Does the volatility of traditional financial markets affect the resilience of the cryptocurrency market?

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1.Introduction

As of the last decade cryptocurrencies have received a lot more attention and has become a major topic in every day media and is integrated to many investment platforms. However cryptocurrencies were already in their early stages since the 1980s. During this time David Chaum published his book on “Blind signatures for untraceable payments”. On top of that he created allegedly the first ever cryptocurrency named ‘ecash’ or “Electronic cash”, with the following properties: the inability of outside parties to determine the payee, timing, or volume of payments made by the other person. Ability of an individual to reveal payment documentation or, in special cases, to determine the payee's identity. Even though Digicash, the company that founded ecash went bankrupt in 1988 it played a major role in setting the foundation for future cryptocurrencies. After this there were various other failed attempts to create a lasting cryptocurrency such as E-gold, Bit-gold, Hashcash and B-money which eventually led to the creation of Bitcoin (Reiff, Rasure, & Kvilhaug, 2022).

Initially cryptocurrencies were designed as a means of payment that eliminated the need for central authority. This was enabled by the introduction of blockchain technology, which allows for the maintenance of a distributed ledger over a network of computers (Wang, et al., 2019).

Overall cryptocurrencies characteristics such as, decentralization, limited supply, volatility, liquidity, security, anonymity, transparency and programmability have led to both its popularity as well as its challenges (Katsiampa, 2020).

As of now the two cryptocurrencies with the biggest market-cap are Bitcoin (561.616 B) and Ethereum (226.733 B) (Yahoo Finance, 2023).

Bitcoin was created in 2009 by an anonymous developer under the alias Satoshi Nakamoto. Since then, hundreds of additional digital currencies have been inspired by bitcoin, giving it enormous global appeal (Peters, Rasure, & Clarine, 2021). At first Bitcoin was mainly used for transactions on the dark web for illegal activities. In the following years after its creates however Bitcoin has gained acceptance as a legitimate form of payment. On top of that its adoption also increased thanks to Bitcoin exchanges facilitating trade. Moreover, the price of Bitcoin has known significant fluctuations, large spikes as well as crashes. some of this volatility can be attributed to the fact that Bitcoin is still a relatively new technology and that speculative demand drives a big part of its value (Baur, Hong, & Lee, 2018).

Ethereum is a block-chain-based platform which has become popular due to its cryptocurrency ether (ETH). Even though Bitcoin and Ethereum have many similarities such as, being decentralized and using blockchain technology they still have a different long-term vision. Bitcoin was primarily designed to serve as a means of payment while Ethereum was designed to be a platform for decentralized applications. Even though Bitcoin is still the most well-known cryptocurrency, Ethereum has emerged as a crucial foundation for many blockchain-based projects due to its emphasis on smart contracts and decentralized apps and has now established itself as a significant participant in the world of cryptocurrencies and blockchain technology thanks to its capabilities and flexibility (Frankenfield, Anderson, & Kvilhaug, 2022).

As a potential substitute for Traditional financial markets, cryptocurrencies have drawn a lot of attention from investors and policymakers over the past 10 years. With millions of users worldwide, the top two cryptocurrencies by market capitalization—Bitcoin and Ethereum, attained previously unheard-of levels of valuation and acceptance. Cryptocurrencies continue to be a risky investment with fast price swings that can cause investors to lose a lot of money, despite their growing importance.

For this research the cryptocurrency index CCi30 will be used to best represent the entirety of the cryptocurrency market. The CCi30 is an index that keeps track of the market capitalization-based top 30 cryptocurrencies' performance. Cryptocurrencies like Bitcoin, Ethereum, Ripple and Bitcoin Cash are included along with many other crypto’s. In this research the cryptocurrency market will be represented by the CCI30, which offers a comprehensive and varied view of the market and its resilience in times of high volatility in traditional financial markets (Rivin, Scevola, & Yaron).

1.1 Research objective

The purpose of this research is to examine the relationship between the volatility of traditional financial markets and the resilience of cryptocurrencies. The aim of is this study is to determine whether and how the volatility of traditional financial markets affects these cryptocurrencies' resilience. The research will involve analyzing data on the fluctuations of traditional financial markets during periods of market turmoil and the corresponding changes in the prices and volatility of the CCi30 cryptocurrency index.

The rationale for this research question is to determine whether volatility in traditional financial markets has an effect on the resilience of the cryptocurrency market. Although they are viewed as a new and developing asset class with potential for investor diversification, cryptocurrencies are also known for their high volatility. Alternately, traditional financial markets have historically been impacted by range of factors, such as political and macroeconomic events. Hence, the purpose of this research topic is to clarify whether there is a connection between these two markets and how they might affect one another. Furthermore, this research could have implications for policymakers and investors to increase understanding of the intricacies of the cryptocurrency market and possible effect on the broader financial system.

1.2 Research question

Does the volatility of traditional financial markets affect the resilience of cryptocurrencies?

A statistical analyses will be used in order to examine the relationships between the variables. Methods such as regression analysis or correlation analysis can be utilized to determine whether or not there is significant relationship between the volatility of traditional financial markets and the resilience of cryptocurrencies.

1.3 Academic and practical relevance

This research aims to contribute on the existing literature on the relationship between cryptocurrencies and traditional financial markets. The goal is to provide valuable insights to future research on the extent to which volatility in traditional financial markets has an effect on the resilience of cryptocurrencies.

Moreover, this research could provide investors and policy makers with useful insights. By understanding the effect of the volatility of traditional financial markets on the resilience of cryptocurrencies investors can make a more informed decision when considering cryptocurrencies as an investment option.

Additionally this study can help policy makers to make judgments on how to incorporate cryptocurrencies into the current financial system. Furthermore, this study can also shed light on how cryptocurrency markets might react to broader economic trends, like financial crises.

2. Literature review

2.1 Relationship traditional financial markets and cryptocurrency market

The relationship between cryptocurrency market and traditional financial markets has generated a lot of discussion and study over the recent years. Numerous studies have made an effort to investigate this relation from different angles utilizing diverse data sources and methodologies. (Kurka, 2019) explores whether there is a connection between cryptocurrencies and traditional assets. This study concluded there is a negative correlation between Bitcoin and traditional asset classes, which indicates that they help investors diversify their portfolios. Nevertheless the study also found there is a positive correlation between Bitcoin and gold, suggesting that Bitcoin is a safe-haven asset.

The high-frequency asymmetric volatility between the main precious metal markets and Bitcoin is examined by (W., Kang, A., & A., 2019). According to this study there is a strong positive correlation between Bitcoin's volatility and that of gold, silver and platinum, indicating that Bitcoin, similar to precious metals can serve as a hedge against economic uncertainty and inflation. (Bouri, Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions, 2017) also found that Bitcoin has several hedging properties against global uncertainties, however this effect was not consistent across all the quantiles.

The quantile spillovers and dependence between Bitcoin, strategic commodities and stocks are investigated by (Urom, Abid, Guesmi, & Chevallier, 2020). According to this study there is a reciprocal relationship between Bitcoin and stocks. However, this effect is more prominent during extreme market events. Furthermore, this study found that Bitcoin is not yet regarded as a commodity or a currency, since it is less connected to strategic commodities.

(Maghyereh & Abdoh, 2021) investigate the time-frequency quantile dependency between global equity markets and Bitcoin. This analysis discovered a bidirectional between the two, yet again this relationship is more pronounced during extreme market conditions. According to this study the dependence between equity markets and Bitcoin differs across time-scales. This suggest that depending on the investment horizon, Bitcoin can have varying hedging properties. The study by (Kostika & Laopodis, 2020) also looks at the dynamic linkages between crypto currencies, exchange rates and the global equity market. The study's findings indicate that there is a bidirectional relationship between exchange rates and cryptocurrencies, with exchange rates having a greater impact on cryptocurrencies. Furthermore the study suggest there is an a unidirectional relationship between cryptocurrencies and global equity markets, with cryptocurrencies having a bigger impact on equities markets.

(Guo, Lu, & Wei, 2021) explores whether Bitcoin has a contagion effect on traditional financial markets. Contagion effects refer to how a shock from one market or asset can transfer to another. According to this study there is evidence of contagion effects from Bitcoin to traditional financial markets, which amplifies during the pandemic. Another study by (Elsayed, Gozgor, & Lau, 2022) with the aim to examine risk transmissions between Bitcoin and traditional financial markets. Specifically focusing on the Covid-19 era and global uncertainties, concludes that global uncertainties have a considerable result on the risk transmission between Bitcoin and traditional financial assets. This study found evidence of bidirectional risk spillovers where meaning shocks in one market can transfer to another. This study reveals that the relationship between the two markets is very dynamic and sensitive to changes in the global economic and political climate.

The aim of (Bouri, Salisu, & Gupta, 2023) was to look into the predictive power of Bitcoin prices on the volatility of returns of the US stock sector. Using a conditional correlation model and a quantile regression framework. The study's findings indicate that Bitcoin prices could potentially be used as an predictive indicator for the stock market. According to the study, Bitcoin prices can be a useful leading indication for the stock market, especially in forecasting high levels of volatility.

2.2 Relationship volatility traditional financial markets and resilience in crypto market

According to (Caferra & Vidal-Tomás, 2021) there is evidence to suggest that there is a link between volatility in traditional financial markets and resilience in the crypto market. The study found that there was high volatility in traditional financial markets during the Covid-19 pandemic, while the cryptocurrency market showed a higher degree of resilience recovering quickly from market downturns. Furthermore, (Bouri, Salisu, & Gupta, 2023) found that, especially during times of extreme market volatility, Bitcoin prices have a significant predictive power for the volatility of some US stock sectors. Moreover (Attarzadeh & Balcilar, 2022) indicates that there is evidence of a dynamic interconnection between resilience of cryptocurrencies and volatility of traditional financial markets, with significant volatility spillovers in both directions, becoming more extreme during market stress. Another study by (Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018) examines the dynamic relationships between cryptocurrencies and other financial assets, including stock indices, currencies, and commodities. The study found that there are significant correlations between several traditional financial assets and cryptocurrencies, and that these relationships are dynamic and fluctuate over time. At last the study suggest that the volatility of traditional financial markets may have an impact on how resilient the cryptocurrency market is.

2.3 cryptocurrency resilience

Before addressing the resilience of the cryptocurrency market it is important to look at what factors determine the resilience of traditional financial markets. (Kauê Dal'Maso Peron, da Fontoura Costa, & Rodrigues, 2012) Uses network theory to analyze the structure and resilience of the financial market. The paper identified several factors that contribute to the resilience of financial markets such as; , the presence of diversified investment portfolios, the degree of market integration, the availability of liquidity, and the ability of market participants to adapt quickly to changing market conditions. Furthermore it is argued that markets with a more decentralized and modular structure may be more resilient compared to markets with a higher degree of interconnectivity and clustering which are susceptible to systemic risks.

(Tang, Liu, & Zhou, 2022) Uses a global perspective to investigate the factors that determine the resilience of traditional financial markets. The paper indicates that financial development, and access to credit and financial institutions, has a significant impact on the resilience of financial markets. Moreover, the significance of regulatory frameworks and macroeconomic stability is also emphasized.

There are numerous studies that examine cryptocurrency resilience and potential factors that could influence this during different time periods.

The study by (Noda, 2020) explores market efficiency by using data from Bitcoin and Ethereum and discovered that the cryptocurrency market has improved in efficiency over time. An increase in market participation and trading volume has resulted in decreased in bid-ask spreads and an increase in price discovery. is principally responsible for the efficiency improvement. It is suggested that the increased market efficiency may conduce to make the Bitcoin market more resilient. As the cryptocurrency market will be more to quickly absorb and process new information.

Factors that could increase the resilience of and efficiency of cryptocurrency markets include: trading platforms, increased liquidity, improved regulatory frameworks, and greater adoption and acceptance of cryptocurrencies by mainstream financial institutions and the general public.

The study by (halfaoui, Gozgor, & Goodell, 2023) investigates the resilience of cryptocurrencies during the Russian-Ukraine war and suggest that cryptocurrencies, and especially Bitcoin was affected by the war. According to the study cryptocurrencies are not entirely resilient to geopolitical risk and can be influenced by outside forces beyond its control. (Melki & Nefzi, 2022) is another study that investigates cryptocurrency resilience during times of market turbulence. According to this study safe haven assets are those that provide profits during times of market turbulence. during the pandemic, cryptocurrencies, particularly Bitcoin and Ethereum, demonstrate substantial safe haven features, because of their shown resilience to outside shocks, this suggests that cryptocurrencies can serve as a dependable store of value and tool for diversification during periods of economic uncertainty. (Nguyen, 2022) Also suggests that Bitcoin can potentially serve as a safe haven asset since there is a low correlation between traditional assets and cryptocurrencies during these periods. Moreover, there was a significant decline in the correlation between Bitcoin and the stock market during the pandemic, indicating its resilience to economic shocks. This implies that Bitcoin has the ability to hedge against stock market volatility and diversify portfolios. (Fernandes, Bouri, Silva, Bejan, & Araujo, 2022) present a similar research namely, the impact of the COVID-19 pandemic on the efficiency of the cryptocurrency market. This study suggest that the crypto currency market may be resilient to outside shocks and found that although the pandemic did generate some short-term market volatility, the market's overall efficiency was not affected. This shows that even in times of crisis, the bitcoin market may be somewhat resilient and stable.

Bitcoin demonstrates the resilience of cryptocurrencies as a tool for portfolio diversification by acting as an effective hedge against liquidity risk in conventional financial markets. According to (Ghabri, Guesmi, & Zantour, 2021) findings, investors may benefit from integrating Bitcoin in their portfolios to reduce liquidity risk and boost portfolio resilience. (Scharnowski, 2021) Is another study that looks at the liquidity and implications for market resilience of crypto currencies. In financial markets liquidity is of very high importance because it ensures market efficiency and stability, as it enables investors to buy and sell assets quickly and efficiently. Without liquidity, markets can become unpredictable and volatile, as investors may find it difficult to buy or sell assets at fair prices, leading to large price swings and potentially distortions in the market. Furthermore, (Scharnowski, 2021) discusses cryptocurrency market resilience and how increasing Bitcoin liquidity might lead to this. Increased liquidity, can decrease price volatility and improve market stability.

2.3.1 Definition of cryptocurrency resilience

All of the before mentioned papers do not explicitly give a definition of cryptocurrency resilience, however a definition could be derived from these papers. Taking into account each of the papers above the term can be regarded as the ability of cryptocurrencies to resist and recover from a variety of external shocks, such as liquidity hazards, geopolitical risks, market inefficiencies, and economic uncertainties. Furthermore, the papers address various aspects of cryptocurrency resilience, such as safe haven characteristics, the relationship between cryptocurrencies and traditional financial markets, the effectiveness and liquidity of the cryptocurrency market and the lasting volatility of cryptocurrency markets. Some papers also look at the network structure, financial development, and the uncertainty of economic policies as potential influences on cryptocurrency resilience. overall, the studies suggest that cryptocurrencies can show varying degrees of resilience depending on the nature and magnitude of the external shock and the underlying factors that influence the cryptocurrency market.

2.4 Concluding cryptocurrency resilience

Summarizing these studies the main factors that determine cryptocurrency resilience are:

Market participation or volume is one of the most important components to the resilience of cryptocurrencies, since higher market participation leads to an increase in liquidity which is the ability to buy or sell a cryptocurrency fast and easily without a significant change in its price. Furthermore market participation can reduce market manipulation and increase trading diversity which helps to reduce herding behavior and other market inefficiencies, consequently further stabilizing the market.

Market efficiency is considered to be another key factor of cryptocurrency resilience. It is the extent to which market prices accurately reflect all available information and react quickly to new information.

Safe-haven properties: a cryptocurrencies ability to serve as a safe haven asset during periods of market or economic uncertainty

Another factor of cryptocurrency resilience is Volatility persistence which is the degree to which volatility in the cryptocurrency market persists over time.

Interconnectedness is also an important components of cryptocurrency resiliency, and is the extent to which cryptocurrencies are interconnected and how they are connected to traditional financial markets.

Dependence and spillovers are another aspect of a cryptocurrency's resiliency and is the extent to which is cryptocurrencies are connected to other financial markets, like equities and commodities.

The last identified factor to cryptocurrency resilience in these studies is the ability of a cryptocurrency to hedge against volatility in other asset classes, such as crude oil and gold.

3. Methodology

This research will be conducted in three stages. First of all we look at the existing research on cryptocurrencies and their resilience and their relationship to traditional financial markets. After that in order to perform the research we have to gather the data, this step will in itself consist of 2 different steps. Firstly it is of high importance to successfully identify periods with high volatility in traditional financial markets.

There are various methods to identify periods of high volatility in traditional financial markets. The first method is to Calculate the daily or weekly returns of a financial market index, like the S&P 500, and then estimating the standard deviation of those returns over a predetermined time period, like 30 days or 90 days. The standard deviation may be a sign of significant volatility if it is higher than usual.

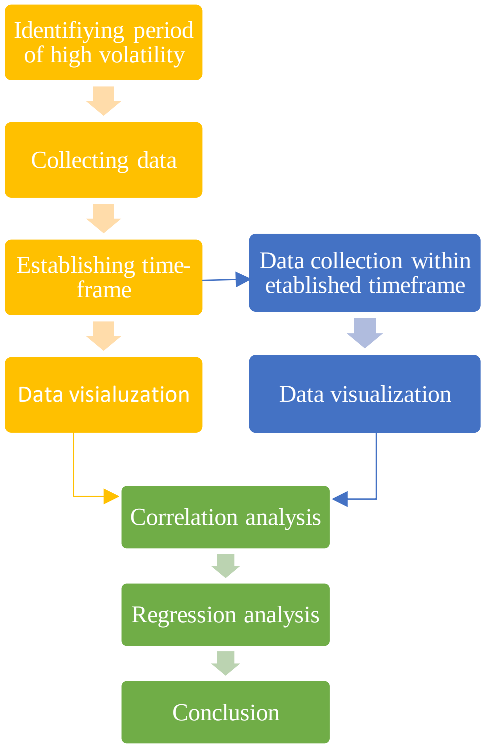
Another method to identify periods of high volatility in traditional financial markets is the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, which considers the market's current conditions and past volatility. Periods of high volatility can be found and the volatility of several time periods can be compared using the GARCH model (Kenton, 2020).

Another approach to identify high volatility in traditional financial markets is to focus on news sentiment in order to find periods of high uncertainty or market turmoil. Such as the Russian-Ukrainian war or the pandemic, which may be associated with high volatility.

Once we have identified these periods of high volatility in traditional markets. We will have to use the corresponding periods of the cryptocurrency market and conduct a correlation analysis and a regression analysis. With the correlation analysis we can examine the methodology the relationship between the volatility of the CCi30 cryptocurrency index which represent the entire cryptocurrency market and the volatility of traditional financial markets. With this method we can compute correlation coefficients to see how strong and in what direction the variables are related. The regression analysis will be used to measure whether the turbulence of established financial markets affects the resilience of cryptocurrencies.

All of the above methods will be used in combination in order to best estimate the effect volatility of traditional financial markets has on the resilience of cryptocurrencies. In order to process this data we will use R-studio.

At last the analysis phase where we will be conducting the research as it was previous planed and gather the results.



Identifying high volatility in traditional financial markets

A combination estimating the standard deviation and the volatility of S&P 500, The GARCH model and focusing on periods of high uncertainty will be utilized in order to effectively gather data on periods of high volatility in traditional financial markets.

Cryptocurrency data collection

The datasets of the cryptocurrency index Cci30 , will be collected from Cci30.com which is a website that specifically real time tracks and portrays data from the 30 largest cryptocurrencies by market capitalization, excluding stablecoins.

5. Data description

5.1 S&P500

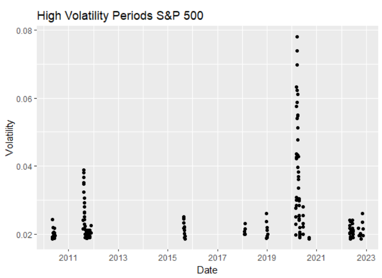
For this research 2 Datasets are needed. First of all data from the S&P500 index is needed in order to identify periods of high volatility in the traditional financial market and data from the cci30 index is needed in order to match these high volatility periods to the same periods, to examine the relationship between volatility in traditional financial markets and volatility in the cryptocurrency market and its resilience. In the literature review it is stated that volatility and Volume could be a factor in the resilience of crypto currencies. Since both of these are measurable variables we will be examining this relationship in this research section of the paper. In order to find the High volatility data in the S&P 500 the GARCH method was used. This study models volatility clustering in financial data using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) approach. The time-varying volatility in the traditional financial dataset can be described as a function of prior error terms using the GARCH model. Furthermore, in this research the GARCH method is employed to calculate the conditional variance of the S&P 500 index time series. Volatility clustering in the S&P 500 is captured by allowing the index variance to be time-varying and dependent on historical data. When predicting this conditional variance or volatility the 95th percentile is used meaning that if a value is higher than this it will be considered a period of high volatility. Furthermore, I chose to look at the high volatility periods since the development of cryptocurrencies started to take rise, so from 2010 to 2023 even though the cci30 index only has data availability from 2015 onwards.

Figure 1 below show a small sample of 10 rows of the high volatility periods matched with the dates, and table 2 shows a visual representation of this data.

Figure 1: Sample data S&P500 high volatility periods.

	Date	Volatility
1	2020-02-27	0.02509519
2	2022-05-23	0.01877769
3	2022-06-10	0.01904751
4	2020-06-11	0.02792252
5	2022-11-11	0.02354313
6	2020-04-14	0.02981779
7	2022-06-13	0.02407373
8	2015-09-08	0.01934988
9	2022-06-14	0.02166008
10	2022-06-24	0.01988808

Figure 2: Plot of high volatility periods S&P 500



5.2 cci30 index

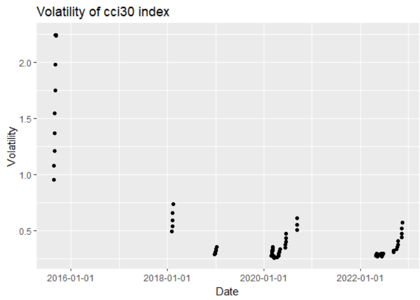
The cci30 index is a similar dataset to that of the S&P 500, however for this data the GARCH method does not have to be used. For this particular dataset the dates of the high period data of the S&P500 have to be matched with the dates of the cci30 index and the volatility has to be determined for this dataset. Data availability for the cci30 index started from the year 2015 onward, this is why only data from this periods onwards in considered in the continuation of this research. Furthermore, there will be two separate datasets and regressions since there is another dataset used of the cci30 index including the variable volume. However, a separate regression will be ran with this data since this dataset includes non-available data and had to be narrowed.

Figure 3 below shows a small sample of 10 rows of the corresponding volatility periods of the cci30 index to the high volatility periods of the S&P500 index, and Figure 2 shows a visual representation of this data.

Figure 3: Sample data cci30 index

	Date	volatility_index
1	2022-05-04	0.2843762
2	2020-03-06	0.3208748
3	2020-04-16	0.2679626
4	2022-06-17	0.2814693
5	2020-03-24	0.2598814
6	2020-05-01	0.3322935
7	2020-04-17	0.2706882
8	2020-04-29	0.3173457
9	2015-09-08	2.2437232
10	2015-08-28	1.3682040

Figure 4: Plot of corresponding volatility periods



5.2.1 cci30 index including volume

Figure 5 below consists of the volatility of the cci30 index and its volume during the corresponding periods. Because, some of the data was not available for this index a separate regression will be ran with this data since this dataset includes non-available data and had to be narrowed. The variable volume is also added to this new dataset.

Figure 5 : Sample data including volatility and volume of the cci30 index and high volatility periods of the S&P 500 index.

	Date	volatility_index	Volume	Volatility
1	2022-05-18	0.2757143	68618276864	0.02368931
2	2020-03-20	0.2595894	102580936704	0.05880461
3	2019-01-04	0.3373649	10802776064	0.02197589
4	2020-04-14	0.2661231	69374607360	0.02981779
5	2020-02-25	0.2729787	93202890752	0.01975546
6	2022-06-22	0.2934821	57523945472	0.01888404
7	2020-04-03	0.2652160	72601059328	0.03611909
8	2022-06-14	0.2753677	83829997568	0.02166008
9	2022-06-17	0.2814693	52773064704	0.02070384
10	2020-04-15	0.2676572	66115956736	0.02838913

5.3 Descriptive statistics of the data

As mentioned earlier different correlation analysis and regressions will be ran with the data shown in figure three and five. Firstly a correlation analysis was run which showed a correlation coefficient of -0.1284502. This means that there is a weak negative correlation between the volatility the S&P500 index representing traditional financial markets and the cci30 index representing the cryptocurrency market. The negative sign indicates that if the volatility of traditional financial markets increases, the volatility of cryptocurrency tends to decrease, and vice versa. The absolute value of the correlation coefficient, however suggests that this relationship is weak.

In the next step of this research a regression has to be run in order to examine the significance and magnitude of the relationship between variables. The regression analysis came up with the following result shown in table 1. For the data not to be biased outliers were taken out of the dataset.

The outcome of the linear regression model shown below where the volatility of the traditional financial market is the independent variable and the volatility of the cryptocurrency market is the dependent variable.

The coefficient of volatility the S&P500 index is related with a p-value of 0.0722, which is bigger than 0.05 and shows that the coefficient is not statistically significant at the 5% level. However it is significant at the 10% level.

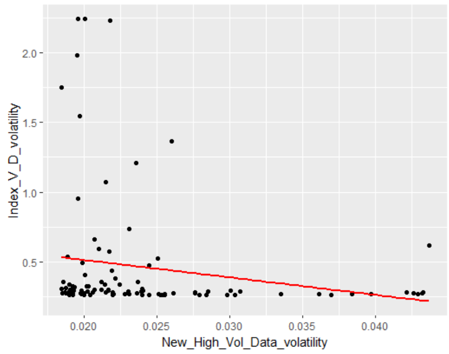
The dependent variable's variation can only be partially explained by the independent variable in the model, according to the R-squared value of 0.03399.

Table 1: Regression analysis Volatility cci30 index ~ Volatility S&P 500

	estimate	Std. error	t-value	Pr(>[t])
Intercept	0.7629	0.1730	4.410	2.75e-05
Volatility S&P500	-12.5376	6.8942	-1.819	0.0722
R-squared	0.03399			
Adj. R-squared	0.02371			
F-value	3.307			
P-value	0.07216			94 DF

Below you can see the regression plotted with on the X-axis the volatility of the S&P500 and on the Y-axis the volatility of the cci30 index. The points are plotted against each other and a regression line is drawn between them.

Figure 6: Regression plot without outliers



5.3.1 Descriptive statistics of the data 2

As mentioned before the data used in this part of the research can be seen in Figure 5. In this table the volume is included and outliers are yet again excluded. The three variables that were utilized to determine the correlation coefficients are the volatility of S&P500 the volatility of the cci30 index and the volume of the cci30 index The correlation coefficients between these variables are displayed in the matrix below. The diagonal component of the matrix naturally has a constant correlation coefficient of 1. The elements outside of the diagonal stand in for the correlation coefficient between two pairs of variables. In this table we look at the correlation between Variable 1 and Variable 3 which is 0.10607064, and the correlation between Variable 1 and Variable 2 which is -0.34175113. This means that there is a moderate negative correlation between Volatility of the S&P500 and volatility of the cci30 index. Furthermore, there is a weak positive correlation between the volatility of the S&P500 and the volume of the cci30 index.

Table 2: Correlation matrix with variables

	Volatility	Volatility index	Volume
Volatility	1.000	-0.34175113	0.10607064
Volatility index	-0.34175113	1.000	-0.07026508
Volume	0.10607064	-0.07026508	1.000

Since there are more variables available in the model it is important to run multiple regression in order to find out whether there are possible interaction playing a role in the results. Four linear regression models are included in the code. Model 1 attempts to forecast volatility of the S&P500 based on volatility of the cci30 index and volume. Model 2 aims to forecast volatility of the cci30 index based on volatility of the S&P500 and volume. Model 3 forecasts volume based on volatility of the S&P500 and volatility of the cci30 index, and Model 4 tries forecasting volatility of the cci30 index based on the interaction between volatility of the S&P500 and volume of the cci30 index.

We can see from the summary result that model 1 has a significant intercept and coefficients for the volatility of the cci30 index. However volume may not be a major predictor of volatility, according to the coefficient's lack of significance. Model 1's adjusted R-squared value is 0.1043

Table 3: Model 1, Volatility ~ volatility_index + volume

	estimate	Std. error	t-value	Pr(>[t])
Intercept	4.765e-02	7.004e-03	6.804	1.05e-09
Volatility index	-6.533e-02	1.913e-02	-3.415	0.000955
Volume	3.184e-14	3.798e-14	0.838	0.404109
R-squared	0.1236			
Adj. R-squared	0.1043			
F-value	6.415			
P-value	0.002477			91 DF

Model 2's intercept and volatility coefficients are both significant, but the volume coefficient is not. This shows that Volatility of the cci30 index may not be significantly predicted by Volume. Model 2's modified R-squared value is 0.09858. The p-value is 0.003308 which is significant at the 5% level.

Table 3: Model 2, Volatility index ~ Volatility + Volume

	estimate	Std. error	t-value	Pr(>[t])
Intercept	3.696e-1	2.165e-2	17.074	<2e-16
Volatility	-1.739e+00	5.092e-1	-3.415	0.000955
Volume	-6.830e-14	1.966e-13	-0.347	0.729046
R-squared	0.118			
Adj. R-squared	0.09858			
F-value	6.085			
P-value	0.003308			91DF

The coefficient of Model 3 volatility of the S&P500 and intercept are both statistically significant, however the coefficient for volatility of the cci30 index is not. Consequently, the volatility of the cci30 index might not be a reliable indicator of volume. For model 3, the adjusted R-squared value is -0.009141. The P value of this model is not significant at the 5% level.

Table 4: Model 3, Volume ~ volatility + volatility index

	estimate	Std. error	t-value	Pr(>[t])
Intercept	7.712e+10	2.223e+10	3.470	0.000799
Volatility	2.407e+11	2.871e+11	0.838	0.404109
Volatility index	-1.940e+10	5.583e+10	-0.347	0.729046
R-squared	0.01256			
Adj. R-squared	-0.00914			
F-value	0.5788			
P-value	0.5626			91 DF

Along with effects of Volatility and Volume, Model 4 also contains an interaction term between the two. The interaction term enables the level of the other variable Volume to influence the impact of one variable Volatility of the S&P500 on the response variable volatility of the cci30 index.

There is no indication that the influence of volatility of the S&P on volatility of the cci30 index depends on the level of volume because the coefficient for the interaction term is not significant at the 0.05 level. However, Volatility and Volume both show sizeable coefficients in this model, indicating that each has a separate impact on the volatility of the cci30 index.

Table 5: Model 4, volatility index ~ volatility * volume

	estimate	Std. error	t-value	Pr(>[t])
Intercept	3.751e-01	4.604e-02	8.148	2.02e-12
Volatility	-1.977e+00	1.832e+00	-1.079	0.284
Volume	-1.331e-13	5.185e-13	-0.257	0.798
Volatility: volume	2.796e-12	2.067e-11	0.135	0.893
R-squared	0.1181			
Adj. R-squared	0.08875			
F-value	4.019			
P-value	0.009852			90 DF

This model's adjusted R-squared value is 0.08959, which indicates that it accounts for nearly 9% of the variance in the volatility index. This is not a very good fit, and it implies that there may be additional predictive factors.

5.3.2 Descriptive data Covid period

In order for this research to be as specific as possible it is also important to take into account the possible effect and bias the covid period can have on the data. This is why for the following steps we introduced a dummy variable to specify the covid periods. Either a '0' for the periods outside of covid or a 1 for the periods that lie within the covid period (2020-06-2021) as can be seen below.

Figure 7: Dataset with dummy variable covid period

	Date	volatility_index	Volatility	Volume	COVID_Period
1	2020-02-25	0.2729787	0.01975546	93202890752	1
2	2022-06-22	0.2934821	0.01888404	57523945472	0
3	2020-04-03	0.2652160	0.03611909	72601059328	1
4	2022-06-14	0.2753677	0.02166008	83829997568	0
5	2022-06-17	0.2814693	0.02070384	52773064704	0
6	2020-04-15	0.2676572	0.02838913	66115956736	1
7	2022-06-10	0.2961714	0.01904751	58473058304	0
8	2020-03-05	0.3080043	0.03069812	81489248256	1
9	2020-03-30	0.2608574	0.04775628	69011709952	1
10	2019-01-04	0.3373649	0.02197589	10802776064	0

As done before a correlation matrix is needed to find out whether there are positive or negative correlations between the different variables.

Table 6: Correlation matrix with covid period

	Volatility	Volatility index	volume	Covid-period
Volatility	1.000	-0.34175	0.106070	0.5322
Volatility index	-0.34175	1.000	-0.070265	-0.08035
Volume	0.10607	-0.07026	1.000	0.1456
Covid-period	0.53224	-0.08035	0.14562	1.000

As already seen before the volatility of traditional financial markets and the volatility of the cryptocurrency index is moderately negative (-0.342). This means that an increase in volatility of traditional financial markets will lead to a decrease in volatility of the cryptocurrency market. Furthermore, the volatility of traditional financial markets and volume of the cryptocurrency market have a 0.106 weak positive correlation. This shows that, despite the correlation being fairly weak, the trading volume of the cryptocurrency market tends to increase as the financial markets' volatility increases. Moreover, the covid period and volatility of traditional financial market have a positive correlation (0.532). This suggests that there was an increase in market volatility during the Covid period (from June 2020 to June 2021). In short, These correlation coefficients point to some possible links between the variables but do not necessarily prove causality. Although the correlations imply that the volatility of traditional financial markets and the covid period may have an effect on the volatility of the cryptocurrency market. However a regression model would be required to determine the statistical significance and magnitude of these relationships.

Table 7: Regression analysis with covid period, volatility index ~ volatility + volume + covid period

	estimate	Std. error	t-value	Pr(>[t])
Intercept	3.711e-01	2.161e-02	17.174	<2e-16
Volatility	-2.136e+00	5.964e-01	-3.581	0.000555
Volume	-9.473e-14	1.970e-13	-0.481	0.631835
Covid period	2.1913e-02	1.730e-02	1.266	0.208674
R-squared	0.1334			
Adj. R-squared	0.1045			
F-value	4.618			
P-value	0.004731			90 DF

When all other factors are held constant, the intercept has a substantial positive effect on the volatility of the cryptocurrency market, with an estimated coefficient of 0.3711 and a significant p-value of 2e-16. Furthermore, volatility is projected to have a coefficient of -2.136 and a significant p-value of (0.000555). This shows that, while leaving all other factors constant, an increase in volatility of traditional financial markets is correlated with a decrease in the volatility of cryptocurrency markets. Moreover, With a p-value of 0.631835 and an estimated coefficient of -9.473e-14, volume is not statistically significant. This suggests that after taking into account the influence of other variables in the model, Volume might not have a significant impact on the volatility of the cryptocurrency market. At last, with a p-value of 0.208674, the estimated coefficient for the covid period is not statistically significant at 0.02191. This implies that there isn't solid proof that the volatility of traditional financial markets is significantly different during the covid period compared to other periods. In total the regression model is statistically significant, which means that at least one of the predictors in the model has a substantial impact on the volatility of cryptocurrencies, according to the F-statistic of 4.618 and p-value of 0.004731.

6. Discussion

According to the data above, there seems to be a weak negative correlation between the volatility of the S&P 500 index, representing traditional financial markets, and the cci30 index, which represents the cryptocurrency market. The volatility of cryptocurrencies has the tendency to decrease as the volatility of traditional financial markets increases, and the other way around. Furthermore, the results of the regression study, revealed that the correlation between the volatility of the cryptocurrency market and the volatility of the S&P 500 index with a p-value of 0.0722 is statistically significant at the 10% level but not at the 5% level. Therefore, the dependent variable's volatility can only be partially explained by the independent variable in the model, according to the R-squared value of 0.03399.

The correlation between the volatility of the S&P 500, the volatility of the cci30 index, and the volume of the cci30 index was also further investigated. The volatility of the S&P 500 and the volatility of the cci30 index were shown to have a moderately negative correlation. Additionally, there is a weak positive association between the volume of the cci30 index and the S&P500's volatility.

For the cci30 index's volatility, Models 1 and 2 produced significant intercepts and coefficients, the coefficient for volume however was not. The S&P500 volatility and intercept coefficients in Model 3 were both statistically significant, however the cci30 index volatility coefficient was not. However, the interaction term was not statistically significant. Model 4 exhibited considerable coefficients for both the volatility and volume, demonstrating that each has a significant impact on the volatility of the cci30 index.

Of the regression including the covid period it can be said that the volatility of traditional financial markets significantly lowers the volatility of cryptocurrency markets, whilst the volume and covid period have no significant influence. These findings imply that volatility in the traditional financial markets might have an impact on the volatility of cryptocurrency market measured by resilience. However, the model's overall explanatory power is modest, and additional variables that affect the resilience of the cryptocurrency market that are not considered in the model may exist.

7. Conclusion and implications on cryptocurrency resilience

The results of this study on how the S&P500 index, which represents the traditional financial market, and the cci30 index, which represents the cryptocurrency market, relate to one another may have a variety of effects on the resilience of each market.

First, there is a weak negative correlation between the volatility of the two markets, which could be a sign of their independence from one another and increase their resilience. Meaning a decrease in one market may not necessarily result in decrease in the other market. This may imply that investors have the chance to diversify their portfolios across both traditional and cryptocurrency markets, thereby possibly lowering their overall risk exposure.

Second, even though there may be some meaningful links between the volatility of the S&P500 index, the volatility of the cci30 index and the volume of the cci30 index, the results of the multiple regression analysis reveal that these are generally weak. This indicates that the cryptocurrency industry might still be developing and has not fully assimilated into the world’s financial system during these examined periods. This lack of integration might be viewed as a weakness in the durability of the bitcoin market, making it more vulnerable to shocks from outside sources and possibly the lack of the same level of institutional support as that of traditional financial markets. The cryptocurrency market may be able to preserve its independence and adaptability in the face of economic and political instability, which might be viewed as a plus for the resilience of the cryptocurrency market.

Overall, the results of this study point to a complicated and still-evolving interaction between the traditional financial markets and the cryptocurrency market. Although there may be some strong connections between these markets, they are generally weak, indicating that each market has a chance to keep its resilience and independence in the face of outside disruptions and shocks.

7.1 Limitations

There are some limits to both correlation and regression analysis that should be taken into account:

While correlation analysis can reveal links between variables, it does not determine a cause-and-effect relationship, consequently correlation does not imply causality. Another limitation is the range of volatility: Volatility cannot accurately gauge the robustness of cryptocurrencies on its own. For a complete understanding, additional elements including liquidity, trading volume, and market capitalisation must be taken into account. Furthermore, market manipulation can cause unpredictably fluctuating prices because cryptocurrency markets are susceptible to fraud and market manipulation. There is a chance that correlation and regression analysis won't properly account for these issues. An accurate assessment of the robustness of cryptocurrencies must take into account these constraints. To fully comprehend the dynamics and resiliency of the cryptocurrency market, more research incorporating more variables and causes are required.

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