The Change in Correlation between Bitcoin Return and Stock Market Indexes Return before and after the Outbreak of Covid-19: The Case of the U.S, Europe, and Hong Kong Stock Markets

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Abstract

This paper uses the DCC-GARCH model and an OLS regression model to examine whether Bitcoin can serve as a diversifier, hedge or safe haven against the U.S., Europe and Hong Kong stock market indexes. It also investigates whether there was a structural break in the dynamic correlation series after the outbreak of Covid-19 using daily price data from Oct. 2014 to Dec. 2021. The result suggests that there was a structural break in the correlations. And Bitcoin only served as a diversifier for the European stock market index before the pandemic. During the pandemic, Bitcoin became a diversifier for all of the three market indexes.

1. Introduction

Bitcoin was created as a digital medium of exchange under the pseudonym of Satoshi Nakamoto on January 3rd, 2009. Bitcoin operates free of any central authority. Instead, all transactions are verified through cryptography by network nodes which can be set up by almost anyone with a computer and recorded in a public distributed ledger called blockchain. Sush process is called 'mining' and the people setting up nodes, also known as 'miners', are rewarded with bitcoin into their own wallets.

On Feb. 19th, 2021, Bitcoin became the fastest asset to surpass 1 trillion-dollar market capitalization using only 12 years, drawing more and more attention to the study of Bitcoin as a financial asset. Brandvold et al. (2015) research into Bitcoin's price discovery between different Bitcoin exchanges using high frequency data and suggest that information share among exchanges evolves significantly over time. Bariviera et al. (2017) focus on the stylized facts in Bitcoin markets. After testing the presence of long memory in Bitcoin's return series from 2011 to 2017 using Hurst exponent, they conclude that Hurst exponent changes significantly during the early years of Bitcoin then stabilizes gradually after 2014. Aviral et al. (2017) investigate whether Bitcoin can hedge global uncertainty using quantile regression and find that Bitcoin fails to serve as a hedge against uncertainty. This paper is mainly a follow-up on Elie et al. (2017)'s research, on the hedge and safe haven properties of Bitcoin, where Bitcoin's relation with world stock indexes, oil and gold was investigated using daily and weekly data from 2011 to 2015. They suggest that Bitcoin cannot serve as a hedge or safe haven against any of the assets under the study but can serve as an effective diversifier for most assets, except for Japanese stocks and commodity indexes.

This research contributes to the literature in that the data used is more up to date (from October 2014 to December 2021) and given that several studies have pointed out that properties of Bitcoin can change significantly over time, whether a structural break occurred in the relation of Bitcoin with major stock indexes after the outbreak of Covid-19 is also investigated, as the price of Bitcoin rose drastically after the outbreak from under 10k to over 50k.

2. Data Description

2.1 Price Series and Break-Point Date

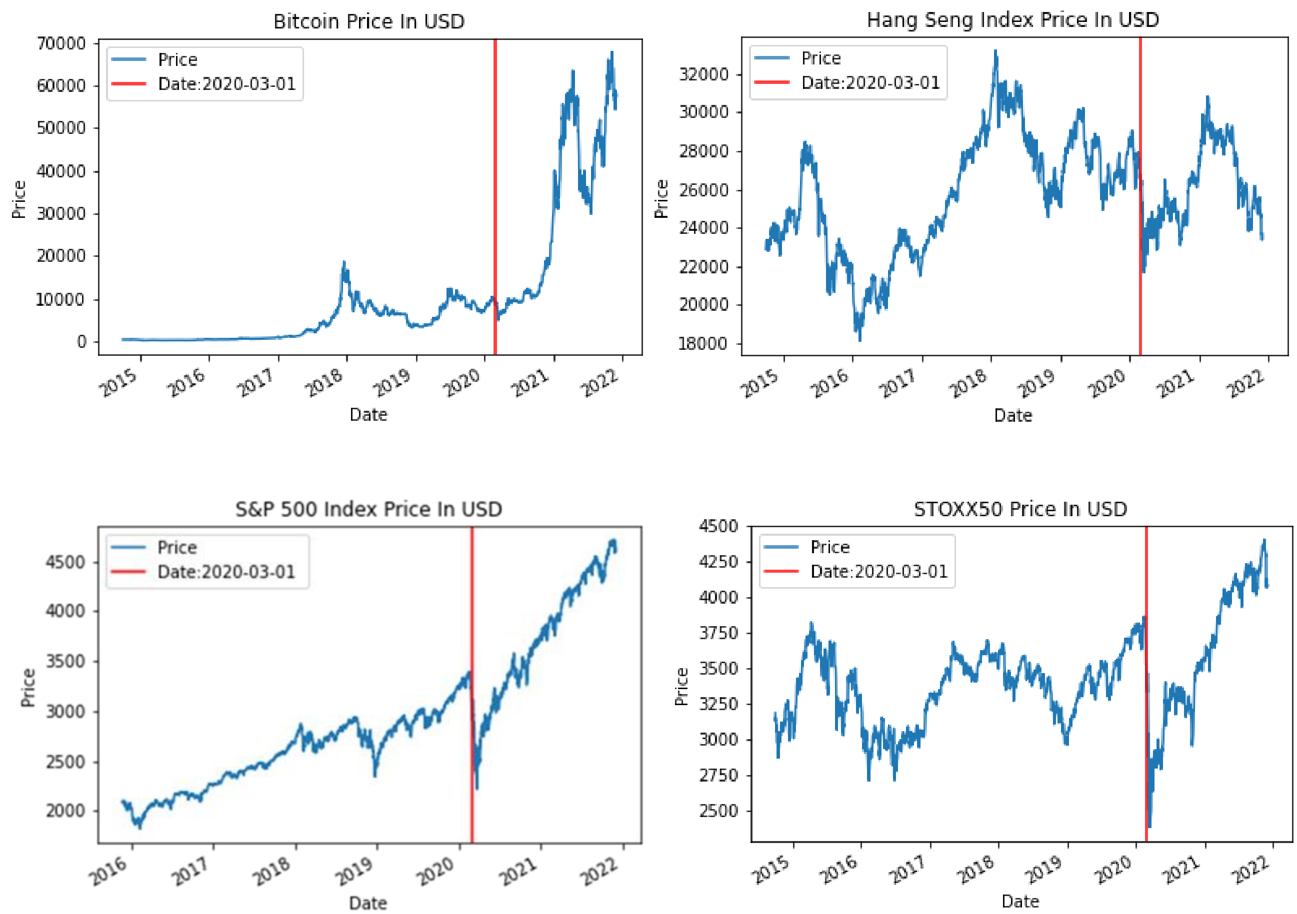
The study uses daily closing price of Bitcoin, S&P500 Index, STOXX50 Index and Hang Seng Index from IC Markets, an Australian online brokerage found in 2007. The three indexes respectively serve as representations of stock market performance in the U.S, Europe, and Hong Kong. The range of data is from October 1st 2014 to December 1st 2021, a total of 1852 trading days.

The break-point date when the hypothesized structural break happened is set to be March 1st, 2020 There are 1397 days before this day and 455 days after in the sample. Although the World Health Organization (WHO) declared Covid-19 a public health emergency of international concern on January 30th, 2020, at that time there were only 98 cases and no deaths in 18 countries outside China (WHO, 2021). The U.S. and countries in Europe started lockdown around mid and late

March, which then severely affected their national economy. Thus, March 1st was chosen to be the break-point date when the hypothesized structural break happened.

The price data is displayed in *figure 1*.

Figure 1



2.2 Percentage Log Return Series

Percentage log return of the price series is computed by the formula below:

$$r_t = 100 \times (ln^{P_t} - ln^{P_{t-1}})$$

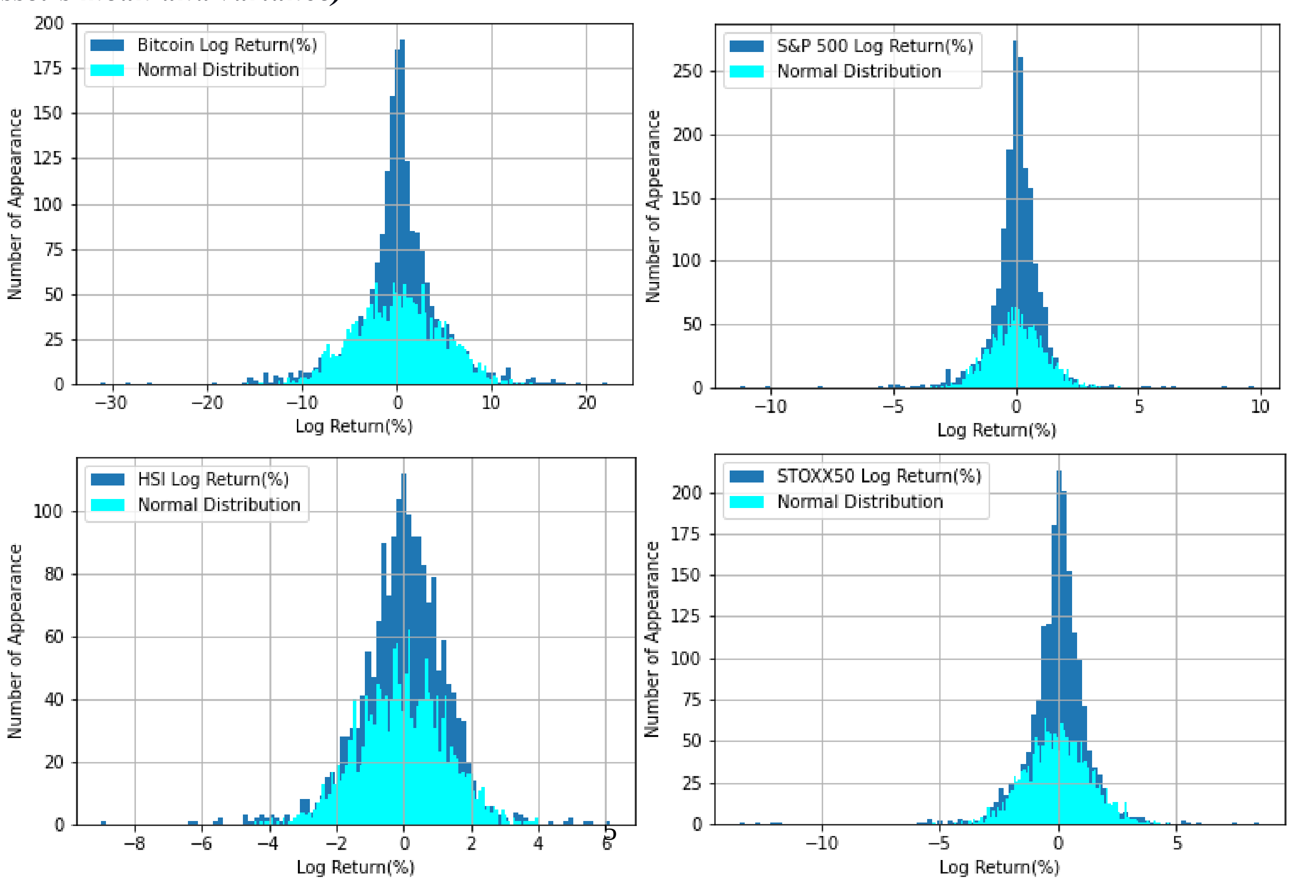
The descriptive statistics of the percentage log return series is shown in *table 1* and their distributions are displayed in *figure 2*.

As shown in *table 1* and *figure 2*, their means are close to 0 with Bitcoin's mean log return being slightly higher. The standard deviation of Bitcoin's log return is also higher given that Bitcoin is more volatile than stock markets (Baur & Dimpfl, 2017). All distributions are left-skewed, and they have fatter tails than normal distribution since their Kurtoses are larger than 3, which fits the typical characteristics of financial asset's return distribution.

Table 1

	Mean	Minimum	Maximum	Std	Skewness	Kurtosis
Bitcoin_r	0.2720	-31.1710	22.15	4.3991	-0.4194	5.2631
S&P500_r	0.0464	-11.2232	9.6808	1.0980	-0.8362	19.1528
HSI_r	0.0019	-8.9795	6.1059	1.2965	-0.5132	3.5340
STOXX_r	0.0138	-13.4476	8.5020	1.3387	-1.7182	19.0012

Figure 2 (Cyan bars represent random sampling result from a normal distribution with each asset's mean and variance)



3. Methodology

3.1 Definition of diversifier, hedge, and safe haven

This research adopts the definition of diversifier, hedge, and safe haven given by Baur and Lucey (2010) and Ratner and Chiu (2013). A diversifier is an asset that has a weak positive correlation with another asset on average. A weak (strong) hedge is an asset that is uncorrelated (negatively correlated) with another asset on average. A weak (strong) safe haven is an asset that is uncorrelated (negatively correlated) with another asset during times of stress.

3.2 Dynamic Conditional Correlation GARCH Model (DCC-GARCH)

The correlations which exist in financial time series are often time-varying in nature (Guesmi & Fattoum, 2014; Singhal & Ghosh, 2016). Hence, it may be unrealistic and limiting in estimating constant correlations between return series. This study applies the bivariate Dynamic Conditional Correlation GARCH Model developed by Engle (2002), which computes time-varying correlations between two variables using their past values and their GARCH volatilities.

The estimation of DCC-GARCH involves two steps. The first step accounts for the conditional heteroskedasticity using a GARCH(1,1) model. In the second step, a time-varying conditional correlation matrix is computed using the standardized residuals from the first step (Elie et al., 2017).

The GARCH(1,1) model is specified as:

$$r_t = \quad \mu_t + \omega\ r_{t-1} + \varepsilon_t$$

where r_t is the vector of the percentage log return of Bitcoin and that of the other asset. μ_t is the conditional mean vector of r_t; and ε_t is a vector of residuals. During estimation, ε_t's underlying distribution is assumed to be Student's t distribution instead of a normal one to account for the large Kurtosis in return series. The variance equation is specified as:

$$h_t = \; c + a \; \varepsilon^2_{t-1} + b \; h_{t-1}$$

where h_t is the conditional variance at time t.

After estimating the GARCH(1,1) model, the DCC equation is given by Q_t, which is a square positive-definite matrix in the form of

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha \; \varepsilon_{t-1}\varepsilon'_{t-1} + \beta \; Q_{t-1}$$

where Q_t is the time-varying unconditional correlation matrix of ε_t . ε_t is a vector of standardized residuals obtained from the first step.

The DCC between assets i and j at time t is then calculated by:

$$\rho_{ij,\; t} = \frac{q_{ij,t}}{\left(\sqrt{q_{ii,\; t}} \; \sqrt{q_{jj,\; t}} \right)}$$

3.3 Determination of diversifier, hedge, and safe haven

This study follows the method used by Ratner and Chiu (2013), where they deployed an OLS regression of the dynamic correlation on dummy variables indicating extreme downside movements of an asset to determine whether the other asset can effectively serve as its diversifier, hedge, or safe haven.

The model is given by:

$$DCC_{\;t} = m_0 + m_1 D(r_{other\;\; asset}\;\; q_{10}) \;+\; m_2 D(r_{other\;\; asset}\;\; q_5) + m_3 D(r_{other\;\; asset}\;\; q_1) + v_{\;t}$$

where DCC_t is the dynamic conditional correlation of Bitcoin with another asset at time t, $\mathrm{D}_{(r_{other\ asset}\ \mathrm{q_i})}$ represents a dummy variable indicating whether at time t, the return of the other asset is in the lower ith quantile of its sample distribution. $\mathrm{v_t}$ is the error term.

Bitcoin is a diversifier against the other asset if $\mathrm{m_0}$ is significantly positive. Bitcoin is a weak (strong) hedge against movements in the other asset if $\mathrm{m_0}$ is zero (negative). Bitcoin is a weak safe haven against movements in the other asset if $\mathrm{m_1}$, $\mathrm{m_2}$ and $\mathrm{m_3}$ are not significantly different from zero. It is considered a strong safe haven if these coefficients are negative.

3.4 Determination of a structural break

A paired sample t-test is conducted between the dynamic conditional correlation from before the break-point date and that from after the break-point date. A statistically significant difference in the result is considered evidence of a structural break.

4. Results

4.1 Structural Break

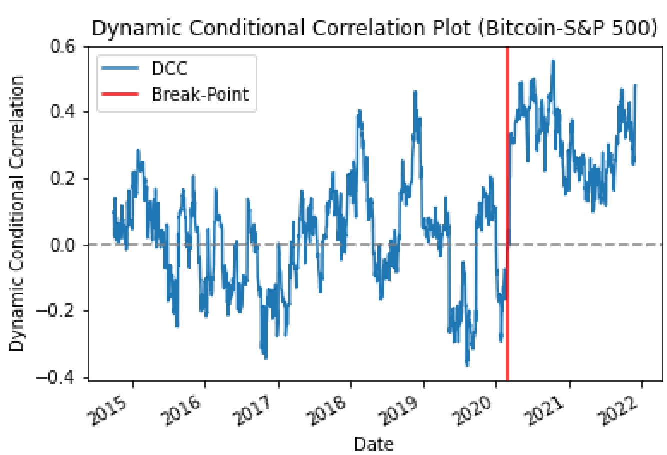
The estimated dynamic conditional correlations are shown in *figure 3*. For the specific parameter estimations of the GARCH model, see Appendix A. The p-values of parameter a and parameter b in the GARCH(1,1)'s variance equation are all statistically significant at 1% level, indicating a valid fit.

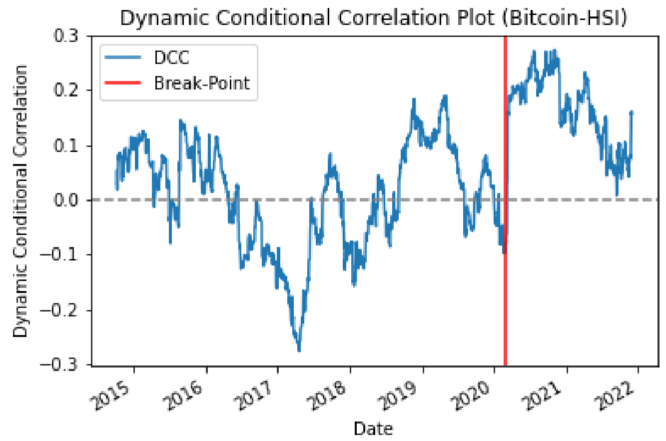
The result of t-test is shown in *table 2*. For all three indexes, their mean values of its correlation with bitcoin become larger after the outbreak of Covid-19 and the difference is statistically significant at 1% level. As also shown in *figure 3*, before the outbreak, the correlations seem to be a mean-reverting series around 0, whereas after, the correlations stayed on the positive side.

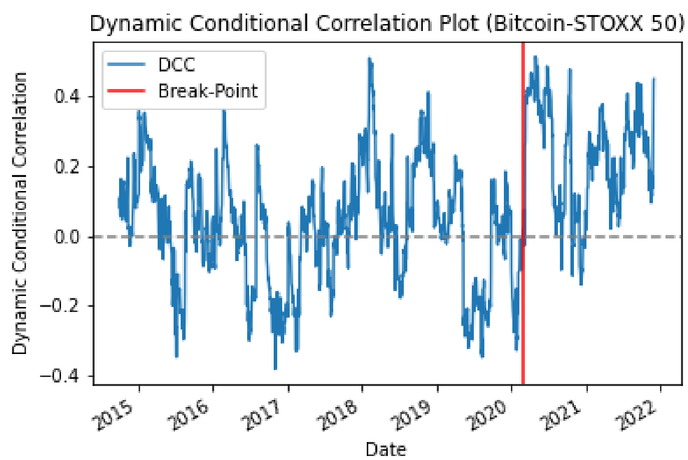
Table 2

DCC with Bitcoin	Mean	Variance	P-value (H_0: Equal Mean)
S&P500 Pre-Pandemic	0.0066	0.0230	0.0000
S&P500 During Pandemic	0.3055	0.0121	
Hang Seng Index Pre-Pandemic	0.0031	0.0090	0.0000
Hang Seng Index During Pandemic	0.1606	0.0049	
STOXX 50 Pre-Pandemic	0.0186	0.0289	0.0000
STOXX 50 During Pandemic	0.2308	0.0226	

Figure 3







4.2 OLS Regression

The result of the OLS Regression is shown in *table 3.* There's no evidence that Bitcoin is a hedge or safe haven for all three stock market indexes both before and during the pandemic. However, during the pandemic, Bitcoin became a diversifier for all the three stock markets, as the regression model's constant is significantly larger than 0, indicating positive correlation on average. Before the pandemic, Bitcoin was only a diversifier for Euro STOXX 50. The result is different from the findings of Elie et al. (2017) that Bitcoin had already served as a diversifier for U.S. stocks from 2011 to 2015.

Table 3

	Before the Outbreak				**After the Outbreak**			
	Constant (m0)	**1% quantile (m3)**	**5% quantile (m2)**	**10% quantile (m1)**	**Constant (m0)**	**1% quantile (m3)**	**5% quantile (m2)**	**10% quantile (m1)**
S&P 500	0.0044	-0.0492	0.0567**	-0.0007	0.3050***	−0.1089**	-0.0443	0.0386
HSI	0.0012	-0.0091	0.0192	0.0103	0.1619***	-0.0092	-0.0292	0.0027
STOXX50	0.0167***	0.0114	-0.0059	0.0211	0.2320***	-0.0178	0.0453	-0.0332

******* indicate statistical significance at 1% level, ****** indicate statistical significance at 5% level.

5. Discussion

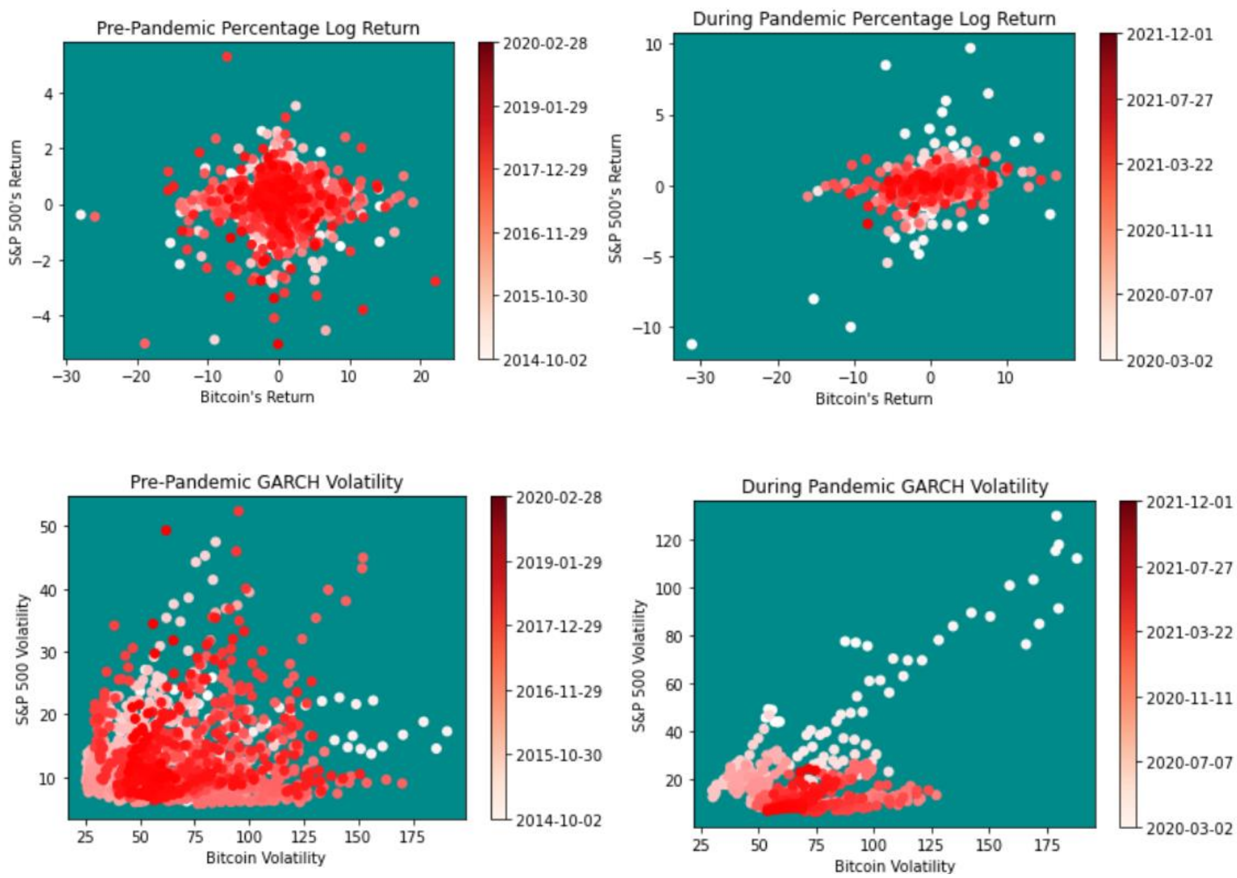
5.1 A Closer Look at the Correlation of Return and the Correlation of Volatility

From the GARCH(1,1) model, the conditional volatility of each asset is also computed. We can easily inspect the change in correlation between Bitcoin and the other asset's volatility as time passes by, as well as the change in correlation between Bitcoin and the other asset's log return, using scatter plots shown in *figure 4*. Given prior result of the study, one should expect that ideally the points during the pandemic in the scatter plot forms a line that slants up from left to right, while the points of Bitcoin with S&P500 and Hang Seng Index before the pandemic exhibits no pattern.

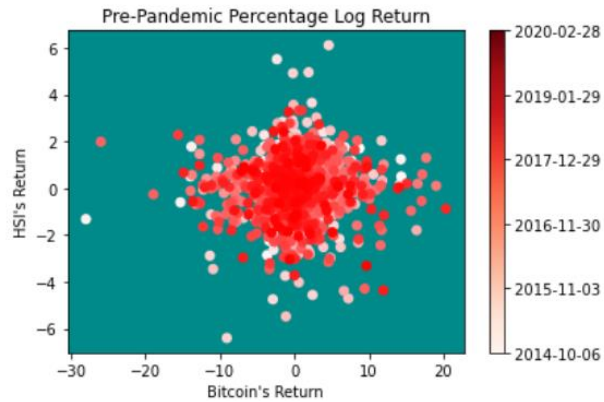
As shown in *figure 4*, it is indeed the case. Most points during the pandemic are around the diagonal. However, one could also see that in the first several months after the break-point date, all markets became extremely volatile, but as time passes by, their values gradually returned to normal. It may indicate a decline in correlation in the future, which can only be determined when more data is generated.

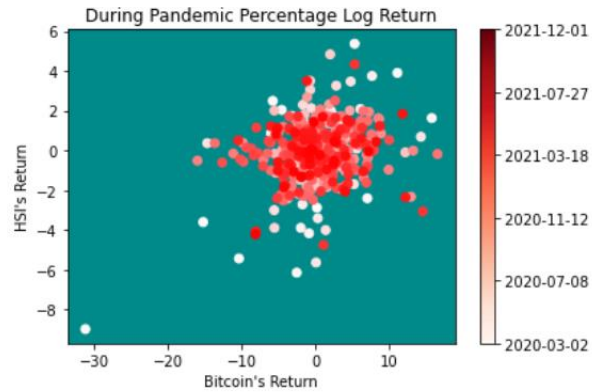
Figure 4 (The darker the color, the more recent the date of the data point.)

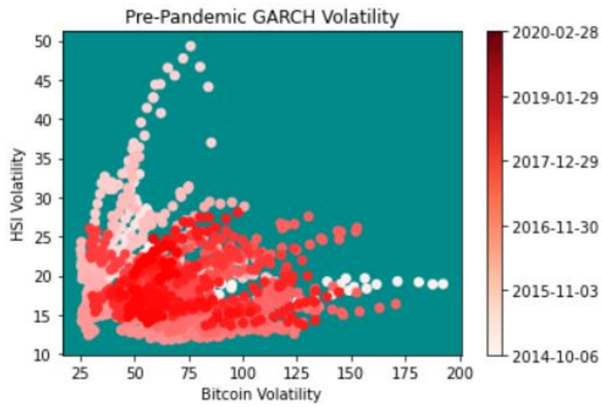
Bitcoin & S&P500

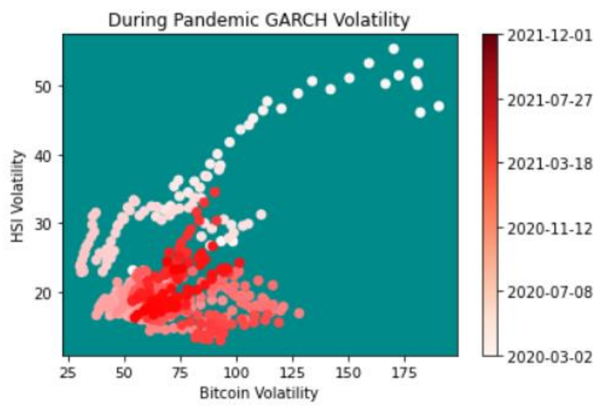


Bitcoin and Hang Seng Index

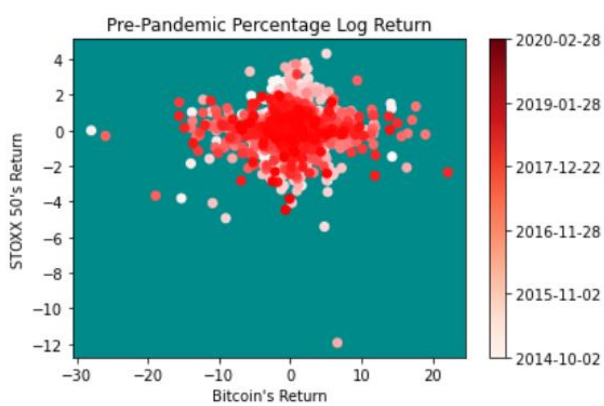


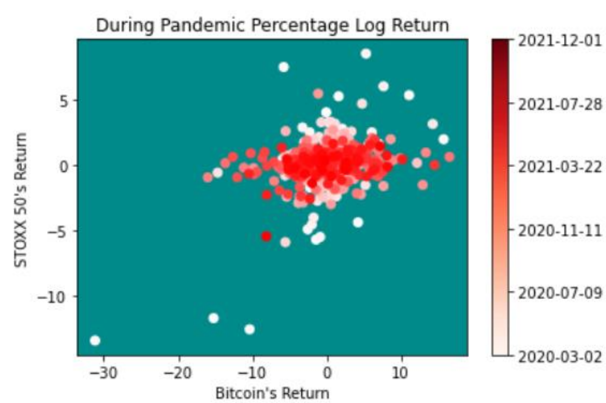


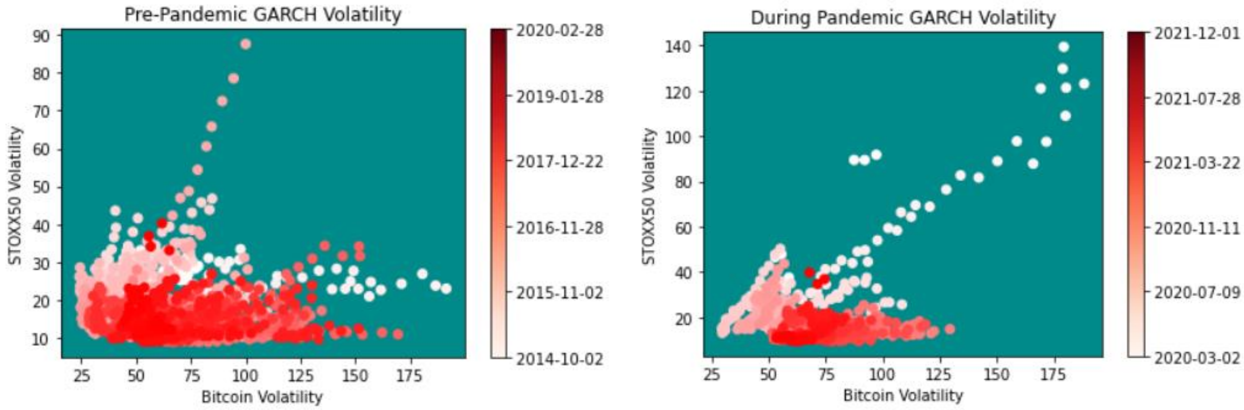




Bitcoin and STOXX50







5.2 Further Study

When studying correlations, there are few studies using timeframe lower than the daily timeframe. It is possibly due to the fact that stock markets usually do not open 24 hours a day while the bitcoin market does. Using low time frame may have the problem of unequal time intervals in the data. However, as different markets become increasingly more integrated given the development of technology and techniques of investing, it's beneficial to investigate correlations in lower timeframes to gain more insight.

The stock markets under investigation in the study can be considered as developed stock markets. One can research into the relation of Bitcoin with developing stock markets, or different types of markets such as the foreign exchange market to investigate Bitcoin's hedging properties against currencies.

One may also investigate the reason why Bitcoin and the U.S., Europe and Hong Kong's stock market indexes became correlated after the outbreak or how likely and how long the relationship will continue.

6. Conclusion

There was a structural break of the correlations between the returns of the three stock indexes and the return of Bitcoin after the Covid-19 outbreak, confirmed by t-test. Their correlations seem mean-reverting around zero before the pandemic but became statistically significantly positive during the pandemic.

Before the pandemic, Bitcoin only served as a diversifier for the European stock market from 2014 to 2020. During the pandemic, Bitcoin becomes a diversifier for all the three stock market indexes. But there’s no evidence of it being a hedge or a safe haven for any of the three markets before or after the Covid-19 outbreak.

In the scatter plot of return and volatility correlation, all three assets and Bitcoin became positively correlated during the pandemic. Additionally, all four assets became extremely volatile in first half of 2020, and gradually returned to normal as time passed by.

References

Aviral T., Elie B., Rangan G., David R. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters 23*, 87-95. Retrieved from https://doi.org/10.1016/j.frl.2017.02.009.

Bariviera AF, Basgall MJ, Hasperué W, et al. (2017). Some stylized facts of the Bitcoin market. *Physica A: Statistical Mechanics and its Applications 484*, 82–90.

Baur D., Dimpfl T. (2017). Realized Bitcoin Volatility. *SSRN Electronic Journal.* Retrieved from 10.2139/ssrn.2949754.

Brandvold M., Molnár P., Vagstad K., Valstad, O.C.A. (2015). Price discovery on Bitcoin exchanges*. The Journal of International Financial Markets 36*, 18–35.

Elie B., Peter M., Georges A., David R., Lars I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters 20*, 192-198. Retrieved from https://doi.org/10.1016/j.frl.2016.09.025.

Engle R.F. (2002). Dynamic conditional correlation – A simple class of multivariate GARCH models. *Journal of Business & Economic Statistics 20*, 339–350.

Khaled G., Salma F. (2014). Return and volatility transmission between oil prices and oil-exporting and oil-importing countries. *Economic Modelling 38*, 305-310. Retrieved from https://doi.org/10.1016/j.econmod.2014.01.022.

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

Shelly S., Sajal G. (2016). Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models. *Resources Policy 50,* 276-288. Retrieved from https://doi.org/10.1016/j.resourpol.2016.10.001.

World Health Organization. (2021). About the Virus. *Coronavirus disease (COVID-19) pandemic*. Retrieved from https://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/novel-coronavirus-2019-ncov

Appendix A: GARCH(1,1) Estimation

A.1 Bitcoin

	coefficient	Std err	p-value	95% Conf. Int.	
μ*	0.2328	0.0537	0.0000	0.1270	0.3380
ω	0.2167	0.1410	0.1240	-0.0594	0.4930
a*	0.1128	0.0158	0.0000	0.0818	0.1440
b*	0.8872	0.0213	0.0000	0.8460	0.9290
ν*	3.2325	0.1630	0.0000	2.9130	3.5520

v stands for degree of freedom of the Student's t distribution, the smaller the ν, the larger the Kurtosis (Kurtosis does not exist for v smaller than 4)
Other coefficients are given in *section 3.2*
* indicates statistical significance at 1% level

A.2 S&P 500

	coefficient	Std err	p-value	Conf. Int.	
μ*	0.0904	0.0129	0.0000	0.0065	0.1160
ω*	0.0284	0.0079	0.0000	0.0129	0.0438
a*	0.2459	0.0375	0.0000	0.1720	0.3200
b*	0.7541	0.0311	0.0000	0.6930	0.8150
ν*	4.8230	0.5360	0.0000	3.7720	5.8740

A.3 Hang Seng Index

	coefficient	Std err	p-value	Conf. Int.	
μ	0.0530	0.0249	0.0332	0.0042	0.1020
ω	0.0338	0.0205	0.0995	-0.0064	0.0741
a*	0.0743	0.0221	0.0000	0.0310	0.1180
b*	0.9065	0.0313	0.0000	0.8450	0.9680
ν*	7.4387	1.2510	0.0000	4.9880	9.8900

A.4 STOXX 50

	coefficient	Std err	p-value	Conf. Int.	
μ*	0.0765	0.0187	0.0000	0.0400	0.113
ω	0.0504	0.0139	0.0002	0.0232	0.0777
a*	0.1867	0.0328	0.0000	0.1220	0.2510
b*	0.7979	0.0290	0.0000	0.7410	0.8550
ν*	4.8859	0.5660	0.0000	3.7770	5.9950