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New Haven: An empirical qualification of Bitcoin among Flight-to-Safety assets in the face of Covid-19 pandemic

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Abstract

This paper uses the Covid-19 crisis to assess whether cryptocurrencies show "safe haven" properties or not. By analyzing the CBOE-Volatility-Index I derive the breaking-point of the crisis to be the 18th-March-2020. I present evidence that Bitcoin, as cryptocurrencies' main representative, fails to act as a "safe haven", throughout a set of correlation and regression analysis. Moreover, I find that also traditional "safe haven" assets do not meet expectations. I present a possible cause, with the presence of strong financial contagion rooted in the novelty of the crisis. Asness' Quality-Minus-Junk is the only asset that showed negative correlation with the market during the financial turmoil.

Keywords: Bitcoin, Covid-19, Flight to Safety, Safe Haven

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1. Introduction

"Our basic thesis for bitcoin is that it is better than gold." – *Tyler Winklevoss*[1]

The year 2021 stands for a milestone in the history of crypto assets[2]. For the first time, the market capitalization surpassed the threshold of 2 trillion USD (CoinMarketCap n.d.). Given the implicit monetary importance of crypto assets and intrinsic similarities to gold, Winklevoss' comparison of both assets is obvious. This paper aims at testing the basic thesis behind. To evaluate whether cryptocurrencies are "better than gold", it is crucial to further define what "better" means, and thus to define the scope of the research.

Even though it is controversially discussed in financial theory, gold is referred to be a "safe haven" investment. Assets of such type reduce losses in times of financial turmoil, as they show reliably negative correlation to the market portfolio. Thus, they play a central role in the investor's attempt to hedge and diversify on a portfolio level, which can be observed in past financial crises. This key mechanism will be subject of further discussion of this paper.

While research on traditional "safe haven" investments is numerous, contributions on crypto assets are limited. In summary, Shahzad et al. (2019) conclude that the use of cryptocurrencies may vary over time but has not been confirmed by the actual use of cryptocurrencies as "safe havens". The reason is simple: Since the rise of Bitcoin in 2009, cryptocurrencies have not faced a severe shock in financial markets on a global scale. With the onset of the crisis caused by Covid-19, this has changed, emphasizing the need to dedicate further research on the topic. Thus, this paper will test the following hypothesis:

[1] Tyler and Cameron Winklevoss in the financial times 1st of December 2016. The twins studied at Harvard and worked closely with Mark Zuckerberg on a disruptive social network. After a legal battle with Zuckerberg they thoroughly focused on digital currencies based on distributed ledger technology.
[2] Crypto Assets refer to any digital assets, which currencies or decentralized applications are based on cryptographic technologies (CoinMarketCap n.d.).

Bitcoin, as a representative of cryptocurrencies has become a “safe haven” asset with the beginning of the financial turmoil, caused by the Covid-19 pandemic.

By doing so, the paper contributes to a controversial debate, as to whether cryptocurrencies bare characteristics of traditional “safe haven” assets. I will use Bitcoin as a representative of cryptocurrencies, given its high market capitalization and long existence. Its performance will be analyzed in relation to a set of traditional “safe haven” assets and controls.

First, I will provide a detailed overview of the literature on crypto assets, their relation to traditional assets to act as a diversifier and on their behavior during the Covid-19 crisis. Furthermore, I will give detailed insights into crises caused by uncertainty and “safe haven” assets.

Secondly, I will carefully derive the breaking point used for further analysis. To do so, the concept of crisis of second momentum caused by uncertainty will be used. Quantitatively, this will be derived from the behavior of the CBOE Volatility Index (VIX), as the measure of financial volatility, including accompanying symptoms like a drop in GDP and a significant increase in unemployment rates. I find that the breaking point is best proxied by the 18th March 2020.

Thirdly, I will present the selection of assets used for the analysis. Besides Bitcoin, “safe haven” assets are represented by gold, High Minus Low (HML) portfolio and the Quality Minus Junk (QMJ) portfolio. This section provides detailed insights into the composition of the assets, especially HML following Fama-French (1993) and QMJ following Assness, Frazzini and Pedersen (2014), respectively. Furthermore, I will present the methodology used to assess cryptocurrencies performance during the Covid-19 crisis. In detail, I will apply a correlation analysis. After evaluating the correlation over the total period, before and after the breaking point, a three-month rolling window correlation analysis will shed light onto the dynamics of correlations among the assets. Then, a regression model will be performed to complement the correlation analysis.

Fourth, I will show detail the results of my empirical study. The correlation analysis indicates that Bitcoin fails to show “safe haven” characteristics as it shows a shift towards high levels of positive correlation with the markets after the onset of the breaking point. Thereby, it can be observed that gold cushioned the first moments of the crisis but then lost its capability to act as a “safe haven” investment with the onset of the breaking point. In this connection, the Quality Minus Junk (QMJ) portfolio is the only selected asset, which shows negative market correlation and thus is able to create returns during falling markets. In order to show “safe haven” characteristics, the Bitcoin should then show a positive coefficient with the QMJ portfolio in the regression model. However, this is not the case within the period examined.

Fifth, I will discuss the results of the correlation and regression analysis. The implications towards Bitcoin are clear. It fails to show “safe haven” properties with the onset of the breaking point. There can be several reasons for that, but the significant positive shift observed within gold’s and HML’s correlation with the market, indicates the presence of strong financial contagion. Considering relevant research, this might be driven by the novelty of the Covid-19 crisis and its new combination of symptoms.

Sixth, I will conclude with a summary of the findings and give an outlook to further research on the topic, especially in order to derive robust implications on the cause of the failure of Bitcoin but also traditional “safe haven” investments.

The dissertation is structured in five sections. Section 2 provides an overview of the relevant literature. In section 3, I present my data and methodology. In section 4, I present the results of the analysis. Section 5 discusses the implications observed in the results. In section 6, I summarize my findings, conclude, and provide an outlook for further research.

2. Literature Review

Due to investors' interest, the resulting increase of market capitalization, the scientific research in the field of cryptocurrencies and their behavior in financial markets accelerated considerably.

In a systematic analysis Corbet et al. (2019) provide a review of empirical literature focusing on major topics related to cryptocurrencies, starting in 2009. The analysis focusses on the various associations of cryptocurrencies, such as astonishing price appreciation, accusation of pricing bubbles, a central dilemma of Central Banks and cyber criminality, influencing the perception of cryptocurrencies as an asset class (Corbet et al. 2019). Corbet et al. (2018) analyzed the behavior of three major cryptocurrencies in relation to gold. The study finds evidence, that cryptocurrencies act relatively isolated from other financial assets. Thus, the result indicates investors benefit by including cryptocurrencies in portfolio construction. The research also limits beneficial characteristics of cryptocurrencies to investors with a short-time horizons (Corbet et al. 2018). By analyzing empirical data of ten major cryptocurrencies, Liu (2019) identifies the opportunity of diversifying portfolios making use of the crypto-market. The significant role of cryptocurrencies in investor portfolios is echoed by the studies of Tiwari et al. (2019) and Gil-Alana et al. (2020), as they find no cointegration between cryptocurrencies and stock market indices, thereby confirming cryptocurrencies as a new asset class with the potential of diversification (Tiwari, Raheem, and Kang 2019; Gil-Alana, Abakah, and Rojo 2020).

Like Corbet et al. (2018), also Omane-Adjepong and Alagidede (2019) make restrictions on the time horizon, in which cryptocurrencies fulfill diversifying functions to be more efficient in the short- to medium-terms rather than in the long-term.

Bouri et al. (2017) examine if the cryptocurrency Bitcoin can act as a "safe haven" and hedge for major world stock indices, bonds, gold, oil, the general commodity index, and the US dollar. The study finds that Bitcoin is a poor hedge but might serve as an instrument of diversification, especially against Asia Pacific stocks. However, Bitcoin's properties to do so vary extensively among horizons.

Focusing on the outbreak of the Covid-19 pandemic, Corbet, Larkin, and Lucey (2020) examine the effect of shift contagion[3] of Bitcoin, Gold and Chinese exchanges. During the inspected period, the volatility relationship between Chinese stock markets and Bitcoin increased significantly, thus indicating that in times of serious financial stress Bitcoin does not act as a "safe haven" nor hedge, findings which are in line with the studies of Conlon and McGee (2020).

Scientific debate, whether cryptocurrencies have the capability to act as a profound diversifier and "safe haven" asset in portfolio construction, is diverse and numerous. Over the last decade, many economists have taken on the topic, generating diverse and partly contradicting results. "Safe havens" proof themselves in times of uncertainty and financial turmoil. In the face of the recent global crisis, caused by the Covid-19 pandemic, there are numerous publications focusing on the role of Gold among the different phases of the crisis (Akhtaruzzaman et al. 2020), the comparison of the performance of safe assets between the pandemic and the global financial crisis (Cheema, Faff, and Szulczyk 2020) and findings of a general loss of effectiveness in flight to safety measures, due to the novelty of the Covid-19 pandemic (Ji, Zhang, and Zhao 2020).

Studies of Corbet et al. (2020), are selecting a similar approach but limit examination solely on the contagion effect, whereas and Conlon and McGee (2020), limit their examination on the downside risk of a proportion of wealth allocated to Bitcoin rather than the S&P500. Thus, existing literature leaves room for related and further research. This paper is ment to broaden

[3] The contagion effect or shift contagion refers to a significant increase in cross-market linkages after a shock. Linkages cover anything from correlation in asset returns, speculative attacks, or the transmission of volatility. High levels of correlation perse do not imply shift contagion, just if the level increased significantly after the event of shock (Claessens and Forbes 2001).

this perspective and to analyzes the relation between a major cryptocurrency, Gold, traditional "safe haven" portfolios and the market.

2.1. "Safe haven" assets

The term is widespread and many investors are aware what "safe havens" mean. In order to obtain a shared understanding and for the purpose of this paper, it is important to carefully elaborate on the main characteristics which stand behind the term "safe havens".

"Safe havens" have various functions within the financial markets. In portfolio construction they are used as a reliable store of value and capital preservation in times of uncertainty. Moreover, they are a key source of liquid and stable collateral during repos[4], they create trust in derivatives markets and are a cornerstone in pricing benchmarking (International Monetary Fund. Monetary and Capital Markets Department 2012).

Existing literature commonly uses two definitions: Firstly and more broadly, "safe havens" are defined as hedges of returns on risky portfolios in times of turbulence, recessions or for risk aversion (Ohnsorge, Wolski, and Zhang 2014). Hedges in this sense may include gold, exchange rates of currencies, or even sovereign bonds. D. Baur and McDermott (2010) analyze the role of gold in the global financial system, especially in respect to its capabilities to act as a "safe haven". Using a descriptive and econometric approach, they distinguish between weak and strong "safe havens". By analyzing severe past financial shocks, they find that gold was a strong "safe haven" and may therefore act as stabilization for major European financial markets and the United States. Beck and Rahbari (2008) are stating that both the Dollar and Euro may act as "safe havens" when it comes to hedging risks rooted in sudden stops globally, in Asia and Latin America as well as in Emerging Europe.

[4] Central- or private Bank repurchase agreements.

A second common approach was to define “safe havens” based on sovereign credit ratings published by rating agencies. This approach shifted in the aftermath of the Global Financial Crisis in 2008, where a variety of best rated assets were reaffirmed by being downgraded during the crisis (Ohnsorge, Wolski, and Zhang 2014; International Monetary Fund. Monetary and Capital Markets Department 2012).

In this paper, I am following the practical definition by Jonathan Spall, director of commodities at Barclays Capital and author of related publications. He describes “safe haven” assets as assets that have the ability to increase in value in times of turbulences and recessions (Spall 2008), thus creating positive first-momentum return and negative correlation with the market.

2.2. Crisis, Shocks, and Uncertainty

Originally the term and mechanism of a shock is derived from the field of medicine, where it describes life-threatening conditions. Applied in general economic terms, shocks are characterized by an unexpected shift in demand or supply. Agents do not have the possibility to react immediately and appropriately. Due to effects of delay, counteracting measures become effective in the medium- and long-term run. Thus, exogeneous effects are followed by endogenous imbalances, requiring economies to find a new macroeconomic equilibrium (Börsch-Supan and Schnabel 2013, 294).

One main driver of shocks is uncertainty, meaning uncertainty among policy makers, economists, and society as a whole. Piffer and Podstawski (2018) as well as Bloom (2013) distinguish between two different types of such shocks, creating significant shifts in the level of uncertainty. Firstly, news shocks, which constitute as first-momentum shocks and secondly uncertainty shocks, which are of second momentum. Differentiation is crucial depending on the type of the shock, as it bears different consequences for the economy. A terrorist attack, for example, bears the fear of further attacks on the one hand (first momentum), and the deep fear of negative long-term effect on the economy, in a second momentum. The second phenomenon is also described as an uncertainty shock and is typically followed by recessionary effects for the real economy (Piffer and Podstawski 2018).

In order to evaluate the outbreak of Covid-19 in its characteristic, this paper makes use of the definition of a shock derived from the literature provided by Frank Knight (1921), Börsch-Supan and Schnabel, as well as Bloom (2013), Piffer and Podstawski (2017). In particular, a shock bears a sudden shift of demand or supply and on the other hand is driven by uncertainty, which affects economies in the mid- and long-term.

3. Data and Methodology

In this section, the data and methodology will be presented. First, and crucial for further analysis, the breaking point is carefully derived. Then, the asset and data selection for traditional "safe havens" and Bitcoin will be described. Thirdly, the section illustrates the methodological approach.

3.1. Breaking Point

It is not surprising that there is not a single method to measure economic uncertainty, given the broad definition of uncertainty and economic shocks caused by it. Literature reaches from using GDP growth as an indicator of uncertainty, the performance of single companies, or the mention of the word "uncertainty" in the news (Bloom 2014; Piffer and Podstawski 2018).

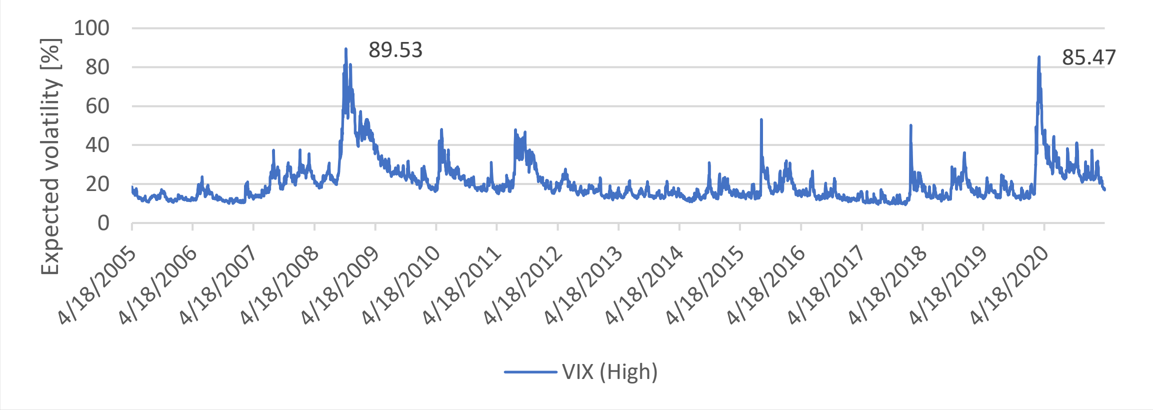
In order to analyze the behavior of Bitcoin during the latest period of turmoil, it is essential to carefully identify the point in time, when financial markets incorporated the effect of the outbreak of Covid-19 in full extent. For the use of this paper, it will be defined as the "breaking point", acting as a ceasure in a ten-year rally in major financial markets.

Fundamentally, and in line with studies by Bloom (2013), this paper makes use of the stock market as a consolidator of information. By incorporating effects of the present on future developments, it thus expresses expectations on the future of the economy (Bodie, Kane, and Marcus 2009).

Within the framework of financial markets, uncertainty is expressed through volatility. Thus, measures of volatility can act as a good proxy for economic uncertainty. To do so, I have made use of the CBOE Volatility Index (VIX) the most common indicator of equity markets volatility (Pesaran, Cesa-Bianchi, and Rebucci 2014). Traded on the Chicago Board Options Exchange, the VIX shows the implied 30-day volatility on the Standard & Poor's 500 stock market index in percent, as it is constructed on the values of corresponding put- and call-options (Bloom 2014). Hence, the VIX acts as investors' "fear gauge" (Whaley 2000), a role which was even strengthened during the global financial crisis in 2008 and is valid beyond the US American market (Neffelli and Resta 2018). Data is downloaded from Yahoo finance, on a daily basis starting in 2005 till the spring of 2021. The VIX indicates the degree of volatility within the financial markets on a relative basis.

Additionally, and in respect to the definition provided before, I will furthermore assess whether or not the outbreak of Covid-19 marks a shock of a second momentum. Hence, the development of international indices, unemployment rates and unemployment, as well as Gross Domestic Product (GDP) in exemplary economies, will be considered to underpin indications provided by the VIX.

Figure 1: CBOE Volatility Index (VIX) from 2005 till 2021



Note: The graph shows the Chicago Board Options Exchange VIX, which shows the implied 30-day volatility on the Standard&Poors 500. Data is presented from 18/04/2005 till 15/04/2021, on a daily basis. The Expected volatility is in percent. It can clearly be observed that the graph bears two peaks. The first in fall 2008 with the onset of the global financial crisis and the second peak in spring 2020, the defined braking point.

Based on the experience of decades, the National Bureau of Economic Research (NBER) states that the VIX rises by 58% on average during recessions (Bloom 2014). *Figure 1: CBOE Volatility Index (VIX) from 2005 till 2021* shows the corresponding VIX index. Given the timeframe of the pandemic, starting with the first cases in December 2019 (see *Table 1: Key Dates of the Covid-19 outbreak*), the VIX surpasses the 58% by 16 days. The highest level of uncertainty within the financial markets is identified on the 18th March 2020, with a VIX peaking at 85.47 %. Considering the price-volatility diagrams of major stock markets (see *Figure 3: Price-Volatility Diagrams for German; US and Chinese Indices*), this event is accompanied by plummeting indices.

Dramatically high levels of the VIX and falling indices indicate the symptom of high degrees of uncertainty, but in respect to the definition given, shocks of second momentum are also accompanied by shifts in demand or supply. In the face of the pandemic in Spring 2020, these characteristics were given, and significant unemployment claims were recorded. In the U.S., 3.28 million claims per week set new historic heights. A value, five times greater than the largest increase per week during the global financial crisis in 2008 (Carlsson-Szlezak, Reeves, and Swartz 2020). From March to April 2020 unemployment rates jumped from 4.4% up to

14.8%, a sharp increase of 236%, as stated by the U.S. Bureau of Labor Statistics (see *Figure 4: Unemployment Rate in the United States in 2020*). At the same time, Gross Domestic Product (GDP), as a measurement of overall domestic production, dropped by close to 9.5 % (see *Figure 5: GDP of the United States from 2018 to 2020*).

Consequently, the breaking point is derived using uncertainty within the financial markets, as a symptom driven by the same components as business cycles, in this case a downswing. The date of the highest forward-looking uncertainty is the 18th March 2020 and thus defines the breaking point for further analysis. To underpin this event and to be in line with the used definitions, this paper additionally examines a shift in supply and/or demand, and particularly the sharp rises in unemployment and unemployment claims as well as a 9.5 % decline in GDP.

3.2. Bitcoin, as the most popular cryptocurrency

The publication of the whitepaper “Bitcoin: A Peer-to-Peer Electronic Cash System” under the pseudonym Satoshi Nakamoto (2009), marks the inception of Bitcoin and with it the start of the rise of cryptocurrencies. More than a decade later, Bitcoin has reached an all-time high, at a market capitalization of more than 1,000 billion USD in April 2021. With a market share of above 45 %, Bitcoin is by far the most traded cryptocurrency (CoinMarketCap n.d.). Besides its popularity, I chose Bitcoin as a representative of cryptocurrencies, because of the accessibility of well-prepared data. This data was retrieved from *yahoofinance.com* over a time span from 10th March 2016 to 9th March 2021, on a daily basis. In order to assure comparability across the asset classes, returns of the adjusted close price of the Bitcoin are calculated, with prices in USD. For further calculations, the risk-free rate is subtracted, and the excess returns are logarithmically normalized.

3.3. "Safe haven" assets

The given paper conducts an analysis of the Bitcoin in relation to assets which are traditionally perceived as "safe havens". The following paragraph will contour the selection of gold, Fama-French Factors (1992,1993 and 1996) and a portfolio construction following Asness et al. (2014) and Quality Minus Junk as representatives of "safe haven" assets, given the definition in *section 2.1*.

First, Gold is perceived to be a showcase of "safe haven" assets, besides U.S. government bonds or the Swiss Franc. Literature on finance underpins that classification is numerous. To evaluate gold's properties and ability to exhibit non-negative returns in times of turmoil and negative returns in stock markets (D. G. Baur, Dimpfl, and Kuck 2021) would exceed the scope of this paper. Hence, this paper is based on previous studies which attribute Gold the properties to meet the definition given above (Erb and Harvey 2013; D. Baur and McDermott 2010; Zivanovic 2020; Spall 2008).

The underlying data hast been sourced via Thomson Reuters / ThomsonOne on the 10th March 2021. Adjusted prices are in USD and on a daily basis from 10th March 2016 till 9th March 2021, and log excess returns are implemented.

Second, I have selected a portfolio following Fama and French (1992 and 1993). Testing the CAPM empirically, their findings show that regression models using the market beta only have limited explanatory power. They further show that stocks with two properties perform superior compared to the market return: (1) Stocks with a lower market capitalization and (2) stocks with a higher book-to-market equity. Thus, and to contradict the Sharpe-Lintner-Black (SLB) model, they present two additional and significant portfolios, which bear positive excess returns not explained by the market returns. Even if the two portfolios are not the risk factors themselves, they act as good proxies for fundamental risk structures. Thus, Fama and French argue that their portfolios constitute risk premiums (Fama and French 1992; 1993).

The portfolio follows the strategy of value investing. Fama-French introduce the factor of book-to-market equity. The portfolio is based on the finding that companies with a high book-to-market equity outperform those with a low ratio and thus create higher returns in the long run (see also Rosenberg, Reid, and Lanstein (1985)).

To construct the factors, stocks in a region are sorted into two groups according to their market capitalization. The range of "Big Companies" lies within the top 90 % of the end of last periods market capitalization of a region, small companies are obtained from the bottom 10 %, respectively. Assigning the stocks, Fama-French (1992, 1993) produce in total six value-weighted portfolios: Small Value (SV); Small Neutral (SN); Small Growth (SG); Big Value (BV); Big Neutral (BN); Big Growth (BG).

Hence, HML consists of the average return of two value portfolios minus the average return of two growth portfolios:

$$HML = \frac{1}{2}(Small\ Value + Big\ Value) - \frac{1}{2}(Small\ Growth + Big\ Growth)$$

The HML portfolio will act as a "safe haven" asset within the regression model performed in this paper.

The second portfolio, which constitutes as a flight to safety, follows Asness, Frazzini and Pedersen (2014). Since Fama-French themselves extended the Capital Asset Pricing model, in a first step, by the factors of size (SMB) and value (HML) in their Fama-French three-factor model (later the factors profitability and investment were added in the Fama-French five-factor model), Asness et al. (2014) extended the Fama-French three-factor model by *quality*. While many of the asset pricing literature focuses on returns, economic consequences of market efficiency are ultimately linked to prices (see also Summers 1986 and Cochrane

2011). Thus, Asness et al. (2014) research revolves around the question whether high quality firms command the highest price to operate and invest in their business or not. To do so, they define quality as a characteristic, investors should pay more for, all else held equal. To make it tangible, the quality-factor is defined by:

$$Quality = (Profitability + Growth + Safety + Payout)$$

Consequently, investors should be willing to pay a higher price for stocks of profitable, stable, high payout and safe companies. Following Asness et al. (2014) and AQR Capital Management, quality is split into four aspects, each is measured by a broad set of metrics. Profitability refers to the sustainable part of profits in relation to the book value is measured, among others, by gross profit over assets, return on equity, cash flow over assets, gross margin and the fraction of earnings composed of cash. Secondly, the growth argument is obtained by averaging each profitability metric over a timespan of the prior five years. Payout is defined using equity and debt net issuance and total net payout over profits. Lastly, companies are perceived to be safe, if they are characterized by a low beta, low idiosyncratic volatility, low leverage, low risk of bankruptcy and low volatility in its return on equity. In order to put each aspect of quality and its measures on equal basis, each variable is converted into ranks, standardized and converted into a z-score (Asness, Frazzini, and Pedersen 2019).

Similarly, Fama-French, Asness et al. (2014) construct the Quality Minus Junk portfolio as the intersection of six value-weighted portfolios formed on size and quality. To obtain the global portfolio, a set of portfolios for each country is formed and weighted with the country’s lagged market capitalization. Each month, the stocks are assigned into two size-groups. For US stocks the breaking point is the median NYSE market equity, while outside the US the break point is the 80th percentile.

$$QMJ = \frac{1}{2}\left(Small\ Quality + Big\ Quality\right) - \frac{1}{2}\left(Small\ Junk + Big\ Junk\right)$$

$$= \frac{1}{2}(Small\ Quality - Small\ Junk) + \frac{1}{2}(Big\ Quality + Big\ Junk)$$

Examination of the Quality Minus Junk portfolio shows that quality is a lasting characteristic. Within the studies, Asness et al. were able to show that stocks characterized by high quality, were also able to display the same characteristic in the future. Thus, high quality in the past and present indicates high quality in the future.

For the sake of consistency among the different portfolios in this examination, the data used is provided by AQR Capital Management LLC (AQR), following Asness, Frazzini and Pedersen (2014). Within the dataset, global developed countries are selected. It needs to be mentioned that the data provided by AQR extends the dataset provided by Kenneth R. French, adding the country, Israel. Returns data itself are taken from a union of the CRISP tape and the Compustat/XpressFeed Global database. If companies are traded in multiple markets, the market of the primary trading vehicle is chosen. All portfolio returns are in USD and do not include currency hedging. Returns are the value-weighted returns of available stocks minus the one-month U.S. Treasury Bill rate. Broken down, a portfolio for each country is constructed and then weighted by the country's total one-period lagged market capitalization.

Portfolio returns (HML and QMJ) are provided on a daily basis. Similar to return data of Bitcoin, the observation period starts on the 10th March 2016 to 9th March 2021. All returns are log excess returns, as it is assumed that stock returns follow a log normal distribution. All data are downloaded in USD and hence all returns are in USD.

The selection of "safe haven" assets is complemented by a set of controls, like the market and three indices in particular, Brent Crude Oil as well as Fama-French Small-Minus-Big (SMB). Further details on their sources are provided in corresponding elements in the Appendix. Overall, the data will be combined in one dataset (.csv format). The programs and tools to conduct this analysis were selected to its purpose. Deep and more detailed analysis (e.g. the regression model) is conducted in R Studio, in some cases (e.g. analysis of the VIX) in Excel.

To sum up, Gold, Fama-French High-Minus-Low (HML) and Asness' Quality-Minus-Junk (QMJ) are selected to put Bitcoin in relation during the Covid-19 pandemic. These assets were selected, because they exhibit "safe haven" properties.

3.4. Methodology

On the basis of the derivation of the breaking point, this section describes the methodology to assess Bitcoin's behavior in relation to common "safe havens" or flight to safety portfolios. To follow the hypothesis that Bitcoin counts among "safe havens" or flight to safety portfolios, several tests and calculations will be performed.

First, to obtain a better understanding of how Bitcoin moves in relation to selected assets, I will perform a correlation analysis. Rooted in modern portfolio theory, correlation coefficients are a common instrument to evaluate the relationship of certain assets. As this paper focuses on times of high volatility, correlation coefficients in two variations will be used. First, and in accordance with Corbet et al. (2020), I will use the correlation coefficient to understand the relationship between Bitcoin and safe assets before and after the breaking point of the Covid-19 pandemic. Second, a dynamic correlation is obtained by implementing a three-month moving window correlation.

For the purpose of better comparability, Bitcoin will be put into relation with "safe havens" as well as the market as a whole. To obtain a dynamic correlation coefficient, coefficients are measured within a moving window of 62 days[5].

[5] 62 trading days are used to proxy the amount of trading days within one quarter of the year. According to the New York Stock Exchange, Q1 2020 covered a period of 62 trading days. In the course of the year a quarters trading days can vary ("NYSE" 2020).

On a scale of -1 (perfect negative correlation) to 1 (perfect positive correlation), the correlation coefficient describes the degree of co-movement between two variables. However, correlation coefficients are not static and move over time. For my analysis, the time around the breaking point is of particular interest, as the movement of selected assets in relation to the market gives insight into their resilience.

In order to test crypto's representative Bitcoin on its "safe haven" properties, it is expected to show negative correlation with the market in times of financial turmoil. Thus, the asset can detach from falling indices and generate returns. Therefore, it meets a central "safe haven" characteristic to restore, or even create value when other assets do not.

Furthermore, I perform a regression analysis. Amongst control variables, Bitcoin's reaction exposed to its first severe shock, namely the Covid-19 pandemic, shall be explained by the sets of assets discussed in this paper. To test the hypothesis that Bitcoin moves up in the circle of "safe havens", the regression takes the form:

$$BTC = MKT + SMB + HML + QMJ + GOLD + \ Dummy +$$
$$Dummy * MKT + Dummy * SMB + Dummy * HML +$$
$$Dummy * QMJ + Dummy * GOLD$$

Besides the variables of interest, the Market (MKT) and the size-adjusted Fama-French portfolio (SMB) represent controls. Furthermore, a Dummy is introduced. Based on the breaking point analysis, the dummy is coded as 0 (before the breaking point) and 1 (equal and after the breaking point). Thus, the regression is able to split the interaction term of Bitcoin with each of the variables, into a period before and after the outbreak of the Covid-19 pandemic.

Following Gauss-Markov's key assumptions, I test the linear regression model. One of the key assumptions here is that there is no heteroskedasticity within the regression's residuals. A variable is said to be heteroskedastic, if the variance, thus the residuals, are not constant or close to it. In order to test for it, I apply the Breusch-Pagan Test, as expressed by:

$$\hat{\sigma}^2 = (\alpha_1 + \sum_{2}^{k} \alpha_i x_i) + error$$

Where $H_0 = all\ regressors\ but\ the\ constant\ are\ zero$ and $H_1 = one\ is\ not\ zero$ (Breusch and Pagan 1979).

In case there is presence of heteroskedasticity, the variance in residuals of the model is not constant. Therefore, I adjust for robust standard errors, for which there are several ways to get correct standard errors (see Zeileis (2004) for more details). This paper makes use of the *lmrob()* function from the *{robustbase}* package, creating standard errors which are robust to outliers (Koller 2012; Salibian-Barrera and Yohai 2006).

In general, the regression analysis may have three different outcomes. Firstly, Bitcoin shows positive coefficients with the interaction effects (coefficient multiplied by the dummy) of the "safe haven" assets, given significance. This scenario would confirm the thesis that Bitcoin showed "safe haven" properties during the crisis, given the fact that the selected "safe haven" assets themselves performed well. Secondly, coefficients with the "safe haven" assets are not significant. Thus, the outcome is inconclusive. Thirdly, coefficients with interaction effects are negative, on a significant level. The hypothesis would then be rejected.

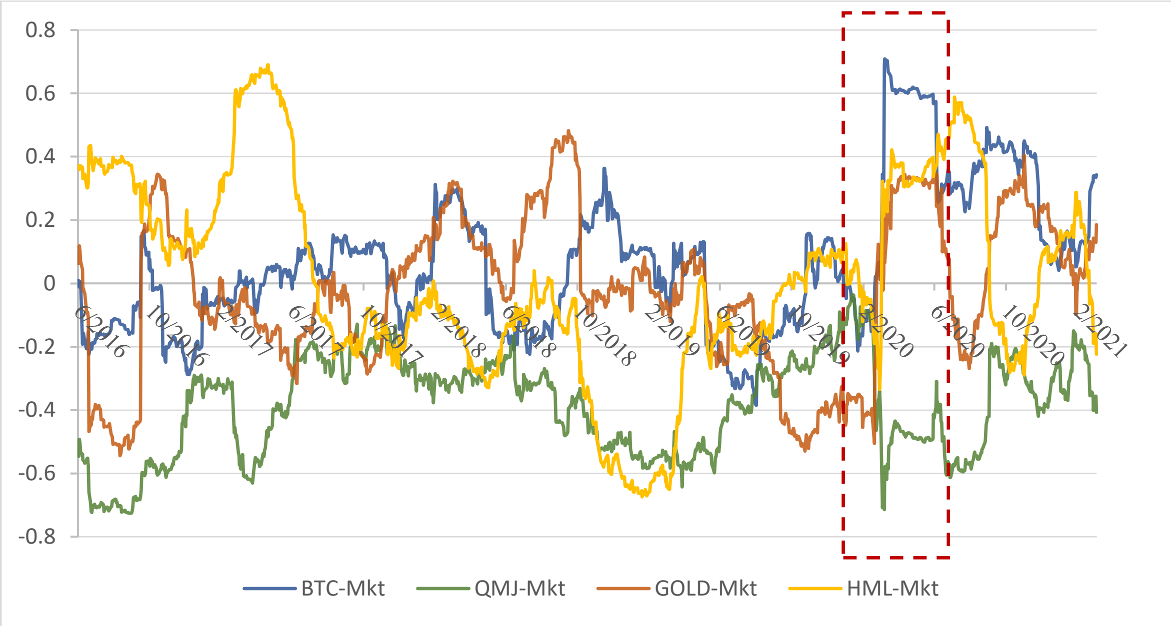
To obtain a holistic picture, I augment the above-mentioned regression. Firstly, I will check the estimators in a scenario without the breaking-point, indicating the outbreak of Covid-19. By omitting the Dummy-Variable in the regression, I will obtain one single estimation over the whole time-series of the study. Hence, complementing the explanatory power of the analysis. Additionally, to assess offsetting effects, I will analyze the relationship between Bitcoin and the individual "safe haven" investments.

4. Empirical results

In this section, I will present the result of the analysis of Bitcoin as cryptocurrency's most wide-spread representative, before and after the outbreak of the Covid-19 pandemic. First, and based on the derivation of the breaking-point, I will discuss the results of the correlation and the moving window correlation analysis. Second, I will assess the results of the regression model. Further, supplementing analysis will be incorporated.

In a first step, I have elaborated the overall correlation of a broad selection of assets. The results are presented in Table 2: Correlations between financial assets and markets, in total, before and after the breaking point, in the Appendix. Over the total sample period of 1304 trading days, BTC shows a positive correlation with the market of 0.19. The value for the total correlation can be broken down into two periods, before and after the outbreak of Covid-19. Before the event of the 18th March 2020, BTC's correlation with the market is characterized by a positive correlation of 0.18. With the date of the breaking point, and the pandemic hitting global financial markets, the correlation shifts up to a value of 0.24. A similar shift can be observed when examining the development of Gold. Before the breaking point, Gold and the market are uncorrelated, given a value of -0.006. With the event, Gold's correlation promptly shifts to a level of 0.22. QMJ portfolio on the other hand is negatively correlated throughout the period of the sample, given an overall correlation of -0.4. A small shift from -0.43 before to -0-35 after the breaking point can be observed. See Table 2: Correlations between financial assets and markets, in total, before and after the breaking point for further insights of the correlation analysis. To cross-check, additional input variables are integrated into the model.

Figure 2: Plot of BTC, QMJ, HML and Gold three-months rolling window correlation with the market



Note: The figure shows the plot of the three-months moving window correlation of the following selected assets with the market: BTC; QMJ; Gold and HML. Return data is logged and covers a period starting 10/03/2016 till 09/03/2021, on a daily basis. The red dashed box highlights the period of interest, around the event of the breaking point (18/03/2020). It can be observed that BTC, Gold and HML are characterized by a shift in correlation towards positive levels. Just the QMJ's correlations with the market shift to stronger negative levels.

To obtain a better understanding of the correlation pattern, Figure 2: Plot of BTC, QMJ, HML and Gold three-months rolling window correlation with the market shows a graph of the five-year rolling window correlation of BTC, Gold and QMJ. The rolling window incorporates the previous 62 observations. All assets are correlated with the market. It is of particular interest, how the assets pattern behaves around the breaking point.

Besides a few shifts, which may occur when applying a rolling window correlation, the graph shows a significant shift in correlations in March 2021. In contrast to Gold and BTC, the QMJ shows negative correlations throughout the examined period. While BTC and Gold switch signs and shift towards a positive correlation after the breaking point, QMJ jumps to strong negative levels. The behavior of Gold and Bitcoin is characterized by co-movement.

Secondly, I performed a regression analysis of the form:

$$BTC = MKT + SMB + HML + QMJ + GOLD + \ Dummy +$$

$$Dummy * MKT + Dummy * SMB + Dummy * HML +$$
$$Dummy * QMJ + Dummy * GOLD$$

The expectation towards the linear regression model is to shed light onto the relationship between BTC and safe assets, during BTC's first severe shock. Thus, the comparison of the interaction terms before and after the breaking point is of particular interest. As the test for heteroskedasticity, the Breusch-Pagan test, has a BP value of 76.5 at a p-value of 0.000, heteroskedasticity is present. Thus, I applied robust standard errors using a lmrob () regression. Thus the estimates remain the same, but the function creates standard errors which are robust to outliers (Koller 2012; Salibian-Barrera and Yohai 2006). For further details, see the R-Script and the output tables in the Appendix. Performing the Breusch-Godfrey Test for autocorrelation on the robust regression does not indicate the presence of autocorrelation within the error terms. Hence, I can proceed without taking care of serial or auto correlation.

Overall, the explanatory power of the regression model is low, at an adjusted R-Squared of 0.031. Only three percent of the movement of BTC can be explained by the input variables. Considering the P-Values, the intercept and Gold without interaction effect show statistical significance with values of 0.002 and 0.001, respectively. All other values show P-Values of 0.2 or above. Gold shows a rather strong positive coefficient with Bitcoin of 0.45. With the introduction of the dummy variable this value increases to 0.48, without statistical significance. See *Table 3: Robust standard regression model* for detailed outputs of the regression model.

In order to obtain further insights, additional regressions were performed. Firstly, a regression without the dummy variable was performed. The output of the regression over the whole time-series of the study shows a similar pattern as the initial regression model. Again, Gold is the only significant coefficient with a value of 0.46, at an adjusted R-Squared of 0.03.

Detailed information on the regressions output is presented in *Table 4: Regression model with no dummies*.

Additionally, I performed further regressions to analyze the relationship between Bitcoin and the individual “safe haven” investments to find out if there were offsetting effects. The results of the initial regression model are underpinned by the outcome of the individual regressions. All of them bear low explanatory power and just Gold has a statistically significant coefficient of 0.43. All regression outputs and R-Scripts are presented in the Appendix.

5. Discussion

I review: To assess whether cryptocurrencies can act as “safe haven” investments, one needs to examine periods of financial turmoil. For this purpose, the given paper puts Bitcoin, as cryptocurrencies’ most prominent representative, in relation with a selection of “safe haven” investments. The examined period focuses on the Covid-19 crisis.

Firstly, the correlation analysis of the controls and selected assets with the market shows significant shifts among all assets. On the basis of the analysis of the VIX, I have defined the breaking point to be the 18th of March 2020. This is supported by the inclusion of selected labor market data and outputs expressed by GDP.

This serves as a more precise proxy than the breaking point defined in studies of Corbet et al. 2020, which assume the breaking point to be end of December 2019.

Findings of Akhtaruzzaman et al. (2020) underpin the proposed breaking point of this paper. In their studies, they differ between several phases, of the Covid-19 crisis, with Phase II characterized by a higher degree of turmoil. They define the beginning of Phase II to be the 17th March 2020 (Akhtaruzzaman et al. 2020), which is precisely one day before the breaking point derived in this paper.

Furthermore, the correlation analysis shows limited "safe haven" characteristics of the selected "safe haven" assets. The QMJ portfolio is the only asset that is able to show negative correlation with the market. With the onset of the breaking point, QMJ shifts significantly towards a stronger negative correlation and thus generates positive returns. At the same time, all other assets including Gold, Bitcoin and the HML portfolio shift towards a rather strong positive correlation with the market. While Gold was able to compensate the first phase of the crisis in end of 2019 and early 2020, the three-month rolling window correlation clearly shows that it loses this capability with the event of the breaking point. The finding reflects studies of Cheema et al. (2020), claiming that investors lost trust in gold as a "safe haven", compared to the global financial crisis of 2008.

Bitcoin as a aspirant of "safe havens", does not meet these expectations. With the onset of the breaking point, the three-month moving window correlation analysis shows a sudden and significant shift towards levels of strong positive correlation with the markets. Bitcoin remains positively correlated with the market throughout the sample period. These findings are supported by the regression analysis. As QMJ portfolio is the only asset that shows "safe haven" properties, in order to act as a "safe haven", Bitcoin should be characterized by a significant positive coefficient with QMJ. This is not the case. Hence, I find indicators that Bitcoin is not a "safe haven" investment.

Corbet et al. (2020) find that Bitcoin is subject to financial contagion during the onset of the pandemic. This is given, if markets or financial assets show a significant increase in cross-market linkages, which is measured by the correlation in asset returns (Claessens and Forbes 2001; Barigozzi, Hallin, and Soccorsi 2019). Gold, HML portfolio and Bitcoin show a sudden increase in correlations. Gold and HML portfolio reverse to low levels shortly after the breaking point, while Bitcoin remains positively correlated with the market. This is a strong indication for the presence of financial contagion.

6. Conclusion

In this paper, I have examined the capability of cryptocurrencies to act as a “safe haven” investment in times of financial turmoil, caused by the Covid-19 pandemic. This was done by performing a correlation analysis as well as a regression model. My findings are that Bitcoin was not able to act as a “safe haven” asset, during the period examined, which was the first severe crisis since cryptocurrencies were broadly adopted. Furthermore, and taking all selected assets into account, it becomes apparent that the QMJ portfolio is the only one, which shows “safe haven” properties.

Prior and central to the analysis, I have shown that the breaking point of the crisis is best proxied by the 18th of March 2020. This contradicts studies by Corbet et al. (2020), who derive the breaking point from the first cases of pneumonia in December of 2019. The derivation in this study which takes market volatility, labor market and outputs in GDP and the empirical implications of the three-month moving window correlation into account, echoes findings of detailed analysis of phases of the Covid-19 crisis by Akhtaruzzaman et al. (2020).

To test the hypothesis whether Bitcoin ascends to “safe haven” assets, expectation towards the analysis performed were clear: (1) Negative correlation with the market during times of financial turmoil and (2) a positive coefficient with “safe haven” assets in the regression model. In summary, the hypothesis cannot be confirmed. My findings clearly show that Bitcoin shifts significantly towards strong positive correlation with the market when indices were falling. Within the regression analysis, Bitcoin only shows a positive coefficient with one of the input variables: Gold. Generally, this would be assumed to be a positive indication. In context with the Covid-19 crisis, this assumption does not hold, because Gold fails to show “safe haven” properties during the Covid-19 crisis.

Ji et al. (2020) have identified a similar pattern and thus see justification to re-evaluate the "safe haven" role of traditional assets. Reason might be the nature of the Covid-19 crisis. Likewise, I have also found traditional safe assets to struggle with the onset of the breaking point. Gold, as the "safe haven" per se, managed to cushion the first cases of pneumonia, but lost its "safe haven" role in March 2020. Studies find indications that gold lost investors' trust (Akhtaruzzaman et al. 2020; Cheema, Faff, and Szulczyk 2020; Ji, Zhang, and Zhao 2020). Only the QMJ portfolio following Asness, Frazzini and Pedersen (2014) can show negative correlation with the market during the examined period.

As far as the future is concerned, this paper raises important questions and the need for further research in two directions. First, it is crucial to obtain a better understanding of what is driving the price and performance of the Bitcoin, in order to understand its role in crises. Second, research on the lack of trust in traditional "safe haven" assets during the crises is vague. Related literature identifies uncertainty and fear as the main driver, rooted in the novelty of symptoms of the Covid-19 pandemic in contrast to previous crisis (see e.g. Ji, Zhang, and Zhao (2020); Barigozzi, Hallin, and Soccorsi (2019)).

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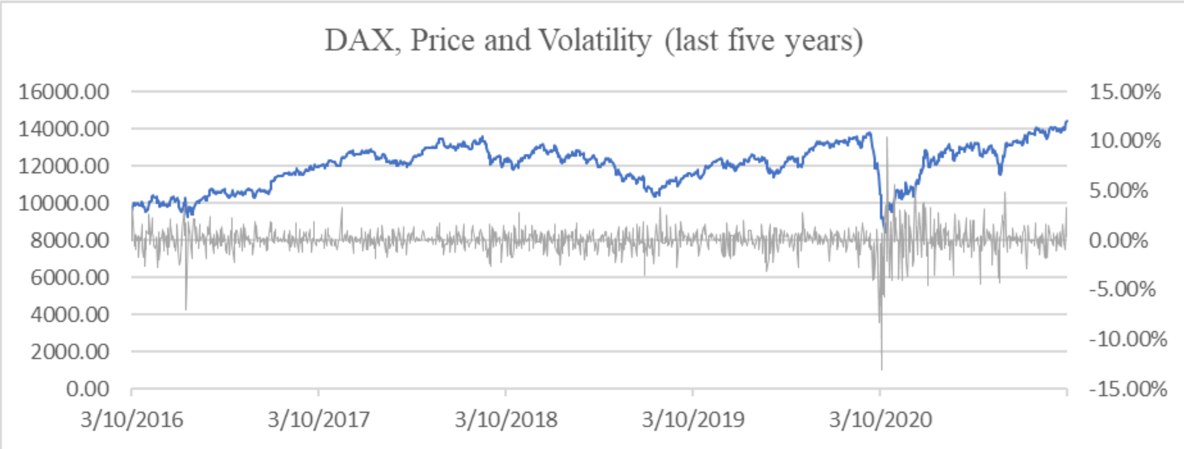
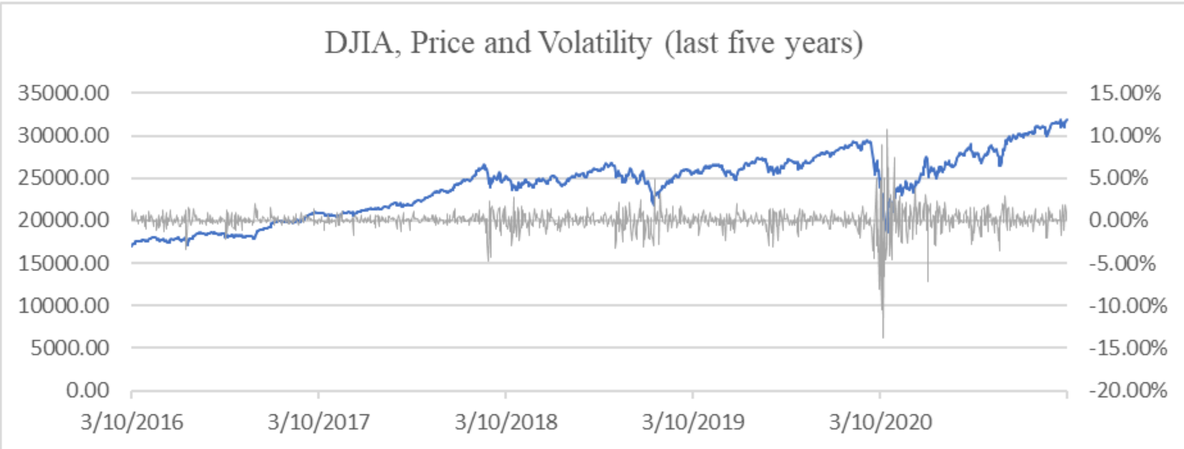
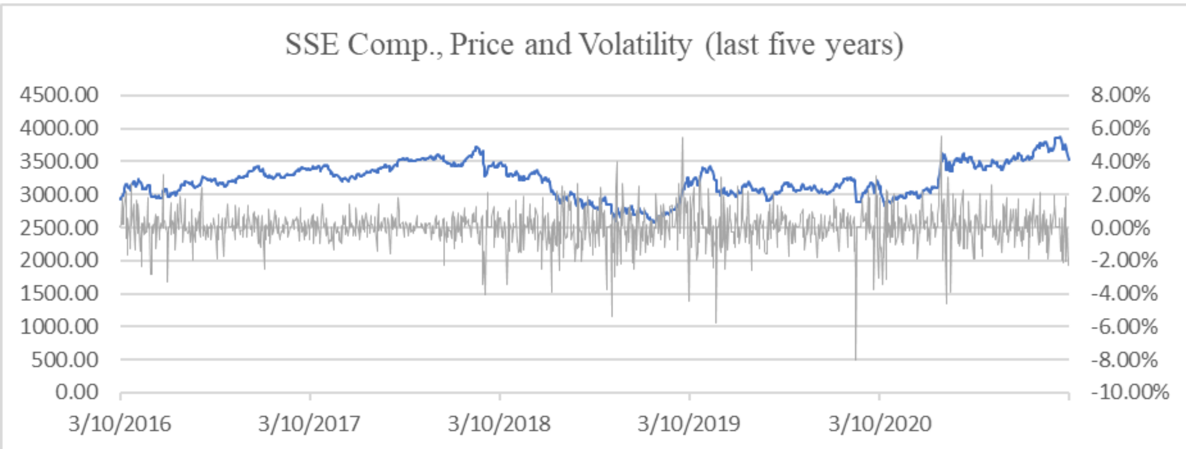
Appendix

Figure 3: Price-Volatility Diagrams for German; US and Chinese Indices

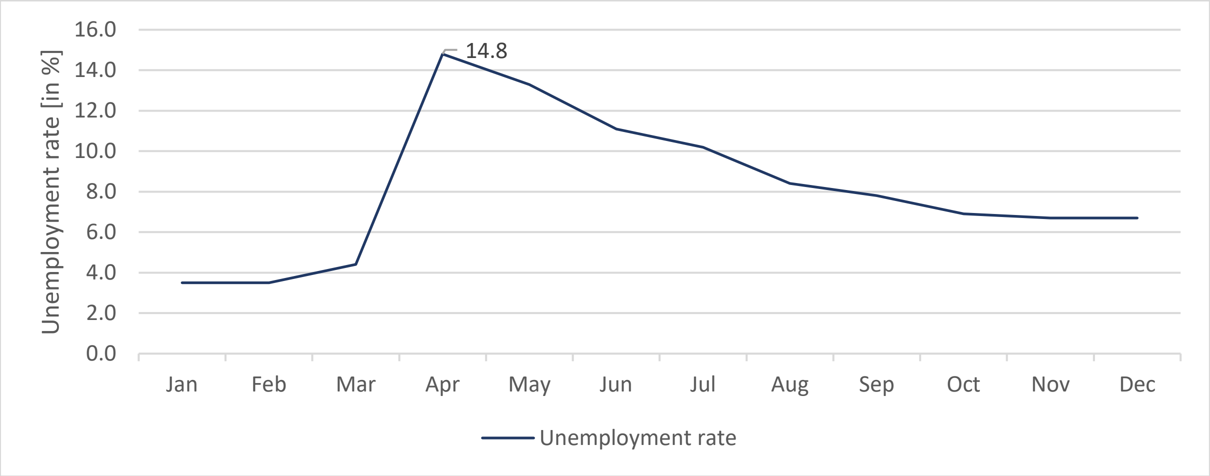






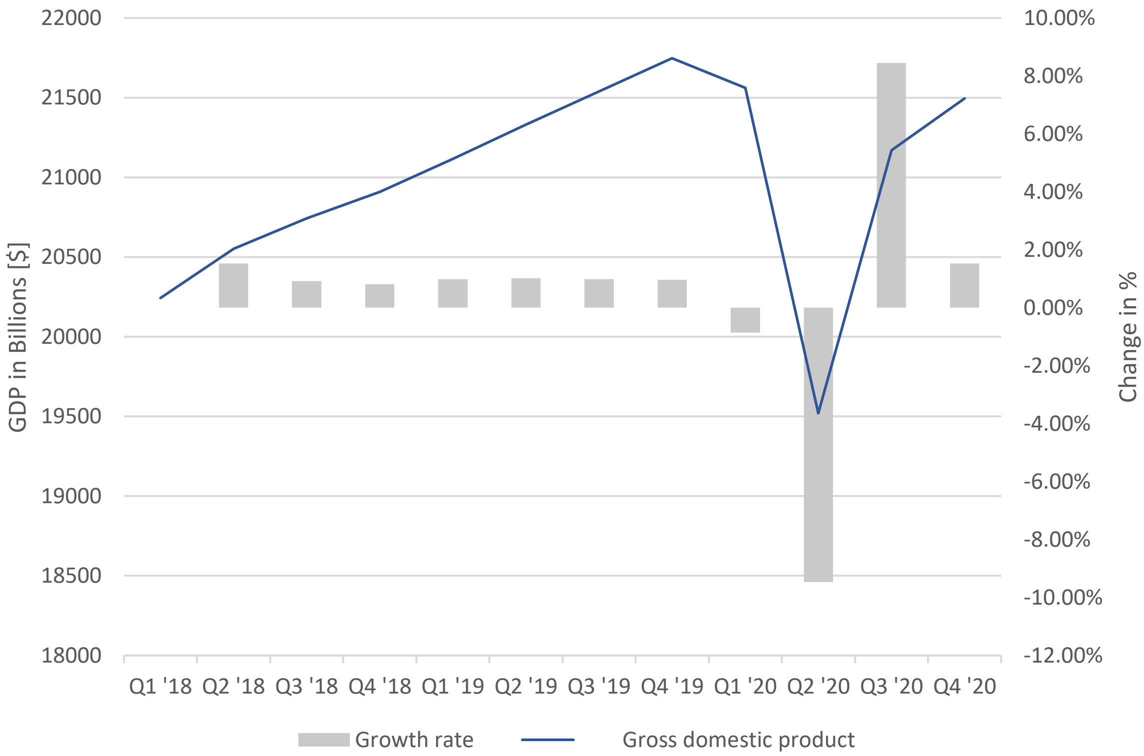
Note: The figure shows Price-Volatility Diagrams of selected indices of equity markets of Germany (Dax), United States (DJIA) and China (SSE Composite A Shares). Data is sourced through Thomson Reuters / ThomsonOne on the 10th March 2021, covering a timeframe starting 10th March 2016 to 10th March 2021. Return data is on a daily basis. It can be observed that in German and US markets volatility increases around March 2020, which is the time of the breaking point. With peaks in volatility, indices are dropping dramatically indicating the financial shock, caused by Conid-19.

Figure 4: Unemployment Rate in the United States in 2020



Note: The graph shows the development of the unemployment rate of the United States in 2020. Starting with levels of c. 4%, unemployment rate increases sharply in March 2020. Unemployment peak at a rate of 14.8%, and slowly decreased after. Data is provided by the U.S. Bureau of Labor Statistic and is sourced on the 20th April 2021 on the institutions proprietary database.

Figure 5: GDP of the United States from 2018 to 2020



Note: The graph shows the development of the Gross Domestic Product (GDP) of the United States over a period of 2018 to 2020. GDP as a measure of a nations output steadily increases till it drops sharply in the second quarter of 2020. From a level of USD 21500 bln in Qi 2020 it drops by c. 10% to a level of USD 19500 bln in Q2 2020. Data is provided by the Bureau of Economic Analysis.

Table 1: Key Dates of the Covid-19 outbreak

Date	Event
December 31, 2019	Cases of pneumonia detected in Wuhan (China) indicating the start of the pandemic
January 5, 2020	China announces that unknown pneumonia cases in Wuhan are not SARS or MERS
January 9, 2020	WHO determines that the outbreak is caused by a novel coronavirus
January 13, 2020	First cross-boarder incident as 2019-nCoV identified in Thailand
January 24, 2020	First public incident of COVID-19 infection in Europe (France)
January 27, 2020	First confirmed case of COVID-19 infection in Germany
January 30, 2020	WHO declares 2019-nCoV as "Public Health Emergency of International Concern"
March 11, 2020	WHO declares COVID-19 to be pandemic
March 13, 2020	WHO reports that Europe had become the epicenter of the pandemic

Note: Key Dates of the spread of Covid-19 pandemic and corresponding events. After the detection of first cases of pneumonia in Wuhan (China) the virus was declared a pandemic in mid-March 2020, shortly before the derived breaking point. Source: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline#!

Table 2: Correlations between financial assets and markets, in total, before and after the breaking point

Total Period Analyzed (1304 observations)

	Mkt	*HML*	*SMB*	*QMJ*	*Dax*	*DJIA*	*SSE Comp.*	*GOLD*	*BRENT*	*BTC*
Mkt	1									
HML	0.103472	1								
SMB	-0.43022	0.055583	1							
QMJ	-0.40448	-0.20365	-0.16663	1						
Dax	0.757982	0.236087	-0.27538	-0.35598	1					
DJIA	0.901491	0.126086	-0.58106	-0.25186	0.625867	1				
SSE Comp	0.273356	0.022443	0.041396	-0.16265	0.22148	0.187123	1			
GOLD	0.08208	-0.08904	0.16163	-0.08645	-0.04183	0.018186	0.064231	1		
BRENT	0.418381	0.241296	-0.12476	-0.36204	0.36161	0.380778	0.16965	0.044953	1	
BTC	0.191952	0.022099	-0.0568	-0.10032	0.153939	0.17581	0.023146	0.129639	0.070883	1

Before the breaking point (1049 observations)

	Mkt	*HML*	*SMB*	*QMJ*	*Dax*	*DJIA*	*SSE Comp.*	*GOLD*	*BRENT*	*BTC*
Mkt	1									
HML	0.014151	1								
SMB	-0.45721	0.086069	1							
QMJ	-0.43039	-0.26789	-0.09486	1						
Dax	0.746154	0.135912	-0.30589	-0.38542	1					
DJIA	0.89085	-0.02313	-0.62943	-0.25788	0.592026	1				
SSE Comp	0.267011	0.044099	0.047568	-0.17657	0.221637	0.173644	1			
GOLD	-0.00557	-0.04367	0.244218	-0.08698	-0.13144	-0.07235	0.052327	1		
BRENT	0.390251	0.238005	-0.12143	-0.441	0.311319	0.35292	0.1943	0.033012	1	
BTC	0.17875	0.041156	-0.07319	-0.06655	0.141554	0.169396	0.012528	0.112333	0.048028	1

After the breaking point (255 observations)

	Mkt	*HML*	*SMB*	*QMJ*	*Dax*	*DJIA*	*SSE Comp.*	*GOLD*	*BRENT*	*BTC*
Mkt	1									
HML	0.197741	1								
SMB	-0.40633	0.027965	1							
QMJ	-0.35331	-0.15748	-0.27378	1						
Dax	0.774684	0.345159	-0.24037	-0.30223	1					
DJIA	0.920066	0.282599	-0.50821	-0.23514	0.679607	1				
SSE Comp	0.295761	-0.00266	0.017301	-0.13552	0.228271	0.223862	1			
GOLD	0.218585	-0.13548	0.016181	-0.08309	0.091892	0.161346	0.093599	1		
BRENT	0.457305	0.260862	-0.14819	-0.23294	0.434616	0.422771	0.115193	0.061172	1	
BTC	0.240231	-0.00287	-0.02858	-0.18813	0.198329	0.206998	0.059711	0.195202	0.132793	1

Note: The three tables show the results of the correlation analysis of the set of assets. A total of 1304 trading days is split by the breaking point (18th March 2020). Thus, the periods before, after and the total amount of trading days are analyzed. In contrast to expectations, traditional "safe haven" assets like Gold, Brent and HML show a shift towards stronger positive levels of correlation with the market during the onset of the breaking point. Bitcoin is also characterized by a shift from 0.18 to 0.24. Just the QMJ portfolio following Asness et al. (2014) can maintain negative correlation while the financial turmoil caused by the Covid-19 crisis. Data of the DAX, SSE Comp, DJIA, Gold, Brent is sourced via Thomson Reuters / ThomsonOne on the 10th March 2021, while the portfolios are provided by AQR Capital Management LLC (AQR).

Table 3: Robust standard regression model

	Dependent variable:
	BTC
Mkt	0.218
	(0.183)
SMB	−0.234
	(0.336)
HML	0.279
	(0.259)
QMJ	−0.254
	(0.378)
Dummy	0.003
	(0.002)
Gold	0.451***
	(0.138)
HML*Dummy	−0.319
	(0.340)
QMJ*Dummy	−0.608
	(0.595)
Gold*Dummy	0.027
	(0.194)
Constant	0.003***
	(0.001)
Observations	1,304
R^2	0.037
Adjusted R^2	0.031
Residual Std. Error	0.027 (df = 1294)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: Regression model with no dummies

	Dependent variable:
	BTC
Mkt	0.216
	(0.172)
SMB	−0.182
	(0.322)
HML	0.061
	(0.151)
QMJ	−0.563*
	(0.308)
GOLD	0.465***
	(0.098)
Constant	0.004***
	(0.001)
Observations	1,304
R^2	0.034
Adjusted R^2	0.031
Residual Std. Error	0.027 (df = 1298)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression model HML

	Dependent variable:
	BTC
Mkt	0.473***
	(0.175)
SMB	0.154
	(0.359)
HML	0.309
	(0.266)
Dummy	0.003
	(0.002)
HML*Dummy	−0.414
	(0.350)
Constant	0.003***
	(0.001)
Observations	1,304
R^2	0.020
Adjusted R^2	0.017
Residual Std. Error	0.027 (df = 1298)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6: Regression model QMJ

	Dependent variable:
	BTC
Mkt	0.316*
	(0.177)
SMB	−0.051
	(0.372)
QMJ	−0.393
	(0.361)
Dummy	0.003
	(0.002)
QMJ*Dummy	−0.408
	(0.593)
Constant	0.003***
	(0.001)
Observations	1,304
R^2	0.020
Adjusted R^2	0.017
Residual Std. Error	0.027 (df = 1298)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression model Gold

	Dependent variable:
	BTC
Mkt	0.321**
	(0.155)
SMB	−0.002
	(0.301)
Gold	0.435***
	(0.134)
Dummy	0.003
	(0.002)
Gold*Dummy	0.048
	(0.192)
Constant	0.003***
	(0.001)
Observations	1,304
R^2	0.033
Adjusted R^2	0.030
Residual Std. Error	0.027 (df = 1298)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 8: Regression model Market

	Dependent variable:
	BTC
Mkt	0.139
	(0.240)
Dummy	0.003
	(0.002)
Mkt*Dummy	0.462
	(0.289)
Constant	0.003***
	(0.001)
Observations	1,304
R^2	0.018
Adjusted R^2	0.016
Residual Std. Error	0.027 (df = 1300)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 6: Script of the R-Studio code

```
# First step: Load data -------------------------------

# import times series data from csv file and create dataframe
log_excess_returns <- read.csv('/Users/Lenovo/Desktop/Regression/log_excess_returns.csv')
# reformat column (characters) to date
log_excess_returns$Date <- as.Date(log_excess_returns$Date,format =  "%m/%d/%Y")


# Second step: Verify assumptions of linear regression ------------------------------

# run linear regression:
# BTC(y) ~ Controls + HML + QMJ + GOLD  + Dummy + HML*Dummy + QMJ*Dummy + GOLD*Dummy
model_diversifier <- lm( log_excess_returns$BTC ~ log_excess_returns$Mkt +
                           log_excess_returns$SMB + log_excess_returns$HML +
                           log_excess_returns$QMJ + log_excess_returns$GOLD +
                           log_excess_returns$Dummy +
                           (log_excess_returns$HML*log_excess_returns$Dummy) +
                           (log_excess_returns$QMJ*log_excess_returns$Dummy) +
                           (log_excess_returns$GOLD*log_excess_returns$Dummy) )
summary(model_diversifier)

### check for heteroscedasticity by doing Breusch Pagan Test,
# Null Hypothesis: homoscedasticity
## install packages
library(lmtest)
bptest(model_diversifier)
### BP value = 76,5 --> p-value = 0,000 --> reject null, definitely heteroscedasticity

## run the regression with robust standard errors
## install relevant package
install.packages('robustbase')
library(robustbase)

## standard regression with all safe haven investments
model_diversifier_robust <- lmrob( log_excess_returns$BTC ~ log_excess_returns$Mkt +
                                     log_excess_returns$SMB +
                                     log_excess_returns$HML + log_excess_returns$QMJ +
                                     log_excess_returns$Dummy +
                                     (log_excess_returns$HML*log_excess_returns$Dummy) +
                                     (log_excess_returns$QMJ*log_excess_returns$Dummy) +
                                     (log_excess_returns$GOLD*log_excess_returns$Dummy) )
summary(model_diversifier_robust)

## check for whether there is serial/auto correlation by doing Breusch-Godfrey Test,
# Null Hypothesis: no serial correlation
## install relevant package
install.packages('zoo')
library(lmtest)
### when testing Breusch-Godfrey of order 1, then no further specification is necessary
# in R, but feeding the regression model
bgtest(model_diversifier_robust)
### BG value = 0.0079 --> p-value = 0.9293 --> accept null, no serial/auto correlation present
## We can proceed without having to take care of serial correlation issues
```

```r

## However, the regression output did not show the effects we were hoping to see
#(stronger pos. linear relationship between BTC and safe haven investments after "the event")

## hence, just for curiosity: checking estimators when there are no dummies
# (running the regression without "the event" over the whole time-series of the study)

model_no_dummy <- lmrob( log_excess_returns$BTC ~ log_excess_returns$Mkt +
                           log_excess_returns$SMB  + log_excess_returns$HML +
                           log_excess_returns$QMJ +log_excess_returns$GOLD)
summary(model_no_dummy)


## Now, I analyze the relationship between BTC and the individual safe haven investments
# (maybe there were outsetting effects).

## HML regression (Regression Output - Appendix Table 5)
model_diversifier_robust_hml <- lmrob( log_excess_returns$BTC ~ log_excess_returns$Mkt +
                                         log_excess_returns$SMB + log_excess_returns$HML +
                                         log_excess_returns$Dummy +
                                         (log_excess_returns$HML*log_excess_returns$Dummy) )
summary(model_diversifier_robust_hml)

## QMJ regression (Regression Output - Appendix Table 6)
model_diversifier_robust_qmj <- lmrob( log_excess_returns$BTC ~ log_excess_returns$Mkt +
                                         log_excess_returns$SMB + log_excess_returns$QMJ +
                                         log_excess_returns$Dummy +
                                         (log_excess_returns$QMJ*log_excess_returns$Dummy) )
summary(model_diversifier_robust_qmj)

## GOLD regression (Regression Output - Appendix Table 7)
model_diversifier_robust_gold <- lmrob( log_excess_returns$BTC ~ log_excess_returns$Mkt +
                                          log_excess_returns$SMB + log_excess_returns$GOLD +
                                          log_excess_returns$Dummy +
                                          (log_excess_returns$GOLD*log_excess_returns$Dummy) )
summary(model_diversifier_robust_gold)

## Mkt regression (Regression Output - Appendix Table 8)
model_diversifier_robust_mkt <- lmrob( log_excess_returns$BTC ~ log_excess_returns$Mkt +
                                           log_excess_returns$Dummy +
                                         (log_excess_returns$Mkt*log_excess_returns$Dummy) )
summary(model_diversifier_robust_mkt)

```

```r
## Now I create appealing outputs per regression model
install.packages("weatherData",repos = "http://cran.us.r-project.org")
install.packages('stargazer')
library(stargazer)

# standard robust regression model
stargazer(model_diversifier_robust, header=FALSE,
          title="Regression model output", type='latex',
          covariate.labels = c("Mkt", "SMB", "HML", "QMJ", "Dummy",
                               "Gold", "HML*Dummy", "QMJ*Dummy", "Gold*Dummy"))

# regression model with no dummies
stargazer(model_no_dummy, header=FALSE,
          title="Regression model output - no dummies -", type='latex')

# HML regression
stargazer(model_diversifier_robust_hml, header=FALSE,
          title="Regression model output - HML -", type='latex',
          covariate.labels = c("Mkt", "SMB", "HML", "Dummy", "HML*Dummy"))

# QMJ regression
stargazer(model_diversifier_robust_qmj, header=FALSE,
          title="Regression model output - QMJ -", type='latex',
          covariate.labels = c("Mkt", "SMB", "QMJ", "Dummy", "QMJ*Dummy"))

# Gold regression
stargazer(model_diversifier_robust_gold, header=FALSE,
          title="Regression model output - Gold -", type='latex',
          covariate.labels = c("Mkt", "SMB", "Gold", "Dummy", "Gold*Dummy"))

# Mkt regression
stargazer(model_diversifier_robust_mkt, header=FALSE,
          title="Regression model output - Market -", type='latex',
          covariate.labels = c("Mkt", "Dummy", "Mkt*Dummy"))

```