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The Effect of Bitcoin on Sector ETFs Before and During the Covid-19 Pandemic

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1. Introduction

The Dutch news article "Het Financiële Dagblad" stated on 30 January 2022 that if Bitcoin decreases in value stock markets will also decrease in value (Brasser, 2022). In figure 1 and 2 below the Global Financial Stability Report from IMF (2021) shows that the market capitalization and the trading volumes on the cryptocurrency market tripled from November 2020 until May 2021. Reasons for this are that the risk-returns on the crypto market are comparable to the risk-returns on current mainstream investment opportunities, which is showed in figure 3 below and investors seek diversification benefits to maximise the risk-return performance of their portfolios (IMF, 2021). Iyer (2022) found that during the Covid-19 pandemic spillovers from price volatility of Bitcoin to the S&P 500 and Russell 2000 indices have increased respectively by about 16 and 17.6 percentage points and the spillovers from returns of Bitcoin to the S&P 500 and Russell 2000 indices respectively 10 and 9.8 percentage points.

Figure 1: The Market Capitalization for Crypto Assets in Billion US dollars (IMF, 2021)

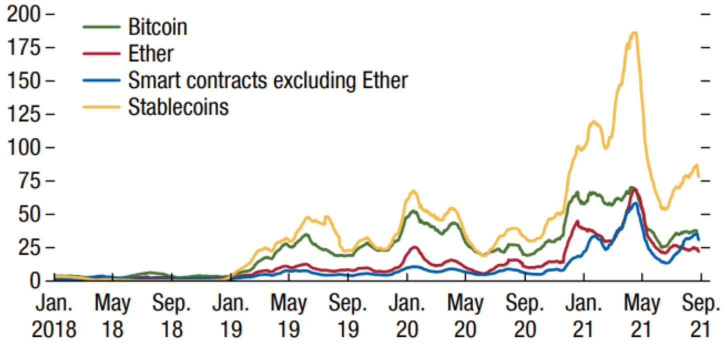
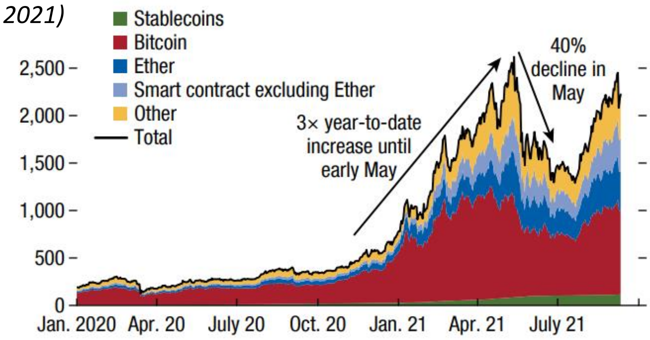
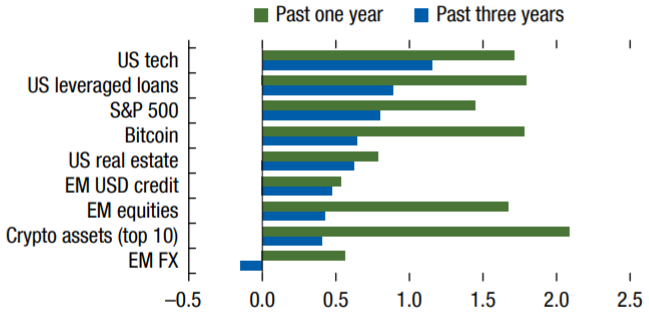


Figure 2: The Daily Trading Volumes on Exchanges in Billion US dollars, 30-day rolling average (IMF, 2021)



Note: figure 1 and 2 from the Global Financial Stability Report of the IMF (2021) shows that the interest in cryptocurrencies increased a lot the last years. The market capitalization and the trading volume tripled from November 2020 until May 2021. However, also the high volatility level on the crypto market is remarkable since after the 300% increase the market declined by 40% in May.

Figure 3: The risk adjusted returns (Sharpe Ratios) of crypto assets and other financial assets (IMF, 2021)



Note: figure 3 from the Global Financial Stability Report of the IMF (2021) shows that when adjusting for risk the risk-return ratio of Bitcoin is approximately as high as the from US tech equities (S&P 500), US leveraged loans and emerging market equities and the risk-return ratio of the top 10 crypto assets is even higher (past year reflects the year 2021 and past three years the years 2018-2021). This implies that the relative attractiveness of cryptocurrencies is comparable to or even better than other mainstream investment opportunities, since they also incur large drawdowns (IMF, 2021).

By analysing different financial products Elfakhani et al. (2008) and Ahmad (2019) illustrate that the rapid development of the globalization increased correlation and Chakrabarti et al. (2021) found contagion effects during the Covid-19 pandemic. The tremendously increased interest in and market capitalization of the cryptocurrency market in combination with the globalization and Covid-19 pandemic caused increased interdependencies between cryptocurrencies and the stock market (Guo et al., 2021). They show that before the Covid-19 pandemic Bitcoin can be used as diversifier, however during the Covid-19 pandemic for the average market and in particular Bitcoin the contagion was higher, faster and easier. Close monitoring of crypto asset markets and the adoption of appropriate regulatory policies are therefore needed to alleviate potential financial stability risks and inform investors of possible unexpected volatility spillovers of Bitcoin (Iyer, 2022).

The dynamic correlation between Bitcoin and 11 different sector portfolios was found to be quite low, varying from 0.0010 (Telecom sector) to 0.0395 (Basic Materials sector) for the sample period August 2011 until November 2018 (Akhtaruzzaman et al., 2020). Damianov & Elsayed (2020) also found low dynamic conditional correlation between 10 sector portfolios and Bitcoin from July 2010 until December 2018. They also showed that adding Bitcoin to the sector portfolios increased the Sharpe and Sortino ratios significantly compared to the sector portfolios excluding Bitcoin. This means that Bitcoin functioned well as a hedge for these different sectors in terms of diversification benefits and increased the risk-return ratio before the Covid-19 Pandemic. Earlier research only studied the interdependencies before the Covid-19 pandemic, however during the pandemic it is not clear yet how the increased Bitcoin spillovers affect different sectors, which is studied in this paper.

Investors are able to diversify risk and increase the risk return ratio by buying directly different financial assets from different countries and industries or passively by buying mutual funds or Exchange Traded Funds (ETFs) (Huang & Lin, 2011). There is an enormously increasing interest in ETFs, since they offer easy accessible exposure to a certain industry, country or asset type, perform well as diversification asset and include low transaction costs (Dorocáková, 2017). Therefore, in this research sector ETFs are used to measure sector exposure since it is reliable that underlying companies are representative for a certain sector and biased self selected processes are not included.

During a period of financial crisis spillover effects increase, since economies are becoming even more connected to each other (Cheung et al., 2010). Due to panic and liquidity problems, volatility on the market increases enormously, which increases the covariance and decreases diversification benefits between different financial products (Patev et al., 2006). The Covid-19 Pandemic started in the beginning of 2020 and included different variants, which resulted in multiple Covid-19 waves. The direct global destructive economic impact can be seen in each scope of the economy (Goodell, 2020). The impact is directly visible since there is a loss of employment productivity, which results in declined sales and services. Also, governments came up with different measures, which resulted in social distancing and lockdowns that disrupt the financial system and economic activities (Notteboom et al. 2021).

1.1 Research Question

As mentioned in the beginning of the introduction Iyer (2022) found that during the Covid-19 pandemic spillovers from Bitcoin on two American stock indices increased significantly. Ghorbel & Jeribi (2021) also studied this relationship and concluded that before the Covid-19 pandemic Bitcoin and gold are considered as a hedge for the US investor, however in the beginning of 2020 the conditional correlation between cryptocurrencies, American indices and an oil index, increased significantly. Due to these spillovers hedge benefits disappeared and it is recommended not to use cryptocurrencies as a safe heaven.

Ghorbel & Jeribi (2021) used the GARCH (1,1) model to estimate conditional volatilities of the assets and used multiple regressions to determine the effect of the conditional volatilities of cryptocurrencies and other assets on two American indices. Here, conditional volatility means that the volatility of a variable depends on the volatility of their past, which is determined by it’s short and long run persistence. This methodology is used in this research and further explained in the methodology section.

Earlier research focused on the interdependencies between Bitcoin and markets and therefore neglect the impact of Bitcoin volatility on different sectors including the presence of ETFs during the Covid-19 Pandemic. This paper focused on determining the effect of the conditional volatility of Bitcoin on the conditional volatility of sector ETFs before and during the Covid-19 pandemic. It is chosen to only focus on this relationship rather than the reversed relationship, because this paper takes the perspective of pure sector investors. Each sector includes different characteristics, which indirectly influences the level of risk for an investor. It is to be determined which pure sector investments are affected by Bitcoin volatility, so investors become aware of possible volatility spillovers of Bitcoin that cause unexpected volatility risk in their sector investments. In particular Bitcoin is chosen rather than other cryptocurrencies to extend the starting date of the sample period and earlier research concluded high co-volatility between the most traded cryptocurrencies (Candila, 2021; Canh et al., 2019). Therefore, the research question remains as follow:

What is the effect of the conditional volatility of Bitcoin on the conditional volatility of different sector ETFs before and during the Covid-19 Pandemic and are there differences?

Before performing the research the sector ETFs are classified as defensive or cyclical sectors. The effect of the conditional variance of Bitcoin on the sector ETFs was found to be close to zero and significant in some cases before the Covid-19 pandemic and during the Covid-19 pandemic the effect was found to be increased positively and significant in all cases , which is consistent with the findings of earlier research. It was also expected and it is found that during the Covid-19 pandemic defensive sectors are less influenced by the conditional Bitcoin volatility than the cyclical sectors due to certain sector characteristics explained in the literature review. However, there was some indicative evidence that by comparing the size of the coefficients between different regressions it seemed to be the case that not all defensive sectors were affected the least and not all cyclical sectors the most by the conditional variance of Bitcoin. Comparing coefficients between different regressions neglects the impact of the standard errors, so this remark was only found as indicative rather than conclusive evidence.

1.2 Relevance and Research Gap

Cryptocurrencies share less common risk features in comparison to securities, precious metals and currencies, wherefore they can be used to hedge traditional financial holdings (Li & Huang, 2020). Moreover, Ahmed (2021) examined to what extend stock prices are sensitive to volatility dynamics of Bitcoin in normal, bear, and bull markets. It was found that the volatility dynamics of the Bitcoin influences the volatility of both developed and emerging markets under different market conditions. In normal times Bitcoin positively affected returns on the equity market and to an increased extend when stock prices were extremely low or high. Umar et al. (2020) also concluded that the influence of cryptocurrencies on stock indices were time-varying. Their findings indicated that negative shocks of price movements of cryptocurrencies influenced the stock indices more than the positive stocks. The societal relevance remains thus as follows: from the investor's perspective it is to be said which specific sector investments include volatility risk of Bitcoin and have opportunities to benefit their portfolio in terms of diversification benefits when adding Bitcoin.

Furthermore, most governments consider cryptocurrencies as an extremely speculative asset class and several European Supervisory Authorities warn investors that cryptocurrencies are decentralized and therefore unregulated products that are exposed to excessive volatility and speculative bubbles (Guo et al., 2021). The findings of this paper illustrate that equity markets were not far behind the extreme volatility of Bitcoin during the Covid-19 pandemic due to the increased interdependencies. Therefore, the practical relevance remains as follows: from the policy makers' perspective it is to be said which sector is influenced the most by the high conditional volatility of Bitcoin, so they can determine which sectors have to be protected and to what extend it is important to compassionate their policies on this.

Moreover, literature did not provide research on the interdependencies between cryptocurrencies and different sectors, in particular sector ETFs. The sample periods of Ghorbel & Jeribi (2021) and Umar et al (2020) are respectively until the first of April 2020 and the 15th of April 2019, which only absorbs the early stage or entirely excludes the pandemic. The sample period of Iyer (2022) is until November 2021, however only the interdependencies between cryptocurrencies and two market indices is studied (S&P 500 and Russell 2000). Thus, the topic is scientifical relevant, since studying the interdependencies in stable and abnormal times until March 2022 extends the sample period of earlier research and by including structural breaks multiple Covid-19 waves are incorporated.

Earlier research did also not consider the relationship of the conditional variance of Bitcoin on the conditional variance of different sectors during the Covid-19 Pandemic, which is interesting to look at from both the policy maker's and investor's perspectives explained above and builds further on the research of Iyer (2022) by examining the risks that cryptocurrencies emerge to the financial system more broadly. Using different sector ETFs that measure the performance of particular sectors with certain country exposure allows diversification within sectors and is less time consuming and biased compared to self selection processes from earlier research. So, the studied effect is based on multiple different companies within one sector rather than one or a few companies (self-selected), which is why the studied interdependence is not biased.

The remainder of the paper is organized as follows. Firstly, the literature overview shows the most important and relevant studies that are needed to come up with hypothesises that help answering the research question. Secondly, the methodology and data are presented to explain respectively how the research is performed and which data is analysed. Finally, the results are presented and compared to earlier outcomes and the conclusion is formed to answer the research question including some limitations and further recommendations.

2. Literature Review

As mentioned in the introduction volatilities of cryptocurrencies are affecting the stock market to some extent. In this paper the effect of Bitcoin on different sector ETFs is studied. The literature overview remains as follows: firstly, there is a concise explanation on ETFs and Bitcoin. Hereafter, the impact of the Covid-19 pandemic and earlier research on interdependencies is illustrated and in the end hypotheses are formed and explained.

2.1 Exchange Traded and Mutual Funds

Exchange traded funds are basically funds traded on the stock exchange (Dickson et al., 2015). They consist of a bunch of securities that allow different types of exposure and diversification options. ETFs are similar to Mutual funds in a way that they are both actively or passively managed by the fund executives, however in comparison to mutually funds ETFs consist of low transaction cost and do not have to be bought directly from the fund platform, but on the exchange market.

Figure 4 (appendix) is a graph from the Investment Company Institute (2019) and shows that the interest and holdings in passive investments increased (ETFs and Index Funds), while the interest in active investments decreased (Active Funds). This could be explained by the fact that Active Funds underperform after fees in comparison to ETFs and Index Funds (Liebi, 2020). ETFs are also far more liquid than mutual funds, since they include more transparency and more often lower transaction costs (Dickson et al., 2015). Prices of ETFs are determined on the market by demand and supply, which is the same as other securities. However, prices of mutual funds are determined by the net asset value, which is calculated by the fund once per day.

Dorocává (2017) illustrates that in the long run passive investment strategies yield higher returns compared to the active investment strategies. Huang and Lin (2011) used the Sharpe ratio and a modified Sharpe ratio that replaces standard deviation for Value at Risk in the equation to identify whether the portfolio with direct indices holdings of different countries benefits by adding 19 iShare ETFs with exposure to Europe, America, Africa and Asian markets. They found that the Sharpe ratios of portfolios including ETFs were higher than the from pure domestic country index portfolios.

Liebi (2020) provides a literature review analysing the effect of ETFs on liquidity, price discovery, volatility and co-movement of the underlying securities. Using earlier research they illustrate that ETFs are highly liquid in stable times, but during times of financial distress ETFs experience significant illiquidity. This might influence results, wherefore the Covid-19 pandemic is incorporated in this study.

Ben-David et al. (2021) classified ETFs in specialised and broad-based ETFs to study the evolution and motives behind new ETFs from 2000 until 2019. Specialised ETFs include thematic ETFs that track multiple industries that are focused on a specific “theme” (clean energy e.g.) and sector / industry ETFs that track a particular industry / sector. broad-based ETFs include strategic beta ETFs that track different investments following a specific rule based system (minimum variance e.g.) and broad-index ETFs that track multiple indices, but exclude strategic beta. The results illustrate that broad-based ETFs have a high level of diversification including low fees and specialised ETFs offer exposure to high trending themes with low diversification and higher fees. In this paper sector ETFs are examined, which are classified as specialised rather than broad-based ETFs. Investing in specific sectors increases the amount of risk and decreases diversification benefits. Therefore, it is interesting to determine the effect of Bitcoin on specific sectors, because it might be one of the risk factors that has to be considered by investors.

Krause et al. (2014) showed that there are significant volatility spillovers of ETFs on the largest underlying securities and Wurgler (2010) shows the importance of studying ETFs, since spillovers may increase the co-movement of different securities within ETFs. This demonstrates that the characteristics and co-movement of the sector ETFs are a well representative of the characteristics and co-movement of the underlying companies within the sectors.

2.2 Bitcoin

The first cryptocurrency is Bitcoin and was founded in 2009 (Chohan, 2022). Bitcoin was meant to be a supplement to fiat money, since the centralized characteristics were criticised during and after the financial crisis. Baur et al (2018) studied whether Bitcoin is a medium of exchange or a speculative investment asset. They find that the minority of Bitcoin holders use them as medium of exchange, which suggests that Bitcoin is held as investment opportunity rather than being used for transactions. Kirkby (2018) confirms this by showing that Bitcoin is extremely volatile, wherefore Bitcoin does not perform well as a store of value. This paper explains due to the fact that monetary policy target price stability for fiat money, Bitcoin will always be higher volatile independent from a significant increase in worldwide acceptance. Cryptocurrencies are namely decentralized, whereas fiat money is centralized.

Bitcoin is used as indicator for the whole crypto market, since Bitcoin has the largest market capitalization and it is assumed that all cryptocurrencies are correlated to each other (Candila, 2021; Cahn et al., 2019). Canh et al (2019) also found that multiple structural breaks exist among the most frequently traded cryptocurrencies from the 5th of August 2014 to the 31st of December 2018. For this reason it is important that structural breaks are incorporated in the study, since the sample period includes also multiple Covid-19 waves. As mentioned in the introduction section the market capitalisation and trading volume of cryptocurrencies increased tremendously last years, which affects the stock market, wherefore the effect of Bitcoin on sector ETFs have to be studied (Iyer, 2022).

2.3 Globalisation and Impact of Covid-19

The increasing globalisation increases financial connectedness between different economies, which increases spillover effects in trade and stock markets. Ahmad (2019) used a panel data set of 83 countries over a 30-year period and found that economic globalisation significantly affects economic growth and positively spillover effects not only for neighbouring countries, but also countries with similarities in political institutions. Globalization increases covariance and decreases diversification benefits between different financial products due to the fact that spillovers and risk-return rates respectively increase and decrease (Elfakhani et al., 2008).

During periods of financial distress there is a lot of uncertainty and extreme volatility on financial markets that leads to even a higher interconnectedness between different financial products. Due to this uncertainty, investors prefer cash and start to sell all kind of financial assets since they are afraid that they are exposed to liquidity problems or have to incur huge losses. This leads to self fulfilling financial crises, because investors fear that others withdraw their money (Goldstein & Pauzner, 2004). Kenourgios et al. (2013) examines the contagion effects across equity market indices, bonds, commodities, foreign exchange and real estate from multiple borders and regions. They concluded that during the global financial crisis of 2007/2008 there was an increasing connectedness among equity markets and across the different types of financial assets. Chakrabarti et al. (2021) show that the Covid-19 pandemic had caused contagion in the global equity market, since the correlation and connectedness of advanced and emerging stock markets increased significantly.

Al-megren et al. (2018) examine the progression and the practical relevance of blockchain beyond theory in corporate, governmental and cross-industry environments by conducting a literature review. Blockchain technology may potentially affect the Internet of Things, health care, supply chain management and government sectors by increasing the productivity and extending technological possibilities. However, earlier research concluded that cryptocurrencies are mainly used for speculative investment opportunities rather than using the unique technology to affect contemporary business processes (Baur et al., 2018).

The literature illustrates different studies that show a lack of connectedness between cryptocurrencies and the technology sector (Ahmed, 2021), the energy sector (Afjal & Sajeef, 2022), the real estate sector and S&P500 (Kuo et al., 2018) and different sector portfolios (Akhtaruzzaman et al., 2020; Damianov & Elsayed, 2020) in stable times. However, all these studies exclude the entire or include just the beginning of the Covid-19 Pandemic, in which the connectedness and interdependencies increased significantly between cryptocurrencies and American stock indices (Ghorbel & Jeribi, 2021; Iyer, 2022), the stock market

(EURONEXT, S&P500, SSE, HSKE, JPXGY and LSE) (Ha, 2022) and the Europe and U.S. stock market (Guo et al., 2021).

Thus, earlier research identified a weak relationship and connectedness between Bitcoin and traditional assets before the Covid-19 Pandemic (Kurka, 2019; Wang et al 2021). However, due to the tripled market capitalization and trading volumes of Bitcoin (figure 1 and 2, appendix), the globalization and the Covid-19 pandemic the correlation between traditional assets and Bitcoin is increased. Therefore, it is in the interest of this paper to determine spillovers from Bitcoin on different sectors.

2.4 Sectors and ETFs

Following Kusek (2018) investors are homogeneous in seeking predictable, transparent and efficient conduct of public agencies. However, they are heterogenous in a way that they are risk seeking or averse and have different perceptions of investment opportunities and information. Investors reallocate their capital among their own preferences that make for example reasonings between defensive or aggressive (cyclical) sectors (Ngene, 2021). Defensive sectors consist of companies that deal with necessity goods and services including inelastic demand independent of economic cycles and cyclical sectors consist of companies that deal with goods and services including elastic demand that really depends on economic cycles.

Defensive sectors are assets with a low volatility and beta, because they are relatively less influenced by economic fluctuations including stable earnings and cyclical sectors vice versa (Novy-marx, 2014). Cyclical sectors have relatively higher returns during economic growth periods and defensive sectors have relatively higher returns during economic crises. Defensive sectors consist of the health care, consumer staples and utilities sectors and are relatively more correlated to each other than to cyclical sectors that consist of the information technology, consumer discretionary, energy, materials, industrials, financials, communication services and real estate sectors that are also more correlated to each other rather than to the defensive sectors.

Earlier research concluded that the performance of defensive sectors is consistent during periods of a recession and the financial market crisis of 2007 / 2008 (Ole-meiludie, Town, & Africa, 2014). The Covid-19 pandemic is influenced by external factors rather than economic factors, wherefore it is to be concluded whether the performance of defensive sectors is still consistent during the Covid-19 pandemic and the effect of Bitcoin on defensive sectors differs from the on cyclical sectors (Choi, 2021).

2.5 Hypotheses

As mentioned before the high volatility of Bitcoin and the interest and market capitalization of this financial product is increasing, which significantly influences investor’s sentiment and stock market fluctuations, especially to an increased extend during the Covid-19 Pandemic. The stock market consists of multiple different sectors, wherefore it has to be examined which sectors are hurt the most and least by this high volatility of Bitcoin.

In this study 11 sectors with exposure in Europe and the United States are examined and divided in two sub groups: defensive sector ETFs (utility, consumer staples and health care sectors) and cyclical sector ETFs (energy, material, industrial, consumer discretionary, financial, information technology, communication services and real estate sector). These sectors are defined by the Global Industry Classification Standard (GICS) and are also used by Smales (2020). He concluded that on the global level all these sectors are significantly influenced by Covid-19.

In this paper the focus is on determining the effect of Bitcoin volatility on different sector ETFs and to conclude which sector ETFs are influenced the most and least by Bitcoin volatility. Literature provides evidence that Bitcoin volatility did not affect the equity market before the Covid-19 pandemic. During a period of high volatility or financial distress spillovers and covariances between different assets increase (Cheung et al., 2010; Patev et al., 2006). Ghorbel & Jeribi (2021) and Iyer (2022) found that Bitcoin volatility positively affects the volatility of different market indices, especially since the Covid-19 pandemic. When forming the first hypothesis it is expected that during the Covid-19 pandemic all sector ETFs are affected by the Bitcoin volatility, but before the Covid-19 Pandemic not. Therefore, the first hypothesis remains as follow:

H1: During the Covid-19 pandemic the conditional variance of bitcoin has an positive effect on the sector ETFs, but before the Covid-19 pandemic this relationship does not hold.

The cyclical sector ETFs consist of goods and services that are expected to be more sensitive and volatile during the Covid-19 pandemic waves than defensive sector ETFs that consist of necessity goods and services. This means that the Bitcoin volatility spillovers are expected to increase to a larger extend for cyclical sector ETFs than for defensive sector ETFs during the Covid-19 pandemic, which results in the following second hypothesis:

H2: During the Covid-19 pandemic the effect of the conditional variance of bitcoin on cyclical sector ETFs is stronger than on defensive sector ETFs.

Guo et al. (2021) concluded that the covariance of Bitcoin and the stock market is really low in stable times, however during the Covid-19 pandemic correlation increases a lot, particularly in Europe and the United States. For this reason sector ETFs with exposure to the Europe and the US stock market are considered and compared to each other.

3. Empirical Methodology

In the literature overview there is showed an overview of earlier research and hypotheses are formed that help to answer the research question. In this chapter the methodology is explained to answer the question how the research is performed. This chapter start with comparing different methods that can be used to study interdependencies. Thereafter, The GARCH model, structural breaks and regression model are explained in depth.

3.1 Studying Interdependencies

In the literature different methodologies are used to study interdependencies, determine risk factors and examine diversification benefits. Panda et al. (2019) used the granger-causality test to explain the direction of causality between the stock markets of Africa and Middle East region and multivariate generalized conditional heteroscedasticity (MGARCH) models to analyse the relationship between the volatilities and co-volatilities of the different markets. Dawar et al. (2021) studied the relationship between crude oil clean energy stock returns by using the quantile regression approach, which accounts for normal, bearish and bullish market conditions with using different quantiles and includes multiple lags. Abdalla & Winker (2012) used multiple univariate GARCH models to estimate and test symmetric and asymmetric conditional volatility of the Egypt and Sudan stock markets. Ghorbel & Jeribi (2021) used the univariate GARCH (1,1) model to determine the conditional volatilities of multiple financial assets and used normal regression models to determine the effect of the volatilities of gold, oil, cryptocurrencies and consumer sentiment on the volatilities of two stock market indices of the United States.

It is in the interest of this paper to identify which sectors are influenced the most by the volatility of Bitcoin and in especially during periods of financial distress. For this reason it is not in the interest of this paper to determine the reversed relationship and to come up with forecasting models that predict future stock prices. Therefore, the methodology of this paper follows the methodology of Ghorbel & Jeribi (2021) in which univariate GARCH models are estimated to predict the conditional variances of the financial assets and subsequently multiple regressions are run to determine the effect of the volatility of Bitcoin on the volatility of different sector ETFs.

3.2 GARCH Model

Ghorbel & Jeribi (2021) used the GARCH model to analyse correlation between the conditional volatility of the US indices (S&P 500 and Nasdaq) and gold, oil prices and cryptocurrencies for the period 01/01/2016 until 01/04/2020 on daily frequency. Here, conditional volatility means that the volatility of a variable depends on the volatility of their past. The basics of the univariate GARCH model are found by Bollerslev (1986) and are an extension on the ARCH model from Engle (1982). GARCH stands for generalized autoregressive conditional heteroskedasticity and can be used to predict the conditional variance of a financial product (h_t) as a function of a constant value (α_0), a short run persistence (α_1), unexpected past shocks (ε_{t-1}^2), a long run persistence of past volatilities (β_1) and finally a conditional variance from the past (h_{t-1}). The GARCH model has therefore the following form:

$$(1) \qquad h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

Ghorbel & Jeribi (2021) considered a sample period of the first of January 2016 until the first of April 2020 on a daily frequency. The GARCH model is an estimation model and since this paper incorporates multiple Covid-19 waves there is accounted for structural breaks in order to increase the reliability and estimation accuracy of the GARCH (1,1) model.

3.3 Structural Breaks

Structural breaks are: “points that are particularly important given the evidence on political unrest/regime changes, geo-political events, financial and economic crises, that may mask or alter the inter-market relationships” (Ewing & Malik, 2013). It is relevant to take into account structural breaks, since structural breaks significantly influence forecast models in time series (Hillebrand, 2005). The GARCH model is used in this paper and is such a forecasting model, which uses the short and long run persistence of different financial assets to determine the conditional variance. Hillebrand (2005) explains that a distinct error in the conditional variance occurs when there is not accounted for structural breaks. Extreme low or high volatilities and error terms namely heavily influence the mean volatility and error term and therefore the estimation model. Lamoureux & Lastrapes (1990) show that structural breaks should be incorporated into a GARCH model, since the standard GARCH models overestimate the underlying volatility persistence.

The sample period is from January 2010 until March 2022, which includes multiple waves of the Corona Pandemic. Ewing and Malik (2013) added different dummies for each structural break to the univariate GARCH model. By adding different dummies for each structural break to the standard univariate GARCH model, multiple Corona waves and other structural breaks are incorporated in the conditional variance estimation. This results in the following model:

(2) $$h_t = \omega + d_1 D_1 + \cdots + d_n D_n + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

,where D_1 , … and D_n are the set of dummy variables, that take a value one from each point of structural break in variance onwards and zero elsewhere (e.g. first Corona wave D_1 and D_2 respectively contain the values 1 and 0 and second Corona wave D_1 and D_2 respectively contain the values 0 and 1). To increase the reliability and decrease the error measure of the conditional variance estimation, multiple structural breaks are incorporated as dummies. The goal of this paper is not to identify the causes of the structural breaks, but increasing the reliability of the GARCH model by determining structural breaks empirically, which affect volatility dynamics. The 'estat sbsingle' command in STATA is used to determine structural breaks and to estimate break dates. The test allows this research to identify dummy variables that are showed in figure 5, 6 and 7 in the appendix.

Figure 8, 9 and 10 from the appendix show the plots of the Europe sector ETFs, US sector ETFs and Bitcoin. Each red vertical line indicates an empirically estimated structural break by the 'estat sbsingle' command. There is no test to check whether these estimated structural breaks are correct, however it seems to be the case that the estimated break dates are right, since the plots show that each red vertical line is close before a structural changed range of daily returns and level of volatilities. Therefore, in this study it is assumed that the 'estat sbsingle' command is an useful and reliable tool to estimate break dates.

3.4 Multiple Regression Models

The univariate GARCH model from Ewing and Malik (2013) estimates conditional variances that are based on short and long run persistence incorporating structural breaks by the use of dummy variables. To determine interdependencies between the volatilities of cryptocurrencies and ETFs the following regression model is used:

(3) $h_t(ETF_{sc}) = \beta_0 + \beta_1 h_t(Bitcoin) + \beta_2 D_{Covid} + \beta_3 Interaction + \beta_{4-7} h_t(Control) + \varepsilon$

where, $h_t(ETF_{sc})$ means the conditional variance of an ETF with s and c respectively indicating a specific sector (11 sectors) and country (Europe or US) exposure, $h_t(Bitcoin)$ the conditional variance of Bitcoin, D_{Covid} the dummy variable that takes a value 0 before and 1 during the Covid-19 pandemic, $Interaction$ the interaction effect between the conditional variance of Bitcoin and the dummy variable, $h_t(Control)$ the conditional variance of the control variables and ε the error term.

By estimating structural breaks it is remarkable that for all sector ETFs there was one extended period of stability, which was in all cases before the first Covid-19 wave. These estimated dates of the first Covid-19 waves vary between the 24th of February 2020 and the 12th of March 2020. For this reason it is assumed that all sectors are influenced significantly by the first Covid-19 wave on the 12th of March 2020. The dummy variable contains therefore a value of 0 before and 1 from this estimated date.

When discussing the first hypothesis the primarily interest lays in the conditional variance of Bitcoin and the interaction effect coefficients, respectively β_1 and β_3. The golden rule indicates that after adding an interaction effect the main effect coefficients of the variables included in the interaction are interpreted in a way that it is assumed that the other variable coefficient has a value of 0. This is not problematic in this regression, since β_1 is interpreted as the coefficient before the Covid-19 pandemic, so D_{Covid} automatically takes a value of 0 and it is not in the interest of this study to interpret β_2. Thus, it is not needed to center the main and interaction effect variables.

Overall, if the beta coefficient is significant, it can be said that the volatility of Bitcoin or the control variable significantly affects the volatility of the ETF. It is expected that before the Covid-19 Pandemic β_1 is close to 0 and significant and during the Covid-19 Pandemic β_3 is significant, positive and higher in comparison to β_1 within each of all regressions. If this is the case results are in line with hypothesis 1 and it is concluded that each sector ETF is positively affected by the Bitcoin volatility during the Covid-19 pandemic, but not before the Covid-19 pandemic.

When testing the second hypothesis it is not allowed to simply compare the size of the coefficients between the different multiple regressions, since the standard errors also play a role (Clogg et al., 1995). In this research the size of the coefficients is only compared as indicative evidence rather than testing hypothesis 2. In order to test hypothesis 2 only the period during the Covid-19 pandemic is studied and the dummy (β_2) and interaction term (β_3) are reformed, because now the dummy and interaction variables are used to demonstrate whether cyclical sector ETFs are more affected by the conditional variance of Bitcoin than the defensive sector ETFs. This results in equation 4:

$$(4)\ h_t(ETF_{sc}) = \beta_0 + \beta_1 h_t(Bitcoin) + \beta_2 D_{Cyclical} + \beta_3 Interaction + \beta_{4-7} h_t(Control) + \varepsilon$$

where, $h_t(ETF_{sc})$ means the conditional variance of an ETF with s and c respectively indicating a specific sector (11 sectors) and country (Europe or US) exposure, $h_t(Bitcoin)$ the conditional variance of Bitcoin, $D_{Cyclical}$ the dummy variable that contains a value 0 for defensive sector ETFs and 1 for cyclical sector ETFs, $Interaction$ the interaction effect between the conditional variance of Bitcoin and the dummy variable, $h_t(Control)$ the conditional variance of the control variables and ε the error term.

The focus is now only on the β_3 coefficient. If this coefficients is positive and significant, cyclical sector ETFs are more affected by the conditional variance of Bitcoin in comparison to defensive sector ETFs and results are in line with hypothesis 2.

4. Data

In this chapter the data sample and period is explained. Thereafter, an analysis of the descriptive statistics and the correlation matrix is showed to identify potential problems and some additional remarks of the STATA process are explained to show possible limitations and assumptions made.

4.1 Data Sample and Period

The data sample consist of 22 sector ETFs (11 Vanguard ETFs with exposure to US and 11 iShares ETFs with exposure to Europe), Bitcoin and some control variables. The considered sample period is from 17 July 2014 until 31 March 2022, which extends the period of earlier research and takes different Covid-19 waves into account. This particular start date is used due to data collection limitations. In this research the control variables GVZ, OVX, VIX and VSTOXX are used to control for impacts of economic and financial uncertainty. The control variables respectively reflect estimates of the 30-day volatility of gold, oil S&P 500 and Euro Stoxx 50 returns. Bensaïda et al. (2022) found that the implied volatilities of gold, oil and S&P 500 (respectively GVZ, OVX and VIX) influenced the US equity sector returns more than the historical and current returns of gold, oil and S&P 500. In this study also Europe ETFs are studied, however Bensaïda et al. (2022) took only the United States into account, so also the VSTOXX index is used to correct for total EU market effects. Price data is gathered from the Eikon Database, the research is performed in STATA 17, all prices are denoted in American dollars and figure 11 from the appendix shows the descriptive statistics of the 22 ETFs, Bitcoin and 4 control variables.

Furthermore, non-trading day observations of Bitcoin are dropped and all price data is synchronized to maintain consistency, which leads to 2,011 observations. Conditional variances are determined with the use of daily returns (r_d) and are calculated in the following way:

(5) $$r_d = \ln\left(\frac{p_t}{p_{t-1}}\right)$$

Figure 11 from the appendix shows that the control variables have the highest standard deviation. A reason for this is that these variables are 30-day estimates of the underlying, which involves a lot of constantly changing consumer sentiments and included a lot of pure noise from the short run. Bitcoin has the highest standard deviation when considering only the dependent and independent variables. This is explained by the fact that Bitcoin is used as a speculative financial asset rather than used for daily business processes, which causes a lot of volatility that is also heavily influenced by pure noise from the short run and unstable consumer sentiments (Baur et al., 2018; Kirkby, 2018). Furthermore, it is remarkable that the defensive sector ETFs (EXH7, VDC, EXV4, VHT, EXH9 and VPU) have the lowest standard deviations compared to the cyclical ETFs within Europe or the United States, which is in common with the theory that defensive sectors include lower volatility in comparison to cyclical sectors, because they include lower profits in periods of economic prosperity and lower losses in periods of economic crises.

The variables are normally distributed if the skewness and kurtosis values lay between +1 and -1. The skewness of the variables EXH2, EXV2, EXH9, EXI5, VCR and VNQ are outside the range of normality, because the values are lower than -1, which means that the distribution of these variables is left skewed. The skewness of the variables VIX and OVX are also outside the range of normality, because the values are greater than +1, which means that the distribution of these variables is right skewed. Furthermore, the kurtosis of the variables indicates whether the data includes heavy tails or outliers. The values are all greater than +1, which is called leptokurtic and indicates that the distribution of the data set has excess kurtosis. This is explained by the fact that the data set consists of daily data, which involves more pure noise with heavier tails and outliers than weekly, monthly or yearly data. Thus, the sector ETFs, Bitcoin and control variables are all far from normally distributed, which is comparable to the data of Ghorbel & Jeribi (2021).

Figure 12 from the appendix and 13 below show the descriptive statistics of respectively estimated conditional variances excluding structural breaks and conditional variances including structural breaks. It is remarkable that in comparison to figure 11 the minimum values are not negative anymore, which makes sense because negative variances do not exist. It is also remarkable that the skewness and kurtosis values are both greater than +1 for all variables, which indicates that the conditional variances are far from normally distributed. This is explained by the fact that daily conditional variances are estimated by the univariate GARCH (1,1) model and includes pure noise from the short run persistence.

The figures also show that the short and long run persistence coefficients (respectively ARCH and GARCH effects) are all significant summing up in most cases below 1, which indicates a good fit of the GARCH model when estimating conditional variances. Unfortunately, in a few cases the sum of alpha and beta coefficients is above 1, which indicates exploding variance over time. This is the case in both estimations for the variables EXV6, EXH7, EXV4, VFH, VGT and BTC, which might cause some problems in the estimations of the conditional variances. For this reason it is assumed that these possible problems do not influence results too much, since the focus of this study is not on the methodology but on coming up with some first results that show how the different sectors are influenced by the conditional Bitcoin volatility before and during the Covid-19 pandemic.

Figure 13: Summary Statistics Conditional Variances Including Structural Breaks

Variable	Obs	Mean	Std. Dev.	Min	Max	Std. Error.	95% Conf. Interval		Skew.	Kurt.	α	t-statistic	β	t-statistic	α + β
EXH1	2011	0.00031	0.00041	0.00013	0.01103	0.00001	0.00029	0.00033	15.359	322.699	0.401	(20.480)	0.392	(9.680)	0.793
EXV6	2011	0.00039	0.00018	0.00022	0.00358	0.00000	0.00038	0.00039	9.692	135.396	0.102	(5.780)	1.029	(8.120)	1.131
EXH4	2011	0.00018	0.00030	0.00007	0.00855	0.00001	0.00017	0.00020	16.408	371.154	0.387	(16.540)	0.474	(9.830)	0.861
EXV5	2011	0.00031	0.00023	0.00017	0.00524	0.00001	0.00030	0.00032	11.764	188.287	0.164	(10.230)	0.784	(9.690)	0.948
EXH7	2011	0.00014	0.00015	0.00005	0.00348	0.00000	0.00014	0.00015	12.828	227.273	0.233	(11.270)	0.901	(12.100)	1.134
EXV4	2011	0.00011	0.00010	0.00003	0.00241	0.00000	0.00011	0.00012	13.244	260.997	0.15	(7.100)	1.202	(10.960)	1.352
EXH2	2011	0.00020	0.00044	0.00006	0.01286	0.00001	0.00018	0.00022	19.421	471.347	0.501	(18.860)	0.378	(8.090)	0.879
EXV3	2011	0.00021	0.00015	0.00013	0.00384	0.00000	0.00020	0.00022	12.165	228.241	0.251	(8.460)	0.415	(4.410)	0.666
EXV2	2011	0.00015	0.00020	0.00008	0.00577	0.00000	0.00014	0.00016	18.635	440.789	0.304	(12.650)	0.427	(6.090)	0.731
EXH9	2011	0.00016	0.00028	0.00005	0.00908	0.00001	0.00015	0.00017	23.822	685.236	0.293	(11.470)	0.701	(11.250)	0.994
EXI5	2011	0.00016	0.00023	0.00005	0.00641	0.00001	0.00015	0.00017	17.257	391.051	0.315	(9.840)	0.643	(9.880)	0.958
VDE	2011	0.00037	0.00045	0.00010	0.00727	0.00001	0.00036	0.00039	10.095	127.891	0.324	(14.170)	0.679	(17.050)	1.003
VAW	2011	0.00017	0.00025	0.00004	0.00529	0.00001	0.00016	0.00018	11.995	187.520	0.378	(12.740)	0.526	(12.650)	0.904
VIS	2011	0.00015	0.00024	0.00004	0.00526	0.00001	0.00014	0.00016	13.043	216.099	0.319	(13.920)	0.585	(14.570)	0.904
VCR	2011	0.00015	0.00022	0.00003	0.00597	0.00000	0.00014	0.00016	14.723	316.513	0.363	(13.430)	0.604	(15.000)	0.967
VDC	2011	0.00008	0.00016	0.00002	0.00404	0.00000	0.00007	0.00009	17.664	377.303	0.321	(11.740)	0.571	(11.380)	0.892
VHT	2011	0.00011	0.00011	0.00004	0.00255	0.00000	0.00011	0.00012	11.441	193.370	0.226	(9.060)	0.718	(11.620)	0.944
VFH	2011	0.00019	0.00035	0.00003	0.00828	0.00001	0.00018	0.00021	13.176	232.594	0.343	(13.360)	0.662	(16.700)	1.005
VGT	2011	0.00019	0.00024	0.00003	0.00628	0.00001	0.00018	0.00020	13.421	275.637	0.257	(10.270)	0.873	(18.190)	1.13
VOX	2011	0.00014	0.00014	0.00004	0.00375	0.00000	0.00013	0.00014	15.095	336.949	0.234	(10.100)	0.731	(11.710)	0.965
VPU	2011	0.00013	0.00024	0.00004	0.00466	0.00001	0.00012	0.00014	13.269	205.360	0.31	(10.780)	0.527	(11.620)	0.837
VNQ	2011	0.00014	0.00024	0.00003	0.00500	0.00001	0.00013	0.00016	12.916	212.444	0.303	(13.390)	0.658	(14.600)	0.961
BTC	2011	0.00223	0.00102	0.00158	0.02487	0.00002	0.00219	0.00228	11.392	193.823	0.081	(5.780)	1.269	(8.700)	1.35

Note: This table depicts the summary statistics of the conditional variances used in the regression models excluding structural breaks. Alpha indicates the ARCH coefficient and beta the GARCH coefficient. Structural breaks are determined by the 'estat sbsingle' command from STATA. Dummies for each structural breaks are used in the univariate GARCH (1,1) model to estimate conditional volatilities more accurately.

Figure 14 and 15 from the appendix shows the pairwise correlation table of the dependent, independent and control variables respectively during and before the Covid-19 pandemic. Firstly, it is remarkable that the correlation between Bitcoin and other assets is higher during the Covid-19 pandemic, which is consistent with results from earlier research. However, the correlation between the sector ETFs did not increase during the Covid-19 pandemic. Note that this is inconsistent with earlier research, because during periods of financial distress the correlation should increase between all kinds of financial assets, but this remark lays not in the interest of this paper.

Furthermore, the correlation of the defensive sectors and Bitcoin is not necessarily lower than the of cyclical sectors and Bitcoin during the Covid-19 pandemic, which is not expected because cyclical sectors are more sensitive to the state of the economy in comparison to defensive sectors. However, it is still in the interest of this paper to determine the effect of Bitcoin on the sector ETFs.

Finally, the indices are correlated to the sector ETFs and to each other. This might cause collinearity problems, since it wrongly increases the standard errors of these coefficients. However, it is not in the interest to interpret the effect of the control variables on the sector ETFs and the correlation between the control variables and Bitcoin is not too high.

4.1 Additional remarks of the STATA process

Structural breaks are incorporated in the GARCH (1,1) model when calculating conditional variances. It is chosen not to include structural breaks in the conditional variances of the control variables, since the control variables are only added to increase the explanatory power of the model and to deal with the omitted variable bias. Moreover, it is not the focus of the study to determine the structural breaks of the control variables.

Furthermore, the ‘estat sbsingle’ command is performed to estimate break dates, which is done after performing a regression model. Unfortunately, the downside of this command was that it can only be used after including non-trading days. The new data set with no gaps was formed by adding linearly interpolated values to the synchronized data set. This adaptation only influences the estimation of the break dates, which might differ to a small extend when estimating the break dates in another way. However, the small variation of the estimation does not affect the interpretation and reliability of the studied coefficients, wherefore it is assumed that the returns were moving linearly on non-trading days.

Moreover, it is chosen to run a regression including a dummy for the period during the Covid-19 pandemic and the interaction term rather than running two separate regressions before and during the Covid-19 pandemic. This is done to increase the number of observations. In chapter 4 the results are showed and compared to earlier research and robustness tests are added to increase the reliability, the internal validity and the external validity of the model.

5. Empirical Results

In this chapter the empirical results are demonstrated and compared to the literature and outstanding theories. Firstly, the multiple regressions are showed and compared to each other to finally answer the research question and hypothesises. Thereafter, some robustness checks are demonstrated to strengthen the reliability of the regression models.

5.1 Results

Figure 16 and 17 below show the regressions including structural breaks and figure 18 and 19 from the appendix show the regressions excluding structural breaks. Both regressions are showed to illustrate whether there are differences between the coefficients from the multiple regression models after including and excluding structural breaks in the estimation of the conditional variances.

Firstly, it is remarkable that the coefficients and significancy levels of the independent variables are almost the same for both the regressions including and excluding structural breaks. Lamoureux & Lastrapes (1990) concluded that the standard GARCH models overestimate the underlying volatility persistence and neglect a distinct error. Therefore, in this paper it is assumed that the estimated conditional variances including structural breaks are more reliable. The results indicate that there are no large differences, although when interpreting the results the main focus is on figure 16 and 17.

The effects of the conditional variance of Bitcoin before the Covid-19 pandemic on the sector ETFs of Europe and the United States are insignificant for all cases, except the health care sector. Namely, for these multiple regressions the coefficient β_1 is insignificant at the significance levels of 0.1%, 1% and 5% and for the health care sector significant at the significance level of 5%. Therefore, there is no evidence that all sector ETFs are affected close to zero by the Bitcoin volatility before the Covid-19 pandemic.

Ghorbel & Jeribi (2021) studied the effect of the conditional volatility of cryptocurrencies on the conditional volatility of the S&P500 and the NASDAQ from the first of January 2016 until the first of April 2020. The underlying companies from the US sector ETFs are comparable to the underlying companies from the American indices, wherefore it was expected that the effect of the conditional volatility of Bitcoin on some of the ETFs of the United States were significant. Therefore, the results of this research before the Covid-19 pandemic are not consistent with the result of Ghorbel & Jeribi (2021), which is explained by the fact that the ETFs include not completely the same underlying assets as the indices and the sample period from this research before the Covid-19 pandemic is from 17 July 2014.

Moreover, the interaction term represents the effect of the conditional variance of Bitcoin during the Covid-19 pandemic on the sector ETFs and is highly significant for all regressions. Namely, for all 22 regressions the coefficient β_3 is highly significant at the significance level of 0.1%. All signs of the coefficients are positive, which indicates that the conditional variance of Bitcoin positively affects the conditional variance of the ETFs. Thus,

Figure 16: Regressions Conditional Volatilities EU ETFs and Bitcoin (Including Structural Breaks)

	(1) EU Energy	(2) EU Materials	(3) EU Industrials	(4) EU Cons Disc	(5) EU Cons Stap	(6) EU Health Care	(7) EU Financials	(8) EU Info Tech	(9) EU Comm Serv	(10) EU Utilities	(11) EU Real Estate
β1 (BTC)	-0.0027	-0.0050	0.0019	-0.0055	-0.0025	-0.0043*	0.0149	-0.0024	0.0036	0.0008	0.0041
	(0.789)	(0.260)	(0.775)	(0.313)	(0.461)	(0.027)	(0.145)	(0.501)	(0.445)	(0.873)	(0.395)
β2 (Dummy)	-0.0005***	-0.0003***	-0.0004***	-0.0003***	-0.0002***	-0.0002***	-0.0006***	-0.0001***	-0.0003***	-0.0006***	-0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β3 (Interaction)	0.2815***	0.1306***	0.2291***	0.1778***	0.1265***	0.0919***	0.3019***	0.0956***	0.1420***	0.3025***	0.1951***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β4 (VIX)	0.0035	0.0010	0.0081***	0.0023	0.0025**	0.0002	0.0165***	0.0037***	0.0084***	0.0064***	0.0065***
	(0.162)	(0.380)	(0.000)	(0.089)	(0.003)	(0.694)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β5 (VSTOXX)	0.0207***	0.0065***	0.0130***	0.0109***	0.0094***	0.0066***	0.0190***	0.0101***	0.0048**	0.0072***	0.0071***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)
β6 (GVZ)	0.0227***	0.0114***	0.0170***	0.0113***	0.0091***	0.0097***	0.0191***	0.0064**	0.0084**	0.0174***	0.0184***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
β7 (OVX)	0.0093***	0.0030***	0.0039**	0.0035**	0.0005	0.0002	0.0025	0.0018**	0.0014	0.0005	0.0008
	(0.000)	(0.001)	(0.004)	(0.001)	(0.446)	(0.621)	(0.222)	(0.010)	(0.148)	(0.578)	(0.430)
β0 (Constant)	0.0000	0.0003***	0.0000	0.0002***	0.0000**	0.0000***	-0.0001***	0.0001***	0.0000	0.0000	0.0000
	(0.284)	(0.000)	(0.061)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.088)	(0.696)	(0.685)
N	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011
Adj. R-sq	0.312	0.291	0.412	0.362	0.436	0.522	0.365	0.336	0.352	0.661	0.483

Note: this table shows following equation 3 multiple regressions of the dummy during the Covid-19 pandemic, the interaction between the Bitcoin and the dummy, the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs of Europe. The conditional variances are calculated by including structural breaks. The significance level of the coefficients is denoted in p-values and divided in the following significance intervals: * = p<0.05, ** = p<0.01 and *** = p<0.001.

Figure 17: Regressions Conditional Volatilities US ETFs and Bitcoin (Including Structural Breaks)

	(1) US Energy	(2) US Materials	(3) US Industrials	(4) US Cons Disc	(5) US Cons Stap	(6) US Health Care	(7) US Financials	(8) US Info Tech	(9) US Comm Serv	(10) US Utilities	(11) US Real Estate
β1 (BTC)	-0.0118	-0.0090	-0.0088	-0.0035	-0.0044	-0.0052*	-0.0115	-0.0063	-0.0040	-0.0079	-0.0088
	(0.283)	(0.117)	(0.093)	(0.415)	(0.157)	(0.031)	(0.115)	(0.191)	(0.124)	(0.181)	(0.097)
β2 (Dummy)	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0002***	-0.0005***	-0.0004***	-0.0003***	-0.0003***	-0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β3 (Interaction)	0.2423***	0.1699***	0.1859***	0.1933***	0.1663***	0.0890***	0.2755***	0.2010***	0.1343***	0.1611***	0.1956***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β4 (VIX)	0.0067*	0.0124***	0.0097***	0.0100***	0.0026***	0.0061***	0.0106***	0.0103***	0.0059***	-0.0006	0.0031*
	(0.013)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.679)	(0.018)
β5 (VSTOXX)	0.0122**	0.0100***	0.0081***	0.0094***	0.0039***	0.0038***	0.0118***	0.0102***	0.0030**	0.0077***	0.0073***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
β6 (GVZ)	0.0489***	0.0262***	0.0250***	0.0218***	0.0187***	0.0134***	0.0448***	0.0234***	0.0140***	0.0263***	0.0265***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β7 (OVX)	0.0130***	0.0037**	0.0041***	0.0031***	0.0015*	0.0008	0.0051***	0.0033***	0.0023***	0.0032**	0.0031**
	(0.000)	(0.001)	(0.000)	(0.000)	(0.015)	(0.102)	(0.000)	(0.001)	(0.000)	(0.007)	(0.003)
β0 (Constant)	0.0000	-0.0001***	-0.0000**	-0.0001***	0.0000	0.0000*	-0.0001***	0.0000	0.0000***	0.0000	0.0000
	(0.266)	(0.001)	(0.004)	(0.000)	(0.064)	(0.044)	(0.000)	(0.082)	(0.001)	(0.897)	(0.705)
N	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011
Adj. R-sq	0.287	0.394	0.439	0.556	0.585	0.467	0.473	0.526	0.599	0.287	0.421

Note: this table shows following equation 3 multiple regressions of the dummy during the Covid-19 pandemic, the interaction between the Bitcoin and the dummy, the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs of the United States. The conditional variances are calculated by including structural breaks. The significance level of the coefficients is denoted in p-values and divided in the following significance intervals: * = p<0.05, ** = p<0.01 and *** = p<0.001.

the higher the conditional volatility of Bitcoin the higher the conditional volatility of all sector ETFs. This is consistent with earlier literature, since Iyer (2022) also found significant increased positive volatility spillovers of Bitcoin on two American indices during the Covid-19 pandemic and Ha (2022) found that since the Covid-19 pandemic the cryptocurrencies (Bitcoin, BNB and Ethereum) became the net transmitters of shocks for the EURONEXT and S&P500 indices.

Furthermore, the adjusted R-squared of the models are in general not as high as the from Ghorbel & Jeribi (2021) and show large differences in explanation power of the regressions among different sectors. The lower adjusted R-squared values are explained by the fact that Ghorbel & Jeribi (2021) studied a different sample period and different dependent and independent variables. The extended sample period of this paper before and during the Covid-19 pandemic absorbs namely multiple Covid-19 waves, which includes more uncertainty and makes it harder to predict a model correctly. Thus, higher variances lead to a decreasing prediction accuracy and results in a lower explanation power. The large differences among the sector ETFs are explained by the fact that the independent variables explain the conditional variance of the sector ETFs differently in terms of significance levels, which directly affects the level of the adjusted R-squared. It is also worth to mention that the control variance shows that most of the sectors of both the United States and Europe are in general affected by the conditional variance of the VSTOXX, VIX, GVZ and OVX indices. This is consistent with Bensaïda et al. (2022), since they also found that the implied volatilities of gold, oil and S&P 500 influenced the US equity sector returns.

The results support hypothesis 1 to some extend, since it is concluded that the effect of the conditional variance of Bitcoin on the sector ETFs increased significantly and positive during the Covid-19 pandemic, however before the Covid-19 pandemic results are not interpretable through insignificant β_1 coefficients, so it cannot be said whether the conditional variance of Bitcoin affects the sector ETFs close to zero and significant before the Covid-19 pandemic.

Nowadays, the market capitalization of Bitcoin is almost comparable to the market capitalization of Tesla, which illustrates the amount of interest and in combination with the Covid-19 pandemic and the globalization why the underlying volatility has an impact on the volatility on the stock market. Bitcoin was already found in 2010, however it took really long before there was a worldwide interest in this cryptocurrency. A too low interest explains why Bitcoin does not affects the stock market before the Covid-19 pandemic, however Ghorbel & Jeribi (2021) had found a relationship from the first of January 2016 until the first of April 2020.

Therefore, as extra test data before the first of January 2016 is dropped and the effect of the conditional Bitcoin volatility on the conditional volatility of sector ETFs is regressed before the 12th of March 2020. These results are showed in figure 20 and 21. It is remarkable that effect of the conditional variance of Bitcoin on the conditional variance of the sector ETFs before the Covid-19 pandemic has become significant in 6 regressions for Europe and in 10 regressions for the United States at the significance levels of 0.001, 0.01 and 0.05. Before the Covid-19 pandemic the sector ETFs of the United States are in general really small negatively affected by the conditional variance of bitcoin and the sector ETFs of Europe are really small negatively and positively affected by the conditional variance of bitcoin. Therefore, after running a separate regression before the Covid-19 pandemic a significant relationship close to zero is found in most cases and it is demonstrated that results are in most cases in line with the first hypothesis.

The significant effects from figure 20 and 21 also indicate that before the Covid-19 pandemic there might be diversification benefits by adding Bitcoin to the materials, health care, industrials, financials, communication services and real estate sector portfolios of Europe and to the all of the sector portfolios of the United States except the communication services sector. However, in order to conclude whether there were indeed diversification benefits the correlation between bitcoin and the sectors and the risk-return ratio has to be studied, which lays not in the interest of this paper.

Hypothesis 2 is tested by using equation 4 and results are shown in figure 22 below. It is remarkable that the number of observations increased enormously in comparison to the earlier regressions, but this is the case because the sector ETFs from Europe and the United States are pooled together in one dependent variable in order to define a dummy for cyclical sectors. For defensive sectors the dummy and interaction variables contain a value of zero and for cyclical sectors the dummy contains a value of 1 and is multiplied by the Bitcoin variable to define the interaction variable. It is remarkable that both the β_1 and β_3 coefficients are positive and significant in Europe and the United States. Thus, overall if the conditional variance of Bitcoin increases with 1 the conditional variance of defensive sectors

Figure 20: Regressions Conditional Volatilities EU ETFs and Bitcoin Before the Covid-19 Pandemic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	EU Energy	EU Materials	EU Industrials	EU Cons Disc	EU Cons Stap	EU Health Care	EU Financials	EU Info Tech	EU Comm Serv	EU Utilities	EU Real Estate
β_1 (BTC)	-0.0037	-0.0190***	0.0140**	-0.0012	0.0002	-0.0052**	0.0370***	0.0007	0.0140*	0.0082	0.0164**
	(0.520)	(0.000)	(0.008)	(0.734)	(0.939)	(0.001)	(0.001)	(0.787)	(0.033)	(0.085)	(0.002)
β_4 (VIX)	0.0132***	0.0035**	0.0222***	0.0102***	0.0076***	0.0018***	0.0407***	0.0091***	0.0177***	0.0147***	0.0188***
	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_5 (VSTOXX)	0.0049**	0.0026	0.0005	0.0002	0.0040***	0.0048***	-0.0017	0.0033***	-0.0019	0.0004	-0.0014
	(0.004)	(0.063)	(0.771)	(0.860)	(0.000)	(0.000)	(0.596)	(0.000)	(0.327)	(0.760)	(0.365)
β_6 (GVZ)	0.0081**	0.0095***	0.0003	-0.003	0.0023	0.0050***	0.0028	-0.0019	0.0005	0.0119***	0.0056*
	(0.006)	(0.000)	(0.905)	(0.095)	(0.0840)	(0.000)	(0.611)	(0.147)	(0.880)	(0.000)	(0.042)
β_7 (OVX)	0.0126***	-0.0006	0.0048*	0.0032*	0.0020	0.0008	0.0075	0.0027*	0.0033	0.0046*	0.0041
	(0.000)	(0.772)	(0.044)	(0.039)	(0.080)	(0.276)	(0.123)	(0.020)	(0.265)	(0.033)	(0.091)
β_0 (Constant)	0.0001***	0.0004***	-0.0000**	0.0002***	0.0000***	0.0001***	-0.0002***	0.0001***	0.0000	0.0000	-0.0000**
	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.714)	(0.062)	(0.009)
N	1094	1094	1094	1094	1094	1094	1094	1094	1094	1094	1094
Adj. R-sq	0.148	0.048	0.243	0.126	0.203	0.186	0.207	0.227	0.107	0.189	0.188

Note: this table shows multiple regressions of the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs of Europe. The sample period is from the first of January 2016 until the 11th of March 2020 and the conditional variances are estimated including structural breaks. The significance level of the coefficients is denoted in p-values and divided in the following confidence intervals: * = p<0.05, ** = p<0.01 and *** = p<0.001.

Figure 21: Regressions Conditional Volatilities US ETFs and Bitcoin Before the Covid-19 Pandemic

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	US Energy	US Materials	US Industrials	US Cons Disc	US Cons Stap	US Health Care	US Financials	US Info Tech	US Comm Serv	US Utilities	US Real Estate
β_1 (BTC)	-0.0190***	-0.0095**	-0.0086**	-0.0080*	-0.0048*	-0.0078***	-0.0131***	-0.0089*	-0.0006	-0.0086***	-0.0084**
	(0.001)	(0.007)	(0.009)	(0.038)	(0.013)	(0.000)	(0.000)	(0.026)	(0.823)	(0.000)	(0.004)
β_4 (VIX)	0.0132***	0.0144***	0.0122***	0.0125***	0.0043***	0.0067***	0.0152***	0.0149***	0.0074***	0.0032***	0.0051***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_5 (VSTOXX)	0.0074***	0.0071***	0.0041***	0.0074***	0.0022***	0.0034***	0.0068***	0.0085***	0.0021**	0.0033***	0.0048***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)
β_6 (GVZ)	0.0124***	0.0146***	0.0187***	0.0152***	0.0104***	0.0097***	0.0295***	0.0156***	0.0107***	0.0112***	0.0106***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_7 (OVX)	0.0267***	0.0079***	0.0083***	0.0102***	0.0043***	0.0031**	0.0107***	0.0103***	0.0045***	0.0044***	0.0066***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_0 (Constant)	0.0001***	-0.0000***	-0.0000***	-0.0001***	0.0000	0.0000**	-0.0001***	-0.0000***	0.0000*	0.0000***	0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.219)	(0.009)	(0.000)	(0.001)	(0.042)	(0.000)	(0.017)
N	1094	1094	1094	1094	1094	1094	1094	1094	1094	1094	1094
Adj. R-sq	0.252	0.385	0.369	0.320	0.252	0.303	0.471	0.363	0.236	0.188	0.197

Note: this table shows multiple regressions of the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs of the United States. The sample period is from the first of January 2016 until the 11th of March 2020 and the conditional variances are estimated including structural breaks. The significance level of the coefficients is denoted in p-values and divided in the following confidence intervals: * = p<0.05, ** = p<0.01 and *** = p<0.001.

Figure 22: Regressions Bitcoin on Defensive and Cyclical Sector ETFs

	β_1 (BTC)	β_2 (Dummy)	β_3 (Interaction)	β_4 (VIX)	β_5 (VSTOXX)	β_6 (GVZ)	β_7 (OVX)	β_0 (Constant)	N	Adj. R-sq
(1) United States	0.1063***	-0.0000*	0.0740***	0.0004	0.0280***	0.0590***	0.0015	-0.0004***	5896	0.410
	(0.000)	(0.049)	(0.000)	(0.776)	(0.000)	(0.000)	(0.061)	(0.000)		
(2) Europe	0.1603***	0.0001**	0.0314***	-0.0107***	0.0559***	0.0349***	-0.0021**	-0.0005***	5896	0.388
	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.000)		

Note: this table shows following equation 4 the multiple regressions of the dummy for cyclical sectors, the interaction between the Bitcoin and the dummy, the conditional variances of Bitcoin and the control variables on the conditional variances of the sector ETFs of the United States and Europe. The sample period is from the 13th of March 2020 until the 31th of March 2022 and the conditional variances are estimated including structural breaks. The significance level of the coefficients is denoted in p-values and divided in the following confidence intervals: * = p<0.05, ** = p<0.01 and *** = p<0.001.

in both Europe and the United States increases with 0.1063 during the Covid-19 pandemic.

When interpreting the β_3 coefficient it can be said that if the conditional variance of Bitcoin increases with 1 the conditional variance of the cyclical sector ETFs in the United States increases with 0.0740 more in comparison to the defensive sector ETFs in the United States. In Europe it can be said that if the conditional variance of Bitcoin increases with 1 the conditional variance of the cyclical sector ETFs increases with 0.0314 more in comparison to the defensive sector ETFs. Therefore, for both Europe and the United States the cyclical sectors are more positively affected by the conditional variance of Bitcoin in comparison to the defensive sectors. Results are thus in line with hypothesis 2.

However, focusing on the β_3 coefficients of figure 16 and 17 show that it seems to be the case that during the Covid-19 pandemic in Europe Bitcoin influences the most the conditional variance of the energy, utilities and financials sectors and the least the conditional variance of the consumer staples, health care and information technology sectors. In the United States it seems to be the case that the energy and financial sectors are affected the most and the health care sector the least by the conditional variance of Bitcoin. This may indicate that some defensive sectors are more affected by the Bitcoin volatility than some cyclical sectors and vice versa. As explained in section 3 the size of the coefficients cannot be compared between different multiple regressions, since standard errors also play a role. Therefore, this remark is only used as indicative rather than conclusive evidence.

5.2 Robustness Checks

By screening the plots of the returns and residuals of the regressions over time it is remarkable that autocorrelation[1] and stationarity[2] problems might influence the results. The returns are namely not perfectly circled around a certain mean and the variances change to a certain extend over time.

5.2.1 Autocorrelation

Groups of clustered observations may lead to autocorrelation in time series data and influence the t-value of the coefficients (Sokal et al., 1978). The t-values tell how well the estimation performs and are calculated in the following way:

$$t = \frac{\beta}{SE} \tag{6}$$

where, β means the coefficient of a variable and SE the standard error. A higher beta coefficient or lower standard error, increases the t-value and thus increases the likelihood that STATA finds an effect between the independent and dependent variable. A smaller beta coefficient or higher standard error, decreases the likelihood that STATA founds a significant effect, so the size of the coefficient and the standard error influence the significance level of the coefficients. The standard error is calculated in the following way:

$$SE = \frac{\sigma}{\sqrt{N}} \tag{7}$$

where, σ means the standard deviation and N the number of observations. The standard error negatively affects the t-value, thus the higher the standard deviation, the lower the t-value and the number of observations positively affects the t-value, thus the higher the number of observations, the higher the t-value. Not taking into account clustered groups affect the results, because similarities are the highest within clusters and the least between clusters (Özkoç, 2020). Neglecting this problem results in a too high number of observations and an underestimate of the standard error, which wrongly increases the t-value of the beta.

[1] Autocorrelation means that there is correlation between the error terms of the variables within a regression model. This increases the unpredictability of the data and decreases the accuracy of the estimation and model.
[2] Stationarity problems occur when the data set has means, variances and covariances that change over time. There are three types of non-stationarity: trend, cycles and random walks stationarity. The problem is explained by the fact that non-stationary data is in general unpredictable and cannot be modelled and forecasted correctly.

During periods of financial distress there is high volatility and clustering (Stádník, 2014). In this research multiple structural breaks and the Covid-19 pandemic are incorporated to account for structural breaks when calculating the conditional variances and accounting for the effect before and during the Covid-19 pandemic when performing the multiple regressions. The purpose of this study is to examine the effect of Bitcoin on different sector ETFs before and during the Covid-19 pandemic, so the multiple structural breaks are not incorporated in the multiple regressions. Using the Durbin-Watson statistic after running regressions shows whether the performed regressions are significantly influenced by autocorrelation and whether it is needed to correct for autocorrelation.

This dataset includes 7 regressors without the intercept and 2,011 observations, which results in the following critical values $d_L = 1.889$ and $d_U = 1.903$ at an alpha of 1 percent. Figure 23 shows that all regressions include positive autocorrelation, so it is needed to correct for autocorrelation.

The Prais Winston method is used to correct for autocorrelation, which is a generalized least square estimator (Prais & Winston, 1954). Figure 24, 25, 26 and 27 below show the results after correcting for autocorrelation. Firstly, it is remarkable that in most the cases the significance levels and signs of the coefficients β_1 and β_3 in figure 24 and 25 have not changed compared to figure 16 and 17. However, the significance levels and signs of the coefficients of figure 26 and 27 have changed in comparison to figure 20 and 21. Before the Covid-19 pandemic it was concluded that the effect of the conditional variance of Bitcoin on the sector ETFs was in most cases close to zero and significant, but after correcting for autocorrelation only the industrials, financials, communication services and real estate sectors in Europe and the energy, health care, utilities and real estate sectors in the United States were close to zero and significant by the conditional variance of Bitcoin.

Therefore, after correcting for autocorrelation it is concluded that during the Covid-19 pandemic all sectors are influenced positively by the conditional variance of Bitcoin and before the Covid-19 pandemic there is evidence that the industrials, financials, communication services and real estate sectors in Europe and the energy, health care, utilities and real estate sectors in the United States were affected close to zero and positive, by the conditional variance of Bitcoin, but there is no evidence for the remainder sector ETFs. Thus, there is some support for hypothesis 1, however not completely.

Figure 24: Prais-Winston Regressions Conditional Volatilities EU ETFs and Bitcoin (Including Structural Breaks)

	(1) EU Energy	(2) EU Materials	(3) EU Industrials	(4) EU Cons Disc	(5) EU Cons Stap	(6) EU Health Care	(7) EU Financials	(8) EU Info Tech	(9) EU Comm Serv	(10) EU Utilities	(11) EU Real Estate
β₁ (BTC)	0.0034	0.0010	0.0059	-0.0021	0.0007	-0.0014	0.0195	-0.0011	0.0059	0.0053	0.0087
	(0.783)	(0.865)	(0.498)	(0.782)	(0.879)	(0.591)	(0.113)	(0.807)	(0.294)	(0.415)	(0.198)
β₂ (Dummy)	-0.0005***	0.0020***	-0.0004***	-0.0003***	0.0000	-0.0002***	-0.0005***	-0.0001***	-0.0003***	-0.0006***	-0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.535)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β₃ (Interaction)	0.2749***	0.0390**	0.2253***	0.1968***	0.1241***	0.1016***	0.2905***	0.0941***	0.1354***	0.2994***	0.1956***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β₄ (VIX)	0.0051	0.0020**	0.0107***	0.0047***	0.0025***	0.0002	0.0197***	0.0042***	0.0096***	0.0077***	0.0095***
	(0.061)	(0.007)	(0.000)	(0.000)	(0.000)	(0.522)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β₅ (VSTOXX)	0.0278***	0.0073***	0.0176***	0.0153***	0.0096***	0.0035***	0.0227***	0.0128***	0.0063**	0.0098***	0.0091***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
β₆ (GVZ)	-0.0012	-0.0014	-0.0011	-0.0043	0.0001	0.0012*	0.0043	0.0005	0.0022	0.0018	0.0014
	(0.851)	(0.417)	(0.786)	(0.105)	(0.9490)	(0.036)	(0.499)	(0.821)	(0.438)	(0.542)	(0.639)
β₇ (OVX)	0.0072***	0.0005	0.0016	0.0006	0.0000	-0.0002	0.0004	0.0009	0.0002	-0.0007	-0.0004
	(0.000)	(0.345)	(0.235)	(0.485)	(0.974)	(0.319)	(0.849)	(0.230)	(0.803)	(0.448)	(0.636)
β₀ (Constant)	0.0000	0.0357	0.0000	0.0002***	0.0000	0.0001***	-0.0002***	0.0001***	0.0000	0.0000	0.0000
	(0.295)	(0.225)	(0.184)	(0.000)	(0.540)	(0.000)	(0.000)	(0.000)	(0.193)	(0.409)	(0.968)
N	2011	1608	2011	2011	2011	1608	2011	2011	2011	2011	2011
Adj. R-sq	0.254	0.413	0.334	0.405	0.458	0.666	0.301	0.295	0.289	0.567	0.391

Note: this table shows following equation 3 multiple regressions of the dummy during the Covid-19 pandemic, the interaction between the Bitcoin and the dummy and the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs of Europe. The Prais-Winston method is used to correct for autocorrelation. The significance level of the coefficients is denoted in p-values and divided in the following confidence intervals: * = $p<0.05$, ** = $p<0.01$ and *** = $p<0.001$.

Figure 25: Prais-Winston Regressions Conditional Volatilities US ETFs and Bitcoin (Including Structural Breaks)

	(1) US Energy	(2) US Materials	(3) US Industrials	(4) US Cons Disc	(5) US Cons Stap	(6) US Health Care	(7) US Financials	(8) US Info Tech	(9) US Comm Serv	(10) US Utilities	(11) US Real Estate
β₁ (BTC)	-0.0104	-0.0071	-0.0070	-0.0032	-0.0022	-0.0047	-0.0093	-0.0028	-0.0069	-0.0055	-0.0092
	(0.486)	(0.352)	(0.322)	(0.589)	(0.622)	(0.152)	(0.349)	(0.698)	(0.063)	(0.500)	(0.190)
β₂ (Dummy)	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0001***	-0.0004***	-0.0007***	-0.0002***	-0.0003***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β₃ (Interaction)	0.2265***	0.1459***	0.1504***	0.1651***	0.1385***	0.0752***	0.2260***	0.1640***	0.1102***	0.1475***	0.1598***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β₄ (VIX)	0.0112***	0.0156***	0.0128***	0.0133***	0.0045***	0.0072***	0.0137***	0.0121***	0.0077***	0.0026	0.0066***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.050)	(0.000)
β₅ (VSTOXX)	0.0117**	0.0090***	0.0052**	0.0074***	0.0033**	0.0014	0.0060*	0.0022	0.0005	0.0095***	0.0040*
	(0.005)	(0.000)	(0.007)	(0.000)	(0.003)	(0.074)	(0.020)	(0.151)	(0.585)	(0.000)	(0.029)
β₆ (GVZ)	0.01	0.0017	-0.0008	0.0016	-0.0022	0.0012	0.0122***	0.0056**	0.0011	-0.0013	-0.0009
	(0.072)	(0.596)	(0.750)	(0.495)	(0.1330)	(0.255)	(0.000)	(0.005)	(0.321)	(0.665)	(0.715)
β₇ (OVX)	0.0033	0.001	0.0012	-0.0006	-0.0002	-0.0008*	0.0015	-0.0008	-0.0002	-0.0002	0.0011
	(0.058)	(0.299)	(0.138)	(0.451)	(0.661)	(0.016)	(0.142)	(0.161)	(0.541)	(0.795)	(0.131)
β₀ (Constant)	0.0002**	0.0000	0.0000	0.0000	0.0000	0.0001***	0.0000	0.0003***	0.0001***	0.0001*	0.0001**
	(0.001)	(0.767)	(0.360)	(0.723)	(0.053)	(0.000)	(0.740)	(0.000)	(0.000)	(0.046)	(0.002)
N	2011	2011	2011	2011	2011	2011	2011	1608	2011	2011	2011
Adj. R-sq	0.204	0.288	0.319	0.425	0.437	0.397	0.334	0.395	0.474	0.201	0.301

Note: this table shows following equation 3 multiple regressions of the dummy during the Covid-19 pandemic, the interaction between the Bitcoin and the dummy and the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs of the United States. The Prais-Winston method is used to correct for autocorrelation. The significance level of the coefficients is denoted in p-values and divided in the following confidence intervals: * = $p<0.05$, ** = $p<0.01$ and *** = $p<0.001$.

Figure 26: Prais-Winston Regressions Conditional Volatilities EU ETFs and Bitcoin Before Covid-19 Pandemic (Including Structural Breaks)

	(1) EU Energy	(2) EU Materials	(3) EU Industrials	(4) EU Cons Disc	(5) EU Cons Stap	(6) EU Health Care	(7) EU Financials	(8) EU Info Tech	(9) EU Comm Serv	(10) EU Utilities	(11) EU Real Estate
β_1 (BTC)	0.0023	-0.0043	0.0167*	0.0005	0.0019	-0.0003	0.0444**	0.0016	0.0183*	0.0118	0.0191*
	(0.753)	(0.524)	(0.020)	(0.919)	(0.631)	(0.871)	(0.002)	(0.621)	(0.030)	(0.087)	(0.012)
β_4 (VIX)	0.0133***	0.0038***	0.0236***	0.0104***	0.0063***	0.0005*	0.0452***	0.0093***	0.0196***	0.0146***	0.0211***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_5 (VSTOXX)	0.0075***	0.0040**	0.0015	0.0009	0.0030**	0.0020***	-0.0022	0.0045***	-0.0027	-0.0001	-0.0027
	(0.001)	(0.004)	(0.478)	(0.510)	(0.002)	(0.000)	(0.612)	(0.000)	(0.288)	(0.953)	(0.216)
β_6 (GVZ)	0.0049	-0.0017	-0.0003	-0.001	0.0002	0.0004	0.0019	-0.0015	0.0006	0.0081**	0.0035
	(0.137)	(0.345)	(0.931)	(0.591)	(0.8780)	(0.394)	(0.769)	(0.309)	(0.865)	(0.003)	(0.268)
β_7 (OVX)	0.0122***	-0.0007	0.0025	0.0005	-0.0002	0.0000	0.0033	0.0016	0.0019	0.0022	0.0014
	(0.000)	(0.604)	(0.318)	(0.726)	(0.865)	(0.905)	(0.527)	(0.178)	(0.531)	(0.297)	(0.577)
β_0 (Constant)	0.0001**	0.0004***	-0.0001*	0.0002***	0.0001***	0.0001***	-0.0002***	0.0001***	0.0000	0.0000	0.0000
	(0.006)	(0.000)	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.486)	(0.575)	(0.083)
N	1094	874	1094	1094	1094	874	1094	1094	1094	1094	1094
Adj. R-sq	0.238	0.038	0.255	0.407	0.207	0.05	0.202	0.356	0.124	0.185	0.206

Note: this table shows multiple regressions of the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs of Europe. The Prais-Winston method is used to correct for autocorrelation. The significance level of the coefficients is denoted in p-values and divided in the following confidence intervals: * = p<0.05, ** = p<0.01 and *** = p<0.001.

Figure 27: Prais-Winston Regressions Conditional Volatilities US ETFs and Bitcoin Before Covid-19 Pandemic (Including Structural Breaks)

	(1) US Energy	(2) US Materials	(3) US Industrials	(4) US Cons Disc	(5) US Cons Stap	(6) US Health Care	(7) US Financials	(8) US Info Tech	(9) US Comm Serv	(10) US Utilities	(11) US Real Estate
β_1 (BTC)	-0.0195**	-0.0083	-0.0076	-0.0088	-0.0044	-0.0073**	-0.0102	-0.0039	-0.0062	-0.0092**	-0.0119**
	(0.008)	(0.091)	(0.119)	(0.113)	(0.126)	(0.010)	(0.065)	(0.535)	(0.089)	(0.004)	(0.006)
β_4 (VIX)	0.0123***	0.0159***	0.0140***	0.0144***	0.0042***	0.0064***	0.0152***	0.0136***	0.0076***	0.0035***	0.0057***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_5 (VSTOXX)	0.0066***	0.0058***	0.0000	0.0033*	0.0020*	0.0017*	0.0033*	0.0016	0.0001	0.0033***	0.0035**
	(0.001)	(0.000)	(0.983)	(0.022)	(0.011)	(0.016)	(0.015)	(0.224)	(0.931)	(0.000)	(0.001)
β_6 (GVZ)	0.002	0.0046*	0.0064***	0.0048*	0.0028*	0.0028**	0.0120***	0.0061***	0.0030*	0.0055***	0.0006
	(0.476)	(0.016)	(0.000)	(0.014)	(0.0120)	(0.004)	(0.000)	(0.000)	(0.011)	(0.000)	(0.657)
β_7 (OVX)	0.0200***	0.0041**	0.0014	0.0039**	0.0012	0.0004	0.0038**	0.0023	0.0016	0.0015	0.0018
	(0.000)	(0.005)	(0.267)	(0.008)	(0.180)	(0.560)	(0.005)	(0.066)	(0.066)	(0.150)	(0.102)
β_0 (Constant)	0.0002***	0.0000	0.0000	0.0000	0.0000**	0.0001***	0.0000	0.0002***	0.0001***	0.0001***	0.0001***
	(0.000)	(0.791)	(0.057)	(0.842)	(0.003)	(0.000)	(0.467)	(0.000)	(0.000)	(0.000)	(0.000)
N	1094	1094	1094	1094	1094	1094	1094	874	1094	1094	1094
Adj. R-sq	0.412	0.389	0.338	0.301	0.191	0.346	0.383	0.302	0.284	0.262	0.238

Note: this table shows multiple regressions of the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs of the United States. The Prais-Winston method is used to correct for autocorrelation. The significance level of the coefficients is denoted in p-values and divided in the following confidence intervals: * = p<0.05, ** = p<0.01 and *** = p<0.001.

Furthermore, it is concluded that positive autocorrelation plays a role, wherefore the multiple Prais Winston regressions are preferred when coming up with indicative evidence that not all defensive sectors are influenced the least and cyclical sectors the most by the conditional variance of Bitcoin. After correcting for autocorrelation figure 24 and 25 show that the conditional variance of the energy, financials and utilities sectors seem to be influenced the most by the conditional variance of Bitcoin and the health care, materials and information technology sectors the least in Europe during the Covid-19 pandemic. In the United States the energy and financials sectors seem to be influenced the most by the conditional variance of Bitcoin and the health care the least during the Covid-19 pandemic.

5.2.1 Stationarity

To test whether the data set is stationary the augmented Dickey-Fuller test is performed (Dickey & Fuller, 1979). 3 lags are included, since autocorrelation is present and affects the results of the augmented Dickey-Fuller tests. H_0 defines that there is an unit root present in the data and H_a that the data is stationary. Figure 28 from the appendix shows the outcome of the test and demonstrates that there are no stationarity problems, since the daily returns of all variables are stationary given a critical value of -2.580 at the 1% level. This is explained by the fact that the lagged coefficients are all negative and significant, which illustrates for all variables that there is a strong enough force that pulls the variables at different points in time back to their constant. Thus, it is not needed to correct for non-stationarity.

6. Summary and Conclusion

The literature shows that the market capitalization of Bitcoin tripled during the Covid-19 pandemic (IMF, 2021), globalization increases spillovers between different financial assets (Ahmad, 2019; Elfakhani et al., 2008), contagion effects exist during periods of financial distress and the Covid-19 pandemic (Kenourgios et al., 2013; Chakrabarti et al., 2021) and during the Covid-19 pandemic the interconnections between Bitcoin and the stock market increased significantly (Ghorbel & Jeribi, 2021; Guo et al., 2021; Ha, 2022; Iyer, 2022).

This research studies the effect of the Bitcoin volatility on the volatility of different sector ETFs by following the methodology of Ghorbel & Jeribi (2021). Conditional variances of 11 different sectors from Europe and the United States, Bitcoin and 4 control variables are estimated using the univariate GARCH (1,1) model from Bollerslev (1986) and structural breaks are included to control for overestimations of the underlying volatility persistence, which is done by adding different dummies for each structural break (Ewing and Malik, 2013). The effect of the Bitcoin volatility on the volatility of different sector ETFs is studied by using multiple regressions, where β_1 and β_3 have the main focus since they respectively reflect the effect of Bitcoin on the sector ETFs before and during the Covid-19 pandemic.

This paper categorized 11 different sectors in defensive and cyclical sectors. It is expected that cyclical sectors are more affected by the Bitcoin volatility then defensive sectors, since cyclical sectors are really dependent on economic cycles and are therefore significantly more volatile than defensive sectors. The first hypothesis illustrates that during the Covid-19 pandemic the conditional variance of Bitcoin affects the conditional variance of the sector ETFs, but before the Covid-19 pandemic not. The second hypothesis illustrates that during the Covid-19 pandemic the effect of conditional variance of Bitcoin is higher on cyclical ETFs than on defensive ETFs.

When restraining the sample period from 2016 until the 11th of March 2020 the results of the multiple regression models show that the effect of Bitcoin volatility on the sector ETFs is close to zero and significant for the industrials, financials, communication services and real estate sectors in Europe and the energy, health care, utilities and real estate sectors in the United States. Unfortunately, there is no evidence found for the remainder of the sector ETFs. This is not completely consistent with the results of Damianov & Elsayed (2020) and Ghorbel & Jeribi (2021) who respectively found statistically significant and small positive correlations between Bitcoin and 10 different industries and statistically significant and a small positive effect of the conditional variance of Bitcoin on the conditional variances of two American indices before the Covid-19 pandemic.

The close to zero and significant coefficients for some sectors strengthens the results of Ghorbel & Jeribi (2021) in a way that it was found that before the Covid-19 pandemic Bitcoin can be seen as diversifier in some cases. However, this study does not deal with the reversed relationship and the risk-return ratio, so it can only be signified that there might have been diversification benefits by adding Bitcoin to these specific sector portfolios.

The results of the multiple regression models also show that during the Covid-19 pandemic the effect of Bitcoin volatility on the sector ETFs is statistically significant and positive for all sector ETFs. This is consistent with earlier research, since they found that during the Covid-19 pandemic interdependencies increased significantly between Bitcoin and the stock market (Ghorbel & Jeribi, 2021; Guo et al., 2021; Ha, 2022; Iyer, 2022).

Therefore, it is concluded that these results are in line with the literature and there is found some support for hypothesis 1.

Furthermore, by using two multiple regressions including a dummy for cyclical sectors and an interaction term that multiplies the dummy by the conditional variance of Bitcoin, it is concluded that during the Covid-19 pandemic the cyclical sector ETFs are overall more influenced by the conditional variance of Bitcoin than the defensive sector ETFs and results are in line with hypothesis 2. However, there is some indicative evidence that not all defensive sectors are affected the least and cyclical sectors the most by the conditional variance of Bitcoin. The results of the Prais Winston regressions are used, since positive autocorrelation exist among all variables. In the United States it seems to be the case that the energy and financials sectors are affected the most and the health care sector the least by the conditional volatility of Bitcoin. In Europe it seems to be the case that the energy, financial, utilities sectors are affected the most and the health care, materials and information technology sectors the least by the Bitcoin volatility. This is not completely in line with hypothesis 2, since the defensive sectors consist of only the consumer staples, health care and utilities sectors. However, the size of coefficients cannot be simply compared between different multiple regressions since standard errors also play a role, therefore this remark is just used as indicative rather than conclusive evidence against hypothesis 2.

The Covid-19 pandemic is more affected by external factors rather than economic factors compared to other periods of financial distress. In general the Covid-19 pandemic was more foreseen compared to the global financial crisis, which started out of nowhere and arrived completely unexpected (Arturo et al., 2020). For this reason, it was possible for governments to take action and come up with Covid-19 policies that shrink the spreading and protect the population against the disease. The governmental policies and Covid-19 waves influenced all sectors significantly, however the communication, health care and consumer staples sectors the least and the energy, consumer discretionary and utilities sectors the most (Goosen, 2022). This explains why the categorization of defensive and cyclical sectors should be considered.

This has consequences for investors, since specific sector investment characteristics change over time, which introduces unexpected volatility risk that might influence pure sector portfolios negatively. It is recommended that risk averse investors have to hedge their portfolios more against unexpected spillovers of volatility risk of Bitcoin that exposes certain sector portfolios to unverified levels of risk. In other to hedge their portfolios option-based strategies are recommended to deal with the possible downside risk of Bitcoin (Ahmed, 2021).

The limitations of this study remain as follow. The univariate GARCH (1,1) model including structural breaks is used to estimate the conditional variances of the financial assets and multiple regression models are performed to identify the effect of the conditional variance of Bitcoin on the conditional variance of sector ETFs. Earlier research used other methodologies that might be more applicable to study interdependencies between Bitcoin and the stock market. Ghorbel & Jeribi (2021) also used multivariate GARCH models to identify spillovers among and between cryptocurrencies and stock market indices and Iyer (2022) used the Diebold-Yilmaz (2012 and 2014) interconnectedness and spillover model to study the interdependencies between Bitcoin and the stock market. However, this paper only focuses on determining the effect of Bitcoin volatility on the volatility of different sectors. The focus on this relationship rather than the reversed relationship is chosen, since the main purpose of the study is to inform pure sector investors of spillovers of unexpected increased volatility risk of Bitcoin. This has also consequences for policymakers, since this supports the argument from Guo et al. (2021) that not only equity markets but also specific sectors are not far behind the extreme volatility of Bitcoin during the Covid-19 pandemic due to increased volatility spillovers.

For further research it is recommended to study the categorization of defensive and cyclical sectors and to inform investors about the unexpected volatility risk of Bitcoin in periods of prosperity and recession. Results of this paper suggest that the influence of Bitcoin volatility on the sector ETFs has increased significantly during the Covid-19 pandemic and the categorization of sectors might have changed since the Covid-19 pandemic through spillovers of volatility risk of Bitcoin. It is interesting to look how the effect of Bitcoin volatility and the categorization develops over time after the Covid-19 pandemic when the global economy slowly recovers and stable growth periods are established in the long run. Furthermore, it is recommended to use other methodologies to study interdependencies between defensive sectors, cyclical sectors and Bitcoin. It is to be concluded how these interdependencies developed during the Covid-19 pandemic and will develop in the long run to conclude whether Bitcoin can be seen as diversifier or that the cryptocurrency has to be considered in the financial risk decision making.

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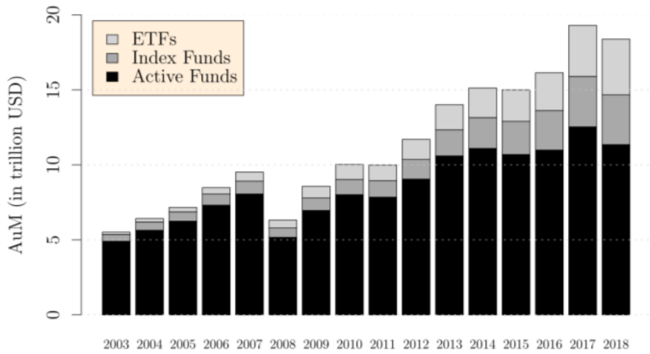
8. Appendix

Figure 4: The Assets under Management (AuM) of Funds in USD



Note: the graph is from Investment Company Institute (2019) and the AuM are measured as the total net assets at the year-end of active funds, index funds and passive ETFs from 2003 until 2018.

Figure 5: Estimated Break Dates Bitcoin

Estimated Break Dates	
#	1
Variable	BTC
SB1 (D1=1 ; Dn=0)	15-08-2014
SB2 (D2=1 ; Dn=0)	18-09-2014
SB3 (D3=1 ; Dn=0)	14-01-2015
SB4 (D4=1 ; Dn=0)	06-11-2015
SB5 (D5=1 ; Dn=0)	12-03-2020
SB6 (D6=1 ; Dn=0)	07-07-2020
SB7 (D7=1 ; Dn=0)	14-06-2021
SB8 (D8=1 ; Dn=0)	12-10-2021
SB9 (D9=1 ; Dn=0)	16-02-2022
SB10 (D10=1 ; Dn=0)	14-03-2022

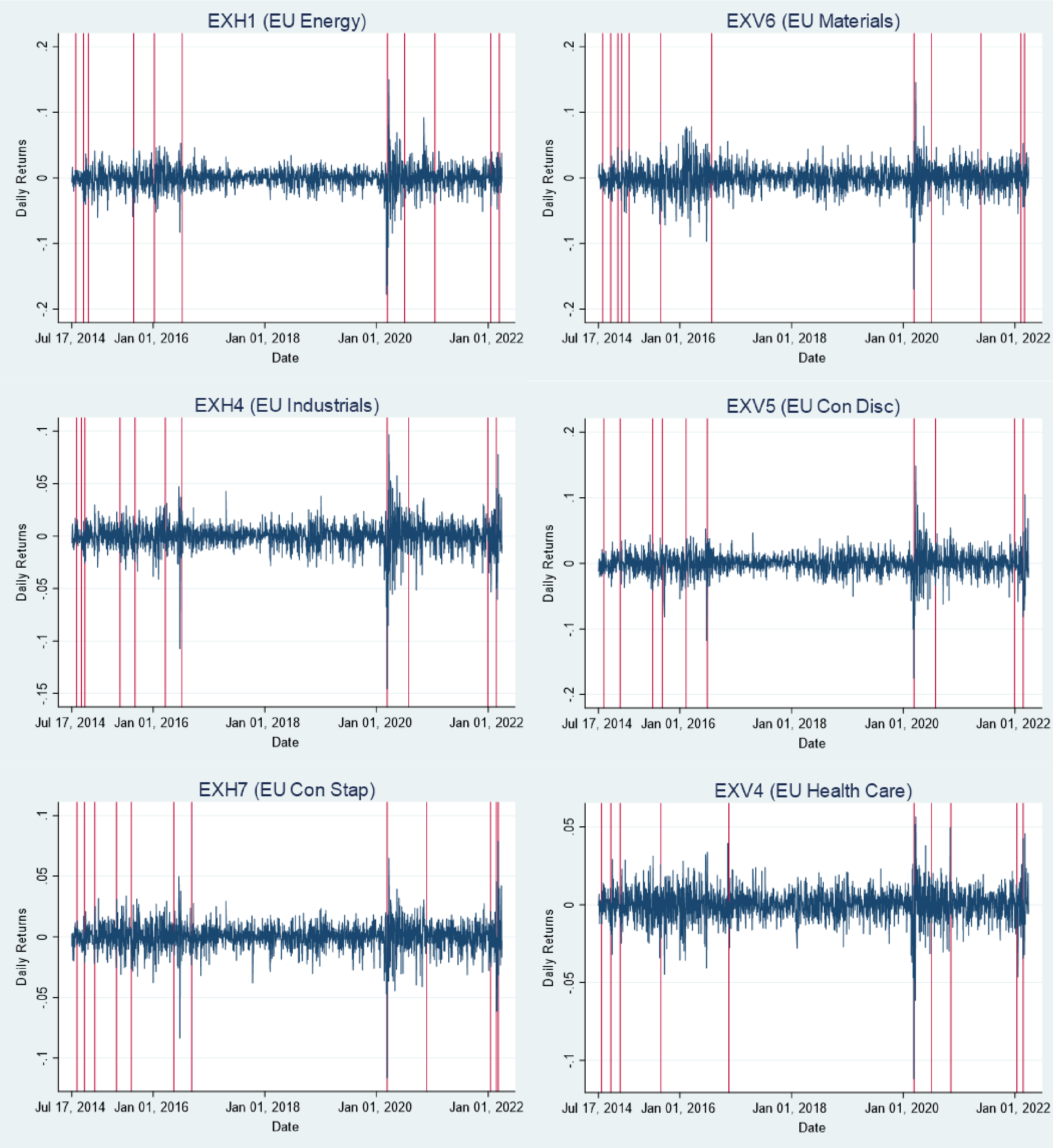
Figure 6: Estimated Break Dates EU sector ETFs

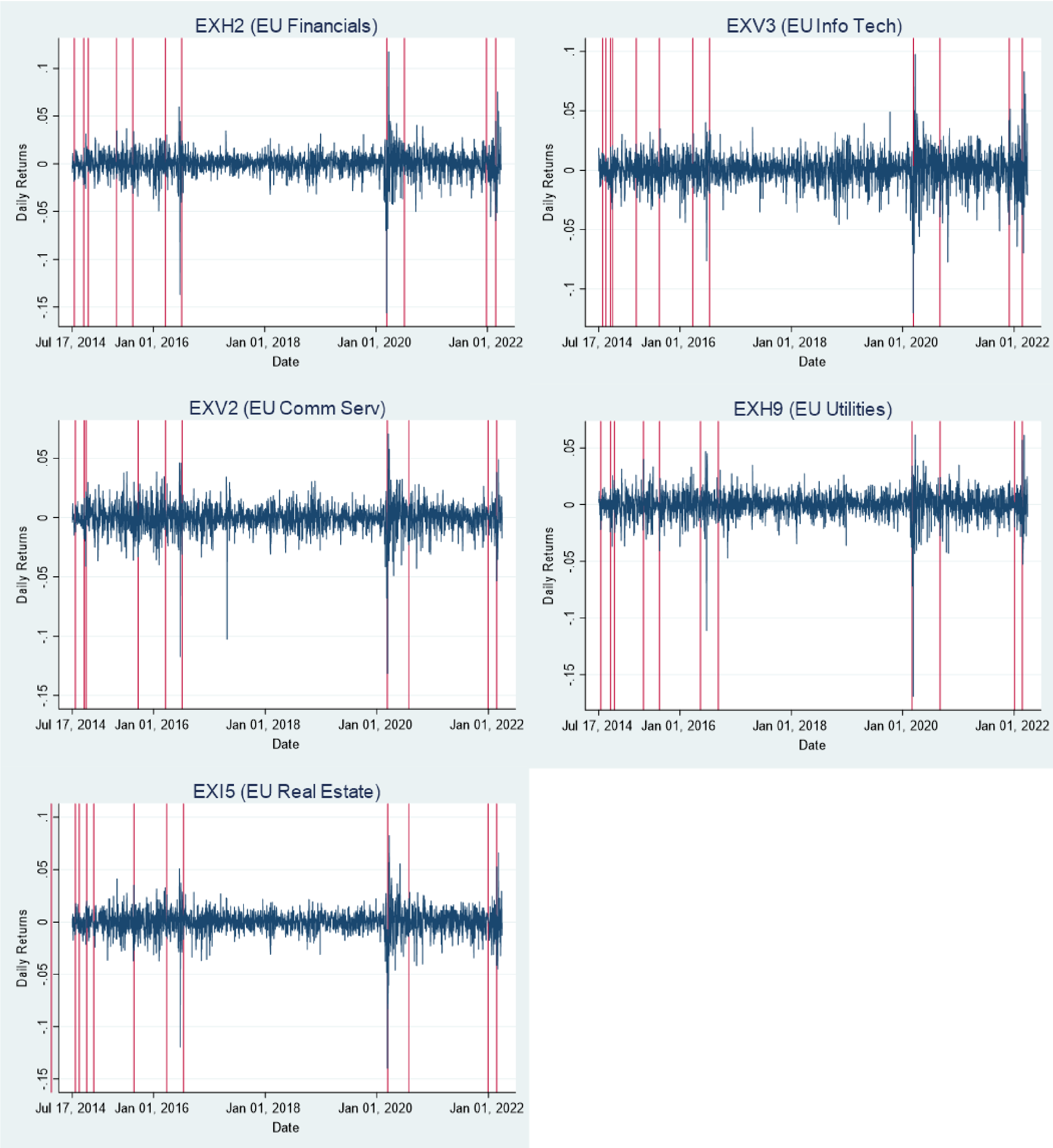
Estimated Break Dates											
#	1	2	3	4	5	6	7	8	9	10	11
Variable	EXH1	EXV6	EXH4	EXV5	EXH7	EXV4	EXH2	EXV3	EXV2	EXH9	EXI5
SB1 (D1=1 ; Dn=0)	13-08-2014	13-08-2014	18-08-2014	05-08-2014	20-08-2014	05-08-2014	01-08-2014	12-08-2014	06-08-2014	01-08-2014	06-08-2014
SB2 (D2=1 ; Dn=0)	02-10-2014	05-10-2014	19-09-2014	06-10-2014	08-10-2014	06-10-2014	01-10-2014	02-09-2014	02-10-2014	02-10-2014	02-09-2014
SB3 (D3=1 ; Dn=0)	03-11-2014	21-11-2014	10-10-2014	05-12-2014	15-12-2014	05-12-2014	31-10-2014	02-10-2014	17-10-2014	29-10-2014	20-10-2014
SB4 (D4=1 ; Dn=0)	26-08-2015	15-12-2014	29-05-2015	28-08-2015	05-05-2015	28-08-2015	04-05-2015	17-10-2014	22-09-2015	06-05-2015	05-12-2014
SB5 (D5=1 ; Dn=0)	08-01-2016	02-02-2015	04-09-2015	15-11-2016	11-08-2015	15-11-2016	19-08-2015	20-03-2015	19-03-2016	20-08-2015	02-03-2014
SB6 (D6=1 ; Dn=0)	08-07-2016	27-08-2015	20-03-2016	12-03-2020	14-05-2016	12-03-2020	20-03-2016	19-08-2015	06-07-2016	14-05-2016	25-08-2015
SB7 (D7=1 ; Dn=0)	12-03-2020	27-07-2016	06-07-2016	04-07-2020	09-09-2016	04-07-2020	06-07-2016	25-03-2016	10-03-2020	09-09-2016	27-03-2016
SB8 (D8=1 ; Dn=0)	04-07-2020	12-03-2020	11-03-2020	09-11-2020	11-03-2020	09-11-2020	11-03-2020	14-07-2016	29-07-2020	02-03-2020	15-07-2016
SB9 (D9=1 ; Dn=0)	18-01-2021	04-07-2020	30-07-2020	14-01-2022	25-11-2020	14-01-2022	05-07-2020	12-03-2020	30-12-2021	03-09-2020	12-03-2020
SB10 (D10=1 ; Dn=0)	19-01-2022	24-05-2021	30-12-2021	24-02-2022	17-01-2022	24-02-2022	26-12-2021	02-09-2020	24-02-2022	04-01-2022	29-07-2020
SB11 (D11=1 ; Dn=0)	15-03-2022	10-02-2022	24-02-2022		24-02-2022		24-02-2022	01-12-2021		24-02-2022	30-12-2021
SB12 (D12=1 ; Dn=0)		04-03-2022			09-03-2022			24-02-2022			24-02-2022

Figure 7: Estimated Break Dates US sector ETFs

	Estimated Break Dates										
#	1	2	3	4	5	6	7	8	9	10	11
Variable	VDE	VAW	VIS	VCR	VDC	VHT	VFH	VGT	VOX	VPU	VNQ
SB1 (D1=1 ; Dn=0)	05-08-2014	05-08-2014	08-08-2014	05-08-2014	01-08-2014	07-08-2014	05-08-2014	13-08-2014	12-08-2014	05-08-2014	11-08-2014
SB2 (D2=1 ; Dn=0)	13-10-2014	28-09-2014	22-09-2014	07-10-2014	09-10-2014	03-10-2014	07-10-2014	10-10-2014	23-10-2014	29-09-2014	08-09-2014
SB3 (D3=1 ; Dn=0)	28-11-2014	12-12-2014	31-10-2014	21-12-2014	04-01-2015	28-10-2014	21-12-2014	08-12-2014	24-08-2015	23-10-2014	18-09-2014
SB4 (D4=1 ; Dn=0)	26-08-2015	26-08-2015	24-08-2015	26-08-2015	26-08-2015	26-08-2015	30-03-2015	26-01-2015	17-05-2017	10-11-2014	24-08-2015
SB5 (D5=1 ; Dn=0)	12-05-2016	15-09-2016	07-05-2017	17-08-2016	30-06-2016	12-04-2016	08-06-2015	25-03-2015	08-10-2018	30-01-2015	28-08-2016
SB6 (D6=1 ; Dn=0)	23-10-2018	22-10-2018	18-10-2018	11-10-2018	17-05-2017	24-02-2020	24-08-2015	08-06-2016	24-02-2020	10-07-2015	27-01-2017
SB7 (D7=1 ; Dn=0)	11-03-2020	25-02-2020	02-03-2020	25-02-2020	27-02-2020	19-06-2020	12-05-2017	08-10-2018	29-06-2020	08-07-2016	11-10-2018
SB8 (D8=1 ; Dn=0)	03-07-2020	20-06-2020	25-06-2020	20-06-2020	22-06-2020	14-11-2020	21-10-2018	25-02-2020	26-12-2021	20-12-2016	11-03-2020
SB9 (D9=1 ; Dn=0)	22-03-2021	11-01-2021	19-01-2021	26-11-2021	04-11-2020	03-01-2022	02-03-2020	14-09-2020	25-01-2022	12-02-2019	03-07-2020
SB10 (D10=1 ; Dn=0)	28-09-2021	20-01-2022	29-11-2021	03-02-2022	13-01-2022	25-02-2022	29-06-2020	02-12-2021	07-02-2022	11-03-2020	29-11-2021
SB11 (D11=1 ; Dn=0)	10-11-2021	04-03-2022	03-02-2022	22-02-2022	24-02-2022		13-01-2021	17-02-2022	09-03-2022	03-07-2020	20-01-2022
SB12 (D12=1 ; Dn=0)	10-03-2022		18-03-2022				29-11-2021	15-03-2022		17-12-2020	01-02-2022
SB13 (D13=1 ; Dn=0)							23-02-2022			17-09-2021	21-03-2022
SB14 (D14=1 ; Dn=0)										26-01-2022	
SB15 (D15=1 ; Dn=0)										01-03-2022	

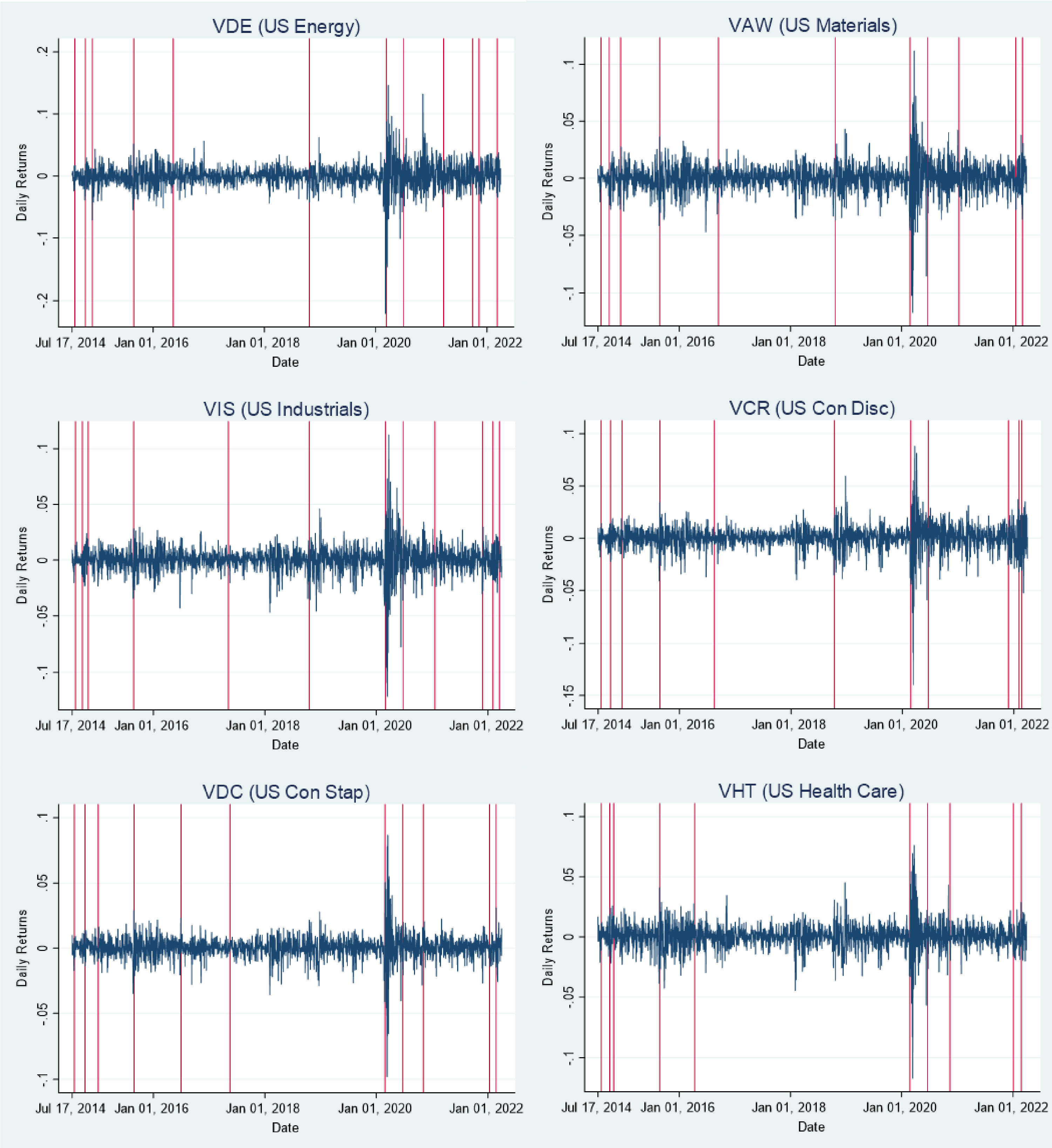
Figure 8: Daily Returns EU ETFs

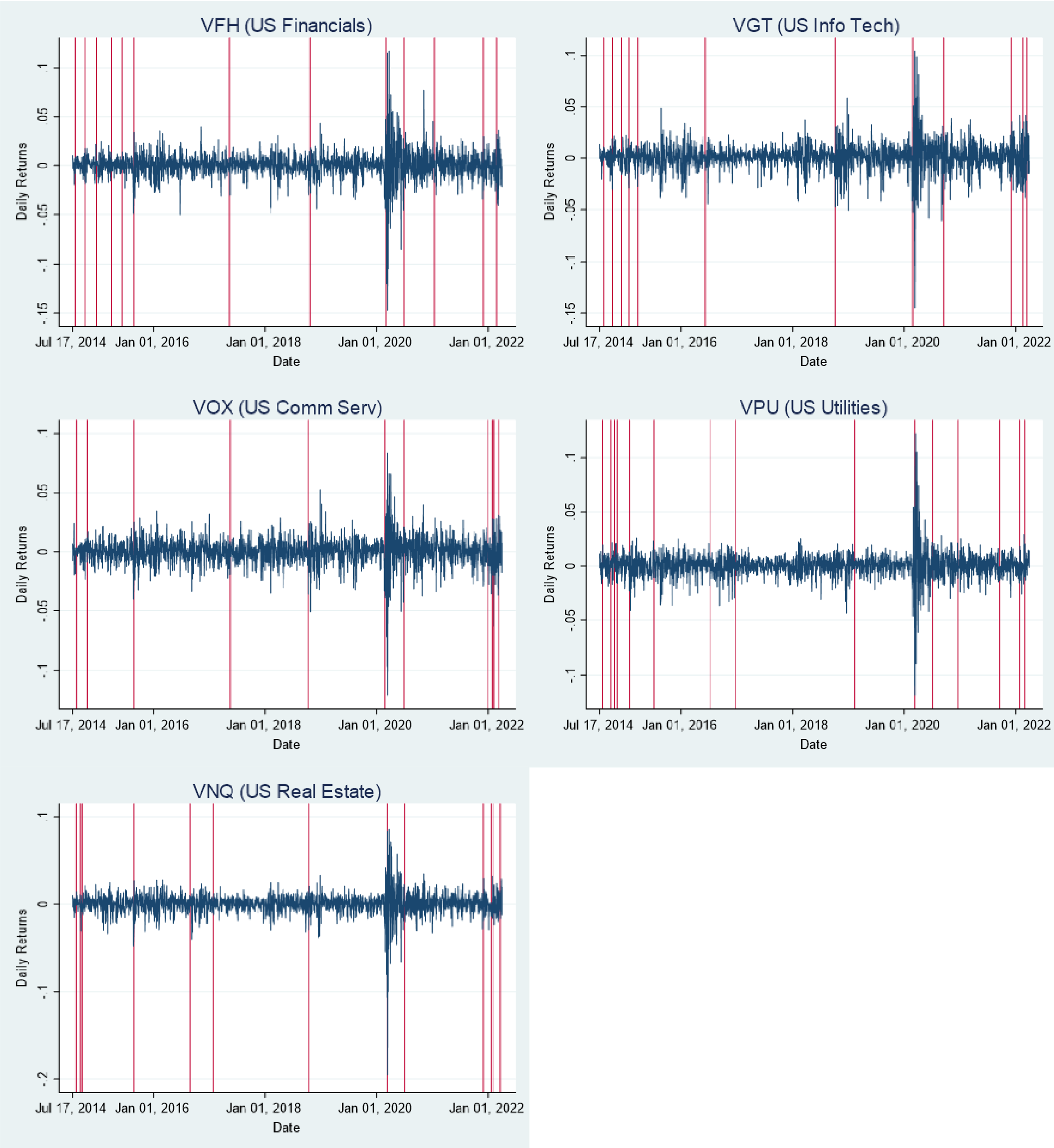




Note: The daily return plots of the EU ETFs indicate that daily returns are normally distributed around zero. The red vertical lines depict structural breaks that are estimated by using the 'estat sbsingle' command from STATA.

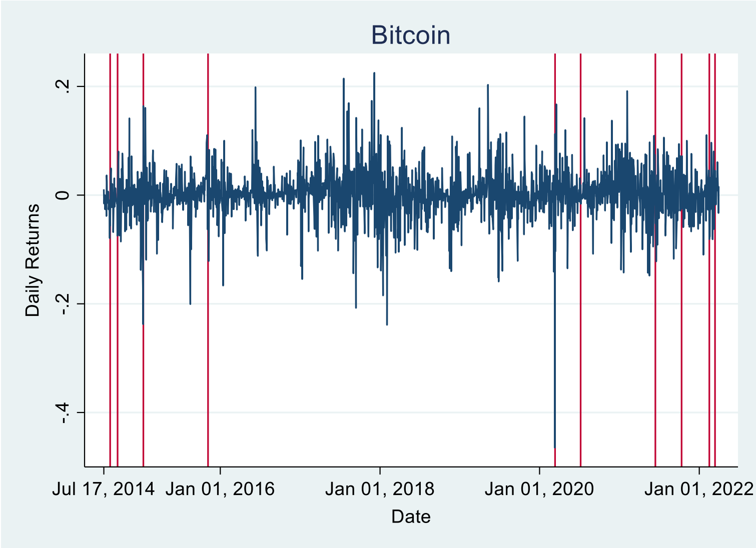
Figure 9: Daily Returns US ETFs





Note: The daily return plots of the US ETFs indicate that daily returns are normally distributed around zero. The red vertical lines depict structural breaks that are estimated by using the ‘estat sbsingle’ command from STATA.

Figure 10: Daily Returns Bitcoin



Note: The daily return plot of Bitcoin indicates that daily returns are normally distributed around zero. The red vertical lines depict structural breaks that are estimated by using the 'estat sbsingle' command from STATA.

Figure 11: Summary Statistics Daily Returns

Variable	Obs	Mean	Std. Dev.	Min	Max	Std. Error.	95% Conf. Interval		Skew.	Kurt.
EXH1	2011	-0.0002	0.0170	-0.1780	0.1500	0.0004	-0.0009	0.0006	-0.749	18.253
EXV6	2011	0.0002	0.0200	-0.1700	0.1460	0.0004	-0.0007	0.0010	-0.314	8.929
EXH4	2011	0.0002	0.0130	-0.1460	0.0970	0.0003	-0.0004	0.0007	-0.971	17.347
EXV5	2011	-0.0001	0.0180	-0.1750	0.1490	0.0004	-0.0008	0.0007	-0.577	14.581
EXH7	2011	0.0001	0.0110	-0.1160	0.0790	0.0003	-0.0004	0.0006	-0.756	12.805
EXV4	2011	0.0001	0.0100	-0.1120	0.0570	0.0002	-0.0003	0.0006	-0.721	12.192
EXH2	2011	0.0002	0.0140	-0.1560	0.1180	0.0003	-0.0004	0.0008	-1.336	22.708
EXV3	2011	0.0003	0.0140	-0.1200	0.0980	0.0003	-0.0003	0.0009	-0.546	9.391
EXV2	2011	-0.0002	0.0120	-0.1310	0.0710	0.0003	-0.0008	0.0003	-1.365	18.31
EXH9	2011	0.0000	0.0120	-0.1690	0.0620	0.0003	-0.0005	0.0005	-1.793	26.059
EXI5	2011	0.0000	0.0120	-0.1400	0.0830	0.0003	-0.0005	0.0005	-1.3	18.957
VDE	2011	-0.0001	0.0190	-0.2210	0.1460	0.0004	-0.0010	0.0007	-0.784	18.803
VAW	2011	0.0003	0.0130	-0.1170	0.1120	0.0003	-0.0003	0.0009	-0.687	14.852
VIS	2011	0.0003	0.0130	-0.1220	0.1120	0.0003	-0.0002	0.0009	-0.835	18.592
VCR	2011	0.0005	0.0120	-0.1400	0.0880	0.0003	0.0000	0.0011	-1.222	18.724
VDC	2011	0.0003	0.0090	-0.0980	0.0870	0.0002	-0.0001	0.0007	-0.339	21.646
VHT	2011	0.0004	0.0110	-0.1170	0.0760	0.0002	-0.0001	0.0009	-0.594	15.048
VFH	2011	0.0004	0.0140	-0.1470	0.1170	0.0003	-0.0003	0.0010	-0.812	21.062
VGT	2011	0.0007	0.0140	-0.1450	0.1040	0.0003	0.0001	0.0013	-0.663	15.572
VOX	2011	0.0002	0.0120	-0.1210	0.0840	0.0003	-0.0004	0.0007	-0.801	14.149
VPU	2011	0.0003	0.0120	-0.1190	0.1220	0.0003	-0.0002	0.0008	-0.342	24.827
VNQ	2011	0.0002	0.0130	-0.1950	0.0860	0.0003	-0.0004	0.0007	-2.162	38.588
BTC	2011	0.0021	0.0450	-0.4650	0.2250	0.0010	0.0002	0.0041	-0.647	12.119
VIX	2011	0.0001	0.0820	-0.3000	0.7680	0.0018	-0.0035	0.0038	1.283	10.081
VSTOXX	2011	0.0001	0.0760	-0.4220	0.4960	0.0017	-0.0032	0.0034	0.728	7.049
GVZ	2011	0.0001	0.0510	-0.2660	0.2980	0.0011	-0.0021	0.0023	0.587	6.216
OVX	2011	0.0006	0.0640	-0.6220	0.8580	0.0014	-0.0023	0.0034	1.879	33.058

Note: The sample period is from 17 July 2014 until 31 March 2022. After synchronizing the price data and calculating daily returns the number of observations are 2,011.

Figure 12: Summary Statistics Conditional Variances Excluding Structural Breaks

Variable	Obs	Mean	Std. Dev.	Min	Max	Std. Error.	95% Conf. Interval		Skew.	Kurt.	α	t-statistic	β	t-statistic	α + β
EXH1	2011	0.00031	0.00040	0.00012	0.00975	0.00001	0.00029	0.00033	14.327	273.539	0.354	(21.320)	0.523	(14.210)	0.877
EXV6	2011	0.00039	0.00018	0.00023	0.00364	0.00000	0.00038	0.00040	9.949	140.765	0.106	(5.840)	0.997	(8.250)	1.103
EXH4	2011	0.00019	0.00028	0.00007	0.00763	0.00001	0.00017	0.00020	15.383	320.745	0.348	(23.790)	0.563	(13.120)	0.911
EXV5	2011	0.00031	0.00021	0.00018	0.00431	0.00000	0.00030	0.00032	11.401	171.329	0.133	(10.500)	0.881	(11.140)	1.014
EXH7	2011	0.00014	0.00015	0.00005	0.00339	0.00000	0.00014	0.00015	12.757	222.892	0.227	(14.880)	0.927	(16.020)	1.154
EXV4	2011	0.00011	0.00009	0.00003	0.00228	0.00000	0.00011	0.00012	12.539	234.092	0.131	(7.060)	1.301	(11.670)	1.432
EXH2	2011	0.00020	0.00042	0.00006	0.01178	0.00001	0.00018	0.00022	18.537	425.433	0.469	(27.840)	0.438	(11.070)	0.907
EXV3	2011	0.00021	0.00014	0.00013	0.00352	0.00000	0.00021	0.00022	11.560	204.578	0.229	(9.000)	0.481	(5.360)	0.710
EXV2	2011	0.00015	0.00019	0.00008	0.00530	0.00000	0.00015	0.00016	17.769	398.679	0.294	(17.830)	0.461	(7.940)	0.755
EXH9	2011	0.00016	0.00027	0.00006	0.00868	0.00001	0.00015	0.00017	23.589	672.578	0.287	(15.200)	0.685	(14.120)	0.972
EXI5	2011	0.00016	0.00023	0.00006	0.00643	0.00001	0.00015	0.00017	17.459	396.083	0.317	(18.840)	0.62	(15.950)	0.937
VDE	2011	0.00037	0.00043	0.00011	0.00710	0.00001	0.00036	0.00039	10.212	131.665	0.321	(16.440)	0.651	(22.500)	0.972
VAW	2011	0.00017	0.00025	0.00004	0.00489	0.00001	0.00016	0.00018	11.765	179.001	0.388	(12.560)	0.533	(11.850)	0.921
VIS	2011	0.00015	0.00024	0.00004	0.00477	0.00001	0.00014	0.00016	12.876	205.276	0.309	(13.350)	0.622	(16.630)	0.931
VCR	2011	0.00015	0.00021	0.00003	0.00511	0.00000	0.00014	0.00016	13.650	269.601	0.333	(11.860)	0.67	(16.550)	1.003
VDC	2011	0.00008	0.00016	0.00002	0.00402	0.00000	0.00007	0.00009	17.171	357.809	0.313	(11.100)	0.587	(11.230)	0.9
VHT	2011	0.00011	0.00011	0.00004	0.00240	0.00000	0.00011	0.00012	11.204	181.138	0.195	(8.940)	0.815	(13.420)	1.01
VFH	2011	0.00019	0.00034	0.00003	0.00823	0.00001	0.00018	0.00021	13.140	231.618	0.336	(13.670)	0.677	(17.570)	1.013
VGT	2011	0.00019	0.00024	0.00003	0.00625	0.00001	0.00018	0.00020	13.383	273.286	0.253	(10.370)	0.886	(18.460)	1.139
VOX	2011	0.00014	0.00013	0.00005	0.00352	0.00000	0.00013	0.00014	14.862	331.875	0.205	(9.890)	0.8	(12.140)	1.005
VPU	2011	0.00013	0.00022	0.00005	0.00414	0.00000	0.00012	0.00014	12.950	192.219	0.274	(10.940)	0.573	(12.160)	0.847
VNQ	2011	0.00015	0.00024	0.00003	0.00514	0.00001	0.00014	0.00016	12.585	200.633	0.298	(12.760)	0.695	(16.030)	0.993
BTC	2011	0.00225	0.00105	0.00159	0.02516	0.00002	0.00220	0.00230	11.213	187.255	0.079	(5.790)	1.314	(8.890)	1.393
VIX	2011	0.00689	0.00357	0.00396	0.05330	0.00008	0.00674	0.00705	6.016	53.780	0.209	(13.400)	0.631	(8.770)	0.84
VSTOXX	2011	0.00584	0.00238	0.00416	0.05306	0.00005	0.00574	0.00595	10.947	170.160	0.15	(6.530)	0.614	(5.360)	0.764
GVZ	2011	0.00267	0.00144	0.00156	0.02194	0.00003	0.00261	0.00273	6.209	57.030	0.215	(8.050)	0.572	(6.440)	0.787
OVX	2011	0.00407	0.00401	0.00263	0.10694	0.00009	0.00390	0.00425	17.544	409.502	0.258	(24.800)	0.332	(8.580)	0.59

Note: This table depicts the summary statistics of the estimated conditional variances that are used in the regression models. Alpha indicates the ARCH coefficient and beta the GARCH coefficient. The conditional variances are estimated by using the univariate GARCH (1,1) model from STATA.

Figure 14: Pairwise Correlations During the Covid-19 Pandemic

Variables	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13	-14	-15	-16	-17	-18	-19	-20	-21	-22	-23	-24	-25	-26	-27
(1) EXH1	1.00	0.74	0.69	0.67	0.57	0.40	0.65	0.54	0.61	0.55	0.60	0.65	0.51	0.51	0.33	0.24	0.28	0.51	0.24	0.27	0.26	0.35	0.15	-0.25	-0.54	-0.10	-0.25
(2) EXV6	0.74	1.00	0.73	0.67	0.63	0.48	0.72	0.62	0.60	0.54	0.56	0.53	0.61	0.53	0.39	0.33	0.36	0.54	0.32	0.33	0.30	0.38	0.23	-0.31	-0.57	-0.08	-0.21
(3) EXH4	0.69	0.73	1.00	0.85	0.86	0.69	0.93	0.86	0.71	0.75	0.81	0.44	0.60	0.61	0.52	0.36	0.46	0.60	0.45	0.45	0.33	0.48	0.21	-0.36	-0.67	-0.22	-0.25
(4) EXV5	0.67	0.67	0.85	1.00	0.78	0.49	0.82	0.70	0.70	0.64	0.70	0.46	0.61	0.60	0.50	0.39	0.41	0.61	0.39	0.42	0.33	0.48	0.18	-0.33	-0.61	-0.18	-0.25
(5) EXH7	0.57	0.63	0.86	0.78	1.00	0.71	0.86	0.80	0.77	0.76	0.74	0.31	0.54	0.52	0.47	0.43	0.47	0.51	0.44	0.44	0.35	0.44	0.18	-0.34	-0.64	-0.22	-0.20
(6) EXV4	0.40	0.48	0.69	0.49	0.71	1.00	0.70	0.72	0.63	0.66	0.57	0.17	0.36	0.32	0.32	0.30	0.45	0.28	0.34	0.32	0.23	0.28	0.16	-0.23	-0.54	-0.24	-0.17
(7) EXH2	0.65	0.72	0.93	0.82	0.86	0.70	1.00	0.85	0.72	0.74	0.82	0.42	0.59	0.59	0.54	0.37	0.49	0.59	0.48	0.48	0.33	0.49	0.22	-0.37	-0.68	-0.23	-0.26
(8) EXV3	0.54	0.62	0.86	0.70	0.80	0.72	0.85	1.00	0.62	0.69	0.72	0.26	0.48	0.45	0.51	0.29	0.44	0.42	0.51	0.45	0.24	0.38	0.26	-0.37	-0.67	-0.20	-0.21
(9) EXV2	0.61	0.60	0.71	0.70	0.77	0.63	0.72	0.62	1.00	0.72	0.63	0.41	0.55	0.49	0.42	0.46	0.46	0.52	0.37	0.40	0.41	0.42	0.17	-0.27	-0.61	-0.20	-0.23
(10) EXH9	0.55	0.54	0.75	0.64	0.76	0.66	0.74	0.69	0.72	1.00	0.69	0.30	0.49	0.48	0.42	0.41	0.45	0.47	0.40	0.41	0.42	0.42	0.18	-0.28	-0.54	-0.18	-0.21
(11) EXI5	0.60	0.56	0.81	0.70	0.74	0.57	0.82	0.72	0.63	0.69	1.00	0.38	0.48	0.48	0.45	0.25	0.36	0.48	0.38	0.39	0.28	0.48	0.15	-0.29	-0.52	-0.26	-0.22
(12) VDE	0.65	0.53	0.44	0.46	0.31	0.17	0.42	0.26	0.41	0.30	0.38	1.00	0.71	0.74	0.52	0.46	0.47	0.76	0.41	0.48	0.43	0.59	0.15	-0.41	-0.31	-0.14	-0.29
(13) VAW	0.51	0.61	0.60	0.61	0.54	0.36	0.59	0.48	0.55	0.49	0.48	0.71	1.00	0.93	0.76	0.73	0.74	0.89	0.68	0.71	0.68	0.79	0.28	-0.57	-0.41	-0.21	-0.27
(14) VIS	0.51	0.53	0.61	0.60	0.52	0.32	0.59	0.45	0.49	0.48	0.48	0.74	0.93	1.00	0.80	0.73	0.75	0.92	0.71	0.73	0.70	0.84	0.24	-0.57	-0.38	-0.20	-0.29
(15) VCR	0.33	0.39	0.52	0.50	0.47	0.32	0.54	0.51	0.42	0.42	0.45	0.52	0.76	0.80	1.00	0.61	0.74	0.73	0.87	0.86	0.53	0.74	0.32	-0.64	-0.37	-0.23	-0.31
(16) VDC	0.24	0.33	0.36	0.39	0.43	0.30	0.37	0.29	0.46	0.41	0.25	0.46	0.73	0.73	0.61	1.00	0.78	0.69	0.66	0.67	0.81	0.74	0.16	-0.48	-0.27	-0.09	-0.22
(17) VHT	0.28	0.36	0.46	0.41	0.47	0.45	0.49	0.44	0.46	0.45	0.36	0.47	0.74	0.75	0.74	0.78	1.00	0.69	0.81	0.77	0.72	0.76	0.21	-0.56	-0.35	-0.19	-0.23
(18) VFH	0.51	0.54	0.60	0.61	0.51	0.28	0.59	0.42	0.52	0.47	0.48	0.76	0.89	0.92	0.73	0.69	0.69	1.00	0.63	0.69	0.66	0.81	0.24	-0.52	-0.39	-0.21	-0.26
(19) VGT	0.24	0.32	0.45	0.39	0.44	0.34	0.48	0.51	0.37	0.40	0.38	0.41	0.68	0.71	0.87	0.66	0.81	0.63	1.00	0.88	0.56	0.69	0.33	-0.66	-0.34	-0.17	-0.28
(20) VOX	0.27	0.33	0.45	0.42	0.44	0.32	0.48	0.45	0.40	0.41	0.39	0.48	0.71	0.73	0.86	0.67	0.77	0.69	0.88	1.00	0.57	0.71	0.31	-0.65	-0.35	-0.20	-0.28
(21) VPU	0.26	0.30	0.33	0.33	0.35	0.23	0.33	0.24	0.41	0.42	0.28	0.43	0.68	0.70	0.53	0.81	0.72	0.66	0.56	0.57	1.00	0.79	0.12	-0.35	-0.20	-0.06	-0.16
(22) VNQ	0.35	0.38	0.48	0.48	0.44	0.28	0.49	0.38	0.42	0.42	0.48	0.59	0.79	0.84	0.74	0.74	0.76	0.81	0.69	0.71	0.79	1.00	0.19	-0.50	-0.26	-0.19	-0.23
(23) BTC	0.15	0.23	0.21	0.18	0.18	0.16	0.22	0.26	0.17	0.18	0.15	0.15	0.28	0.24	0.32	0.16	0.21	0.24	0.33	0.31	0.12	0.19	1.00	-0.32	-0.23	-0.01	-0.13
(24) VIX	-0.25	-0.31	-0.36	-0.33	-0.34	-0.23	-0.37	-0.37	-0.27	-0.28	-0.29	-0.41	-0.57	-0.57	-0.64	-0.48	-0.56	-0.52	-0.66	-0.65	-0.35	-0.50	-0.32	1.00	0.51	0.31	0.36
(25) VSTOXX	-0.54	-0.57	-0.67	-0.61	-0.64	-0.54	-0.68	-0.67	-0.61	-0.54	-0.52	-0.31	-0.41	-0.38	-0.37	-0.27	-0.35	-0.39	-0.34	-0.35	-0.20	-0.26	-0.23	0.51	1.00	0.24	0.29
(26) GVZ	-0.10	-0.08	-0.22	-0.18	-0.22	-0.24	-0.23	-0.20	-0.20	-0.18	-0.26	-0.14	-0.21	-0.20	-0.23	-0.09	-0.19	-0.21	-0.17	-0.20	-0.06	-0.19	-0.01	0.31	0.24	1.00	0.21
(27) OVX	-0.25	-0.21	-0.25	-0.25	-0.20	-0.17	-0.26	-0.21	-0.23	-0.21	-0.22	-0.29	-0.27	-0.29	-0.31	-0.22	-0.23	-0.26	-0.28	-0.28	-0.16	-0.23	-0.13	0.36	0.29	0.21	1.00

Note: The Pairwise correlation table shows a correlation matrix between the dependent, independent and control variables during the Covid-19 Pandemic. The colours illustrate more intensive green markings or red markings for respectively higher positive or negative correlation values.

Figure 15: Pairwise Correlations Before the Covid-19 Pandemic

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
(1) EXH1	1.00	0.77	0.75	0.65	0.62	0.57	0.69	0.61	0.65	0.67	0.53	0.67	0.56	0.53	0.45	0.36	0.36	0.51	0.42	0.43	0.26	0.32	0.13	-0.39	-0.51	-0.29	-0.43
(2) EXV6	0.77	1.00	0.73	0.65	0.57	0.50	0.66	0.59	0.55	0.54	0.49	0.53	0.57	0.51	0.43	0.29	0.34	0.48	0.41	0.39	0.15	0.26	0.11	-0.38	-0.49	-0.27	-0.32
(3) EXH4	0.75	0.73	1.00	0.82	0.82	0.75	0.91	0.85	0.75	0.74	0.72	0.47	0.58	0.58	0.53	0.41	0.44	0.55	0.51	0.46	0.24	0.35	0.11	-0.47	-0.64	-0.30	-0.31
(4) EXV5	0.65	0.65	0.82	1.00	0.69	0.60	0.78	0.73	0.67	0.61	0.60	0.44	0.52	0.52	0.50	0.34	0.39	0.51	0.46	0.41	0.16	0.28	0.10	-0.42	-0.59	-0.27	-0.27
(5) EXH7	0.62	0.57	0.82	0.69	1.00	0.77	0.81	0.76	0.76	0.78	0.76	0.34	0.45	0.46	0.46	0.47	0.40	0.42	0.45	0.40	0.31	0.38	0.10	-0.43	-0.57	-0.24	-0.28
(6) EXV4	0.57	0.50	0.75	0.60	0.77	1.00	0.75	0.71	0.70	0.69	0.66	0.32	0.42	0.42	0.41	0.41	0.47	0.41	0.40	0.38	0.29	0.35	0.10	-0.39	-0.57	-0.23	-0.25
(7) EXH2	0.69	0.66	0.91	0.78	0.81	0.75	1.00	0.81	0.77	0.75	0.75	0.42	0.52	0.53	0.50	0.40	0.43	0.54	0.48	0.42	0.23	0.33	0.10	-0.44	-0.61	-0.29	-0.29
(8) EXV3	0.61	0.59	0.85	0.73	0.76	0.71	0.81	1.00	0.67	0.65	0.65	0.38	0.50	0.51	0.51	0.36	0.44	0.47	0.54	0.43	0.20	0.31	0.10	-0.45	-0.64	-0.28	-0.28
(9) EXV2	0.65	0.55	0.75	0.67	0.76	0.70	0.77	0.67	1.00	0.78	0.72	0.36	0.42	0.41	0.40	0.39	0.34	0.43	0.36	0.39	0.29	0.34	0.10	-0.36	-0.53	-0.23	-0.26
(10) EXH9	0.67	0.54	0.74	0.61	0.78	0.69	0.75	0.65	0.78	1.00	0.76	0.35	0.40	0.39	0.36	0.42	0.33	0.37	0.35	0.35	0.40	0.39	0.15	-0.34	-0.48	-0.22	-0.26
(11) EXI5	0.53	0.49	0.72	0.60	0.76	0.66	0.75	0.65	0.72	0.76	1.00	0.29	0.38	0.38	0.39	0.40	0.33	0.35	0.36	0.32	0.32	0.41	0.11	-0.36	-0.43	-0.21	-0.23
(12) VDE	0.67	0.53	0.47	0.44	0.34	0.32	0.42	0.38	0.36	0.35	0.29	1.00	0.76	0.72	0.64	0.49	0.55	0.68	0.60	0.59	0.32	0.41	0.10	-0.55	-0.35	-0.31	-0.49
(13) VAW	0.56	0.57	0.58	0.52	0.45	0.42	0.52	0.50	0.42	0.40	0.38	0.76	1.00	0.89	0.80	0.65	0.71	0.80	0.77	0.69	0.39	0.53	0.10	-0.69	-0.44	-0.36	-0.41
(14) VIS	0.53	0.51	0.58	0.52	0.46	0.42	0.53	0.51	0.41	0.39	0.38	0.72	0.89	1.00	0.87	0.69	0.75	0.87	0.83	0.74	0.41	0.57	0.10	-0.74	-0.47	-0.39	-0.39
(15) VCR	0.45	0.43	0.53	0.50	0.46	0.41	0.50	0.51	0.40	0.36	0.39	0.64	0.80	0.87	1.00	0.71	0.77	0.81	0.87	0.78	0.41	0.60	0.10	-0.74	-0.44	-0.37	-0.37
(16) VDC	0.36	0.29	0.41	0.34	0.47	0.41	0.40	0.36	0.39	0.42	0.40	0.49	0.65	0.69	0.71	1.00	0.66	0.64	0.65	0.65	0.68	0.70	0.09	-0.60	-0.34	-0.32	-0.30
(17) VHT	0.36	0.34	0.44	0.39	0.40	0.47	0.43	0.44	0.34	0.33	0.33	0.55	0.71	0.75	0.77	0.66	1.00	0.72	0.77	0.66	0.42	0.55	0.09	-0.70	-0.40	-0.35	-0.32
(18) VFH	0.51	0.48	0.55	0.51	0.42	0.41	0.54	0.47	0.43	0.37	0.35	0.68	0.80	0.87	0.81	0.64	0.72	1.00	0.76	0.69	0.35	0.53	0.11	-0.70	-0.48	-0.42	-0.39
(19) VGT	0.42	0.41	0.51	0.46	0.45	0.40	0.48	0.54	0.36	0.35	0.36	0.60	0.77	0.83	0.87	0.65	0.77	0.76	1.00	0.73	0.38	0.53	0.10	-0.76	-0.44	-0.38	-0.36
(20) VOX	0.43	0.39	0.46	0.41	0.40	0.38	0.42	0.43	0.39	0.35	0.32	0.59	0.69	0.74	0.78	0.65	0.66	0.69	0.73	1.00	0.44	0.56	0.09	-0.63	-0.39	-0.34	-0.34
(21) VPU	0.26	0.15	0.24	0.16	0.31	0.29	0.23	0.20	0.29	0.40	0.32	0.32	0.39	0.41	0.41	0.68	0.42	0.35	0.38	0.44	1.00	0.70	0.07	-0.35	-0.19	-0.21	-0.19
(22) VNQ	0.32	0.26	0.35	0.28	0.38	0.35	0.33	0.31	0.34	0.39	0.41	0.41	0.53	0.57	0.60	0.70	0.55	0.53	0.53	0.56	0.70	1.00	0.09	-0.48	-0.28	-0.26	-0.24
(23) BTC	0.13	0.11	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.15	0.11	0.10	0.10	0.10	0.10	0.09	0.09	0.11	0.10	0.09	0.07	0.09	1.00	-0.07	-0.03	0.03	-0.03
(24) VIX	-0.39	-0.38	-0.47	-0.42	-0.43	-0.39	-0.44	-0.45	-0.36	-0.34	-0.36	-0.55	-0.69	-0.74	-0.74	-0.60	-0.70	-0.70	-0.76	-0.63	-0.35	-0.48	-0.07	1.00	0.54	0.45	0.38
(25) VSTOXX	-0.51	-0.49	-0.64	-0.59	-0.57	-0.57	-0.61	-0.64	-0.53	-0.48	-0.43	-0.35	-0.44	-0.47	-0.44	-0.34	-0.40	-0.48	-0.44	-0.39	-0.19	-0.28	-0.03	0.54	1.00	0.34	0.30
(26) GVZ	-0.29	-0.27	-0.30	-0.27	-0.24	-0.23	-0.29	-0.28	-0.23	-0.22	-0.21	-0.31	-0.36	-0.39	-0.37	-0.32	-0.35	-0.42	-0.38	-0.34	-0.21	-0.26	0.03	0.45	0.34	1.00	0.33
(27) OVX	-0.43	-0.32	-0.31	-0.27	-0.28	-0.25	-0.29	-0.28	-0.26	-0.26	-0.23	-0.49	-0.41	-0.39	-0.37	-0.30	-0.32	-0.39	-0.36	-0.34	-0.19	-0.24	-0.03	0.38	0.30	0.33	1.00

Note: The Pairwise correlation table shows a correlation matrix between the dependent, independent and control variables before the Covid-19 Pandemic. The colours illustrate more intensive green markings or red markings for respectively higher positive or negative correlation value.

Figure 18: Regressions Conditional Volatilities EU ETFs and Bitcoin (Excluding Structural Breaks)

	(1) EU Energy	(2) EU Materials	(3) EU Industrials	(4) EU Cons Disc	(5) EU Cons Stap	(6) EU Health Care	(7) EU Financials	(8) EU Info Tech	(9) EU Comm Serv	(10) EU Utilities	(11) EU Real Estate
β_1 (BTC)	-0.0031	-0.0044	0.0020	-0.0046	-0.0020	-0.0042*	0.0139	-0.0024	0.0034	0.0017	0.0047
	(0.736)	(0.309)	(0.734)	(0.329)	(0.522)	(0.023)	(0.142)	(0.459)	(0.442)	(0.701)	(0.319)
β_2 (Dummy)	-0.0005***	-0.0003***	-0.0004***	-0.0003***	-0.0002***	-0.0002***	-0.0005***	-0.0001***	-0.0003***	-0.0006***	-0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_3 (Interaction)	0.2784***	0.1335***	0.2187***	0.1535***	0.1240***	0.0849***	0.2892***	0.0917***	0.1317***	0.2817***	0.1898***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_4 (VIX)	0.0017	0.0010	0.0077***	0.0016	0.0027***	0.0000	0.0162***	0.0036***	0.0082***	0.0068***	0.0071***
	(0.481)	(0.379)	(0.000)	(0.180)	(0.001)	(0.925)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_5 (VSTOXX)	0.0206***	0.0069***	0.0120***	0.0094***	0.0092***	0.0064***	0.0180***	0.0095***	0.0048**	0.0068***	0.0067***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)
β_6 (GVZ)	0.0226***	0.0109***	0.0161***	0.0098***	0.0084***	0.0089***	0.0181***	0.0057**	0.0085***	0.0164***	0.0175***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
β_7 (OVX)	0.0083***	0.0029**	0.0033**	0.0028**	0.0002	0.0000	0.0018	0.0016*	0.0011	0.0003	0.0005
	(0.000)	(0.002)	(0.008)	(0.004)	(0.713)	(0.953)	(0.353)	(0.021)	(0.219)	(0.758)	(0.619)
β_0 (Constant)	0.0001	0.0003***	0.0000	0.0002***	0.0000***	0.0001***	-0.0001***	0.0001***	0.0000	0.0000	0.0000
	(0.076)	(0.000)	(0.194)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.051)	(0.624)	(0.729)
N	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011
Adj. R-sq	0.319	0.293	0.422	0.344	0.429	0.483	0.364	0.339	0.333	0.637	0.460

Note: this table shows following equation 3 multiple regressions of the dummy during the Covid-19 pandemic, the interaction between the Bitcoin and the dummy and the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs from Europe. The conditional variances are calculated excluding structural breaks. The significance level of the coefficients is denoted in p-values and divided in the following confidence intervals: * = $p<0.05$, ** = $p<0.01$ and *** = $p<0.001$.

Figure 19: Regressions Conditional Volatilities US ETFs and Bitcoin (Excluding Structural Breaks)

	(1) US Energy	(2) US Materials	(3) US Industrials	(4) US Cons Disc	(5) US Cons Stap	(6) US Health Care	(7) US Financials	(8) US Info Tech	(9) US Comm Serv	(10) US Utilities	(11) US Real Estate
β_1 (BTC)	-0.0103	-0.0082	-0.0084	-0.0031	-0.0041	-0.0051*	-0.0115	-0.0058	-0.0035	-0.0073	-0.0087
	(0.314)	(0.149)	(0.102)	(0.434)	(0.164)	(0.026)	(0.099)	(0.214)	(0.132)	(0.169)	(0.094)
β_2 (Dummy)	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0002***	-0.0005***	-0.0004***	-0.0002***	-0.0002***	-0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_3 (Interaction)	0.2385***	0.1633***	0.1787***	0.1773***	0.1586***	0.0792***	0.2743***	0.1989***	0.1211***	0.1423***	0.1943***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_4 (VIX)	0.0069**	0.0116***	0.0089***	0.0088***	0.0025***	0.0051***	0.0104***	0.0101***	0.0049***	-0.0009	0.0027*
	(0.008)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.532)	(0.046)
β_5 (VSTOXX)	0.0121**	0.0100***	0.0085***	0.0089***	0.0039***	0.0035***	0.0117***	0.0101***	0.0025**	0.0074***	0.0076***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)
β_6 (GVZ)	0.0471***	0.0259***	0.0240***	0.0200***	0.0180***	0.0126***	0.0440***	0.0227***	0.0124***	0.0242***	0.0268***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.0000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_7 (OVX)	0.0120***	0.0030*	0.0035**	0.0025**	0.001	0.0005	0.0047**	0.0031**	0.0022***	0.0024*	0.0027*
	(0.000)	(0.012)	(0.001)	(0.003)	(0.106)	(0.260)	(0.001)	(0.001)	(0.000)	(0.028)	(0.013)
β_0 (Constant)	0.0000	-0.0001**	-0.0000*	-0.0000***	0.0000	0.0000***	-0.0001***	0.0000	0.0000***	0.0000	0.0000
	(0.163)	(0.005)	(0.013)	(0.001)	(0.147)	(0.000)	(0.000)	(0.130)	(0.000)	(0.435)	(0.904)
N	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011	2011
Adj. R-sq	0.292	0.362	0.413	0.540	0.566	0.415	0.473	0.517	0.579	0.266	0.408

Note: this table shows following equation 3 multiple regressions of the dummy during the Covid-19 pandemic, the interaction between the Bitcoin and the dummy and the conditional variances of Bitcoin and the control variables on the conditional variance of the 11 different sector ETFs from the United States. The conditional variances are calculated excluding structural breaks. The significance level of the coefficients is denoted in p-values and divided in the following confidence intervals: * = $p<0.05$, ** = $p<0.01$ and *** = $p<0.001$.

Figure 23: Durbin Watson Statistics Multiple Regressions

#	Regression Model	DW-Statistic	Conclusion	#	Regression Model	DW-Statistic	Conclusion
1	EU Energy	1.216	Positive Autocorrelation	12	US Energy	0.628	Positive Autocorrelation
2	EU Materials	0.313	Positive Autocorrelation	13	US Materials	0.811	Positive Autocorrelation
3	EU Industrials	1.082	Positive Autocorrelation	14	US Industrials	0.627	Positive Autocorrelation
4	EU Cons Disc	0.567	Positive Autocorrelation	15	US Cons Disc	0.775	Positive Autocorrelation
5	EU Cons Stap	0.419	Positive Autocorrelation	16	US Cons Stap	0.611	Positive Autocorrelation
6	EU Health Care	0.268	Positive Autocorrelation	17	US Health Care	0.490	Positive Autocorrelation
7	EU Financials	1.243	Positive Autocorrelation	18	US Financials	0.545	Positive Autocorrelation
8	EU Info Tech	1.175	Positive Autocorrelation	19	US Info Tech	0.396	Positive Autocorrelation
9	EU Comm Serv	1.223	Positive Autocorrelation	20	US Comm Serv	0.507	Positive Autocorrelation
10	EU Utilities	0.976	Positive Autocorrelation	21	US Utilities	0.655	Positive Autocorrelation
11	EU Real Estate	0.958	Positive Autocorrelation	22	US Real Estate	0.527	Positive Autocorrelation

Figure 28: Augmented Dickey-Fuller test

Variable	Test Statistic	Variable	Test Statistic
EXH1	-6.967	VDE	-3.932
EXV6	-7.923	VAW	-7.344
EXH4	-8.126	VIS	-7.225
EXV5	-6.242	VCR	-6.991
EXH7	-8.987	VDC	-9.730
EXV4	-9.115	VHT	-7.499
EXH2	-6.348	VFH	-7.523
EXV3	-8.406	VGT	-6.478
EXV2	-8.592	VOX	-7.981
EXH9	-10.239	VPU	-10.638
EXI5	-7.785	VNQ	-9.374
BTC	-5.191		