ERASMUS UNIVERSITY ROTTERDAM

ERASMUS SCHOOL OF ECONOMICS

Bachelor Thesis Economics & Business

The interrelation between returns, trading volume and volatility in the cryptocurrency market

Author: Dylan Wolter

Student number: 426360

Thesis supervisor: Mr. Sebastian Vogel

Second reader: [title and name of second reader]

Finish date: 12 July 2023

ABSTRACT

In this thesis, I examine the interrelationship between return, trading volume and volatility in the cryptocurrency market. I collected daily and weekly data during the period of July 26, 2017 to December 31, 2022 for the three largest cryptocurrencies (bitcoin, ether and binance coin), utilizing multiple univariate and multivariate regression models I analyze the variables that can explain cryptocurrency return, trading volume and volatility. I find that all the cryptocurrencies investigated in this thesis exhibit no trading volume-return interrelationship. However, the interrelation between trading volume and volatility is significant across the cryptocurrency market. Lastly, I discover that cryptocurrency assets display a varying volatility-return interrelationship, with binance coin revealing a significant positive interrelation and bitcoin and ether displaying no relationship.

Keywords: Cryptocurrency, Asset Return, Trading Volume, Volatility

JEL codes: G120

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1 Introduction

From being called cyber currencies in the 1980's to an expected global market size of 11.71 billion U.S. dollars by 2030, cryptocurrencies have taken the global interest of many investors (Grand View Research, 2022). Cryptocurrencies refer to virtual money or digital currencies that grant you the possibility to transfer funds without intermediaries over the internet. Cryptocurrency relies on a digital bookkeeping system called Blockchain. Starting with the relevancy of bitcoin (BTC), the first decentralized cryptocurrency, in 2009 many new cryptocurrencies emerged in the crypto market. The most popular of which being ether (ETH) and binance coin (BNB). Cryptocurrency differs from traditional currencies in many ways. Currently the value of a U.S. dollar investment fluctuates based on factors like national interest rates and government policy. Cryptocurrencies however trade at prices based on the perceived value of their associated platforms and projects (Bianchi, 2020). With its low entry barrier and high availability of data the cryptocurrency market is a growing interest of academic research. The interpretation of return, trading volume and volatility in the cryptocurrency market is not yet clear. In this paper I study the relationship between these factors in the cryptocurrency market. The interpretation of these factors will help future investors in the cryptocurrency market make more informed investment decisions.

Previous papers which examine the relationship between price, trading volume and volatility in the stock market have found that for some countries returns cause trading volume and vice versa. The results indicate that trading volume contributes some information to the returns process (Chen et al., 2001). Focusing on the relationship in the crypto market, research on this relationship for the largest cryptocurrency bitcoin concludes that daily volatility is correlated with and can be predicted by the trading volume of bitcoin (Aalborg et al., 2019). However, the weekly volatility does not show similar results. On the contrary research by Balcilar et al. (2017) fails to detect Granger causality of volume causing returns. This might be a result of the differing data used in the research with the latter using data preceding the bitcoin boom of 2017. Showing that differing data horizons may conclude unexpected results. Extending this to different cryptocurrencies with research by Bouri et al. (2018), which finds evidence of Granger causality from trading volume to the returns of the seven largest cryptocurrencies. This research uses a very different method to previous research with the use of a copula-quantile causality approach. Also mentioning that the causality is not present when considering price volatility. The research suggests that there is a relationship between these factors for the cryptocurrency market but that this might differ between the different cryptocurrencies.

In this paper I replicate the research by Aalborg et al. (2019) on the three cryptocurrencies with the largest market capitalization: bitcoin, ether and binance coin. Much less is known about cryptocurrencies other than bitcoin as much of the previous research on the cryptocurrency market solely focuses on the cryptocurrency with the largest market capitalization: bitcoin. Cryptocurrencies like ether and binance coin are compelling for testing the validity of the findings by Aalborg et al. (2019) because of the fundamental differences between these cryptocurrencies such as the identity management of their ledger writers, consensus algorithms and the coin supply attached to the cryptocurrencies. This fundamental difference between cryptocurrencies might translate into differences of measured returns, trading volume and volatility of the associated cryptocurrencies. Evidence indicates that these factors have a determining factor on cryptocurrency performance and financial influence (Li and Whinston, 2020). It remains unclear if the interpretation of returns, trading volume and volatility differ between cryptocurrencies or are similar across the cryptocurrency market. Studying bitcoin, ether and binance coin instead of solely focusing on bitcoin may extend our understanding of this interpretation in the cryptocurrency market. In this thesis, I will explore these ideas in greater detail by answering the following research question: "What is the interrelation between return, trading volume and volatility in the cryptocurrency market?"

The main variables of interest of this study are return, trading volume and volatility. Multiple univariate and multivariate regression models are estimated using daily and weekly data for the period of July 26, 2017 to December 31, 2022, with return, trading volume and volatility as dependent variables. The models do not exclusively consist of the aforementioned variables, moreover unique addresses, VIX index and google trends are used as independent variables. The data on cryptocurrency prices and trading volume is collected from coinmarketcap.com. The returns (in U.S. dollars) are calculated by converting cryptocurrency prices into returns to make them stationary. Trading volume is standardized by subtracting the average volume from the original sample data volume and dividing by the standard deviation of the average volume. The volatility used in this study is based on the concept of historical volatility utilized by Kaya and Mostowfi (2022) in their study of the cryptocurrency market. In my analysis I use the concept of historical volatility with a look-back period of six months. The data used for the calculation of historical volatility is extracted the return data previously mentioned. Unique addresses represent a single user's account and are transformed in a similar way to the returns to better fit the data. Data for Unique addresses is collected from sentiment.net, messari.io bscscan.com and coinmetrics.io. Similarly, the VIX index is transformed in this way and is extracted from Yahoo Finance. The data collected from Google trends was altered following research by Bijl et al. (2016), in which they transformed the data by standardizing it in an identical manner to the trading volume mentioned above. The unit of analysis is cryptocurrency, with each model focusing on factors collected from a specific cryptocurrency. The data on cryptocurrencies used in this paper are collected from many different sources, with its beginning point depicted by its availability.

I hypothesize that trading volume will have a significant effect on volatility with this effect being larger for bitcoin than for ether and binance coin. Due to bitcoin occupying the largest market capitalization, I expect to find that the market will follow the movements of bitcoin even if this is to a lesser extent. This should be visible in the results for the multivariate regression model using volatility as the dependent variable. Furthermore, my expectations are that trading volume will have no significant effect on the returns in the cryptocurrency market, which should be visible in the insignificant effect of this factor in the return's multivariate regression model. This is partly due to my belief that the returns of cryptocurrencies will replicate those of other financial assets. However, I do expect that the volatility and return in the cryptocurrency market may have correlations to factors not previously mentioned in research on different financial assets. From these results, I believe other researchers will have the incentive to explore the relationship between return, trading volume and volatility more profoundly between different cryptocurrencies. Moreover, the methods used in this paper will serve future researchers in investigating the factors that impact the cryptocurrency market in more detail.

The structure of the paper is as follows: Section 2 presents the theoretical framework, Section 3 describes the data, Section 4 outlines the methodology, Section 5 examines the results and provides a discussion, Section 6 concludes.

CHAPTER 2 Theoretical Framework

2.1 Cryptocurrencies

In our contemporary society the phenomenon known as cryptocurrency is accruing significant attention. From one point of view, it is built on a new technology of which the potential is not yet fully understood. Conversely, in its current form, it satisfies comparable functions as more traditional assets. Relying on its transmission of digital information, cryptocurrencies use cryptographic systems to legitimize unique transactions. Theoretical literature on cryptocurrencies suggests that several factors are potentially of importance in the valuation of cryptocurrencies.

For the purpose of this research, I will first give an in-depth examination of the cryptocurrency market, as this will provide some context to how the cryptocurrencies used in this research (i.e., bitcoin, ether and binance coin) differ from one another.

2.1.1 Bitcoin

Starting with the first decentralized cryptocurrency to appear on the market in 2009: bitcoin. According to Webster's dictionary, bitcoin is defined as a digital currency created for use in peer-to-peer online transactions (Merriam-Webster, n.d.). The academic definition of bitcoin is comparable: As a peer-to-peer electronic cash system enabling online transactions to be sent directly from one party to another without having to go through a financial institution (Nakamoto, 2008). Moreover, some researchers find similarities between bitcoin's features and those of gold and fiat money such as the U.S. dollar, defining bitcoin as a synthetic commodity money (Selgin, 2015). Bitcoin's popularity among practitioners soared in the late 2000's in response to the discernible failures of central banks and governments during the great recession of 2008 and the European sovereign debt crisis. Moreover, the reason for the sudden surge in popularity of bitcoin is because, unlike conventional currencies, bitcoin is fully decentralized and does not rely on central banks or government input. To dive deeper into this topic, I will provide a description of how bitcoin was introduced and its intricacies.

Bitcoin was introduced as a solution to the reliance of commerce on financial institutions serving as trusted third parties when dealing with electronic payments. The model currently in use by businesses with online transactions suffers from the weakness that financial organizations cannot make completely non-reversible transactions. Financial institutions must resolve disputes when they occur and reverse transactions when needed. This problem falls away when dealing with in person transactions, because of the use of physical currency. However, online transactions do not have a mechanism in place that does not involve a trusted third party. Nakamoto (2008) believes that what is needed to eliminate this complication is the use of an electronic payment system based on cryptographic proof rather than trust. This resolves the need of a trusted third party to be involved in an online transaction. The irreversible nature of these transactions will protect online businesses from fraud.

Bitcoin is an electronic coin which is defined as a chain of digital signatures. Each owner of a coin transfers it to the next by digitally signing a hash[1] of the coins previous transaction and attaching the public key of the next owner together with the hash to the coin's information. A hash is used to encrypt the data. The problem that arises in such a digital transaction is that the seller cannot verify that one of the previous owners did not double-spend the involved coin. Double spending is a problem that occurs with transactions using digital currencies, where the same currency is being spent multiple times. To combat this problem, the seller requires information on previous owners that indicates that they did not sign any earlier transactions using the coin. Nakamoto's solution to this problem, without the use of a third party, was by making all past transactions of a coin publicly available. The seller requires proof that at the time of a transaction, the majority of nodes[2] agreed that it was the first received. Moreover, a node supports the network by validating and relaying transactions. The proof the seller requires starts with the timestamp server.

A timestamp server functions by timestamping and widely publishing a hash of a block[3] of items. Moreover, this timestamp proves to sellers that the data must have existed at the time of a transaction. This procedure is then repeated for each proceeding timestamp, thus creating a chain in which each timestamp includes and is reinforced by the hash of the previous timestamp. For the implementation of a peer-to-peer distributed timestamp server an authentication system must be in place. The proof-of-work entails scanning for a hashed value that begins with a number of zero bits. For the timestamp network, an incrementing nonce[4] is implemented to the block until a value is found that gives the block's hash the required zero bits. After the proof-of-work is satisfied the block is considered valid and cannot be changed without redoing all the aforementioned steps. Furthermore, as blocks are subsequently chained to the current one the number of steps to change the block increases exponentially as it would additionally include redoing the steps of the proceeding blocks. This makes it difficult for users of the network to change previous records of a coin.

The network runs following a set number of steps. Firstly, whenever a new transaction occurs, it is broadcasted to all nodes. Secondly, nodes gather the new transactions into a block. Additionally, each node finds a difficult proof-of-work for its block and proceeds to broadcast its block when it has done so. Next, nodes accept the broadcasted block only if all transactions corresponding to the block are valid and not spent. Finally, nodes accept the block by using its hash when creating the next block in the chain. Moreover,

[1] Hashing is inputting text of any length through a hash function, for example SHA-256, which produces an output of a fixed length.
[2] A node is a computer that is connected to a cryptocurrency network.
[3] A block is part of a blockchain and stores data on transactions.
[4] A nonce is a number that increments each time the hash in use is not valid.

nodes consider the longest chain of blocks to be the correct one and work to extend the blockchain. The first transaction in a block starts a new coin owned by the creator of the block. The reward for creating a block therefore provides incentive for nodes to reinforce the network and additionally distributes coins into circulation. When enough blocks are created after spent transactions these old spent transactions are hashed in a Merkle tree [5] to save space. A user of the network can verify a payment by searching the longest proof-of-work chain for the block the transaction is timestamped in and obtaining the Merkle tree linked to the transaction.

Finally, a user of the network maintains privacy while making transactions because their public key is anonymous. This anonymity allows users to see the amount corresponding to a transaction while not being able to link the transaction to a specific user. Similarly, the stock exchange has a system where the time and size of trades are made public but do not disclose the parties involved in the aforementioned trade.

2.1.2 Ethereum

Due to bitcoin being the original blockchain protocol, it is not surprising that it dominates the cryptocurrency markets. However, there is keen evidence that this dominance might be changing (Bouoiyour and Selmi, 2017). The second largest coin on the cryptocurrency by market capitalization, ether, is a growing competitor of bitcoin. Ether is the cryptocurrency that is traded and is supported by the Ethereum blockchain network. Ethereum was developed in November 2013 by Vitalik Buterin with the goal of designing a more generalized blockchain platform (Buterin, 2014). Ethereum is a public and open source[6] blockchain which can be utilized as a decentralized ledger. Ethereum provides the possibility to build applications that benefit from the properties of blockchains without the necessity of generating a unique blockchain for each new application in contrast to bitcoin. Ethereum uses Turing-complete[7] programming language enabling nodes to create smart contracts[8] on blockchain. Smart contracts have the advantage compared to conventional contracts because they reduce risk, cut down on administration and service costs and improve the efficiency of business processes (Zheng et al., 2020). In the literature this phenomenon is indicated as the blockchain 2.0 era, where applications can be built on smart contracts, healthcare, commercial services and secure data exchange (Wang et al., 2021). Ethereum technology is anticipated to enhance smart contract applications making intricate financial and physical supply chain procedures automatic.

[5] A Merkle tree consists of a root hash that branches out into the hashes of old spent transactions.
[6] Open source refers to software for which the original source code is made freely available and may be redistributed and modified.
[7] Turing-complete refers to any real-world general-purpose computer that can simulate the aspects of any other real-world general-purpose computer.
[8] Smart contracts are programs stored on a blockchain that run when predetermined conditions are met.

2.1.3 Binance Coin

The final cryptocurrency used in this research is binance coin (BNB). Binance coin is currently the third largest cryptocurrency by market capitalization (coinmarketcap, 2023). Furthermore, it is relatively newer than the other cryptocurrencies in this research as it was developed using ERC-20[9] as an Ethereum token by Changpeng Zhao in 2017 and later moved to Binance Smart Chain (BSC) in 2020. Moreover, the Binance Smart Chain provides the Ethereum virtual machine and smart contract capabilities without reduction in throughput and network congestion. The Binance Smart Chain was rebranded in 2022 to the BNB Smart Chain to separate itself from the Binance exchange. The smart contract of binance coin is one of the most used ERC-20 contracts on the Ethereum platform (Sun and Yu, 2020). The Binance exchange sustaining more than 1.4 million transactions per second is, as of April 2021, the largest cryptocurrency exchange in terms of volume value in the market (Mallick, 2020). Thus, binance coin is a platform token[10] issued by the Binance exchange but runs on the Ethereum blockchain. Binance coin is primarily used to pay transaction and trading fees on the Binance exchange but can also pay for goods and services like bitcoin and ether (Watorek et al., 2020). Binance coin, similar to ether for the Ethereum blockchain, is used for gas fees [11] on the BNB Smart Chain.

2.2 Market indicators

The market might be unpredictable, with the wants and needs of market agents changing over time, however its unpredictability may be changing. Research on the stock and cryptocurrency market grows daily. The dramatic shifts in daily life and businesses during the pandemic era have sparked many interests on the influencers in the market (Shamshiripour, 2020). Market indicators assist as quantitative estimates traders use for predicting trends and fluctuations in markets. Moreover, market indicators are tools researchers use to explain their expectations of the market. Finally, market indicators are a group of technical indicators and commonly contain ratios and formulas.

In the next sections, I will give information on earlier research of the market indicators I use in this paper (i.e., return, trading volume and volatility), as this will provide some indication to how the market indicators differ from each other when it pertains to the cryptocurrency market.

2.2.1 Return

For the examination in this study, I must first explain what I mean by return, as the definition powers how I measure it in the context of the cryptocurrency market. Conforming to non-technical definitions, return in

[9] ERC-20 stands for "Ethereum request for comment 20" and defines a set of rules that developers can use to create a token on the Ethereum blockchain.
[10] A platform token benefits the blockchain where it operates, gaining enhanced security and capability to support transactional activity.
[11] Gas fees refers to fees paid in exchange for interactions with a blockchain.

business terms is normally regarded as giving or producing a particular amount of money as a profit or loss (cf. The Oxford English Dictionary Online, 2001). In terms of the market the definition is as follows: The positive or negative change in value of an investment or asset over time (MoneySense, 2023). Furthermore, extending this to the cryptocurrency market the returns are usually viewed as the difference in daily or weekly price changes (Aalborg et al., 2019).

Colianni et al. (2015) introduced the research of returns in the cryptocurrency market, drawing the conclusion that Twitter data relating to cryptocurrencies can be utilized to predict whether the price of bitcoin will increase or decrease over a set time frame. The idea sparked Lamon et al. (2017) to dive deeper into the cryptocurrency market, analyzing the ability that news and social media data has in predicting price fluctuations for bitcoin, litecoin and ether. Moreover, the research concludes that the model created can predict the largest price increases and decreases correctly.

Since the cryptocurrency boom of 2017 (Cross et al., 2021), according to Khedr et al. (2020), the research publications on price prediction have been increasing. Moreover, since 2018, researchers have been broadening the research from bitcoin primarily to the price prediction in the cryptocurrency market as a whole. Past literature on price prediction in the cryptocurrency market can be categorized by the conventional statistical or machine learning techniques utilized. Roy et al. (2018) implement an ARIMA, autoregressive and moving-average model on 2013 to 2017 bitcoin data for bitcoin price forecasting, finding that the ARIMA-model predicted the bitcoin price with an accuracy of 90.31 percent. Moreover, previous research by Georgoula and Pournarkis (2015) using time series analysis found a lower accuracy of 89.6 percent. A Bayesian regression was used by Shah and Zhang (2014) for bitcoin price prediction, exhibiting a strategy that can double an investment in less than sixty days. Bouri et al. (2019) utilize a logistic regression on seven cryptocurrencies to research how the change in cryptocurrency price can depend on each other, concluding that the change in price of one cryptocurrency depends on the price change in other cryptocurrencies. Uras et al. (2020) apply linear and multiple linear regressions to forecast bitcoin price changes built on a daily bitcoin price series from 2015 to 2018, showing that both models can predict the bitcoin price changes. Similarly, Poongodi et al. (2020) demonstrate that linear regressions can be used to predict ether prices with an accuracy of 85.46 percent. Moreover, Jain et al. (2018) build a multiple linear regression model analyzing tweets on litecoin and bitcoin for predicting price changes, identifying that litercoin's price prediction is more accurate than that of bitcoin when looking at tweet sentiments. Future improvements in the accuracy of price prediction in the cryptocurrency market will be achieved by applying federated and distributed learning (Patel et al., 2022).

2.2.2 Trading volume

A considerable amount of literature has been published on trading volume and its effects in the stock market. However, there has been relatively little literature published on the effects of trading volume in the cryptocurrency market specifically. Academic literature defines trading volume as: The total number of shares exchanged in a specified time interval (Qiu et al., 2009). However, when it pertains to the cryptocurrency market, trading volume is defined as: The total number of coins that have been exchanged between buyers and sellers of a determined asset throughout trading hours of a specific day (Coinmarketcap, 2023).

The literature on trading volume in the cryptocurrency market was initiated by Moore and Christin (2013). In their research they examined trading volume data on forty cryptocurrency exchanges to investigate the effect on a cryptocurrency exchange's survival time. Moreover, the research finds that the trading volume of a cryptocurrency exchange is negatively correlated with the probability of the cryptocurrency exchange closing prematurely. Urquhart (2018) extends the research of trading volume in the cryptocurrency market, constructing a vector autoregressive model to examine the variables that influence bitcoin attention. The research finds that bitcoin attention is significantly driven by previous day trading volume. Similarly, Shen et al. (2019) use a Granger causality test to show that previous day tweets drive the next day trading volume of bitcoin significantly. Furthermore, Nasir et al. (2019) predict that policies implemented by government and monetary authorities in both developed and developing economies around the world may change the influence that Google searches have on the trading volume of cryptocurrencies. Ante et al. (2020) is influenced by effects of trading volume in other financial markets, showing the increase in trading volume before transactions are confirmed on a blockchain network (Chae, 2005). Moreover, this increase is explained by the change in trading behavior of informed traders[12] promptly after learning about upcoming transactions. Kamau (2022) investigates the relationship between transaction costs and trading volume, concluding that trading volume is positively correlated with transaction costs. Finally, Lahmiri et al. (2022) find that changes in trading volume are self similar, random and chaotic. Thus, showing the potential of predicting trading volume data in the cryptocurrency market.

2.2.3 Volatility

The research to date has focused on the effects of volatility in a multitude of asset classes, but for the purpose of this study I focus on the volatility in the cryptocurrency market of which the research is currently limited. First I must make clear how I define volatility in this study, because the measurements used in this study are driven by its definition. The Webster dictionary defines volatility in financial terms as: A tendency to change quickly and unpredictably (Merriam-Webster, n.d.). However, volatility in the cryptocurrency market, similar to in stock market research, is academically defined as: The changeableness of the variable under consideration; a variable is more volatile if the variable fluctuates more over a specific period of time (Daly, 2008).

[12] An informed trader is a trader that operates a bitcoin node.

The first systematic study of volatility in the cryptocurrency market was reported by Vejačka in 2014. Moreover, his research indicated considerably higher volatility in cryptocurrency exchange rates in comparison to commodities, basic indices and money pairs (Vejačka, 2014). This paper was promptly followed by research on the influence of monetary policy on bitcoin volatility by Corbet, Mchugh and Meegan (2014). The authors find that interest rate changes and quantitative easing [13] announcements both have influence on bitcoin volatility. Similar to returns in the cryptocurrency market, the soaring increase in market value of cryptocurrencies during 2017 has highlighted the importance of analyzing the volatility of the aforementioned hugely speculative digital assets (Kyriazis, 2021). Aharon and Qadan (2018) investigate the presence of the day-of-the-week effect on bitcoin's volatility, concluding that bitcoin volatility similar to classic financial assets present a Monday effect. Thus, the volatility of bitcoin appears to be significantly higher on monday. Researching the effects that S&P 500 volatility has on long-term bitcoin volatility Conrad et al. (2018) observe a highly significant negative effect of S&P 500 realized volatility on long-term bitcoin volatility. Furthermore, the research finds a positive and significant effect of S&P 500 volatility risk premium on long-term bitcoin volatility. Cheikh et al. (2020) utilize GARCH models to examine the presence of asymmetric volatility dynamics in the cryptocurrency market. Moreover, the research finds that for most cryptocurrencies good news has more influence on volatility in comparison to bad news. Strengthening this result, Fakhfekh and Jeribi (2019) implement an innovative GARCH model to estimate cryptocurrency volatility. The results discover that cryptocurrency volatility increases more in response to positive shocks than concerning negative shocks. Furthermore, Baur and Dimpfl (2018), one of the most cited articles on cryptocurrency volatility (Almeida and Gonçalves, 2022), find similarly that volatility increases more in response to positive shocks than in response to negative shocks, suggesting an asymmetric effect that differs to the effect commonly observed in stock markets. Future research on cryptocurrency volatility will focus on the regulatory inferences of substantial levels of volatility in the cryptocurrency market (Kyriazis, 2021). However, existing research furthermore fails to identify the role of investor behavior in cryptocurrency volatility prediction (Fang et al., 2020).

2.3 Relationship between market indicators

Several studies have revealed that market indicators are a useful measurement of financial performance for numerous asset classes. With the easy accessibility of information in our globally integrated world, stakeholders in capital markets can examine market indicators readily. The fluctuations in market performance indicators are influenced by flow of information. Traders keep track of the relationship between these aforementioned market indicators in light of their own trading strategies (Mubarik et al., 2009). However, previous literature by Fang et al. (2014) discovered mixed findings pertaining to

[13] Quantitative easing is the introduction of new money into the money supply by a central bank.

relationship between technical indicators, stating that there is still no clear answer to whether analysis of these market indicators is useful.

In the following section, I will present the previous literature on the relationship between market indicators studied in the paper (i.e., relationship between returns, trading volume and volatility). This section may offer some evidence to results found in the interrelation of the preceding market indicators in the cryptocurrency market.

2.3.1 Returns and trading volume

The relationship between trading volume and return has been studied across many asset classes. For example, Lee and Riu (2002) examine the dynamic relationship between stock market trading volume and returns during the period of 1973 to 1999. The research finds that trading volume does not Granger cause returns in the stock market. Conversely, Ciner (2002) extends the research of the volume-return relation by investigating the relationship between trading volume and daily price changes for platinum, rubber and gold futures contracts. The author discovered that volume has a significant positive relationship with absolute returns in the commodity futures market. However, causality tests resulted in volume being unable to forecast future returns. Other research from the equities literature by Gervais et al. (2001) tests whether stock market trading volume has any instructive role in predicting stock returns during the period of 1963 to 1996. In order to investigate their main hypothesis, the authors use daily and weekly stock market data to construct zero investment portfolios and reference returns portfolios. Moreover, each portfolio has a holding period of 1, 10, 20, 50, 100 trading days, in which there is no rebalancing of the portfolio, after its formation. The results of the research show that trading volume can significantly predict stock returns utilizing both daily and weekly data when the holding horizon is 1, 10 and 20 trading days. However, the results using daily data are insignificant for longer holding periods than 20 trading days. Concerning the cryptocurrency market, different measurements and data sets have been used in the investigation of trading volume relations to returns. For the period before the boom of bitcoin in 2017, Kristoufek (2015) uses data from 2011 to 2014 on bitcoin volume and price to analyze their relationship. The research finds that volume has a negative relationship with bitcoin price. Conversely, looking at research including data after the bitcoin boom, Sovbetov (2018) uses an ARDL technique to examine the factors that influence prices of the five most common cryptocurrencies (i.e., bitcoin, dash, monero, ether and litecoin) during the period of 2010 to 2018. The results show that trading volume is a significant determinant of price for all five included cryptocurrencies. Similarly, research focused solely on bitcoin during the aforementioned period, Alaoui et al. (2019) employed a multifractal detrended cross correlation analysis on bitcoin market data from 2010 to 2018 to study the cross correlation between price and trading volume. The research concludes that bitcoin trading volume and price interrelate mutually nonlinearly. Another estimation employed by Katsiampa et al. (2018) is the peaks-over-threshold method. Moreover, the study examined daily data for the eight major cryptocurrencies during the period of 2013 to 2017 to establish the dependence between trading volume and returns during extreme market events. The results indicate, irrespective of the cryptocurrency considered, a significant dependence between trading volume and returns. Similarly, utilizing the same method, recent research by Chan et al. (2022) used data on bitcoin and ether during the three-year period of 2017 to 2020 to investigate the extreme dependence between high frequency cryptocurrency volume and returns. Contradicting the results from Katsiampa et al. (2018), the authors find a weak positive correlation between volume and returns during extreme market events. Thus, concluding that volume does not significantly influence price levels during extreme events in the cryptocurrency market. Next to the aforementioned methods, various other measurements have been used to study the relation between trading volume and returns in the cryptocurrency market. Hau et al. (2021) present a quantile-on-quantile regression approach to investigate the significance of bitcoin volume predictability for bitcoin returns during the period of 2013 to 2017. The research shows a positive influence of the lagged volume on high bitcoin returns (upper quantiles) as well as a negative influence of bitcoin volume on low returns (lower quantiles). Detailed examination of the relationship between trading volume and returns for several cryptocurrencies pre- and during the COVID-19 period by Foroutan and Lahmiri (2022) showed that in the pre-COVID-19 period chainlink and monero exhibit a causal relationship from returns to trading volume. Moreover, ether, ripple, litecoin, eos and cardano results find a causal relation during the COVID-19 period. Conversely, the causal relation from trading volume to returns is only present for litecoin in the pre-COVID-19 period, while for the period during COVID-19 trading volume Granger causes returns for tether and chainlink. Other studies have considered the relationship between trading volume and the occurrence of bubble[14] periods in the cryptocurrency market. For example, Enoksen and Landsnes (2019) extends the paper by Phillips et al. (2015), who tested for bubble periods in the stock market, to examine the possible predictors of bubble periods in the cryptocurrency market. The estimations reveal a multitude of bubble periods in all researched cryptocurrencies. Moreover, the results indicate that trading volume is a factor that can predict the aforementioned bubbles, thus concluding that a higher trading volume is positively correlated with the existence of bubble periods for all investigated cryptocurrencies.

All-inclusive, past literature on the relation of trading volume and return in the cryptocurrency market implies that the cryptocurrency, time period and method utilized can lead to differing results. This research replicates the methods used by Aalborg et al. (2019), who measure how returns and trading volume of bitcoin specifically depend on other variables during the period of 2012 to 2017. I collected data from the three cryptocurrencies with the largest market capitalization (i.e., bitcoin, ether and binance coin) during the period after the cryptocurrency boom of July 26, 2017 to December 31, 2022 (Cross et al., 2021). The variables used in this research are comparable to those by Aalborg et al. (2019). However, the data on the variables differ as they are from a period after the cryptocurrency boom and are on multiple

[14] A bubble is characterized as an economic cycle with a rapid escalation of market value, specifically in the price of assets.

cryptocurrencies not solely focused on bitcoin. The data on different cryptocurrencies other than bitcoin are particularly interesting for investigation as the fundamental differences between cryptocurrencies could translate into differences of measured dependents of returns and trading volume. Moreover, evidence indicates that the cryptocurrency that is researched might matter for the dependents that returns exhibits (e.g., Sovbotov 2018; Katsiampa et al. 2018; Foroutan and Lahmiri 2022). The data used in this research is from a substantial period following the cryptocurrency boom of 2017. This is potentially interesting because there exists a profound distinction in the effects of variables on returns preceding and succeeding an extreme event. The variables of cryptocurrencies that may have an effect on returns before COVID-19 for example, have been shown to not exhibit those effects in the years following the COVID-19 outbreak (Foroutan and Lahmiri, 2022). Similarly interesting, there exists very little research on data collected after 2020 as much of the research was published quickly following the cryptocurrency boom or the appearance of COVID-19. To investigate the interrelationship between trading volume and returns, following past literature by Gervais et al. (2001), I test whether cryptocurrency trading volume influences returns and whether cryptocurrency returns influence trading volume. Thus, I propose and examine the following hypotheses:

Hypothesis 1: *Changes in cryptocurrency trading volume affect changes in returns during the period of July 26, 2017 to December 31, 2022.*

Hypothesis 2: *Changes in cryptocurrency returns affect changes in trading volume during the period of July 26, 2017 to December 31, 2022.*

2.3.2 Returns and volatility

Several theories have been proposed to the relationship between volatility and returns, some focusing on the relationship in the stock market, others on how volatility can predict returns in the futures market. For example, Chan et al. (2004) study data of four futures contracts on Chinese futures exchanges (i.e., copper, mung beans, soybeans and wheat) to examine the relationship between returns and daily volatility. The researchers find a greater effect of negative returns on daily volatility than positive returns have on daily volatility, thus concluding that returns exhibit an asymmetric effect on daily volatility. Similarly for literature on the stock market, Li et al. (2005) examine the 12 largest international stock markets to study the interrelation of volatility and expected stock returns. Using an EGARCH-M model, the authors obtain an insignificant positive relationship for ten of the 12 international stock markets. However, utilizing a semiparametric conditional variance, the results indicate a significant negative relationship between returns and volatility in six of the 12 international stock markets during the period of 1980 to 2001. There exists a considerable body of literature on the intricacies of the interrelation of returns and volatility among many asset classes as exemplified above, however the cryptocurrency market is rather young, thus the literature concerning the relationship in the cryptocurrency market is limited (Caporale, 2019). Early research by Bouri et al. (2017) investigates the interrelation of bitcoin returns and volatility around the bitcoin price crash of 2013. The results for the period of 2011 to 2016 exhibit evidence of an asymmetric volatility-return relation. This view is supported by Wang (2021), who examined the returns and volatility of bitcoin utilizing the daily closing price of bitcoin during the period of 2013 to 2020. Illustrating similarly that the volatility and returns of bitcoin have an asymmetric relationship. Furthermore, Sapuric et al. (2022) corroborate the previous findings in their research employing an EGARCH model on bitcoin returns and volatility during the period of 2010 to 2017. The authors observe an asymmetric relationship of bitcoin volatility and returns, specifying that the relationship implies an anti-leverage effect: The unexpected increase in bitcoin returns would influence a rise in bitcoin volatility more heavily than the unexpected fall in bitcoin returns of a similar degree. Conversely, Zhang et al. (2018) utilize a GJR model to investigate eight cryptocurrencies during the period of 2013 to 2018. The results indicate the presence of a leverage effect during this period for six of the eight cryptocurrencies researched. In parallel to the effects of trading volume on cryptocurrency prices, Sovbetov (2018) provides results indicating that volatility has an instrumental impact on long and short run cryptocurrency prices. Similarly, Liu and Serletis (2019) use GARCH-in-mean models to test if there is interdependence between returns and volatility for three cryptocurrencies (i.e., bitcoin, litecoin and ether). The results imply that a higher ether volatility is accompanied by higher returns. Moreover, litecoin volatility exhibits a statistically significant impact on the direction and size of litecoin's price. This interrelation has also been explored during specific time periods where the volatility is extreme. For example, Cross et al. (2021) analyze whether the volatility and expected returns of four cryptocurrencies (i.e., bitcoin, ether, litecoin and ripple) are interdependent during the cryptocurrency bubble of 2017 to 2018. The results suggest a positive relationship between litecoin and ripple volatility and returns during the boom of 2017, however bitcoin and ether exhibit no relationship throughout the same span of time. Moreover, the authors believe that the size of the market capitalization of bitcoin and ether could be a possible explanation of the results, stating that investors perceive bitcoin and ether as more reliable in comparison to litecoin and ripple. In contrast to the cryptocurrency boom, results on the period after the boom of 2017, known as the bust of 2018 to 2019, indicates a negative interrelation of returns and volatility for all four of the investigated cryptocurrencies. Another example of extreme volatility was during the COVID-19 pandemic. Foroutan and Lahmiri (2022) find that the relation between returns and volatility is significant during the COVID-19 pandemic for tether, ripple, eos, monero, ether and bitcoin cash. However, the results indicate that the pre-pandemic relationship for all the investigated cryptocurrencies is not significant. While the focus of past literature has been on the volatility of cryptocurrencies, Zhang and Li (2020) explore the effect of idiosyncratic volatility in the cross-section of cryptocurrency returns. The study utilizes a portfolio level analysis and FAMA-MacBeth regressions to show that idiosyncratic volatility has a positive relationship to cryptocurrency expected returns. A comparable study by Leirvik (2022), focusses on the idiosyncratic volatility of market liquidity in relation to the returns of the five cryptocurrencies with the largest market capitalization (i.e., bitcoin, ether, ripple, bitcoin cash and litecoin). The author uses a bid-ask spread estimator derived by Corwin and Schultz (2012) and a linear regression model to analyze the relationship. Moreover, the results suggest a significant positive relation between the cryptocurrency returns and the volatility of liquidity. However the authors state that the relationship is time-varying. Furthermore, the author shows that the relationship is positive but the lowest for bitcoin among the investigated cryptocurrencies, indicating that investors evaluate liquidity less risky for bitcoin in comparison to the other cryptocurrencies studied. Additionally, concluding that the popularity of bitcoin in particular might be a possible explanation for variance in investor evaluation.

Overall, finding any systematic behavior pattern of market return-volatility relations is a topic of important research in financial economics (Berument and Doğan, 2011). I replicate the methods by Aalborg et al. (2019) that estimates the returns-volatility interrelationship of bitcoin during the period of 2012 to 2017. To the best of my knowledge, little or no studies have adopted these methods to explore the dynamic returns-volatility interrelationship for multiple market leading cryptocurrencies. The data used in this research differs from that of Aalborg et al. (2019) as it focuses on the time period of July 26, 2017 to December 31, 2022 and the cryptocurrencies with the largest market capitalization (i.e., bitcoin, ether and binance coin). Past literature has shown that the market capitalization of the investigated cryptocurrencies may result in differing estimates of the relationship between returns and volatility (Leirvik, 2022; Cross et al., 2021).

The variables investigated in this research are comparable to past literature, however the data used in this research differentiates itself from past literature by including considerable data after the initial cryptocurrency boom of 2017, together with data before, during and after the COVID-19 pandemic. Moreover, literature by Foroutan and Lahmiri (2022) and Cevik et al. (2023) display that extreme events as mentioned previously can have differing influences on the returns and volatility of the leading cryptocurrencies by market capitalization. The data period I use in this research is potentially interesting as the cryptocurrency market development has recently evolved from being considered unimportant to capitalizing at an intermediate sized stock exchange level (Wątorek et al., 2021). Moreover, this provides a unique possibility to investigate the cryptocurrencies relationships evolution during a short period. Thus, I present and analyze the following hypotheses:

Hypothesis 3: *Changes in cryptocurrency volatility affect changes in returns during the period of July 26, 2017 to December 31, 2022.*

Hypothesis 4: *Changes in cryptocurrency returns affect changes in volatility during the period of July 26, 2017 to December 31, 2022.*

2.3.3 Trading volume and volatility

Researchers, regulators and investors have a growing interest in understanding the relation between trading volume and the volatility of asset returns. Moreover, a considerable volume of work has recently emerged examining the connection between trading volume and volatility for a multitude of asset classes. The market break of 1987, a period of extremely high levels of trading volume and volatility, is considered a possible cause of the increase in literature on this relationship (Foster and Viswanathan, 1993). For example, Sarwar (2003) utilizes the future volatility of the U.S. dollar/British pound exchange rate, approximated with the implied and IGARCH volatilities, and currency options trading volume to examine the volatility-trading volume interrelation of currency options. The results show a strong simultaneous positive reaction between the option volume and the exchange rate volatility. Similarly, Park et al. (1999) contribute to the literature by examining the relationship between the trading activity of equity options and the underlying equity volatilities during a seven month period in 1991. The results indicate that trading activity significantly influences conditional volatility in the equity options markets. Moreover, unexpected trading activities specifically, result in a more significant influence. Focussing on the literature on this interrelationship in the stock market, Lee and Riu (2002) find the existence of a positive feedback interrelation between volatility and trading volume for the New York, Tokyo and London stock markets. Similarly for the Pakistani stock market, Mubarik and Javid (2009) display a significant positive interrelation between trading volume and volatility. Furthermore, Mahajan and Singh (2009) find evidence of a significant positive correlation between volatility and volume for India's premier stock exchange, the Bombay Stock Exchange. The analysis additionally documents proof of causality from volatility to trading volume. With respect to the cryptocurrency market, the first study that investigates the interrelation between trade volume and volatility was by Letra (2016). The author analyzes the dynamics of the cryptocurrency market using a GARCH model on daily bitcoin data. The results demonstrate that an increase in trade volume foments a higher bitcoin volatility. Balcilar et al. (2017) extend the literature on this interrelation by utilizing a non-parametric causality-in-quantiles test. In contrast to the previous literature findings, the results show that trading volume has no forecasting power for bitcoin volatility. Contradicting both of the researches previously mentioned, Conrad et al. (2018) inspect bitcoin data during the period of 2013 to 2017, using a GARCH-MIDAS model, to find a significant negative influence of trading volume on bitcoin volatility. Speculating that an increase in trading volume is associated with an increased estimate of trust by investors, thus resulting in a lower volatility of bitcoin. Badenhorst (2018) investigates derivative and spot volumes in the cryptocurrency market to analyze the relation between bitcoin trading volume and volatility. The research employed an ARCH (1.1) model and a Granger-causality test on the bitcoin data from 2014 to 2018. The results indicate the presence of a significant positive effect from spot trading volume on cryptocurrency volatility, however the effect of derivative market trading volume on bitcoin volatility is still uncertain. Next to the previously mentioned methods, numerous other estimations have been utilized to examine the interrelation between volatility and trading volume. Wang et al. (2020) suggest the use of the realized variance, proposed to measure the hourly volatility of bitcoin by Anderson and Bollerslev (1998), and hourly trading volume share to estimate the intraday bitcoin regularities on the bitstamp exchange during the period of 2015 to 2018. The researchers implement the Granger causality test to investigate the relationship between the two intraday variables for bitcoin. The results find a bilateral causality interrelation between realized variance and the intraday trading volume for bitcoin during the period of 2015 to 2018. Similarly suggesting Granger causality, Bouri et al. (2019) use a copula-quantile causality approach on daily data of the seven largest cryptocurrencies by market capitalization during the period of 2013 to 2017 (i.e., bitcoin, ether, ripple, litecoin, nem, dash and stellar). The results reveal significant documentation of trading volume Granger causing cryptocurrency volatility for litecoin, nem and dash, when the level of volatility is low. The impact of the COVID-19 pandemic on the interrelation between trading volume and volatility in the cryptocurrency market was examined by Corbet et al. (2022). The study identifies and investigates two different stages during the COVID-19 pandemic, the first stage consists of data covering the period between the Wuhan initial outbreak in late 2019 and the second stage covers the period after the World Health Organisation (WHO) announced international transmission. The authors use a DCC-GARCH model to estimate the results. The study presents results that indicate that the volatility before the COVID-19 pandemic is significantly affected by the lagged shocks of volume changes for the majority of the twelve largest cryptocurrencies by market capitalization. Moreover, the effects increase throughout both stages during the COVID-19 pandemic.

All in all, the past literature on the relationship between trading volume and volatility displays the importance of this interrelation to scholars and practitioners to characterize and forecast the market of an asset (Sapuric, 2020). In this research I replicate methods used by Aalborg et al. (2019) to estimate the relationship between trading volume and volatility. This relation for the market leading cryptocurrencies, according to my understanding, has not been investigated for the period of July 26, 2017 to December 31, 2022 utilizing these methods in previous literature. Differing from the research by Aalborg et al. (2019) the data I use is specifically interesting for research as it consists of a period with high levels of volatility, as a result of the cryptocurrency boom of 2017 and COVID-19 pandemic. Previous research has suggested that cryptocurrencies consisting of differences in market capitalization may lead to differing estimation of the relation between trading volume and volatility (Bouri et al., 2019; Corbet et al., 2022). Similarly, events such as the cryptocurrency boom and crash additionally to the COVID-19 pandemic has shown to influence the level of interrelation between cryptocurrency variables (Cevik et al., 2023; Corbet et al., 2022; Cross et al., 2021; Foroutan and Lahmiri, 2022). Previous studies have mostly focused on the trading volume-volatility relationship for bitcoin solely (Aalborg et al., 2019; Badenhorst, 2018; Conrad et al., 2018; Letra, 2016; Wang et al., 2020), I broaden the literature in the cryptocurrency market by exploring the relation for bitcoin, ether and binance coin. Thus, I present and investigate the following hypotheses:

Hypothesis 5: *Changes in cryptocurrency trading volume affect changes in volatility during the period of July 26, 2017 to December 31, 2022.*

Hypothesis 6: *Changes in cryptocurrency volatility affect changes in trading volume during the period of July 26, 2017 to December 31, 2022.*

CHAPTER 3 Data

3.1 Dataset description

In this study, I utilize a dataset of 1417 observations including both daily and weekly values for all investigated variables for the three largest cryptocurrencies by market capitalization: bitcoin, ether and binance coin. The sample data is extracted by accessing online databases from coinmarketcap.com, santiment.net, messari.io, bscscan.com, coinmetrics.io, Yahoo Finance and Google trends. Moreover, the dataset consists of sample data between the period of July 26, 2017 to December 31, 2022. The year 2017 is chosen as the starting point of my data because it depicts the start of the cryptocurrency boom in addition to July 26, 2017 being the beginning point of the available data on binance coin. Moreover, the total cryptocurrency market capitalization increased to a peak of 535 billion dollars from a start point of 16 billion dollars in 2017, however the start of 2018 consisted of a market crash resulting in a 400 billion dollar loss in total cryptocurrency market capitalization (Cross et al., 2021). The boom and crash of the cryptocurrency market during the period of 2017 to 2018 in addition to the COVID-19 pandemic period of 2019 to 2022, which has been shown to have a causal relationship to cryptocurrency prices (Demir et al., 2020), makes this span of data particularly interesting for academic research.

3.2 Main variables of interest

Returns, defined as a change in value of a cryptocurrency investment or asset over time (MoneySense, 2023), are obtained by extracting and converting the daily and weekly bitcoin, ether and binance coin prices from coinmarketcap.com during the period between July 26, 2017 and December 31, 2022. Moreover, by transforming cryptocurrency prices I make the **returns** stationary. The variable is constructed, for all 1417 daily and 282 weekly observations of the investigated cryptocurrencies, utilizing the following equation:

$$r_t = \log(Price_t) - \log(Price_{t-1}),$$

where r is the calculated **returns**, t is the subscript for time and the prices are logarithmically transformed. There are distinct differences between the level of returns in the cryptocurrency market. For example, the highest level of daily and weekly return is exhibited by binance coin, the smallest investigated cryptocurrency. On the other hand, the lowest level of return is for bitcoin for both the daily and weekly data. The average return is similar across all three studied cryptocurrencies.

Volatility is calculated in this research using the methods by Kaya and Mostowfi (2022) in their study of volatility strategies for highly liquid cryptocurrencies. Moreover, the authors utilize the concept of historical volatility as a measurement to study the long and short strategy returns. The largest cryptocurrencies by market capitalization, are generally, highly liquid in comparison to the smallest cryptocurrencies by market capitalization (Liu, 2021). In this research I utilize the concept of historical volatility to compute the volatility of bitcoin, ether and binance coin. Moreover, I calculate the historical volatility with a look-back period of six months. Kaya and Mostowfi (2022) find that a six-month look-back period, in comparison to a one- or three-month look-back period, for historical volatility is more statistically significant to generate returns. For the calculation, I utilize the previously calculated daily and weekly **returns** data for the three investigated cryptocurrencies. The variable of historical volatility is computed by first calculating the standard deviation using the following equation for bitcoin, ether and binance coin:

$$SD_t = \frac{\sum(Return - \overline{Return})^2}{n-1},$$

with SD being the calculated standard deviation, n denotes the number of data points, t as the subscript of time and **return** is the previously calculated cryptocurrency returns. The standard deviation is then annualized to obtain the historical volatility. The daily and weekly historical volatilities are calculated using the following formulas:

$$Volatility_t^d = SD \times \sqrt{262} \;\&$$

$$Volatility_t^w = SD \times \sqrt{52}\,,$$

where d and w denote daily and weekly, t is the subscript of time and SD is the standard deviation. As can be expected, the variable is different between the leading cryptocurrency bitcoin and the smaller cryptocurrencies ether and binance coin. The average **volatility** for bitcoin seems considerably lower than for ether and binance coin at 0.33, a possible explanation for this is the previously mentioned trust by investors in bitcoin due to its market capitalization.

Trading volume, defined as the number of coins exchanged during a specific time period, data are extracted from coinmarketcap.com for each cryptocurrency investigated separately. The collected data combines trading volumes on centralized and decentralized cryptocurrency exchanges to create the variable utilized in the rest of the analysis. For the data to maintain its quality I standardize the obtained daily and weekly trading volume data utilizing the following formula:

$$Trading\ volume_t = \frac{trading\ data_t - \overline{trading\ data_{t-1}}}{\sigma(trading\ data_{t-1})},$$

with **Trading volume** denoting the variable of interest, trading data being defined as the initially congregated data and t as the subscript for time. An aspect that is interesting from the calculated data is that the **trading volume** of binance coin is particularly high during the year 2021 in comparison to the preceding period and the period following 2021. A possible explanation for the high **trading volume** during the year 2021 is the launch of the Binance Smart Chain (BSC) in late 2020.

3.3 Control variables

Unique addresses, interpreted as a single cryptocurrency exchange user's account, daily and weekly data is collected from historical data and charts from santiment.net, messari.io, bscscan.com and coinmetrics.io for bitcoin, ether and binance coin individually. In a comparative manner to the **returns**, I modify the variable to better fit the data employing the following equation:

$$Unique\ addresses_t = \log(address\ data_t) - \log(address\ data_{t-1}),$$

with **unique addresses** being the variable used in further analysis, t as the subscript for time and the address data denoting the initially extracted data. Furthermore, the address data is logarithmically modified. The daily and weekly kurtosis[15] for binance coin data is substantially larger than for bitcoin and ether. Moreover, the large kurtosis implies that there are many fluctuations away from the average of binance coin's **unique addresses**.

VIX index, representing the stock market's expectations for volatility, data is assembled utilizing the Yahoo Finance database for both daily and weekly data. In contrast to previously mentioned variables, the VIX index is stationary, thus the data does not need to be transformed identically to the nonstationary variables trading data and transaction data. However, the variable is transformed to better fit the data using a formula comparable to that of the **returns** and **unique addresses**. The formula is as follows:

$$VIX_t = \log(VIX\ data_t) - \log(VIX\ data_{t-1}),$$

where **VIX** is the variable representing the VIX index in the remainder of this research, t is the subscript for time and VIX data is the data collected from Yahoo Finance which is logarithmically transmuted. The data implies that the daily and weekly level of fear in the stock market is somewhat comparable.

Google trends, reflects the amount of google searches for a specific cryptocurrency (i.e., bitcoin, ether and binance coin) over a certain period of time, daily and weekly data is downloaded from the Google trends website. The attained Google trends data is then standardized for further analysis utilizing methods introduced by Bijl et al. (2016). The standardization aids in further analyses by making the data more comparable between the different types of cryptocurrencies. The data is standardized using the formula that follows:

[15] Kurtosis is a statistical measurement of the combined weight of a distribution's tails relative to the mean.

$$Google\ trends_t = \frac{trends\ data_t - \overline{trends\ data_{t-1}}}{\sigma(trends\ data_{t-1})},$$

where **Google trends** is the calculated variable used in further analyses, t is the subscript of time and trends data is the originally acquired data from the Google trends website. As can be expected, the amount of daily and weekly google searches for all three investigated cryptocurrencies steadily increase throughout the years. A possible explanation for this is the steadily growing popularity of cryptocurrencies during the past five years.

3.4 Descriptive statistics

Table 1 presents the descriptive statistics for the daily investigated bitcoin variables: return, volatility, trading volume, unique addresses, VIX index and Google trends. Similarly, Table 2 and Table 3 present descriptive statistics covering the daily data for ether and binance coin variables. An interesting aspect comparing the daily descriptive statistics is that binance coin has a considerably higher skewness to the right and kurtosis for four of the six variables. Possible implications are that the daily data on binance coin consists of a large asymmetric and non normal distribution. Furthermore, the data on trading volume consists of a remarkable number of outliers, with the maximum values being considerably higher than the mean and minimum values for bitcoin, ether and binance coin. Descriptive statistics covering weekly data of the investigated variables are displayed in Table 4, Table 5 and Table 6. Similarly, binance coin exhibits for four of the six variables a high kurtosis. However, the weekly google trends data has an unusually large standard deviation in comparison to the daily google trends data for all three cryptocurrencies. Overall, the mean and standard deviation of the return, volatility, unique addresses and VIX index variables are fairly consistent across the daily and weekly descriptive statistics.

Table 1
Descriptive statistics for bitcoin daily variables.

Bitcoin	Mean	Median	Min	Max	Std.dev.	Skewness	Kurtosis
Return	0.00	0.00	-0.20	0.10	0.02	-0.80	9.19
Volatility	0.33	0.33	0.19	0.52	0.07	0.46	-0.57
Trading volume	1.39	0.79	-1.40	27.42	2.09	2.33	17.54
Unique addresses	0.00	0.00	-0.19	0.20	0.04	0.02	2.23
VIX index	0.00	0.00	-0.12	0.33	0.04	1.51	8.63
Google Trends	0.21	-0.07	-1.44	6.64	1.31	0.92	0.70

Table 2
Descriptive statistics for ether daily variables.

Ether	Mean	Median	Min	Max	Std.dev.	Skewness	Kurtosis
Return	0.00	0.00	-0.24	0.15	0.03	-0.71	7.89
Volatility	0.44	0.44	0.28	0.71	0.09	0.45	-0.20
Trading volume	1.81	1.45	-2.11	13.29	2.31	0.88	1.06
Unique addresses	0.00	0.00	-0.35	0.45	0.04	0.24	16.79
VIX index	0.00	0.00	-0.12	0.33	0.04	1.54	8.63
Google Trends	0.16	0.08	-2.53	4.63	1.14	0.57	0.24

Table 3
Descriptive statistics for binance coin daily variables.

Binance coin	Mean	Median	Min	Max	Std.dev.	Skewness	Kurtosis
Return	0.00	0.00	-0.36	0.52	0.04	1.73	40.10
Volatility	0.45	0.38	0.17	1.40	0.20	1.93	4.65
Trading volume	4.19	1.10	-1.26	120.36	9.45	4.46	30.61
Unique addresses	0.00	0.00	-2.03	1.83	0.21	-1.00	31.16
VIX index	0.00	0.00	-0.12	0.33	0.04	1.51	8.63
Google Trends	-0.02	0.12	-3.74	3.71	1.37	-0.39	0.25

Table 4
Descriptive Statistics for bitcoin weekly variables.

Bitcoin	Mean	Median	Min	Max	Std.dev.	Skewness	Kurtosis
Return	0.00	0.01	-0.18	0.14	0.05	-0.45	1.30
Volatility	0.33	0.32	0.17	0.63	0.10	1.11	0.95
Trading volume	1.37	0.69	-1.63	11.54	2.39	1.53	2.60
Unique addresses	0.00	0.00	-0.22	0.21	0.05	0.13	3.15
VIX index	0.00	-0.01	-0.22	0.37	0.07	0.85	3.32
Google Trends	0.83	-0.04	-0.80	10.37	1.92	2.10	4.94

Table 5
Descriptive statistics for ether weekly variables.

Ether	Mean	Median	Min	Max	Std.dev.	Skewness	Kurtosis
Return	0.00	0.00	-0.23	0.21	0.06	-0.36	1.85
Volatility	0.45	0.43	0.27	0.81	0.13	0.77	-0.09
Trading volume	1.96	1.55	-1.88	9.89	2.55	0.77	0.07
Unique addresses	0.00	0.01	-0.26	0.21	0.07	-0.10	1.18
VIX index	0.00	-0.01	-0.22	0.37	0.07	0.85	3.32
Google Trends	2.04	0.14	-3.14	18.67	4.24	1.55	2.01

Table 6
Descriptive statistics for binance coin weekly variables.

Binance coin	Mean	Median	Min	Max	Std.dev.	Skewness	Kurtosis
Return	0.01	0.00	-0.33	0.83	0.09	3.01	23.09
Volatility	0.46	0.39	0.18	1.68	0.25	1.81	3.63
Trading volume	3.13	1.14	-1.29	49.13	6.18	3.63	17.71
Unique addresses	0.02	0.00	-2.44	2.32	0.41	-0.09	16.42
VIX index	0.00	-0.01	-0.22	0.37	0.07	0.85	3.32
Google Trends	7.63	0.08	-1.83	106.80	18.60	2.78	8.21

CHAPTER 4 Method

In this section, I put forward the univariate and multivariate regressions that will be utilized to analyze the interrelations between cryptocurrency return, trading volume and volatility. Univariate regressions are employed to characterize the relationship between a single dependent variable and an independent variable, additionally aiding in understanding the distribution of variable values. On the other hand, multivariate regressions provide an alternative examination of the relationship between several variables. Following the method by Aalborg et al. (2019), I analyze the predictability of the main variables of interest by using a predictive univariate and multivariate regression model. The regression models are created for daily and weekly data separately. To combat difficulties with heteroscedasticity[16], I use robust standard errors to estimate the results. Robust standard errors perform more effectively than model-based standard errors in large sample sizes. To test the six research hypotheses, I use the the following models:

$$Return_t = \beta_0 + \beta_1 Trading\ volume_t + \beta_2 Volatility_t + \beta_3 \boldsymbol{Control\ Variables}_t + \in_t,$$

$$Trading\ volume_t = \beta_0 + \beta_1 Return_t + \beta_2 Volatility_t + \beta_3 \boldsymbol{Control\ Variables}_t + \in_t,$$

$$Volatility_t = \beta_0 + \beta_1 Return_t + \beta_2 Trading\ volume_t + \beta_3 \boldsymbol{Control\ Variables}_t + \in_t,$$

where t is the subscript for time, β_0 signifies the intercept, $\in$ being the error term and **Control Variables** denotes the variables: Unique addresses, VIX index and Google trends. For the inference of the predictive capabilities of the independent variables I utilize the models that follow:

$$Return_t = \beta_0 + \beta_1 Trading\ volume_{t-1} + \beta_2 Volatility_{t-1} + \beta_3 \boldsymbol{Control\ Variables}_{t-1} + \in_t,$$

$$Trading\ volume_t = \beta_0 + \beta_1 Return_{t-1} + \beta_2 Volatility_{t-1} + \beta_3 \boldsymbol{Control\ Variables}_{t-1} + \in_t,$$

$$Volatility_t = \beta_0 + \beta_1 Return_{t-1} + \beta_2 Trading\ volume_{t-1} + \beta_3 \boldsymbol{Control\ Variables}_{t-1} + \in_t,$$

with t, **Control Variables**, β_0 and $\in$ being similar to the three aforementioned models. I examine the models to inspect the existence of a statistically significant interrelation between return, volatility and trading volume in addition to providing an interpretation of results in regard to the predictability of the dependent variables.

[16] Heteroscedasticity refers to a situation in which the residual term's variance is non constant in a regression model.

CHAPTER 5 Results & Discussion

Results are presented in separate tables for daily and weekly models for bitcoin, ether and binance coin. Each table includes five univariate regressions and one multivariate regression, which is presented in the last column of the table, for the specific daily or weekly cryptocurrency data. The Ordinary Least Squares method is utilized to estimate the models. Moreover, the estimated coefficient represents the change in the dependent variable corresponding to an increase of the independent variable of one unit. A coefficient accompanied by one, two or three stars (*) indicates the statistical significance of the variable, with one star representing a statistical significance at the five percent level, two stars at the one percent level and three stars indicating statistical significance at the 0.1 percent level. In the last row of the table, I report the R^2 for both the univariate and multivariate models. The R^2 is interpreted as the proportion of variability in the dependent variable that is explained by the independent variables. For example, a R^2 value of 0.67 indicates that the independent variables are on average able to explain 67 percent of the variation of the dependent variable in the model.

5.1 Models utilizing daily data

5.1.1 Bitcoin

The results from estimating the variables with influence on daily bitcoin return are represented in Table 7.

Table 7
Regression results estimated from daily bitcoin data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Trading volume	0.00					0.00
	(0.433)					(0.520)
Volatility		-0.00				-0.01
		(-0.532)				(-0.803)
Unique Addresses			-0.00			0.00
			(-0.100)			(0.020)
VIX index				-0.13^{***}		-0.13^{***}
				(-5.075)		(-5.135)
Google Trends					-0.00	-0.00
					(-0.616)	(-0.719)
Constant	0.00	0.00	0.00	0.00	0.00	0.00
	(0.655)	(0.785)	(1.046)	(1.137)	(1.292)	(1.010)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.000	0.000	0.000	0.050	0.001	0.051

The model shows that trading volume, volatility, unique addresses and Google trends are insignificant in explaining daily bitcoin returns for both the univariate and multivariate regressions. However, the VIX index is for both regressions a significant explanatory variable for bitcoin returns, indicating that a negative relationship exists between a change in the VIX index and the daily bitcoin returns. The univariate model for VIX index has a R^2 of 0.050 on average and the R^2 of the multivariate model is 0.051 on average, which means that the VIX index on average can explain five percent of the variance in the daily bitcoin return. The model predicting daily bitcoin return is presented in Table 25 in appendix A. In contrast to the previous model, the unique addresses variable is significant in both the univariate and multivariate regressions. The VIX index is insignificant in addition to the other investigated variables for both regressions. The results indicate that on average the unique addresses variable can significantly predict daily bitcoin returns. However, the univariate and multivariate regressions have an R^2 value of 0.04, implying that the model can only describe four percent of the variance in bitcoin returns on average.

The model showing the variables influencing daily bitcoin trading volume is presented in Table 8.

Table 8
Regression results estimated from daily bitcoin data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	1.52					1.83
	(0.431)					(0.523)
Volatility		1.05				1.15*
		(1.785)				(2.092)
Unique Addresses			-0.01			-0.12
			(-0.010)			(-0.083)
VIX index				-0.60		-0.35
				(-0.405)		(-0.226)
Google Trends					0.23***	0.23***
					(5.232)	(5.274)
Constant	1.39***	1.05***	1.39***	1.39***	1.35***	0.96***
	(24.990)	(4.911)	(25.042)	(25.040)	(23.587)	(4.666)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.000	0.001	0.000	0.000	0.021	0.023

The model exhibits that the variables return, unique addresses and VIX index are insignificant for both regressions. The variable volatility is insignificant in the univariate regression but is positively significant in explaining bitcoin trading volume in the multivariate regression. Similarly, the Google trends variable is significant in the multivariate regression in addition to being significant in the univariate regression. The multivariate regression has a R^2 value of only 0.023. The model predicting daily bitcoin trading volume is shown in Table 26 in Appendix A. The table exhibits that all variables are insignificant in bitcoin trading volume prediction aside from the Google trends variable which demonstrates a significant positive influence on predicting bitcoin trading volume for both the univariate and multivariate regressions. Similarly to the previous model, the R^2 value is low at 0.012.

The estimations of bitcoin daily volatility are presented in the model in Table 9. Trading volume is the only significant variable explaining bitcoin daily volatility; however, the variable is not significant in the univariate regression. The multivariate regression can explain 0.4 percent of the variance in bitcoin volatility on average. The predictability of bitcoin volatility is shown in Table 27 in Appendix A. The model exhibits not only a significant trading volume coefficient for the multivariate regression but a similarly significant coefficient for the univariate regression. Again, the model can only explain 0.4 percent of the variance of bitcoin daily volatility on average.

Table 9
Regression results estimated from daily bitcoin data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	-0.05					-0.08
	(-0.535)					(-0.809)
Trading volume		0.00				0.00^{*}
		(1.747)				(2.006)
Unique Addresses			-0.02			-0.01
			(-0.291)			(-0.255)
VIX index				-0.05		-0.06
				(-0.800)		(-0.934)
Google Trends					-0.00	-0.00
					(-0.890)	(-1.140)
Constant	0.33^{***}	0.33^{***}	0.33^{***}	0.33^{***}	0.33^{***}	0.33^{***}
	(167.667)	(158.039)	(167.636)	(167.716)	(171.399)	(157.791)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.000	0.001	0.000	0.001	0.001	0.004

5.1.2 Ether

The model for ether daily return is presented in Table 10. All investigated variables are insignificant except for the VIX index. Similarly to bitcoin, ether daily return exhibits a negative relationship with the VIX index for both the univariate and multivariate regressions. The R^2 value of the model is 0.064, which means that the model explains on average little of the variance of ether returns. In Table 28 in Appendix A, the model for predicting ether daily return is presented. The model suggests that volatility has influence on ether daily return prediction in the univariate and multivariate regression, as it has a significant positive coefficient. All other variables are insignificant both in the univariate and multivariate regressions. The R^2 value of the model is lower than that of the ether daily return model at 0.004.

Table 10
Regression results estimated from daily ether data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Trading volume	0.00					0.00
	(0.638)					(0.335)
Volatility		0.01				0.01
		(1.681)				(1.262)
Unique Addresses			0.03			0.03
			(1.469)			(1.756)
VIX index				-0.18***		-0.18***
				(-5.985)		(-6.021)
Google Trends					0.00	0.00
					(1.581)	(1.353)
Constant	0.00	-0.01	0.00	0.00	0.00	-0.00
	(0.036)	(-1.566)	(0.749)	(0.856)	(0.514)	(-1.182)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.001	0.002	0.002	0.057	0.003	0.064

Table 11 puts forward the model for ether daily trading volume. The coefficients of volatility and Google trends estimated in the model are statistically significant for both the univariate and multivariate regression. However, the other investigated variables are statistically insignificant. The R^2 value of the model is 0.227, which is relatively high in comparison to the other investigated models. Table 29 in Appendix A predicts ether daily trading volume, indicating similar significance for both the univariate and multivariate regression of the variables volatility and Google trends. The R^2 value of the predictive multivariate model is 0.186, explaining on average 18.6 percent of the variance in ether trading volume.

Table 11
Regression results estimated from daily ether data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	2.11					0.92
	(0.633)					(0.334)
Volatility		-1.93**				-3.14***
		(-3.156)				(-5.964)
Unique Addresses			2.07			0.78
			(1.265)			(0.640)
VIX index				1.88		1.61
				(1.032)		(0.970)
Google Trends					0.93***	0.95***
					(17.140)	(17.320)
Constant	1.81***	2.66***	1.81***	1.81***	1.67***	3.04***
	(29.526)	(9.307)	(29.633)	(29.603)	(31.252)	(11.938)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.001	0.006	0.001	0.001	0.210	0.227

The results from estimating the variables on daily ether volatility are represented in Table 12.

Table 12
Regression results estimated from daily ether data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	0.16					0.12
	(1.637)					(1.240)
Trading volume		-0.00**				-0.01***
		(-2.970)				(-5.670)
Unique Addresses			0.03			0.02
			(0.514)			(0.384)
VIX index				-0.07		-0.04
				(-0.949)		(-0.555)
Google Trends					0.01***	0.01***
					(4.180)	(6.256)
Constant	0.44***	0.45***	0.44***	0.44***	0.44***	0.45***
	(175.581)	(131.828)	(175.471)	(175.542)	(175.408)	(129.798)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.002	0.006	0.000	0.001	0.011	0.033

The model shows significant coefficients for both the univariate and multivariate regressions for the variables of trading volume and Google trends. All other investigated variables are insignificant. The model explains 3.3 percent of the variance of ether volatility in the multivariate regression. The predictive model of daily ether volatility is presented in Table 30 in Appendix A. The predictability of ether volatility is significant for the variables of trading volume and Google trends, both for the univariate and multivariate regressions. The R^2 of the predictive model is low at a value of 0.033.

5.1.3 Binance coin

Daily binance coin data is utilized to estimate the daily binance coin return in Table 13. Results indicate a significant effect of volatility, unique addresses and VIX index on binance coin returns for both univariate and multivariate regressions. Conversely, trading volume and Google trends do not exhibit significance in the univariate regression but the Google trends coefficient in the multivariate regression is significant. The R^2 value of the model is 9.1 percent. The model in Table 31 in Appendix A represents the predictability of binance coin return using daily data. The model indicates a significant coefficient for Google trends for the univariate regression but not for the multivariate regression. Additionally, volatility coefficients are significant for both univariate and multivariate regressions. All other variables are insignificant. The R^2 value is 2.4 percent for the univariate volatility regression and 2.7 percent for the multivariate regression.

Table 13
Regression results estimated from daily binance coin data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Trading volume	0.00					0.00
	(1.478)					(1.850)
Volatility		0.03*				0.03**
		(2.448)				(2.623)
Unique Addresses			0.02**			0.02**
			(2.661)			(2.668)
VIX index				-0.19***		-0.20***
				(-3.940)		(-4.228)
Google Trends					0.00	0.00*
					(1.309)	(2.432)
Constant	0.00	-0.01*	0.00*	0.00*	0.00*	-0.01**
	(0.769)	(-2.234)	(2.417)	(2.545)	(2.463)	(-2.704)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.008	0.024	0.015	0.035	0.002	0.091

Table 14 represents regressions with daily binance coin trading volume as the dependent variable. The only significant coefficients are for the variable Google trends, for both the univariate and multivariate regression. The model indicates an R^2 value of 0.066 for the univariate regression and 0.078 for the multivariate regression. Table 32 in Appendix A represents regressions predicting daily binance coin trading volume. The model shows return and Google trends are statistically significant in predicting binance coin trading volume in the multivariate regression. However, only Google trends is statistically significant in the univariate regression. The multivariate regression model has a R^2 value of 0.098.

Table 14
Regression results estimated from daily binance coin data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	22.96					28.44
	(1.297)					(1.571)
Volatility		1.13				-1.65
		(1.067)				(-1.831)
Unique Addresses			0.56			0.15
			(0.957)			(0.219)
VIX index				-2.92		5.15
				(-0.485)		(0.787)
Google Trends					-1.77***	-1.85***
					(-6.822)	(-7.649)
Constant	4.15***	3.69***	4.20***	4.20***	4.17***	4.85***
	(17.135)	(8.679)	(16.728)	(16.717)	(17.176)	(12.475)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.008	0.001	0.000	0.000	0.066	0.078

Table 15
Regression results estimated from daily binance coin data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	0.84^{**}					0.95^{**}
	(2.770)					(2.933)
Trading volume		0.00				-0.00
		(1.226)				(-1.520)
Unique Addresses			0.03			0.01
			(0.965)			(0.416)
VIX index				0.11		0.33^{*}
				(0.716)		(2.131)
Google Trends					-0.02^{***}	-0.02^{***}
					(-5.313)	(-6.024)
Constant	0.45^{***}	0.45^{***}	0.45^{***}	0.45^{***}	0.45^{***}	0.45^{***}
	(86.321)	(74.130)	(86.320)	(86.237)	(87.067)	(75.558)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.024	0.001	0.001	0.000	0.023	0.054

Table 15 puts forward the model for binance coin daily volatility. The model suggests the existence of a statistically significant influence of return and Google trend variables on binance coin volatility for both the univariate and multivariate regression. Moreover, the model indicates a significant effect of the VIX index variable solely in the multivariate regression. The model has an R^2 value of 0.024, 0.023 and 0.054 for the return univariate, Google trends univariate and multivariate regressions. From the predicitive regression model in Table 33 in Appendix A, the variable of return and Google trends can predict binance coin daily volatility for both the univariate and multivariate regressions. However, the coefficient of trading volume is only significant in the multivariate regression. The R^2 value of the predictive multivariate model is 5.2 percent.

5.2 Models utilizing weekly data

5.2.1 Bitcoin

Results from estimating variables explaining weekly bitcoin return are summarized in Table 16. The model suggests that unique addresses significantly influence weekly bitcoin returns for both the univariate and multivariate regressions. On the other hand, trading volume, volatility, VIX index and Google trends variables are insignificant. The model has a R^2 value of 0.122 for the multivariate regression, which indicates that the independent variables on average indicate 12.2 percent of the variance of weekly bitcoin return. The results for the predictive weekly bitcoin return model are represented in Table 34 in Appendix B. The model displays a statistically significant coefficient of VIX index for predicting weekly bitcoin return for both the univariate and multivariate regressions. The R^2 value is 6.1 percent for the univariate VIX index regression and 6.9 percent for the multivariate regression.

Table 16
Regression results estimated from weekly bitcoin data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Trading volume	0.00					0.00
	(1.759)					(1.860)
Volatility		-0.02				-0.01
		(-0.418)				(-0.296)
Unique Addresses			0.31***			0.29***
			(5.894)			(5.640)
VIX index				-0.08		-0.04
				(-1.966)		(-0.971)
Google Trends					0.00	0.00
					(0.213)	(0.355)
Constant	-0.00	0.01	0.00	0.00	0.00	0.00
	(-0.096)	(0.676)	(0.901)	(0.921)	(0.769)	(0.226)
Observations	281	281	281	281	281	281
R^2	0.011	0.001	0.108	0.015	0.000	0.122

The model suggests that unique addresses significantly influence weekly bitcoin returns for both the univariate and multivariate regressions. On the other hand, trading volume, volatility, VIX index and Google trends variables are insignificant. The model has a R^2 value of 0.122 for the multivariate regression, which indicates that the independent variables on average indicate 12.2 percent of the variance of weekly bitcoin return. The results for the predictive weekly bitcoin return model are represented in Table 34 in Appendix B. The model displays a statistically significant coefficient of VIX index for predicting weekly bitcoin return for both the univariate and multivariate regressions. The R^2 value is 6.1 percent for the univariate VIX index regression and 6.9 percent for the multivariate regression.

Regressions utilizing weekly bitcoin data on weekly bitcoin trading volume are shown in Table 17. The considered variables are all insignificant and the multivariate regression has a low R^2 value of 1.3 percent. Table 35 in appendix B displays the predictability of weekly bitcoin trading volume, which indicates that weekly bitcoin return can significantly predict bitcoin weekly trading volume for both the univariate and multivariate regressions.

The model presented in Table 18 analyses the variable that influences weekly bitcoin volatility. Analysis implies that none of the investigated variables have significant influence on weekly bitcoin volatility. The model has an extremely low R^2 value of 0.009. The model investigating the predictability of weekly bitcoin volatility is shown in Table 36 in Appendix B, similarly to the previous model, indicates that no variable in the analysis can significantly predict bitcoin weekly volatility. The R^2 value corresponding to the model is 0.010.

Table 17
Regression results estimated from weekly bitcoin data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	5.17					5.65
	(1.681)					(1.778)
Volatility		-0.53				-0.39
		(-0.525)				(-0.387)
Unique Addresses			0.64			-0.84
			(0.217)			(-0.270)
VIX index				0.77		1.08
				(0.527)		(0.685)
Google Trends					-0.03	-0.03
					(-0.454)	(-0.485)
Constant	1.37***	1.56***	1.38***	1.38***	1.41***	1.53***
	(9.684)	(3.591)	(9.682)	(9.683)	(8.535)	(3.386)
Observations	281	281	281	281	281	281
R^2	0.011	0.000	0.000	0.001	0.001	0.013

Table 18
Regression results estimated from weekly bitcoin data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	-0.07					-0.05
	(-0.418)					(-0.295)
Trading volume		-0.00				-0.00
		(-0.539)				(-0.394)
Unique Addresses			-0.09			-0.10
			(-0.488)			(-0.540)
VIX index				-0.09		-0.10
				(-0.817)		(-1.058)
Google Trends					0.00	0.00
					(0.721)	(0.712)
Constant	0.33***	0.34***	0.33***	0.33***	0.33***	0.33***
	(56.010)	(50.933)	(56.235)	(56.336)	(50.537)	(45.579)
Observations	281	281	281	281	281	281
R^2	0.001	0.000	0.002	0.004	0.001	0.009

5.2.2 Ether

Table 19 illustrates the model estimating weekly ether variables on weekly ether return. All coefficients in the model are insignificant except for the coefficient for the variable Google trends in the univariate regression model. The value of R^2 is indicated to be 0.047. The predictive model for weekly ether return is presented in Table 37 in Appendix B. The variables trading volume, volatility, unique addresses and Google trends are all insignificant in predicting weekly ether returns. However, for both the univariate and multivariate regressions the variable VIX index can significantly predict weekly ether returns. The multivariate regression model can on average explain 10.2 percent of the variance of weekly ether returns.

Table 19
Regression results estimated from weekly ether data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Trading volume	0.00					0.00
	(1.930)					(1.544)
Volatility		0.00				0.00
		(0.166)				(0.148)
Unique Addresses			0.08			0.07
			(1.504)			(1.290)
VIX index				-0.03		-0.03
				(-0.625)		(-0.607)
Google Trends					0.00*	0.00
					(2.156)	(1.926)
Constant	-0.00	0.00	0.00	0.00	-0.00	-0.01
	(-1.003)	(0.017)	(0.609)	(0.657)	(-0.681)	(-0.640)
Observations	281	281	281	281	281	281
R^2	0.018	0.000	0.007	0.001	0.028	0.047

The model for weekly ether trading volume is presented in Table 20. The results suggest a positive significant influence of Google trends on weekly ether trading volume for both the univariate and multivariate regression. The model displays no significant coefficients for any of the other examined variables. The R^2 value is 5.5 percent for the regression model including all the investigated variables. Table 38 in Appendix B presents the results of estimating the variables that can predict weekly ether trading volume. The model indicates that the variables of return and Google trends can significantly predict weekly ether trading volume for both the univariate and multivariate regression. The model has an R^2 value of 0.047.

Table 21 illustrates the weekly ether volatility model. The estimated coefficients do not show any significant explanatory power on weekly ether volatility. The R^2 value of the model is low at 0.012. The predictive model for weekly ether volatility is shown in Table 39 in Appendix B. Similarly to the previous model, none of the variables have significant predictive power for weekly ether volatility. The value R^2 value equals 0.5 percent.

Table 20
Regression results estimated from weekly ether data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	5.60					4.35
	(1.859)					(1.460)
Volatility		-0.95				-0.85
		(-0.892)				(-0.809)
Unique Addresses			2.81			2.47
			(1.247)			(1.109)
VIX index				2.55		2.73
				(1.302)		(1.353)
Google Trends					0.11**	0.10*
					(3.198)	(2.577)
Constant	1.96***	2.40***	1.97***	1.97***	1.75***	2.13***
	(12.895)	(4.289)	(12.913)	(12.915)	(10.094)	(3.741)
Observations	281	281	281	281	281	281
R^2	0.018	0.002	0.005	0.005	0.033	0.055

Table 21
Regression results estimated from weekly ether data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	0.02					0.02
	(0.166)					(0.147)
Trading volume		-0.00				-0.00
		(-0.882)				(-0.809)
Unique Addresses			0.03			0.02
			(0.236)			(0.195)
VIX index				-0.18		-0.17
				(-1.643)		(-1.567)
Google Trends					0.00	0.00
					(0.089)	(0.176)
Constant	0.45***	0.45***	0.45***	0.45***	0.45***	0.45***
	(60.340)	(45.361)	(60.275)	(60.638)	(53.322)	(43.072)
Observations	281	281	281	281	281	281
R^2	0.000	0.002	0.000	0.010	0.000	0.012

5.2.3 Binance coin

The results from estimating the variables with influence on weekly binance coin return are presented in Table 22. The model indicates that the variables of volatility and unique addresses significantly influence weekly binance coin returns for both the univariate and multivariate models. The coefficients of trading volume, VIX index and Google trends are all insignificant. The value of the R^2 statistic is 17.3 percent for the full regression model. Results from the predictive weekly binance coin return model in table 40 in Appendix B display significant predictive power of the volatility variable for the univariate regression and trading volume, Google trends in addition to volatility in the multivariate regression. The R^2 value is 11.6 percent for the univariate volatility regression and 15.3 percent for the multivariate regression.

Table 22
Regression results estimated from weekly binance coin data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Trading volume	0.00					0.00
	(1.330)					(0.259)
Volatility		0.13*				0.12*
		(2.162)				(2.011)
Unique Addresses			0.06*			0.05*
			(2.418)			(2.482)
VIX index				-0.09		-0.08
				(-1.244)		(-1.136)
Google Trends					0.00	0.00
					(1.598)	(0.246)
Constant	0.00	-0.05*	0.01*	0.01*	0.01	-0.05*
	(0.743)	(-1.984)	(1.995)	(2.080)	(1.301)	(-2.099)
Observations	281	281	281	281	281	281
R^2	0.019	0.110	0.068	0.005	0.011	0.173

The estimations of weekly binance coin trading volume is presented in the model in Table 23. The model shows a significant positive coefficient for volatility and Google trends for both the univariate and multivariate regression. The coefficients for volatility are relatively large at 3.78 for the univariate regression and 2.11 for the multivariate regression in comparison to previously investigated models. The R^2 for the full regression displays a value of 65.1 percent. The predictability of weekly binance coin trading volume is shown in Table 41 in Appendix B. The model exhibits a significant positive coefficient for both volatility and Google trends variables for the univariate regression model in addition to the multivariate regression model. The model has a relatively high R^2 value of 0.672 in comparison to the other investigated models.

Table 24 illustrates the model for weekly binance coin volatility. The results suggest that both the variables of return and trading volume can significantly explain the weekly binance coin volatility for both the univariate and multivariate regressions. The model has an R^2 value of 12.6 percent. The predictive model for weekly binance coin volatility is shown in Table 42 in Appendix B. The model indicates that the return variable has significant predictive power on weekly binance coin volatility for both the univariate and multivariate regression. The variable trading volume has a significant coefficient for the univariate regression, but not the multivariate regression. The R^2 of the multivariate regression is 0.082.

Table 23
Regression results estimated from weekly binance coin data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	9.20					1.50
	(1.087)					(0.243)
Volatility		3.78^{*}				2.11^{*}
		(2.054)				(2.140)
Unique Addresses			0.98			0.48
			(1.776)			(0.953)
VIX index				0.94		0.46
				(0.178)		(0.115)
Google Trends					0.27^{***}	0.26^{***}
					(12.382)	(12.984)
Constant	3.06^{***}	1.43^{*}	3.14^{***}	3.16^{***}	1.12^{***}	0.14
	(8.575)	(2.115)	(8.562)	(8.550)	(7.472)	(0.331)
Observations	281	281	281	281	281	281
R^2	0.019	0.021	0.004	0.000	0.640	0.651

Table 24
Regression results estimated from weekly binance coin data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
Return	0.84^{***}					0.79^{**}
	(3.408)					(3.009)
Trading volume		0.01^{***}				0.01^{*}
		(3.714)				(2.579)
Unique Addresses			0.06			0.01
			(1.277)			(0.223)
VIX index				-0.08		-0.01
				(-0.410)		(-0.035)
Google Trends					0.00	-0.00
					(1.435)	(-1.894)
Constant	0.45^{***}	0.44^{***}	0.46^{***}	0.46^{***}	0.45^{***}	0.44^{***}
	(32.361)	(26.334)	(32.349)	(32.070)	(28.758)	(27.194)
Observations	281	281	281	281	281	281
R^2	0.110	0.021	0.011	0.001	0.005	0.126

5.3 Hypotheses

5.3.1 Hypothesis 1 and Hypothesis 2

In conclusion, hypothesis 1 which states that changes in cryptocurrency trading volume affects changes in cryptocurrency returns, is rejected based on the results. Moreover, none of the models with dependent variable of return for both the daily and weekly data have a significant coefficient of the variable trading volume for any investigated cryptocurrency. Similarly, I reject hypothesis 2, stating that cryptocurrency return changes affect changes in cryptocurrency trading volume. The results contrast with previous findings by Katsiampa et al. (2018) and Sovbetov (2018), who study the volume-return relationship for multiple cryptocurrencies. A possible explanation for this difference in results is that the sample span in previous literature does not include the pivotal period between 2017 and 2020 where the cryptocurrency market was characterized by periods of high price volatility.

5.3.2 Hypothesis 3 and Hypothesis 4

The models that investigate hypothesis 3 and hypothesis 4 display contrasting results. I find incomplete support for hypothesis 3 which states that cryptocurrency volatility changes affect cryptocurrency return changes. The volatility coefficients for daily and weekly regressions with binance coin return as the dependent variable substantiate hypothesis 3. However, the models for bitcoin and ether both using daily and weekly data reject hypothesis 3. Overall, I conclude that the cryptocurrency market in full rejects the hypothesis. Moreover, the models for binance coin have low explanatory power.

Similarly, I can partially support hypothesis 4, stating that changes in cryptocurrency return affect changes in cryptocurrency volatility, from the results. The daily and weekly volatility model for binance coin confirms the hypothesis, however bitcoin and ether models reject hypothesis 4 for both daily and weekly time horizons. In general, for the cryptocurrency market hypothesis 4 is rejected as the binance coin model can explain relatively little of the variance in binance coin volatility on average.

The findings are similar to past literature by Liu and Serletis (2019) and Cross et al. (2021) that studied a different context (litecoin and ripple) for the interdependence of cryptocurrency return and volatility. This displays that if the cryptocurrency market does have a significant relationship between volatility and return, this relationship is not similar across different cryptocurrency assets.

5.3.3 Hypothesis 5 and Hypothesis 6

Varying results are exhibited for the models estimating hypothesis 5. Thus, I discover limited support for the hypothesis, which states that cryptocurrency trading volume changes affect cryptocurrency volatility changes. While the daily model for bitcoin and ether validates the idea, the effect vanishes in the weekly model. Comparably, for the binance coin models the weekly model confirms the idea, however the daily model rejects the hypothesis. Interestingly, previous literature finds similar results pertaining to bitcoin and ether, which implies an effect of trading volume on volatility in the case of daily data and not weekly data (Aalborg et al., 2019; Conrad et al., 2018; Letra, 2016). However, the discovery for weekly binance coin has not been previously investigated in the literature. A possible explanation for this difference is that bitcoin and ether are much closer in market capitalization in comparison to binance coin, thus exhibiting results differing from the relatively smaller cryptocurrency: binance coin.

Given the disparate results of the models with trading volume as the dependent variable, I can only partially support Hypothesis 6. The hypothesis states that a change in cryptocurrency volatility affects a change in cryptocurrency trading volume. Similarly to the previous hypothesis, the effect exists for all three of the investigated cryptocurrencies, however the effect vanishes for bitcoin and ether using weekly data and disappears when utilizing daily binance coin data. The explanatory power is relatively large in the weekly binance coin model and the daily ether trading volume model in comparison to the other researched models. Unusually, the coefficient is positive for binance coin and negative for ether. The past research on this effect is very limited as most of the literature is in the study of the opposite effect, however the findings imply that cryptocurrency volatility can explain the trading volume for a number of cryptocurrencies.

5.4 Control variables

The only control variable with significant explanatory power for all researched cryptocurrency return is the VIX index, which is a negative effect. Moreover, this is only the case for a daily time horizon this effect is not significant for weekly cryptocurrency returns. No previous study reports any significant relationship between VIX index and return. Cryptocurrency trading volume can be significantly explained by the Google trends variable implied by the results. Five of the six models with trading volume as the dependent variable display a significant positive coefficient both for daily and weekly data. This finding is comparable to the results by Shen et al. (2019), where they investigate if tweets drive the trading volume of bitcoin. This could imply that general online activity regarding a specific cryptocurrency could significantly explain trading volume. The investigated control variables do not indicate any significant influence across both daily and weekly horizons for cryptocurrency volatility. Moreover, the models present low explanatory power when it pertains to models with daily volatility as the dependent variable. This finding is different from previous literature with comparable control variables by Aalborg et al. (2019), who find that Google trends and unique addresses are significant influencers of volatility during the period of 2012 to 2017. A possible reason for this difference in results is that the sample data for Google trends and unique addresses during the period of 2012 to 2017 is significantly different to the data used in this research. Moreover, during the period of 2012 to 2017 the number of Google searches and unique addresses for the cryptocurrency market are relatively small in comparison to the period of 2017 to 2022.

CHAPTER 6 Conclusion

In this paper I have explored the interpretation of return, trading volume and volatility for the three largest cryptocurrencies by market capitalization: bitcoin, ether and binance coin. Previous literature has exhibited that an interrelationship exists between volatility and trading volume for bitcoin specifically, however it remains unclear if the interpretations differ between cryptocurrencies or are similar across the cryptocurrency market. This study differentiates itself from the existing literature by investigating binance coin in particular, in spite of the fact that cryptocurrencies have fundamental differences between them no previous research has investigated binance coin return, trading volume and volatility relationships. Thus, the question I investigated in this thesis was: “What is the interrelation between return, trading volume and volatility in the cryptocurrency market?”

To investigate the research question, I collected daily and weekly cryptocurrency data spanning the period of July 26, 2017 to December 31, 2022. Utilizing multiple univariate and multivariate regression models I estimate the variables that can explain and predict cryptocurrency return, trading volume and volatility. The analysis of both the daily and weekly cryptocurrency data indicates no significant interrelationship between trading volume and return in the cryptocurrency market. Analyzing the relationship between volatility and return, I find that the relationship differs between cryptocurrencies, with binance coin presenting a significant positive relationship and bitcoin and ether exhibiting no relation. Examining the trading volume-volatility relation, I discovered that the daily and weekly interrelation differs in the cryptocurrency market. Moreover, bitcoin and ether present a significant daily relationship and binance coin on a weekly basis. These models in particular exhibit a relatively high value of explanatory power.

In conclusion, despite the fact that previous literature shows an interrelationship between trading volume and return for multiple cryptocurrencies, by including a more recent data horizon, I find that the cryptocurrency market exhibits no trading volume-return interrelationship. Looking at the volatility-return interrelation for bitcoin, ether and binance coin, in addition to combining the results with past research for different cryptocurrencies, I conclude that the interrelation is not persistent across the cryptocurrency market. Moreover, different cryptocurrency assets have varying volatility-return interrelations. Finally, this study concludes, in accordance with previous studies on bitcoin and ether, that the cryptocurrency market exhibits an interrelationship between trading volume and volatility.

From a practical point of view, cryptocurrency investors are intrigued by the predictability of the main variables of interest. To that extend this thesis concludes that the amount of Google searches for a specific cryptocurrency can significantly predict trading volume of that cryptocurrency. Similarly daily volatility can be predicted by investigating daily trading volume values. This suggests that market participants in the cryptocurrency market are recommended to monitor both Google trends and trading volume information prior to making investment decisions.

Unfortunately, I was unable to examine the same sample period of 2012 to 2017, as the research I replicate by Aalborg et al. (2019). Despite the fact that investigation of this period may give an interesting comparison of results, the cryptocurrency market data during that period largely consisted of bitcoin data. Moreover, ether and binance coin data is not available during the full-length period of 2012 to 2017.

Another possible limitation of this thesis is the fact that the interrelationships between returns, trading volume and volatility in the cryptocurrency market might vary when considering differing portfolio holding horizons. Past literature has suggested that the relationship between trading volume and returns is significant during shorter holding periods of 1, 10 and 20 trading days, in contrast to being insignificant when considering longer holding periods. Future researchers are encouraged to investigate whether the duration of the holding horizon may have an influence on the interrelationship between returns, trading volume and volatility utilizing the sample period, similar to the one used in this thesis, of July 26, 2017 to December 31, 2022. This can potentially provide differing results, which to date, have not yet been examined in the literature.

REFERENCES

Aalborg, H. A., Molnár, P., & de Vries, J. E. (2019). What can explain the price, volatility and trading volume of Bitcoin?. *Finance Research Letters*, *29*, 255-265.

Aharon, D. Y., & Qadan, M. (2019). Bitcoin and the day-of-the-week effect. *Finance Research Letters*, *31*.

Almeida, J., & Gonçalves, T. C. (2022). A systematic literature review of volatility and risk management on cryptocurrency investment: A methodological point of view. *Risks*, *10*(5), 107.

Andersen, T. G., & Bollerslev, T. (1997). Answering the critics: Yes, ARCH models do provide good volatility forecasts.

Ante, L. (2020). Bitcoin transactions, information asymmetry and trading volume. *Bitcoin Transactions, Information Asymmetry and Trading Volume (June 2, 2020). Lennart Ante. Bitcoin transactions, information asymmetry and trading volume. Quantitative Finance and Economics*, *4*(3), 365-381.

Badenhorst, J. J. (2018). *Effect of bitcoin spot and derivative trading volumes on price volatility* (Doctoral dissertation, University of Pretoria).

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, *64*, 74-81.

Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters*, *173*, 148-151.

Berument, H., & Doğan, N. (2011). Stock market return and volatility relationship: Monday effect. *International Journal of Economic Perspectives*, *5*(2), 175-185.

Bianchi, D. (2020). Cryptocurrencies as an asset class? An empirical assessment. *The Journal of Alternative Investments*, *23*(2), 162-179.

Bijl, L., Kringhaug, G., Molnár, P., & Sandvik, E. (2016). Google searches and stock returns. *International Review of Financial Analysis*, *45*, 150-156.

Binance (BNB) blockchain Explorer - BscScan. (n.d.). https://bscscan.com/

Blockchain.com | Be early to the future of finance. (n.d.). Retrieved 19 April 2023, from https://www.blockchain.com

Bouri, E., Azzi, G., & Dyhrberg, A. H. (2017). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. *Economics*, *11*(1).

Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics*, *50*(55), 5935-5949.

Bouri, E., Lau, C. K. M., Lucey, B., & Roubaud, D. (2019). Trading volume and the predictability of return and volatility in the cryptocurrency market. *Finance Research Letters*, *29*, 340-346.

Bouri, E., Shahzad, S. J. H., & Roubaud, D. (2019). Co-explosivity in the cryptocurrency market. *Finance Research Letters*, *29*, 178-183.

Buterin, V. (2014). A next-generation smart contract and decentralized application platform. *white paper*, *3*(37), 2-1.

Caporale, G. M., & Plastun, A. (2019). The day of the week effect in the cryptocurrency market. *Finance Research Letters*, *31*.

Cevik, E. I., Gunay, S., Dibooglu, S., & Yıldırım, D. Ç. (2023). The impact of expected and unexpected events on Bitcoin price development: Introduction of futures market and COVID-19. *Finance Research Letters*, *54*, 103768.

Chan, K. C., Fung, H. G., & Leung, W. K. (2004). Daily volatility behavior in Chinese futures markets. *Journal of International Financial Markets, Institutions and Money*, *14*(5), 491-505.

Chan, S., Chu, J., Zhang, Y., & Nadarajah, S. (2022). An extreme value analysis of the tail relationships between returns and volumes for high frequency cryptocurrencies. *Research in International Business and Finance*, *59*, 101541.

Cheikh, N. B., Zaied, Y. B., & Chevallier, J. (2020). Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models. *Finance Research Letters*, *35*, 101293.

Chen, G. M., Firth, M., & Rui, O. M. (2001). The dynamic relation between stock returns, trading volume, and volatility. *Financial Review*, *36*(3), 153-174.

Colianni, S., Rosales, S., & Signorotti, M. (2015). Algorithmic trading of cryptocurrency based on Twitter sentiment analysis. *CS229 Project*, *1*(5), 1-4.

Conrad, C., Custovic, A., & Ghysels, E. (2018). Long-and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. *Journal of Risk and Financial Management*, *11*(2), 23.

Corbet, S., Hou, Y. G., Hu, Y., Larkin, C., Lucey, B., & Oxley, L. (2022). Cryptocurrency liquidity and volatility interrelationships during the COVID-19 pandemic. *Finance Research Letters*, *45*, 102137.

Corbet, S., McHugh, G., & Meegan, A. (2014). The influence of central bank monetary policy announcements on cryptocurrency return volatility. *Investment management and financial innovations*, (14, Iss. 4), 60-72.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, *7*(2), 174-196.

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The journal of finance*, *67*(2), 719-760.

Cross, J. L., Hou, C., & Trinh, K. (2021). Returns, volatility and the cryptocurrency bubble of 2017–18. *Economic Modelling*, *104*, 105643.

'Cryptocurrency Market Worth $11.71 Billion By 2030'. Accessed 19 April 2023. https://www.grandviewresearch.com/press-release/global-cryptocurrency-market.

Cryptocurrency Prices, Charts And Market Capitalizations. (n.d.). CoinMarketCap. Retrieved 19 April 2023, from https://coinmarketcap.com/

Crypto Research, Data, and Tools. (n.d.). Messari. https://messari.io/

Daly, K. (2008). Financial volatility: Issues and measuring techniques. *Physica A: statistical mechanics and its applications*, *387*(11), 2377-2393.

Demir, E., Bilgin, M. H., Karabulut, G., & Doker, A. C. (2020). The relationship between cryptocurrencies and COVID-19 pandemic. *Eurasian Economic Review*, *10*, 349-360.

Dictionary, O. E. (1989). Oxford english dictionary. *Simpson, Ja & Weiner, Esc*, *3*.

Ebens, H. (1999). Realized stock volatility. *Department of Economics, Johns Hopkins University*.

El Alaoui, M., Bouri, E., & Roubaud, D. (2019). Bitcoin price–volume: A multifractal cross-correlation approach. *Finance Research Letters*, *31*.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), 339-350.

Enoksen, F. A., Landsnes, C. J., Lučivjanská, K., & Molnár, P. (2020). Understanding risk of bubbles in cryptocurrencies. *Journal of Economic Behavior & Organization*, *176*, 129-144.

Fakhfekh, M., & Jeribi, A. (2020). Volatility dynamics of crypto-currencies' returns: Evidence from asymmetric and long memory GARCH models. *Research in International Business and Finance*, *51*, 101075.

Fang, J., Qin, Y., & Jacobsen, B. (2014). Technical market indicators: An overview. *Journal of behavioral and experimental finance*, *4*, 25-56.

Fang, T., Su, Z., & Yin, L. (2020). Economic fundamentals or investor perceptions? The role of uncertainty in predicting long-term cryptocurrency volatility. *International Review of Financial Analysis*, *71*, 101566.

Foroutan, P., & Lahmiri, S. (2022). The effect of COVID-19 pandemic on return-volume and return-volatility relationships in cryptocurrency markets. *Chaos, Solitons & Fractals*, *162*, 112443.

Foster, F. D., & Viswanathan, S. (1993). Variations in trading volume, return volatility, and trading costs: Evidence on recent price formation models. *The Journal of Finance*, *48*(1), 187-211.

Georgoula, I., Pournarakis, D., Bilanakos, C., Sotiropoulos, D., & Giaglis, G. M. (2015). Using time-series and sentiment analysis to detect the determinants of bitcoin prices. *Available at SSRN 2607167*.

Gervais, S., Kaniel, R., & Mingelgrin, D. H. (2001). The high-volume return premium. *The Journal of Finance*, *56*(3), 877-919.

Google Trends. (n.d.). Retrieved 19 April 2023, from https://trends.google.com/home

Hau, L., Zhu, H., Shahbaz, M., & Sun, W. (2021). Does transaction activity predict Bitcoin returns? Evidence from quantile-on-quantile analysis. *The North American Journal of Economics and Finance*, *55*, 101297.

Jain, A., Tripathi, S., Dwivedi, H. D., & Saxena, P. (2018, August). Forecasting price of cryptocurrencies using tweets sentiment analysis. In *2018 eleventh international conference on contemporary computing (IC3)* (pp. 1-7). IEEE.

Kamau, C. G. (2022). The Cryptocurrency Market in Kenya: A Review of Awareness and Participation by the Youth. *Journal of Asian Business Strategy*, *12*(1), 49-56.

Katsiampa, P., Gkillas, K., & Longin, F. (2018). Cryptocurrency market activity during extremely volatile periods. *Available at SSRN 3220781*.

Kaya, O., & Mostowfi, M. (2022). Low-volatility strategies for highly liquid cryptocurrencies. *Finance Research Letters*, *46*, 102422.

Khedr, A. M., Arif, I., El-Bannany, M., Alhashmi, S. M., & Sreedharan, M. (2021). Cryptocurrency price prediction using traditional statistical and machine-learning techniques: A survey. *Intelligent Systems in Accounting, Finance and Management*, *28*(1), 3-34.

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PloS one*, *10*(4), e0123923.

Kyriazis, N. A. (2021). A survey on volatility fluctuations in the decentralized cryptocurrency financial assets. *Journal of Risk and Financial Management*, *14*(7), 293.

Lahmiri, S., Bekiros, S., & Bezzina, F. (2022). Complexity analysis and forecasting of variations in cryptocurrency trading volume with support vector regression tuned by Bayesian optimization under different kernels: An empirical comparison from a large dataset. *Expert Systems with Applications*, *209*, 118349.

Lamon, C., Nielsen, E., & Redondo, E. (2017). Cryptocurrency price prediction using news and social media sentiment. *SMU Data Sci. Rev*, *1*(3), 1-22.

Lee, B. S., & Rui, O. M. (2002). The dynamic relationship between stock returns and trading volume: Domestic and cross-country evidence. *Journal of Banking & Finance*, *26*(1), 51-78.

Leirvik, T. (2022). Cryptocurrency returns and the volatility of liquidity. *Finance Research Letters*, *44*, 102031.

Letra, I. J. S. (2016). *What drives cryptocurrency value? A volatility and predictability analysis* (Doctoral dissertation, Universidade de Lisboa (Portugal)).

Li, Q., Yang, J., Hsiao, C., & Chang, Y. J. (2005). The relationship between stock returns and volatility in international stock markets. *Journal of Empirical Finance*, *12*(5), 650-665.

Liu, J., & Serletis, A. (2019). Volatility in the cryptocurrency market. *Open Economies Review*, *30*, 779-811.

Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*, *77*(2), 1133-1177.

Li, X., & Whinston, A. B. (2020). Analyzing cryptocurrencies. *Information Systems Frontiers*, *22*, 17-22.

Mahajan, S., & Singh, B. (2009). The empirical investigation of relationship between return, volume and volatility dynamics in Indian stock market. *Eurasian Journal of Business and Economics*, *2*(4), 113-137.

MALLICK, S. K. (2020). Causal relationship between Crypto currencies: An Analytical Study between Bitcoin and Binance Coin. *Journal of Contemporary Issues in Business and Government| Vol*, *26*(2), 2172.

Merriam-Webster's Collegiate Dictionary (10th ed.). (1999). Merriam-Webster Incorporated.

Metrics, C. (2023, June 8). *Home - Coin Metrics*. Coin Metrics. https://coinmetrics.io/

MoneySense. (2023, March 20). What are stock market returns? - MoneySense. https://www.moneysense.ca/glossary/what-are-stock-market-returns/#:~:text=A%20stock%20market%20return%20is,a%20loss%20on%20the%20investment

Moore, T., & Christin, N. (2013). Beware the middleman: Empirical analysis of Bitcoin-exchange risk. In *Financial Cryptography and Data Security: 17th International Conference, FC 2013, Okinawa, Japan, April 1-5, 2013, Revised Selected Papers 17* (pp. 25-33). Springer Berlin Heidelberg.

Mubarik, F., & Javid, A. Y. (2009). Relationship between stock return, trading volume and volatility: Evidence from Pakistani stock market. *Asia Pacific Journal of Finance and Banking Research*, *3*(3).

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Decentralized business review*, 21260.

Nasir, M. A., Huynh, T. L. D., Nguyen, S. P., & Duong, D. (2019). Forecasting cryptocurrency returns and volume using search engines. *Financial Innovation*, *5*(1), 1-13.

Park, T. H., Switzer, L. N., & Bedrossian, R. (1999). The interactions between trading volume and volatility: evidence from the equity options markets. *Applied Financial Economics*, *9*(6), 627-637.

Patel, N. P., Parekh, R., Thakkar, N., Gupta, R., Tanwar, S., Sharma, G., ... & Sharma, R. (2022). Fusion in cryptocurrency price prediction: a decade survey on recent advancements, architecture, and potential future directions. *IEEE Access*, *10*, 34511-34538.

Phillips, P. C., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International economic review*, *56*(4), 1043-1078.

Poongodi, M., Sharma, A., Vijayakumar, V., Bhardwaj, V., Sharma, A. P., Iqbal, R., & Kumar, R. (2020). Prediction of the price of Ethereum blockchain cryptocurrency in an industrial finance system. *Computers & Electrical Engineering*, *81*, 106527.

Qiu, T., Zhong, L. X., Chen, G., & Wu, X. R. (2009). Statistical properties of trading volume of Chinese stocks. *Physica A: Statistical Mechanics and its Applications*, *388*(12), 2427-2434.

Roy, S., Nanjiba, S., & Chakrabarty, A. (2018, December). Bitcoin price forecasting using time series analysis. In *2018 21st International Conference of Computer and Information Technology (ICCIT)* (pp. 1-5). IEEE.

Santiment - See what other crypto traders are missing. (n.d.). https://santiment.net/

Sapuric, S., Kokkinaki, A., & Georgiou, I. (2022). The relationship between Bitcoin returns, volatility and volume: asymmetric GARCH modeling. *Journal of Enterprise Information Management*, *35*(6), 1506-1521.

Sarwar, G. (2003). The interrelation of price volatility and trading volume of currency options. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *23*(7), 681-700.

Selgin, G. (2015). Synthetic commodity money. *Journal of Financial Stability*, *17*, 92-99.

Shah, D., & Zhang, K. (2014, September). Bayesian regression and Bitcoin. In *2014 52nd annual Allerton conference on communication, control, and computing (Allerton)* (pp. 409-414). IEEE.

Shamshiripour, A., Rahimi, E., Shabanpour, R., & Mohammadian, A. K. (2020). How is COVID-19 reshaping activity-travel behavior? Evidence from a comprehensive survey in Chicago. *Transportation research interdisciplinary perspectives*, *7*, 100216.

Shen, D., Urquhart, A., & Wang, P. (2019). Does twitter predict Bitcoin?. *Economics Letters*, *174*, 118-122.

Sovbetov, Y. (2018). Factors influencing cryptocurrency prices: Evidence from bitcoin, ethereum, dash, litecoin, and monero. *Journal of Economics and Financial Analysis*, *2*(2), 1-27.

Sun, T., & Yu, W. (2020). A formal verification framework for security issues of blockchain smart contracts. *Electronics*, *9*(2), 255.

Urquhart, A. (2018). What causes the attention of Bitcoin?. *Economics Letters*, *166*, 40-44.

Vejačka, M. (2014). Basic aspects of cryptocurrencies. *Journal of Economy, Business and Financing*, *2*(2), 75-83.

Wang, C. (2021). Different GARCH models analysis of returns and volatility in Bitcoin. *Data Science in Finance and Economics*, *1*(1), 37-59.

Wang, J. N., Liu, H. C., & Hsu, Y. T. (2020). Time-of-day periodicities of trading volume and volatility in Bitcoin exchange: does the stock market matter?. *Finance Research Letters*, *34*, 101243.

Wang, Z., Jin, H., Dai, W., Choo, K. K. R., & Zou, D. (2021). Ethereum smart contract security research: survey and future research opportunities. *Frontiers of Computer Science*, *15*, 1-18.

Wątorek, M., Drożdż, S., Kwapień, J., Minati, L., Oświęcimka, P., & Stanuszek, M. (2021). Multiscale characteristics of the emerging global cryptocurrency market. *Physics Reports*, *901*, 1-82.

Yahoo Finance—Stock Market Live, Quotes, Business & Finance News. (n.d.). Retrieved 19 April 2023, from https://finance.yahoo.com/

Zhang, W., & Li, Y. (2020). Is idiosyncratic volatility priced in cryptocurrency markets?. *Research in International Business and Finance*, *54*, 101252.

Zhang, W., Wang, P., Li, X., & Shen, D. (2018). Some stylized facts of the cryptocurrency market. *Applied Economics*, *50*(55), 5950-5965.

Zheng, Z., Xie, S., Dai, H. N., Chen, W., Chen, X., Weng, J., & Imran, M. (2020). An overview on smart contracts: Challenges, advances and platforms. *Future Generation Computer Systems*, *105*, 475-491.

APPENDIX A – Daily predictive results

Table 25
Predictive results estimated from daily bitcoin data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Trading\ volume_{t-1}$	0.00					0.00
	(0.136)					(0.098)
$Volatility_{t-1}$		0.00				0.00
		(0.067)				(0.079)
$Unique\ Addresses_{t-1}$			0.03^{*}			0.03^{*}
			(2.241)			(2.228)
$VIX\ index_{t-1}$				-0.00		-0.00
				(-0.122)		(-0.152)
$Google\ Trends_{t-1}$					0.00	0.00
					(0.290)	(0.239)
Constant	0.00	0.00	0.00	0.00	0.00	0.00
	(0.820)	(0.149)	(1.041)	(1.047)	(1.001)	(0.110)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.000	0.000	0.004	0.000	0.000	0.004

Table 26
Predictive results estimated from daily bitcoin data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	2.57					4.16
	(0.651)					(1.121)
$Volatility_{t-1}$		0.67				0.79
		(1.128)				(1.378)
$Unique\ Addresses_{t-1}$			0.16			0.05
			(0.120)			(0.034)
$VIX\ index_{t-1}$				2.89		3.45
				(1.188)		(1.416)
$Google\ Trends_{t-1}$					0.14^{***}	0.14^{***}
					(3.408)	(3.453)
Constant	1.39^{***}	1.17^{***}	1.39^{***}	1.39^{***}	1.36^{***}	1.10^{***}
	(24.939)	(5.432)	(25.052)	(25.136)	(23.727)	(5.161)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.001	0.001	0.000	0.002	0.008	0.012

Table 27
Predictive results estimated from daily bitcoin data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	-0.05					-0.08
	(-0.501)					(-0.751)
$Trading\ volume_{t-1}$		0.00^{*}				0.00^{*}
		(1.992)				(2.241)
$Unique\ Addresses_{t-1}$			-0.02			-0.02
			(-0.359)			(-0.329)
$VIX\ index_{t-1}$				-0.05		-0.06
				(-0.709)		(-0.830)
$Google\ Trends_{t-1}$					-0.00	-0.00
					(-0.786)	(-1.057)
Constant	0.33^{***}	0.33^{***}	0.33^{***}	0.33^{***}	0.33^{***}	0.33^{***}
	(167.671)	(158.145)	(167.641)	(167.713)	(171.431)	(157.913)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.000	0.002	0.000	0.001	0.000	0.004

Table 28
Predictive results estimated from daily ether data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Trading\ volume_{t-1}$	0.00					0.00
	(0.127)					(0.554)
$Volatility_{t-1}$		0.02^{*}				0.02^{*}
		(2.265)				(2.323)
$Unique\ Addresses_{t-1}$			0.00			-0.00
			(0.009)			(-0.009)
$VIX\ index_{t-1}$				-0.00		-0.00
				(-0.145)		(-0.105)
$Google\ Trends_{t-1}$					-0.00	-0.00
					(-0.073)	(-0.562)
Constant	0.00	-0.01^{*}	0.00	0.00	0.00	-0.01^{*}
	(0.542)	(-2.083)	(0.766)	(0.768)	(0.786)	(-2.143)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.000	0.004	0.000	0.000	0.000	0.004

Table 29
Predictive results estimated from daily ether data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	3.94					3.35
	(1.219)					(1.263)
$Volatility_{t-1}$		-2.27***				-3.36***
		(-3.783)				(-6.317)
$Unique\ Addresses_{t-1}$			1.33			0.07
			(0.826)			(0.058)
$VIX\ index_{t-1}$				2.31		2.51
				(1.218)		(1.434)
$Google\ Trends_{t-1}$					0.82***	0.85***
					(15.382)	(15.743)
Constant	1.81***	2.81***	1.81***	1.81***	1.68***	3.15***
	(29.575)	(9.938)	(29.607)	(29.615)	(30.436)	(12.264)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.002	0.009	0.001	0.001	0.165	0.186

Table 30
Predictive results estimated from daily ether data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	0.14					0.11
	(1.481)					(1.132)
$Trading\ volume_{t-1}$		-0.00**				-0.01***
		(-2.870)				(-5.559)
$Unique\ Addresses_{t-1}$			0.03			0.02
			(0.470)			(0.339)
$VIX\ index_{t-1}$				-0.06		-0.03
				(-0.774)		(-0.406)
$Google\ Trends_{t-1}$					0.01***	0.01***
					(4.222)	(6.224)
Constant	0.44***	0.45***	0.44***	0.44***	0.44***	0.45***
	(175.550)	(131.832)	(175.463)	(175.524)	(175.493)	(129.719)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.002	0.006	0.000	0.001	0.011	0.033

Table 31
Predictive results estimated from daily binance coin data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Trading\ volume_{t-1}$	-0.00					-0.00
	(-0.284)					(-0.656)
$Volatility_{t-1}$		0.03*				0.03*
		(2.437)				(2.291)
$Unique\ Addresses_{t-1}$			-0.00			-0.00
			(-0.887)			(-0.975)
$VIX\ index_{t-1}$				0.02		0.02
				(0.691)		(0.627)
$Google\ Trends_{t-1}$					-0.00*	-0.00
					(-2.333)	(-1.585)
Constant	0.00*	-0.01*	0.00*	0.00*	0.00*	-0.01*
	(2.316)	(-2.223)	(2.460)	(2.446)	(2.432)	(-1.998)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.000	0.024	0.000	0.000	0.004	0.027

Table 32
Predictive results estimated from daily binance coin data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	17.55					24.40*
	(1.465)					(2.021)
$Volatility_{t-1}$		1.41				-1.53
		(1.295)				(-1.704)
$Unique\ Addresses_{t-1}$			0.79			0.48
			(1.409)			(0.695)
$VIX\ index_{t-1}$				4.24		11.89
				(0.657)		(1.732)
$Google\ Trends_{t-1}$					-2.05***	-2.12***
					(-9.089)	(-9.793)
Constant	4.16***	3.57***	4.20***	4.20***	4.17***	4.80***
	(16.875)	(8.247)	(16.731)	(16.733)	(17.482)	(12.432)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.005	0.001	0.000	0.000	0.089	0.098

Table 33
Predictive results estimated from daily binance coin data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	0.80^{**}					0.92^{***}
	(3.108)					(3.298)
$Trading\ volume_{t-1}$		0.00				-0.00^{*}
		(0.653)				(-2.138)
$Unique\ Addresses_{t-1}$			0.02			0.00
			(0.664)			(0.109)
$VIX\ index_{t-1}$				0.08		0.29
				(0.531)		(1.913)
$Google\ Trends_{t-1}$					-0.02^{***}	-0.02^{***}
					(-5.475)	(-6.214)
Constant	0.45^{***}	0.45^{***}	0.45^{***}	0.45^{***}	0.45^{***}	0.45^{***}
	(86.568)	(74.371)	(86.246)	(86.242)	(87.096)	(75.870)
Observations	1417	1417	1417	1417	1417	1417
R^2	0.022	0.000	0.000	0.000	0.023	0.052

APPENDIX B – Weekly predictive results

Table 34
Predictive results estimated from weekly bitcoin data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Trading\ volume_{t-1}$	0.00					0.00
	(0.840)					(0.885)
$Volatility_{t-1}$		0.01				0.01
		(0.360)				(0.272)
$Unique\ Addresses_{t-1}$			0.10			0.05
			(1.477)			(0.782)
$VIX\ index_{t-1}$				-0.17***		-0.16***
				(-3.536)		(-3.424)
$Google\ Trends_{t-1}$					-0.00	-0.00
					(-0.724)	(-0.770)
Constant	0.00	-0.00	0.00	0.00	0.00	-0.00
	(0.461)	(-0.147)	(0.887)	(1.000)	(1.317)	(-0.042)
Observations	281	281	281	281	281	281
R^2	0.002	0.001	0.011	0.061	0.004	0.069

Table 35
Predictive results estimated from weekly bitcoin data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	7.19*					7.19*
	(2.442)					(2.457)
$Volatility_{t-1}$		-0.83				-0.64
		(-0.833)				(-0.642)
$Unique\ Addresses_{t-1}$			2.47			0.43
			(0.858)			(0.145)
$VIX\ index_{t-1}$				0.34		0.87
				(0.225)		(0.537)
$Google\ Trends_{t-1}$					-0.07	-0.07
					(-1.063)	(-1.071)
Constant	1.36***	1.66***	1.38***	1.38***	1.44***	1.64***
	(9.687)	(3.881)	(9.698)	(9.673)	(8.734)	(3.710)
Observations	281	281	281	281	281	281
R^2	0.021	0.001	0.003	0.000	0.003	0.025

Table 36
Predictive results estimated from weekly bitcoin data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	-0.06					-0.02
	(-0.348)					(-0.106)
$Trading\ volume_{t-1}$		-0.00				-0.00
		(-0.408)				(-0.308)
$Unique\ Addresses_{t-1}$			-0.13			-0.13
			(-0.705)			(-0.721)
$VIX\ index_{t-1}$				-0.03		-0.05
				(-0.308)		(-0.533)
$Google\ Trends_{t-1}$					0.00	0.00
					(1.411)	(1.397)
Constant	0.33^{***}	0.33^{***}	0.33^{***}	0.33^{***}	0.33^{***}	0.33^{***}
	(56.063)	(51.017)	(56.314)	(56.250)	(50.510)	(45.143)
Observations	281	281	281	281	281	281
R^2	0.001	0.000	0.004	0.001	0.005	0.010

Table 37
Predictive results estimated from weekly ether data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Trading\ volume_{t-1}$	0.00					0.00
	(0.159)					(0.119)
$Volatility_{t-1}$		0.03				0.02
		(1.101)				(0.741)
$Unique\ Addresses_{t-1}$			0.09			0.08
			(1.656)			(1.415)
$VIX\ index_{t-1}$				-0.25^{***}		-0.24^{***}
				(-4.476)		(-4.388)
$Google\ Trends_{t-1}$					0.00	0.00
					(1.383)	(1.382)
Constant	0.00	-0.01	0.00	0.00	-0.00	-0.01
	(0.442)	(-0.869)	(0.596)	(0.762)	(-0.240)	(-0.809)
Observations	281	281	281	281	281	281
R^2	0.000	0.004	0.010	0.082	0.012	0.102

Table 38
Predictive results estimated from weekly ether data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	6.44**					5.65*
	(2.781)					(2.464)
$Volatility_{t-1}$		-1.33				-1.36
		(-1.307)				(-1.351)
$Unique\ Addresses_{t-1}$			0.39			-0.11
			(0.155)			(-0.044)
$VIX\ index_{t-1}$				1.09		1.09
				(0.575)		(0.577)
$Google\ Trends_{t-1}$					0.09**	0.08*
					(2.716)	(2.290)
Constant	1.95***	2.57***	1.97***	1.97***	1.78***	2.40***
	(12.949)	(4.709)	(12.854)	(12.878)	(10.191)	(4.340)
Observations	281	281	281	281	281	281
R^2	0.024	0.004	0.000	0.001	0.024	0.047

Table 39
Predictive results estimated from weekly ether data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	0.07					0.07
	(0.526)					(0.493)
$Trading\ volume_{t-1}$		-0.00				-0.00
		(-0.690)				(-0.793)
$Unique\ Addresses_{t-1}$			0.04			0.04
			(0.345)			(0.316)
$VIX\ index_{t-1}$				-0.07		-0.06
				(-0.582)		(-0.502)
$Google\ Trends_{t-1}$					0.00	0.00
					(0.333)	(0.331)
Constant	0.45***	0.45***	0.45***	0.45***	0.45***	0.45***
	(60.388)	(45.554)	(60.375)	(60.403)	(53.113)	(42.615)
Observations	281	281	281	281	281	281
R^2	0.001	0.001	0.000	0.001	0.000	0.005

Table 40
Predictive results estimated from weekly binance coin data using OLS on dependent variable: return. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Trading\ volume_{t-1}$	-0.00					-0.00^{**}
	(-0.649)					(-2.863)
$Volatility_{t-1}$		0.13^{*}				0.14^{*}
		(2.259)				(2.345)
$Unique\ Addresses_{t-1}$			0.02			0.01
			(1.055)			(0.720)
$VIX\ index_{t-1}$				-0.09		-0.10
				(-0.659)		(-0.897)
$Google\ Trends_{t-1}$					0.00	0.00^{**}
					(0.499)	(2.743)
Constant	0.01^{*}	-0.05^{*}	0.01^{*}	0.01^{*}	0.01	-0.05^{*}
	(2.111)	(-2.085)	(2.052)	(2.119)	(1.735)	(-2.142)
Observations	281	281	281	281	281	281
R^2	0.002	0.116	0.005	0.004	0.001	0.153

Table 41
Predictive results estimated from weekly binance coin data using OLS on dependent variable: trading volume. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	10.45					2.91
	(1.360)					(0.662)
$Volatility_{t-1}$		4.16^{*}				2.70^{**}
		(2.139)				(2.641)
$Unique\ Addresses_{t-1}$			0.49			-0.14
			(0.956)			(-0.262)
$VIX\ index_{t-1}$				0.62		0.09
				(0.161)		(0.034)
$Google\ Trends_{t-1}$					0.27^{***}	0.27^{***}
					(9.387)	(9.962)
Constant	3.04^{***}	1.23	3.15^{***}	3.16^{***}	1.10^{***}	-0.16
	(8.863)	(1.718)	(8.549)	(8.548)	(6.821)	(-0.342)
Observations	281	281	281	281	281	281
R^2	0.025	0.028	0.001	0.000	0.655	0.672

Table 42
Predictive results estimated from weekly binance coin data using OLS on dependent variable: volatility. Standard errors are indicated in parentheses. *, ** and *** indicate the statistical significance (5%, 1% and 0.1%).

	(1)	(2)	(3)	(4)	(5)	(6)
$Return_{t-1}$	0.69***					0.67***
	(4.091)					(3.720)
$Trading\ volume_{t-1}$		0.00*				0.00
		(2.237)				(1.707)
$Unique\ Addresses_{t-1}$			0.05			0.00
			(1.061)			(0.121)
$VIX\ index_{t-1}$				0.11		0.17
				(0.461)		(0.688)
$Google\ Trends_{t-1}$					0.00	-0.00
					(0.850)	(-1.338)
Constant	0.45***	0.45***	0.46***	0.46***	0.46***	0.44***
	(32.285)	(26.318)	(32.188)	(32.162)	(28.612)	(26.761)
Observations	281	281	281	281	281	281
R^2	0.073	0.008	0.007	0.001	0.001	0.082