.4052 | 0.0650% | 0.1608% | 0.4045 | 1.0017 |
| Jan/20 | 0.0879% | 0.1483% | 0.5931 | 0.0852% | 0.1519% | 0.5611 | 1.0571 | 0.0820% | 0.1454% | 0.5641 | 0.0815% | 0.1432% | 0.5695 | 0.9904 |
| Feb/20 | 0.0872% | 0.1509% | 0.5780 | 0.0839% | 0.1542% | 0.5444 | 1.0618 | 0.0794% | 0.1562% | 0.5081 | 0.0792% | 0.1504% | 0.5267 | 0.9648 |
| Mar/20 | 0.0770% | 0.1999% | 0.3853 | 0.0771% | 0.1952% | 0.3952 | 0.9750 | 0.0646% | 0.2559% | 0.2524 | 0.0646% | 0.2372% | 0.2725 | 0.9262 |
| Apr/20 | 0.0818% | 0.2248% | 0.3641 | 0.0827% | 0.2126% | 0.3891 | 0.9357 | 0.0796% | 0.2666% | 0.2984 | 0.0795% | 0.2391% | 0.3326 | 0.8974 |
| May/20 | 0.0733% | 0.3304% | 0.2218 | 0.0766% | 0.3667% | 0.2088 | 1.0622 | 0.0725% | 0.2941% | 0.2466 | 0.0673% | 0.3412% | 0.1971 | 1.2510 |
| Jun/20 | 0.0751% | 0.3888% | 0.1931 | 0.0778% | 0.4060% | 0.1916 | 1.0079 | 0.0726% | 0.3091% | 0.2350 | 0.0673% | 0.2782% | 0.2420 | 0.9711 |
| Jul/20 | 0.0759% | 0.4166% | 0.1822 | 0.0850% | 0.4514% | 0.1884 | 0.9671 | 0.0706% | 0.2922% | 0.2417 | 0.0705% | 0.3397% | 0.2076 | 1.1641 |
| Aug/20 | 0.0757% | 0.4961% | 0.1526 | 0.0786% | 0.3634% | 0.2163 | 0.7053 | 0.0653% | 0.3009% | 0.2171 | 0.0682% | 0.3113% | 0.2191 | 0.9910 |
| Average | 0.0762% | 0.2508% | 0.3661 | 0.0770% | 0.2493% | 0.3590 | 1.0041 | 0.0712% | 0.2221% | 0.3526 | 0.0707% | 0.2246% | 0.3516 | 1.0162 |
| Frequency | | | | | | | 66.67% | | | | | | | 41.67% |

When looking at the mean-variance optimized TPs, it becomes evident that the benchmark portfolio outperforms the test portfolio the majority of the time. With an average SoR of 0.4034 compared to the benchmark average of 0.4090, the inclusion of Bitcoin only leads to superior performance for the portfolios optimized at the end of January, February, and April 2020. While two of these months registered high global financial market stress, the test portfolio mostly underperformed when the months of COVID-19 stress were included. This is mainly attributable to the fact that the test portfolio noted a relatively larger average downside standard deviation, while only reporting a slightly better average return than the benchmark. Contrary to this finding, eight of the 12 mean-CVaR optimized test TPs outperform the benchmark with a higher SoR, namely for the portfolios optimized at the end of all months except March, April, July, and August 2020. It is, however, noteworthy that the aforementioned exceptions are portfolios, including return data from bullish market conditions, thereby questioning Bitcoin's enhancing value for portfolios under the COVID-19 pandemic. Notably, the average SoR of the test TPs, measured at 0.3661, as well as of the benchmark TPs, reported at 0.3590, lie below the average SoRs of the mean-variance optimized portfolios.

Turning to the GMVPs, it quickly becomes apparent that the inclusion of Bitcoin into the mean-variance optimized test portfolios reduces the risk-adjusted returns as compared to not holding an investment in Bitcoin. All test portfolios, which have received a weight allocation to Bitcoin, clearly underperform compared to their respective benchmark. A different finding emerges when turning to the mean-CVaR optimized GMVPs. Despite having a lower average SoR than the mean-variance optimized portfolios, the mean-CVaR test GMVP outperforms its benchmark for the portfolios optimized at the end of September, October, December 2019, as well as May and July 2020. For the remaining seven months, the benchmark portfolio renders higher SoRs, thereby providing no conclusive image of Bitcoin's ability to generate risk-return efficiency in general and under the COVID-19 crisis.

#### *6.3.3.5. Risk-Return Metric – Adjusted Sharpe Ratio*

Lastly, the empirical findings from the ASR analysis, which measures the risk-adjusted return on MCVaR, are summarized in Table 15. Commencing with the TPs, and as discussed in section 6.3.3.2., the mean-variance optimized test TPs register a notable increase in the portfolio's MCVaR upon inclusion of Bitcoin. This results in an average ASR of 0.1268, which ranks below the benchmark ASR measured at 0.1288, as only the test portfolios optimized at the end of January and April 2020 outperform the benchmark. Under the mean-CVaR optimization, the test TPs perform slightly better than the benchmark with an average ASR of 0.1127 as compared to a benchmark ASR of 0.1124. Nonetheless, six of the test portfolios register an inferior ASR performance compared to the benchmark, which all include return data from under the COVID-19 crisis.

**Table 15:** Performance Metric: Adjusted Sharpe Ratio

Adjusted Sharpe Ratio

Mean-Variance Optimization

| | Mean | MCVaR | ASR | Mean | MCVaR | ASR | Relative | Mean | MCVaR | ASR | Mean | MCVaR | ASR | Relative |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sep/19 | 0.0750% | 0.5091% | 0.1472 | 0.0734% | 0.4880% | 0.1503 | 0.9792 | 0.0724% | 0.5063% | 0.1431 | 0.0724% | 0.5063% | 0.1431 | 1.0000 |
| Oct/19 | 0.0668% | 0.5578% | 0.1198 | 0.0663% | 0.5483% | 0.1210 | 0.9908 | 0.0652% | 0.5285% | 0.1235 | 0.0652% | 0.5285% | 0.1235 | 1.0000 |
| Nov/19 | 0.0683% | 0.5166% | 0.1322 | 0.0683% | 0.5166% | 0.1322 | 1.0000 | 0.0645% | 0.5235% | 0.1231 | 0.0645% | 0.5235% | 0.1231 | 1.0000 |
| Dec/19 | 0.0668% | 0.5083% | 0.1314 | 0.0668% | 0.5083% | 0.1314 | 1.0000 | 0.0637% | 0.5259% | 0.1212 | 0.0642% | 0.5213% | 0.1232 | 0.9840 |
| Jan/20 | 0.0858% | 0.4609% | 0.1861 | 0.0851% | 0.4653% | 0.1829 | 1.0175 | 0.0791% | 0.4686% | 0.1688 | 0.0782% | 0.4702% | 0.1662 | 1.0156 |
| Feb/20 | 0.0843% | 0.4904% | 0.1720 | 0.0849% | 0.4920% | 0.1725 | 0.9971 | 0.0766% | 0.5045% | 0.1519 | 0.0767% | 0.5054% | 0.1519 | 1.0002 |
| Mar/20 | 0.0766% | 0.6084% | 0.1258 | 0.0763% | 0.5993% | 0.1273 | 0.9887 | 0.0699% | 0.6787% | 0.1029 | 0.0699% | 0.6787% | 0.1029 | 1.0000 |
| Apr/20 | 0.0860% | 0.6167% | 0.1394 | 0.0854% | 0.6182% | 0.1382 | 1.0091 | 0.0831% | 0.6880% | 0.1208 | 0.0831% | 0.6880% | 0.1208 | 1.0000 |
| May/20 | 0.0785% | 0.7184% | 0.1093 | 0.0781% | 0.6770% | 0.1153 | 0.9481 | 0.0767% | 0.7011% | 0.1094 | 0.0767% | 0.7005% | 0.1095 | 0.9993 |
| Jun/20 | 0.0783% | 0.8204% | 0.0954 | 0.0768% | 0.7346% | 0.1045 | 0.9126 | 0.0753% | 0.7189% | 0.1047 | 0.0753% | 0.7183% | 0.1048 | 0.9993 |
| Jul/20 | 0.0791% | 0.8810% | 0.0898 | 0.0788% | 0.8468% | 0.0931 | 0.9646 | 0.0730% | 0.7260% | 0.1005 | 0.0730% | 0.7254% | 0.1006 | 0.9992 |
| Aug/20 | 0.0725% | 0.9903% | 0.0732 | 0.0717% | 0.9257% | 0.0775 | 0.9449 | 0.0655% | 0.7228% | 0.0905 | 0.0654% | 0.7224% | 0.0906 | 0.9995 |
| Average | 0.0765% | 0.6399% | 0.1268 | 0.0760% | 0.6183% | 0.1288 | 0.9794 | 0.0721% | 0.6077% | 0.1217 | 0.0721% | 0.6074% | 0.1217 | 0.9998 |
| Frequency | | | | | | | 16.67% | | | | | | | 16.67% |

Mean-CVaR Optimization

| | TP - Test | | | TP - Benchmark | | | Relative | GMVP - Test | | | GMVP - Benchmark | | | Relative |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | MCVaR | ASR | Mean | MCVaR | ASR | Relative | Mean | MCVaR | ASR | Mean | MCVaR | ASR | Relative |
| Sep/19 | 0.0770% | 0.5269% | 0.1461 | 0.0732% | 0.5145% | 0.1423 | 1.0271 | 0.0729% | 0.4967% | 0.1468 | 0.0729% | 0.4967% | 0.1468 | 1.0000 |
| Oct/19 | 0.0667% | 0.5432% | 0.1229 | 0.0669% | 0.5809% | 0.1153 | 1.0661 | 0.0653% | 0.5299% | 0.1232 | 0.0653% | 0.5299% | 0.1232 | 1.0000 |
| Nov/19 | 0.0695% | 0.4905% | 0.1417 | 0.0695% | 0.4905% | 0.1417 | 1.0000 | 0.0654% | 0.5157% | 0.1267 | 0.0666% | 0.5113% | 0.1303 | 0.9723 |
| Dec/19 | 0.0677% | 0.4809% | 0.1408 | 0.0677% | 0.4809% | 0.1408 | 1.0000 | 0.0646% | 0.5128% | 0.1259 | 0.0650% | 0.5227% | 0.1244 | 1.0123 |
| Jan/20 | 0.0879% | 0.4484% | 0.1961 | 0.0852% | 0.4742% | 0.1798 | 1.0909 | 0.0820% | 0.4617% | 0.1777 | 0.0815% | 0.4570% | 0.1784 | 0.9959 |
| Feb/20 | 0.0872% | 0.4671% | 0.1867 | 0.0839% | 0.4862% | 0.1726 | 1.0813 | 0.0794% | 0.4871% | 0.1630 | 0.0792% | 0.4830% | 0.1639 | 0.9941 |
| Mar/20 | 0.0770% | 0.6331% | 0.1217 | 0.0771% | 0.6072% | 0.1270 | 0.9578 | 0.0646% | 1.0156% | 0.0636 | 0.0646% | 0.8748% | 0.0739 | 0.8609 |
| Apr/20 | 0.0818% | 0.7549% | 0.1084 | 0.0827% | 0.7044% | 0.1174 | 0.9233 | 0.0796% | 1.0273% | 0.0775 | 0.0795% | 0.8637% | 0.0921 | 0.8414 |
| May/20 | 0.0733% | 1.3484% | 0.0544 | 0.0766% | 1.2966% | 0.0591 | 0.9203 | 0.0725% | 1.1929% | 0.0608 | 0.0673% | 1.3271% | 0.0507 | 1.1995 |
| Jun/20 | 0.0751% | 1.5657% | 0.0479 | 0.0778% | 1.4477% | 0.0537 | 0.8925 | 0.0726% | 1.2329% | 0.0589 | 0.0673% | 1.1143% | 0.0604 | 0.9751 |
| Jul/20 | 0.0759% | 1.6283% | 0.0466 | 0.0850% | 1.6768% | 0.0507 | 0.9193 | 0.0706% | 1.1756% | 0.0601 | 0.0705% | 1.3252% | 0.0532 | 1.1287 |
| Aug/20 | 0.0757% | 1.9562% | 0.0387 | 0.0786% | 1.6236% | 0.0484 | 0.7990 | 0.0653% | 1.1885% | 0.0550 | 0.0682% | 1.1872% | 0.0574 | 0.9569 |
| Average | 0.0762% | 0.9036% | 0.1127 | 0.0770% | 0.8653% | 0.1124 | 0.9731 | 0.0712% | 0.8197% | 0.1033 | 0.0707% | 0.8077% | 0.1046 | 0.9948 |
| Frequency | | | | | | | 33.33% | | | | | | | 25.00% |

The mean-variance optimized test and benchmark GMVPs report the same average ASR of 0.1217. This is partly explainable by the fact that Bitcoin's weight is 0% for five of the 12 test portfolios, resulting in the same performance of the respective test and benchmark GMVPs. Only the GMVPs optimized at the end of January and February 2020 outperform the benchmark. A similar light is shed on the situation by the mean-CVaR optimized GMVPs for which only the test portfolios optimized at the end of December 2019, May 2020, and July 2020 perform better than the benchmark. Here, the average ASR of the benchmark, registered at 0.1046, is higher than for the portfolios containing Bitcoin.

Among the two optimization strategies, the mean-variance portfolios perform better than the respective mean-CVaR portfolios on all performance metrics. Moreover, it becomes clear that conclusions about the superiority of the test or benchmark portfolios highly depend on the performance metric as well as optimization assumption. No conclusive image arises upon whether the inclusion of Bitcoin into a diversified portfolio enhances portfolio performance during the COVID-19 crisis.

# 7. Discussion

This section is dedicated to the discussion of the empirical results and is divided into two parts. First, the empirical results of Analysis I, II and III are interpreted following Figure 3. The obtained findings are critically assessed and placed in context to the existing literature and theory on the topic. Second, this section reflects upon the implications of the interpreted findings for market participants. Thereby, this section reveals the central contribution of this thesis and serves as a starting point for future research within the field.

## 7.1. Interpretation – Analysis I

Does Bitcoin correlate negatively with other assets amid the COVID-19 crisis by increasing in value while the value of other assets decreases? And, hence, can investors fly to safety by investing in Bitcoin during the COVID-19 crisis and in times of market turmoil in general? These questions are fundamental to the discussion of the empirical results proposed by Analysis I and to find evidence for or against the first sub-hypothesis.

Undeniably, the results from Analysis I are predominantly providing evidence for Bitcoin's lack of safe haven properties during the COVID-19 crisis as well as during other times of financial market distress. For the vast majority of the considered asset indices, more specifically the world, developing and emerging equity market indices, the country-specific equity indices of the US, Hong Kong, UK, France, and Germany, as well as bond, commodity, and real estate indices, Bitcoin does not provide safe haven capabilities during COVID-19 and other times of market stress. This resembles the findings of Klein, Pham Thu, and Walther (2018) and Naeem *et al.* (2020), who rule out any safe haven potential of Bitcoin, as well as Conlon, Corbet, and Mcgee (2020), who find that Bitcoin does not carry safe haven properties for the majority of international equity indices. Except for the crude oil index, with which Bitcoin exhibits a minimal but negative correlation on average, the empirical results of Analysis I discredit not only Bitcoin's safe haven characteristics but also its hedging potential. In line with Dutta *et al.* (2020), Bitcoin's hedging capability against crude oil on average is, however, offset by positive marginal effects for the COVID-19 periods, which uncovers that Bitcoin merely acts as a diversifier against crude oil under market turmoil. This stands in contrast to the findings presented by Selmi *et al.* (2018), who show that Bitcoin can serve as a safe haven against extreme global oil price movements. Despite the fact that the regression results do not establish any support for Bitcoin's safe haven potential against the aforementioned indices, the results do provide evidence for Bitcoin carrying profound diversification benefits, as all average correlation coefficients ($c_0$) between Bitcoin and the respective indices are remarkably low. This finding corresponds to the results presented in the widely cited study by Bouri *et al.* (2017), who conclude that Bitcoin is primarily suitable for diversification purposes.

In contrast to this study's prevailing finding that Bitcoin serves as a mere diversifier, three noteworthy results concerning the correlations between Bitcoin and the gold index, the S&P BSE 500 equity index, and the USD Currency Portfolio have emerged. First, as repeatedly established by several studies, gold has been the primary subject of study regarding safe haven phenomena (Dyhrberg, 2016a; Klein, Pham Thu and Walther, 2018; Naeem *et al.*, 2020). This thesis finds that Bitcoin and gold are positively correlated on average and become even more correlated amid the COVID-19 period. As gold is expected to be a safe haven during crises, it is notable that Bitcoin becomes more correlated with gold during a period of increased market stress. Consequently, this provides points to ponder on whether the rejection of Bitcoin's safe haven properties is reasonable. To support this argument and detect similarities between the return fluctuations of Bitcoin and gold, further investigation is necessary in the context of the COVID-19 crisis and in addition to the already existing strand of literature comparing the two assets (Dyhrberg, 2016b; Henriques and Sadorsky, 2018; Klein, Pham Thu and Walther, 2018).

Second, this thesis finds support for the previous findings of Brière, Oosterlinck, and Szafarz (2015), Bedi and Nashier (2020), and Platanakis and Urquhart (2020) in advocating that Bitcoin does hold safe haven properties in some instances. In line with Stensås *et al.* (2019), who argue that Bitcoin is an effective hedge against developing countries, this thesis discloses that Bitcoin acts as a hedge in general as well as a modest safe haven against the Indian equity index during the COVID-19 period. This becomes evident through the significant negative $c_0$ coefficients as well as the negative or insignificantly different from zero marginal effects of the COVID-19 and lowest quantile periods. Additionally, the findings were substantiated by graphically displaying the correlations and returns for both Bitcoin and the S&P BSE 500. This revealed that the safe haven capability does not only apply to Bitcoin but is observable for both Bitcoin against the S&P BSE 500, and vice versa. In fact, Bitcoin only acted as a safe haven against the S&P BSE 500 for the short-term period between March 20th and April 10th, 2020 amidst COVID-19. Evidently, this was caused by an extensive price drop in the S&P BSE 500 as a result of Indian Prime Minister Narenda Modi's declaration of a nationwide lockdown on March 24th, 2020 (Myupchar, 2020), whilst Bitcoin's price surged. Throughout the COVID-19 period, it appears that the Indian equity market has been hit extremely hard, which stands in contradiction to existing research suggesting emerging markets to generally recover from crises more quickly (Ohmeyer and Hansen, 2020).

Third, and similar to the above, the correlation between Bitcoin and the USD Currency Portfolio is significantly negative on average, thereby uncovering Bitcoin's hedging potential, as previously established by Dyhrberg (2016a). In addition, the empirical results point out significant negative marginal effects during the COVID-19 period, which, together with Figure 4, provide evidence in favor of Bitcoin's safe haven properties for several occasions during the COVID-19 period. As dwelled upon in the empirical results section, the USD Currency Portfolio generally holds its value and reports only minor price drops amid the COVID-19 crisis. However, it can be advocated that Bitcoin noticed price surges during precisely the minor price drops of the USD Currency Portfolio, thereby leading Bitcoin to act as a minimal safe haven against the USD Currency Portfolio. This is compatible with experts suggesting that Bitcoin and gold are the only two assets that can be considered as a safe haven against the US dollar, as all assets dependent on governments and corporations (e.g., bonds and stocks) are significantly exposed to fluctuations in the dollar (Shevchenko, 2020). Nevertheless, the value of this finding needs to be seen in a critical light, as it appears questionable that investors would seek a safe haven investment against the US dollar, which in fact has been regarded as a safe haven investment itself (Dyhrberg, 2016a; Baur, Dimpfl and Kuck, 2018). Additionally, the correlations between Bitcoin and the US Dollar might even suggest that the US Dollar serves as a safe haven against Bitcoin at certain points during the COVID-19 period. According to the theoretical definitions, however, Bitcoin has been found to provide safe haven capabilities against decreases in the USD Currency Portfolio, but only for short horizons of no more than two weeks.

Consequently, and harmonious with Bouri *et al.* (2017) and Dyhrberg (2016b), this thesis finds that Bitcoin's safe haven capabilities against both the S&P BSE 500 and the USD Currency Portfolio only persist for a short time horizon. Furthermore, the fact that Bitcoin only carries safe haven properties against two assets and for short time periods alludes to Bitcoin's minor role as a safe haven. Finally, it is noteworthy that Bitcoin's marginal safe haven capabilities vary across time, asset classes, and geography. The latter should also be seen in light of the fact that financial markets around the world have reacted very differently to the crisis after the first severe downturn experienced by all countries in March, thereby suggesting regional differences in Bitcoin's safe haven potential (Ohmeyer and Hansen, 2020).

## 7.2. Interpretation – Analysis II

In continuation of the previous section, the following adds to the discussion on Bitcoin's modest safe haven properties by taking the importance of liquidity into account. Consequently, the question is raised whether the identified safe haven capabilities of Bitcoin hold when acknowledging the crucial aspect of liquidity. This leads to finding evidence in favor of or against the second sub-hypothesis.

Commencing with the implicit costs of trading, Bitcoin's liquidity has irrefutably improved over time, given that the bid-ask percentage spread continuously declined after a peak in September 2014. For the entire sample period from 2013 to 2020, Bitcoin registers the highest bid-ask spreads when compared to gold, Apple, and Twitter. Given that the width of the bid-ask spread is primarily determined by trading volume and volatility (Bodie, Kane and Marcus, 2018), Bitcoin's high volatility and still developing trading volume in its early years might explain the high bid-ask spreads reported for Bitcoin in that period. When looking at a more recent data sample from September 2019 through August 2020, it becomes apparent that the bid-ask spread of Bitcoin is, in fact, lower than the pronounced safe haven of gold. This suggests that Bitcoin performs relatively well in terms of liquidity in comparison to gold, which has been advocated to be persistently liquid. Focusing on a shorter COVID-19 period from February 24$^{th}$ to April 10$^{th}$, 2020, it is evident that the bid-ask spreads of all considered assets rise as a consequence of increased COVID-19 related market stress. This is a common finding during periods of market crisis and high volatility, at which market dealers inflate spreads to account for higher risk, driving up the cost of trading at the same time at which asset prices are usually falling (Wrobel, 2017). Surprisingly, Bitcoin continues to outperform gold and performs approximately similar to Apple and Twitter during this period, which supports Bitcoin's safe haven capability and raises questions about gold's safe haven properties amid COVID-19. To verify or reject this presumption, it is necessary to initiate a comprehensive examination of gold's safe haven abilities, which remains out of scope. Bitcoin's relatively strong liquidity, however, stands in contradiction to an earlier study by Smales (2019), who disregards Bitcoin's safe haven capabilities based on its low liquidity. This differing finding is partly explainable by the fact that Smales (2019) only includes data up until 2018, whereas this thesis finds a significant improvement in the bid-ask spread in the period from September 2019 through August 2020.

Looking at the explicit costs of trading Bitcoins, the transaction fees related to using the Bitcoin network proved to diminish with time, as the long COVID-19 sub-period exhibited a remarkably lower average and maximum transaction fee compared to the highest observed value in December 2017. During the short COVID-19 sub-period, the mean and maximum observed transaction fees dropped even further, thus accentuating the low transaction costs amid high COVID-19 related financial market stress. Even though this endorses the safe haven capability of Bitcoin, one striking finding should not be neglected. In line with results established by Schmitz and Hoffmann (2020), it is noteworthy to recognize the observed positive relationship between Bitcoin's transaction demand and transaction costs. The primary reason for the observed relationship is the block's limited capacity to include transactions. As a consequence, a backlog of unconfirmed transactions is created, which are waiting for a miner to select and include them into a block. Since miners prioritize the transactions paying them the highest fees, investors can affect the probability of their transactions to be added to the blockchain as fast as possible by bidding higher transaction fees. This gains importance when trading volume increases and multiple transactions compete against each other, which is usually what happens with safe haven assets during crises (Dwyer, 2015; Ryan, 2019). In case Bitcoin was a safe haven, one would expect demand to increase for Bitcoin during times of crises when investors seek to flee to safety. However, demand appeared to not rise significantly during the COVID-19 period, suggesting that investors did not vastly perceive Bitcoin to be a safe haven. If Bitcoin, nonetheless, were to be a safe haven during financial crises and demand would rise, the positive relationship between demand and transaction fees would diminish the attractiveness of investing in Bitcoin for safe haven purposes, as Bitcoin could then no longer be bought and sold at stable and low costs. Nonetheless, Bitcoin's transaction costs and bid-ask spreads remained relatively low throughout the COVID-19 period, thus supporting Bitcoin's modest safe haven properties during this period.

## 7.3. Interpretation – Analysis III

What role does Bitcoin play in the optimal portfolio construction of diversified portfolios? Would an investment in Bitcoin have led to the enhancement of a US investor's portfolio's performance amid the COVID-19 crisis? These are the central questions addressed in Analysis III to find evidence for or against the third sub-hypothesis.

Across the mean-variance as well as mean-CVaR optimization, the empirical findings proved Bitcoin to hold an average weight greater than zero for both the 12 test TPs and the 12 test GMVPs. While this indicates that Bitcoin can be a valuable component of a US investor's diversified portfolio, the fact that none of the portfolios allocate more than 0.715% of their investment to Bitcoin alludes to its minor role in optimal portfolio construction. As established by the regression coefficients in Analysis I, the positive weight allocation to Bitcoin is explicable by the low correlations between Bitcoin and the world equity, bond, commodity, currency, and real estate index considered in the diversified portfolios. Despite not offering significant safe haven capabilities, the regression coefficients suggested Bitcoin to serve as an effective diversifier for all five assets. The small magnitude of the positive weight allocation to Bitcoin needs to be seen in light of its relatively high return but also high standard deviation and MCVaR, which are especially penalized in the GMVPs, resulting in smaller average weight allocations to Bitcoin than in the TPs. The latter is in line with what theory would suggest, because GMVPs seek to minimize the respective portfolio risk measure. Generally, this study's weight allocation findings appear to be in line with previous research, which concludes that Bitcoin's diversification benefits render it a valuable portfolio addition (Brière, Oosterlinck and Szafarz, 2015; Platanakis, Sutcliffe and Urquhart, 2018; Kajtazi and Moro, 2019; Bedi and Nashier, 2020; Platanakis and Urquhart, 2020; Schmitz and Hoffmann, 2020). However, it is critical to note that the suggested optimal portfolio weights seem highly dependent on the chosen optimization framework, dataset, and considered asset universe, since several of the aforementioned authors find the optimal weight allocation to Bitcoin to be significantly larger than the findings of this study. The more recent articles of Bedi and Nashier (2020) and Schmitz and Hoffmann (2020), on the contrary, report low portfolio weight allocations to Bitcoin similar to this thesis. Considering that this study's two optimization frameworks also render similar but varying results, an examination of the sensitivities of additional optimization parameters as well as considering other optimization approaches would be required to challenge the presented findings.

While the average weight allocation across the 12 portfolios provides an insightful overview, it is important to discuss the development of the weight allocation to Bitcoin over time to set the overall averages into perspective and avoid potential miss-interpretations caused by single extreme observations. Of particular interest are the weight allocations of the portfolios, which were optimized on the basis of data including returns from periods reporting high COVID-19 related financial stress, namely February to August 2020. Throughout this period and across both optimization estimators, the empirical results showed that Bitcoin's weight in the TPs remained positive, with a slight decreasing trend from February to May 2020. This indicates that Bitcoin served as a valuable addition to a diversified TP during the entire COVID-19 observation period. Zooming in on the GMVPs, the empirical results report that Bitcoin should have received little attention during the months showing high COVID-19 related stress with the mean-variance optimal weights being zero or close to zero percent for all portfolios. On the contrary, the mean-CVaR optimized GMVP weights remained positive throughout the COVID-19 period, and, interestingly, reported higher Bitcoin weights than the TPs from February to April 2020. In line with the results of Symitsi and Chalvatzis (2019), this uncovers that Bitcoin, despite its overall high volatility and MCVaR, could have been of interest to risk-averse investors during months reflecting the effects of high global market stress. At this point, it is important to stress that Bitcoin's weight development throughout the COVID-19 period is a result of the inclusion of one (more) month of weekly return data from under the COVID-19 crisis, but also the exclusion of one month of weekly return data from the beginning of the two-year rolling window of data. Therefore, inferences about the impact of COVID-19 on the weight development should be drawn mindfully.

Remarkably, the mean-CVaR optimized Bitcoin weights of all TPs and GMVPs are larger than the corresponding mean-variance weights. This uncovers that investors focusing on downside risk-adjusted returns would end with a higher investment in Bitcoin than investors considering volatility adjusted returns. Arguably, the former gains importance during times of crises in which investors are less occupied with positive volatility, but are rather worried about potential losses. To further explore the downside risk reduction potential of including Bitcoin into a diversified portfolio, Analysis III compared the MVaR and MCVaR of the optimized test portfolios, including Bitcoin, and the optimized benchmark portfolios, excluding Bitcoin. While an investment allocation to Bitcoin resulted in a modest reduction of MVaR and MCVaR for some portfolios, Bitcoin's relatively high individual MVaR and MCVaR led the majority of the test portfolios to underperform in terms of tail risk reduction. Especially, the test portfolios, including return data from the COVID-19 crisis, showcased no consistent downside risk reduction. These results are in agreement with Conlon, Corbet, and Mcgee (2020) as well as Conlon and Mcgee (2020), who find evidence of increased downside risk for portfolios holding an allocation to Bitcoin during the early COVID-19 crisis. As expected when optimizing portfolios on the basis of return over CVaR, the mean-CVaR portfolios outperform their respective benchmark more frequently than the mean-variance portfolios. However, interestingly, the average MVaR and MCVaR of both the test and benchmark TPs and GMVPs appear to be higher under the mean-CVaR optimization than under the mean-variance approach. Hence, investors holding the mean-variance optimized portfolios would have experienced less downside risk than investors with mean-CVaR optimized portfolios. While it is surprising that the mean-CVaR optimized portfolios do not consistently outperform the benchmark and instead realize higher MCVaR values than the mean-variance portfolios, it is important to remember that the mean-CVaR portfolio weights were computed on the basis of generated scenarios which try to mimic the empirical distribution of the assets in statistical software. This allows the optimization to run based on more generated tail observations than what is possible for the MVaR and MCVaR calculations which base themselves on estimations and the current dataset.

Despite the importance of downside risk reduction, investors are unlikely to consider an investment in Bitcoin for MVaR and MCVaR purposes in isolation. Instead, their allocation decisions will consider the tradeoff between risk and return, why the SR, SoR, and ASR of the test and benchmark portfolios were compared. Harmonious to the findings of the reviewed literature (Brière, Oosterlinck and Szafarz, 2015; Platanakis, Sutcliffe and Urquhart, 2018; Kajtazi and Moro, 2019; Bedi and Nashier, 2020; Platanakis and Urquhart, 2020), this study finds that including a small proportion of Bitcoin improves the SR for an investor for all but two of the mean-variance optimized TPs. Notably, the test portfolios are found to be especially favorable when compared to the benchmark during times of high COVID-19 related market stress. On the contrary, the inclusion of Bitcoin in mean-CVaR optimized TPs reduced the SR during the COVID-19 period. When looking at the GMVPs, the mean-variance test portfolios generally outperform the benchmark or do not include an investment in Bitcoin at all. Many of the portfolios, outperforming the benchmark, contained return data from under the COVID-19 related bear market, thereby advocating that the inclusion of Bitcoin was preferable during the COVID-19 crisis. The mean-CVaR optimized GMVPs provide an inconclusive image on the contribution of Bitcoin to the SR performance. The test portfolios realize both a higher and lower SR than the benchmark, showing no clear cohesion to the impact of COVID-19 related stress.

To further make sense of the risk-return implications of including Bitcoin in a diversified portfolio, the SoR suggests that an investment in Bitcoin leads to a deterioration of the downside risk-adjusted return for the majority of the mean-variance TPs and GMVPs. While the mean-CVaR test TPs and GMVPs outperform their respective benchmark more frequently, the exceptions to this pattern are portfolios including return data from bullish market conditions, thereby questioning Bitcoin's downside risk-return enhancing value for portfolios under the COVID-19 pandemic. These findings thus only partially support previous research by Kajtazi and Moro (2019) as well as Platanakis and Urquhart (2020), who reported Bitcoin portfolios to carry higher SoRs than a benchmark.

Further substantiating the risk-return characteristics of holding an investment in Bitcoin throughout the COVID-19 period, the mean-variance optimized TPs and GMVPs mostly register a notable increase in the portfolio's MCVaR and a corresponding decrease in ASR upon inclusion of Bitcoin. Under the mean-CVaR optimization, the test portfolios outperform the benchmark more frequently, but register an inferior ASR performance in most of the portfolios including return data from under the COVID-19 crisis.

Among the two optimization strategies, the mean-variance portfolios perform better than the respective mean-CVaR portfolio on all performance metrics. Moreover, it becomes clear that conclusions about the superiority of the test or benchmark portfolios highly depend on the performance metric as well as optimization assumption. Overall, an investment in Bitcoin has the potential to increase the risk-return tradeoff of a diversified portfolio but proves less suitable and consistent for investors seeking to reduce their portfolio's downside risk amid the COVID-19 crisis.

## 7.4. Discussion of Implications

After having discussed the empirical findings of Analysis I, II, and III, the following section explores the implications of the interpreted findings for market participants.

For investors, the results outlined above imply that a position in Bitcoin can be utilized as an effective diversifier for a variety of asset index investments on average as well as during the COVID-19 crisis. The results further suggest that investors should only see Bitcoin as a modest safe haven against investments in the Indian S&P BSE 500 and the USD Currency Portfolio, which can only be used for short horizons at a time. In terms of liquidity, the results showed that investors were able to buy and sell Bitcoin relatively quickly and at relatively low transaction costs amid the COVID-19 crisis.

However, investors should be wary of the fact that transaction costs appear positively correlated with transaction demand, which indicates that costs might rise when more investors seek out Bitcoin. US investors in pursuit of portfolio diversification during the COVID-19 period were found to enhance the value of their optimal risky portfolios (TPs) by including an investment in Bitcoin both when caring about return over variance and return over CVaR. While including Bitcoin into a diversified portfolio is less favorable for risk-averse investors aiming to reduce their portfolio's variance, investors seeking to minimize their portfolio's CVaR are suggested to hold a small position in Bitcoin. Overall, an investment in Bitcoin has the potential to increase the SR of a portfolio but proves less suitable and consistent for investors seeking to reduce their portfolio's downside risk or increase the SoR and ASR amid the COVID-19 crisis.

While this list of implications provides insights for market participants alike, it also creates the question: For which investors would an investment in Bitcoin under the COVID-19 crisis have been most relevant? Firstly, investments in Bitcoin appear most suitable for retail investors. Even though Bitcoins can be traded on secondary markets, the limited number of available Bitcoins might render this study's results less relevant for institutional investors, who deal with large funds. In order to extend the relevance of the findings to institutional investors, it might be of value to study similarities between Bitcoin and other cryptocurrencies to infer whether they could utilize various cryptocurrencies as effective diversifiers and short-term safe havens against certain other assets. Secondly, the results indicate that investments in Bitcoin could have only served as a short-term safe haven against a few assets. Therefore, investing in Bitcoin to reduce the impact of COVID-19 related market fluctuations might only have been of value for active, short-term, and high-frequency speculative investors. For longer-term investors, and even short-term retail investors close to retirement, an investment in Bitcoin for the purpose of hedging risk would have been less useful given Bitcoin's high volatility and the overall sound performance of the financial markets after initial market shocks in March 2020. The latter is touched upon in the succeeding paragraph. Thirdly, an investment in Bitcoin would have proven valuable for a US retail investor holding a diversified risky portfolio, who wishes to maximize the return on variance and CVaR or minimize overall CVaR under the COVID-19 crisis. The low optimal weight allocation to Bitcoin ensures that investors enjoy the diversification benefit of Bitcoin without compromising the entire portfolio's risk level given Bitcoin's highly volatile nature. Given that the findings are based on a diversified portfolio consisting of global asset indices, the implications for portfolio investors might be generalizable to investors from other geographical regions than the US. Differences in the implications for investors from outside the US might, however, arise from changing the currency denominations. Lastly, and based on slight performance differences depending on the chosen optimization framework, this study's findings suggest that investors optimizing their portfolios on the basis of the mean-variance framework obtained higher performance than those with mean-CVaR optimized portfolios.

After having thoroughly discussed Bitcoin's investment characteristics during the COVID-19 period, two questions abide: Why do implications deriving from Bitcoin's behavior during past months matter? And, can lessons learned from Bitcoin's investment properties during the COVID-19 crisis be generalized to other periods of market stress? According to the efficient market hypothesis, past performance should not be an indicator of future performance, thereby posing a limit to the lessons that can be derived from this study and applied to future crises. Furthermore, it is questionable whether global financial markets even encountered sufficient instances of acute market stress during 2020 to permit the use of the word financial crisis and to draw accurate inferences about Bitcoin's safe haven potential during such times. Back in March 2020, various signs suggested that the world was at the outset of a new financial market crisis. Stock declines of greater magnitude than under the financial crisis of 2008 were noted, yields on even the most secure government bonds rose, and the most uncertain parts of the credit market, used for company financing, appeared close to freezing as market participants sought out cash. However, this course of events proved to be of short duration with stock markets reviving within weeks, credit markets thawing, the pursuit of cash calming down, and the wave of expected bankruptcies, which could have become problematic for banks, remaining absent. The S&P 500, for example, had reached its bottom on March 23rd, 2020 followed by an increase of about 60% ever since, reaching its pre-COVID-19 level already on August 17th, 2020. As a consequence of, for example, an extensive list of liquidity and borrowing programs of central banks as well as a significantly stronger banking system than in the 2000s, global financial markets appear to be in better condition than the real economy (Praefke, 2020). Thus, while the COVID-19 pandemic has undoubtedly caused a health crisis, it can arguably not yet be referred to as a financial crisis. In retrospect, it is therefore doubtful whether it would have made sense to seek out safe haven investments during the COVID-19 crisis. While global financial stress indicators reported increased stress levels from February through August 2020, the lack of a longer-lasting and acute financial crisis amid COVID-19 renders it questionable whether the findings of this thesis can accurately address the shortcoming of the existing literature, namely that Bitcoin's safe haven properties have not yet been tested during a period of global market crisis. While global financial markets experienced stress levels unparalleled since the financial crisis of 2008 in March 2020, substantial geographical differences in the impact of COVID-19 on financial markets were registered. Therefore, inferences about the generalizability of Bitcoin's safe haven potential against short-term fluctuations during the COVID-19 crisis should be made with care.

After having dwelled upon Bitcoin's limited ability to serve as a safe haven against short term fluctuations as well as the lack of a severe COVID-19 related financial crisis to properly test Bitcoin's properties, this discussion opens up for the questions: What are the longer-term consequences of the COVID-19 crisis for financial markets? Could Bitcoin act as a storage of wealth when adopting a more long-term perspective than what this thesis allows for? Against a backdrop of uncertain rises and falls of COVID-19 cases and governmental interventions, decreasing GDPs, economic slowdown, and spiking unemployment numbers, governments and central banks worldwide continue to undertake wide-reaching economic stimulus initiatives. In light of the unprecedented amount of money pumped into the economy, the likelihood of inducing future inflation and destabilization of fiat currencies is deemed realistic (Shevchenko, 2020). Within this context, Bitcoin's decentralized nature, independence of country-specific monetary policies, and supply cap at 21 million Bitcoins provide points to ponder on whether its scarcity could provide Bitcoin with an innate value and lead the digital currency to serve as an inflation-resistant hedge. Considering the low levels of observed inflation since Bitcoin's inception, it proves challenging to study Bitcoin's ability to hedge inflation. Nonetheless, it appears vital to monitor and study Bitcoin's properties in inflationary environments in the future given that inflation is a major threat to people's wealth and especially pensions.

# 8. Conclusion

Against a backdrop of a looming crisis, many investors embark on a search for refuge against losses in financial markets, which typically leads them into the avenue of safe haven assets. While a variety of traditional assets have been established to carry safe haven properties, of late, a narrative surrounding Bitcoin's potential to be of value to investors during crises has emerged. Given that the persisting COVID-19 pandemic has caused the first instance of severe global financial market stress since Bitcoin began trading, this thesis set out to test the viability of previous conclusions about Bitcoin's investment characteristics during market stress by investigating the following research hypothesis: *Bitcoin acts as a safe haven against an international sample of asset indices and serves as a performance-enhancing addition to a diversified portfolio during the COVID-19 pandemic.* To test and operationalize the research hypothesis, three sub-hypotheses were deductively developed to guide a three-fold analysis of the subject matter.

Taking departure in the time-varying correlations extracted from a fitted DCC GARCH model on weekly return data, regression analyses were run to test whether *Bitcoin's time-varying correlation with an international sample of asset indices is negative during the COVID-19 pandemic* (SHI), which would suggest Bitcoin to be a safe haven. Predominantly, the empirical results provide evidence against sub-hypothesis I by highlighting Bitcoin's profound diversifying abilities but lack of safe haven properties against the vast majority of considered asset indices during the COVID-19 pandemic and other periods of market stress. This reflects in Bitcoin's low, but significantly positive, correlations with the considered world, developing and emerging equity indices, the country-specific equity indices of the US, Hong Kong, UK, France, and Germany, as well as all chosen bond, commodity, and real estate indices during these periods. As an exception, the regression and graphical analyses reported Bitcoin to serve as a modest safe haven against the Indian S&P BSE 500 equity index and the USD Currency Portfolio during the pandemic. However, Bitcoin only proved to do so for a few short horizons at a time. Thus, Bitcoin showcased limited, short-lived, as well as time- and geography-dependent safe haven characteristics during the hitherto COVID-19 pandemic.

To test whether the modest safe haven capabilities of Bitcoin held when acknowledging the crucial aspect of liquidity, it was investigated whether *investors can buy and sell Bitcoin relatively quickly and at relatively low transaction costs during the COVID-19 pandemic* (SHII). Despite rising bid-ask spreads as a consequence of increased COVID-19 related market stress, the empirical results found support for sub-hypothesis II by underlining Bitcoin's relatively low bid-ask spreads compared to gold as well as similar bid-ask spreads compared to the stocks of Apple and Twitter. Moreover, an examination of the transaction fees related to trading Bitcoin accentuated its low transaction costs amid high COVID-19 related financial market stress. Despite the fact that the liquidity characteristics generally endorsed Bitcoin's safe haven capabilities, a positive relationship between Bitcoin's transaction demand and transaction costs was observed. If Bitcoin were to be a safe haven, it is not approbating that transaction costs rise in line with demand, as higher fees during a flight-to-safety would diminish the attractiveness of investing in Bitcoin for safe haven purposes. During the COVID-19 pandemic, transaction demand did not appear to rise significantly, suggesting that investors did not vastly perceive Bitcoin to be a safe haven. Nonetheless, both the transaction costs and bid-ask spreads remained relatively low throughout the COVID-19 period, thereby approving Bitcoin's modest safe haven properties during this period.

Extending the analytical perspective to a portfolio setting, this thesis also examined whether *an investment allocation to Bitcoin enhances the risk-return characteristics and downside-risk reduction performance of a diversified portfolio during the COVID-19 pandemic* (SHIII). On the basis of a two-year rolling data window as well as by applying both mean-variance and mean-CVaR portfolio optimization, this thesis computed 96 diversified portfolios consisting of test (incl. Bitcoin) and benchmark (excl. Bitcoin) TPs and GMVPs. While the empirical findings proved Bitcoin to hold an average weight greater than zero across all optimized test portfolios, the results alluded to Bitcoin's minor role in portfolio optimization as none of the portfolios allocated more than 0.715% of their investment to Bitcoin. The weight allocation to Bitcoin over time indicated that Bitcoin served as a valuable addition to a diversified TP throughout COVID-19 related financial stress. While Bitcoin's high volatility got penalized by little to no weights in the mean-variance GMVPs, the results showed that Bitcoin was of value to risk-averse investors optimizing their GMVPs on the basis of mean-CVaR. Through the comparison of the test and benchmark portfolios' performance on the downside risk and risk-return parameters of MVaR, MCVaR, SR, SoR, and ASR, it became apparent that an investment in Bitcoin increased the risk-return tradeoffs of a diversified portfolio amid the COVID-19 crisis to some extent. However, Bitcoin proved less suitable and consistent for investors seeking to reduce their portfolio's downside risk or increase their return over downside standard deviation or MCVaR during the hitherto COVID-19 pandemic. Hence, the evidence only partly supports the third sub-hypothesis.

Drawing upon the conflicting findings of the sub-hypotheses, it is indispensable to reject the research hypothesis. Bitcoin acted as a short-term and relatively liquid safe haven against only two out of 23 examined asset indices. It solely enhanced the performance of a diversified portfolio to a certain extent in terms of risk-return tradeoff and to a lesser extent in terms of downside risk reduction during the investigated COVID-19 period. Thus, Bitcoin proved to be of most relevance to short-term oriented, high-frequency, and speculative retail investors under the COVID-19 pandemic.

On a concluding note, and to the best of the authors' knowledge, this study is the first of its kind to provide academicians and market participants with a comprehensive examination of Bitcoin's investment properties amid severe global financial market stress. However, it is crucial to recapitulate this study's discussion in questioning whether global financial markets have encountered sufficient instances of severe financial stress beyond the month of March and throughout 2020 to draw accurate and generalizable inferences about Bitcoin's value potential during crises. Hence, while this study's COVID-19 findings part ways with Bitcoin's safe haven narrative, this thesis also stresses the importance of putting the narrative to further tests during future periods of financial crises. At the moment of writing, the world finds itself amid a severe second wave of COVID-19 cases, unsettled BREXIT disputes, as well as at the outset of an important US presidential election, which all bear uncertain consequences for the global economy and financial markets. In this light, it is aspired that this thesis serves as a source of inspiration for investigating Bitcoin's investment properties during the upcoming unpredictable months, thereby gaining more insights into Bitcoin's potential to create value for investors during crises.

## 8.1. Future Research

Throughout this thesis, limitations and unanticipated findings have been suggested for further research to substantiate the knowledge within the field of Bitcoin, safe havens, and optimal portfolio construction. At the time of writing, a second wave of imposed lockdowns is commencing, as worldwide COVID-19 cases intensify. It is questionable whether governments and central banks are adept to, once more, provide extensive economic support packages to prevent bankruptcies and elude a severe financial crisis. Hence, the forthcoming months will prove interesting, why the methodological approach undertaken by this thesis is suggested to be replicated to a more extensive COVID-19 period at a later stage. In addition, as touched upon in Chapter 7, the vast COVID-19 related economic support packages result in an enormous amount of money being pumped into society, which could induce future inflation. As Bitcoin was only investigated in regard to providing safe haven properties in the short run and inflation has been absent for the past decade, it is of great relevance to investors and pension funds to uncover whether Bitcoin could serve as a hedge against inflation.

Moreover, as acknowledged in the discussion section, this thesis' findings apply mostly to retail investors, as a finite amount of Bitcoin supply might inhibit investments into Bitcoin by a large group of institutional investors. As Bitcoin can enhance the risk-return tradeoff of a diversified portfolio, institutional investors may take advantage from a study exploring whether Bitcoin's diversification benefits can be extended to other cryptocurrencies in order to increase the investment possibilities.

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