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Can Investor Attention Predict Cryptocurrency Returns, Trading Volume and Volatility?

An Empirical Analysis on Bitcoin, Ethereum and Binance Coin

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ABSTRACT

This thesis investigates whether investor attention, measured by Google search queries, influences the return, volatility, and trading volume of cryptocurrencies. Bitcoin, Ethereum, and Binance Coin are examined, as they were the three largest cryptocurrencies based on market capitalization as of April 2021. Weekly data on the cryptocurrency characteristics as well as on Google Trends data over the period October 2017 to April 2021 is used in vector autoregression models and in Granger causality tests to evaluate the relationship between investor attention and the cryptocurrency variables. Regarding return, investor attention is the Granger cause of returns only for Binance Coin with a significant positive effect. Past returns, on the other hand, lead to more investor attention in the following week for all three cryptocurrencies, which indicates that if a cryptocurrency has a higher past performance, investors pay more attention to it. Investor attention also positively impacts the volume of Binance Coin, while there is no predictive power on the trading volume of Bitcoin and Ethereum. Significant evidence of a relationship between investor attention and the volatility of both Bitcoin and Binance Coin is found, as an increase in investor attention leads to more volatile cryptocurrencies. For all three coins, the results demonstrate that volatility is also a significant driver of investor attention. These results complement the existing literature on the predictability of cryptocurrency characteristics and investor attention and contribute to the understanding of the dynamics of cryptocurrencies.

Keywords Behavioural Finance · Investor Attention · Google Trends · Cryptocurrency
JEL Classification G12, G14, G40, G41

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1. INTRODUCTION

The market value of the cryptocurrency market exceeded $2 trillion in April 2021, partly because of a rally in the coin Ethereum, which is the second-largest digital coin. The cryptocurrency market is currently booming more than ever, with a market capitalization that has doubled in just two months due to the extreme rise in participation of both retail and institutional investors (Kharpal, 2021). The COVID-19 pandemic has contributed to this increased demand in cryptocurrencies because of several reasons. Cryptocurrencies have become a more attractive option compared to alternatives like stocks since they can be traded anywhere in the world. This can mitigate the liquidity constraints that are likely to arise if local governments restrict trading activity as part of a lockdown. Additionally, the fact that cryptocurrencies are not managed by a central bank makes them more attractive during a crisis (Jabotinsky & Sarel, 2021). Investors might expect that a pandemic causes central banks to intervene in the market, while cryptocurrencies are not affected by shocks to traditional markets (Corbet, Meegan, Larkin, Lucey & Yarovaya, 2018).

The cryptocurrency market is different compared to the traditional markets because of the specific characteristics of cryptocurrencies as well as their performance. Chuen, Guo, and Wang (2017) describe the characteristics of Bitcoin, the most popular cryptocurrency with the largest market capitalization. Unlike traditional money, Bitcoin is decentralized, meaning that no institution or group controls it, but the offer is rather determined by an algorithm. In addition, there are low transaction fees accompanied with a transfer and there is large flexibility as Bitcoin wallets can be easily set up without regulations. These characteristics make cryptocurrencies attractive for investors, but it is not all that bright and rosy. Bitcoin is mainly used as a speculative investment despite or because of its high volatility and high yields (Baur, Hong & Lee, 2018). High volatility can be destructive for long-term investors since it can create fear and uncertainty and as a result lead to panic selling (Spaventa, 2020). Furthermore, several papers have found evidence that Bitcoin prices are prone to substantial bubbles (Cheah & Fry, 2015; Cheung, Roca & Su, 2015; Enoksen, Landsnes, Lučivjanská & Molnár, 2020).

Market conditions like these have often been explained in the light of traditional finance, but behavioral finance could offer more complete and relevant explanations for the performances observed in the cryptocurrency market. One of these explanations is investor sentiment. Baker and Wurgler (2007) broadly define investor sentiment as the belief about future cash flows and investment risks that is not justified by the facts at hand or the “propensity to speculate”. Liu and Tsyvinski (2018) conclude that cryptocurrency returns can be predicted by two factors specific to the markets: momentum and investor attention. In line with these results, more recent research finds that investor attention regarding Bitcoin has an information effect to predict Bitcoin's volatility and that it can play a critical role in the predictability of Bitcoin price changes (Eom, Kaizoji, Kang & Pichl, 2019).

Research on the effects of investor attention on cryptocurrency has not been around for more than 10 years since it is a relatively new market, but it is a growing field of interest. Literature on the relationship between investor attention and Bitcoin returns is growing and recent research on other crypto coins like Ripple and Ethereum has also gained more attention (Eom et al., 2019; Lin, 2020, Subramaniam & Chakraborty, 2020; Choi, 2021). Because of a vast increase in the number of cryptocurrencies over the past years, research has not been able to keep up with these ongoing market changes. One of the biggest risers as of last month is Binance Coin, a coin that has cemented its position as one of the world's largest cryptocurrencies after a 53% rise in just 7 days in the first two weeks of April 2021. Binance Coin, also known as BNB, was issued by the world's largest cryptocurrency exchange Binance in 2017 and has a market capitalization of $95 billion in April 2021, according to CoinMarketCap.com (Kharif, 2021).

More and more coins are gaining the attention of individual and institutional investors but little to no research has been done on the 3 biggest coins based on market capitalization as of April 30, 2021, which is the end date in the chosen period. The three coins with the highest market capitalization at that date were Bitcoin, Ethereum, and Binance Coin. Because of the increased importance of Binance Coin in the cryptocurrency ecosystem as well as the large role the two biggest coins play, this thesis will study the effects of investor attention on the returns of Bitcoin, Ethereum, and Binance coin. This leads to the following research question:

> **What is the effect of investor attention on the returns, volatility, and trading volume of the cryptocurrency market, specifically for Bitcoin, Ethereum, and Binance Coin, during the period October 2017 – April 2021?**

The following hypotheses will be tested, which will be further discussed in chapter 2:
H1: Investor attention has a significant impact on returns for Bitcoin, Ethereum, and Binance Coin.
H2: Investor attention has a significant impact on trading volume for Bitcoin, Ethereum, and Binance Coin.
H3: Investor attention has a significant impact on volatility for Bitcoin, Ethereum, and Binance Coin.

To answer the research question, two datasets are collected. Data on the returns, volatility, and trading volume of Bitcoin, Ethereum, and Binance Coin are obtained from the website CoinMarketCap (https://coinmarketcap.com/). Data on the closing prices of the three coins will be used for this research from the period October 15, 2017, to April 30, 2021. Google Trends will be used as a measure of investor attention. The Google Search Volume Index (GSVI) indicates how much interest a specific topic or search term is bringing about and is measured in values between 0 and 100, where 0 refers to a period in which search volume does not meet a designated threshold, while a value of 100 is a period in which the highest relative volume was observed (Bank, Larch & Peter, 2011). The following keywords will be used as a proxy for investor attention: "Bitcoin", "Ethereum" and "Binance Coin".

In order to establish a relationship between the variables, a vector autoregression model (VAR) and a Granger causality test will be conducted. Before a VAR model can be used, the first step is to test if the data is stationary using the Augmented Dickey-Fuller test (ADF). After the stationarity has been validated, the relationship between investor attention (measured by the Google Trends index) and the cryptocurrency variables can be examined. The lag length of the VAR model will be determined by the Akaike Information Criteria (AIC), in line with similar previous research. In addition to the VAR model, a Granger causality test will be conducted to test whether there is a linear causal relationship between the cryptocurrency variables and investor attention. Two robustness tests will be conducted to check if the coefficients change when controlling for a different period and additional variables.

The results of this thesis are as follows. As for return, investor attention is the Granger cause of returns only for Binance Coin with a significant positive effect. A higher return, on the other hand, leads to more investor attention in the following week for all three cryptocurrencies. Investor attention also positively impacts the volume of Binance Coin, while there is no predictive power on the trading volume of Bitcoin and Ethereum. Trading volume exerts significant influence on investor attention for Ethereum with the second lag of volume negatively impacting the attention investors have. There is significant evidence of a relationship between investor attention and the volatility of both Bitcoin and Binance Coin, as an increase in investor attention leads to more volatile cryptocurrencies. For all three coins, the results demonstrate that volatility is also a significant driver of investor attention: an increase in volatility leads to a decrease in investor attention in the following week. The obtained results do not change much during bubble periods when compared to the full sample analysis, but the effect of Bitcoin's volume on investor attention, however, becomes statistically significant. Additionally, some control variables that could influence the cryptocurrency characteristics are added, which are the S&P500 return, gold, VIX, and WTI oil. The original results do not change much after controlling for the additional variables for both Bitcoin and Ethereum, but an increase in return of WTI oil leads to fewer Google searches for Ethereum after two weeks. As for Binance Coin, the coefficients on the relation between the cryptocurrency variables and investor attention do not alter much. The control variables VIX and gold exert some negative influence on Binance Coin return and higher gold returns lead to higher volatility, but all on the 10% significance level.

In the next chapter, literature on investor attention and cryptocurrencies will be discussed and the hypotheses are formulated. Chapter 3 covers the main data sources used, how it is collected and some figures and descriptive statistics. Following this chapter, the fourth chapter will focus on the methodology that will be used in this paper. Chapter 5 will cover the empirical results obtained, including robustness checks. In the last chapter, the main research question is answered using the formulated hypotheses and the study is concluded. Next to this, the limitations of this thesis will be discussed as well as recommendations for future research.

2. LITERATURE REVIEW

2.1. Investor Attention

2.1.1 Traditional Finance

The traditional finance view is reflected by the idea of the Efficient Market Hypothesis (EMH). The idea behind the EMH is that a market is efficient if prices "fully reflect" all available information (Fama, 1970). The EMH is based on three theoretical arguments, the most important one being the idea that investors are rational, which implicitly implies that assets are valued rationally. The second argument is that investors carefully consider all the information that is available to them before making their investment decisions, so their decision-making is consistent. The final idea is that an agent pursues self-interest (Muhammad, 2009). Fama (1970) introduced three forms of market efficiency: the weak, semi-strong, and strong form. In the weak form of the EMH, all public past market information is already priced into the prices of securities. The semi-strong form develops the assumption of the previous form and builds onto this with the assumption that prices of securities adjust quickly to the new publicly available information. In the strong form, security prices reflect all available information, both public and private. One of the most well-known applications of the traditional finance view is the Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965). The CAPM defines the expected return of an asset as the risk-free rate plus a risk premium and has assumptions that are based on the EMH.

2.1.2 Behavioural Finance

The traditional finance view has been challenged in the past decades in the field of behavioural finance. Even though traditional finance theories could explain important aspects like how to price securities based on the CAPM, certain market anomalies like bubbles or market overreaction could not find their explanations in these theories. The prospect theory by Kahneman and Tversky (1979), often regarded as the first theory in behavioural finance, shows that agents do not always act rationally and therefore is of great importance for behavioural finance. Kahneman and Tversky (1979) found that people underweight outcomes that are probable compared to outcomes that are certain, which is called the certainty effect. Another tendency people tend to have when choosing between two options is that they ignore components that are common in both options to simplify their focus on what is different, which is known as the isolation effect.

One of the first papers where the EMH does not hold is by De Bondt and Thaler (1985), who documented that stock prices overreact and that portfolios of prior "losers" are found to outperform prior "winners". Huberman and Regev (2001) have also found evidence against the EMH. In their paper, a news reaction was analyzed and they found that there was a strong and permanent reaction to stock prices and that spillover effects were present for companies in the same industry, suggesting that prices are likely to move even though there is no new news.

Additional market anomalies like the momentum effect, post-earnings announcement shock, and bubbles that could not find their basis in traditional finance have been explained by behavioural finance theories (Grinblatt & Han, 2002; Daniel, Hirshleifer & Subrahmanyam, 2005). When confronted with a financial decision, people are prone to biases, which are systematic errors of judgments (Kahneman & Riepe, 1998). Some of these biases include over-optimism, overconfidence, and hindsight bias, which is a tendency where people overestimate their ability to predict an event even though it has already happened. Research on the effect of overconfident managers or CEOs on decision-making shows that these managers overestimate the returns on their investment projects and view external funds as excessively expensive, causing business investment disruptions (Malmendier & Tate, 2005).

2.1.3 Investor Attention

Another obstacle individual investors can run into is their limited attention. Investors are confronted with thousands of stocks when making their investment decisions, but they are constrained by their so-called “bounded rationality”. This phrase, coined by Simon (1957), challenged the traditional finance idea of rational agents. His theory states that even though investors might want to make rational decisions, he or she is simply not able to because of limited knowledge and/or time. Rather than making the most efficient decision, an investor will make a decision that is the most “satisficing”. Satisficing, a conjunction of the words satisfy and suffice, refers to a situation where the outcome of a decision is not fully optimal but at least satisfactory or good enough in that circumstance. Because investors are faced with these limitations, they tend to only consider assets that have caught their attention, for example through social media, newspapers, television, or word of mouth.

Many previous papers have focussed on the limited attention investors have and the impact of this on financial markets. Merton (1987) conducted one of the first studies to show that investor attention is important when it comes to the pricing of securities. He theorized that the majority of investors will avoid stocks they do not have sufficient information on in markets where information is incomplete. Investors who do trade these neglected stocks, rationally demand higher returns to compensate the smaller investor base and to offset the risk they carry with a relatively small group. This theory is also called the “investor recognition hypothesis”.

Peng and Xiong (2006) added to this literature with their research on the effect of investors’ attention on asset-price dynamics. An important finding is that investors tend to focus more on information at the market and sector level than on company-specific information. Seasholes and Wu (2007) studied trading behaviour and attention-grabbing stocks on the Shanghai Stock Exchange. They hypothesized that there should be more first-time purchases of a particular stock the day after an event that attracts attention compared to other days, since events that attract attention help individual investors to reduce the number of stocks considered. In line with their prediction, they found statistically significant evidence that individual investors who have not previously owned a particular stock buy that specific stock in large numbers after an attention-grabbing event occurred.

Barber and Odean (2008) tested if the buying behaviour of individual investors is more heavily influenced by attention than their selling behaviour. In addition, they also compared the buying behaviour of individual investors to the buying behaviour of professional investors. Three proxies were used as a measure for investor attention: the abnormal daily trading volume of a stock, the one-day return of a stock, and whether the firm has had a news appearance that day. They found that individual investors are usually buyers on high attention days while professional investors are likely to indulge in purchases driven by attention. Based on their results, they hypothesized that many investors consider only buying stocks after they have gained their attention, which is in line with the findings of Seasholes and Wu (2007).

Fang and Peress (2009) examined the cross-sectional relation between mass media coverage and stock returns since mass media plays a huge role in spreading information to a wide audience. Stocks without media coverage achieve higher returns than stocks with high media coverage, even after adjusting for known risk factors like market, size, and momentum. Stocks that receive less attention have a higher idiosyncratic risk and should therefore earn a higher return, in line with Merton's theory of investor recognition (1987). The authors have also shown that a portfolio that goes long in stocks with media coverage and goes short in stocks with no media coverage realizes 3% per year on average.

Yuan (2015) used news events to measure investor attention, similar to research done by Barber and Odean (2008). Dow Jones record events and front-page news events from both the New York Times and the Los Angeles Times were used to explore the ability of market-wide, high-profile events to predict trading patterns and market returns. There is a high impact of attention on the trading behaviour of investors, especially for the highly visible indices like the Dow Jones and Nasdaq. The more economically meaningful indices like the New York Stock Exchange and the S&P500 did not show this strong impact, which suggests that pure attention, rather than economic information, is a driver of trading decisions. After an attention-grabbing event, individuals tend to sell their stocks, resulting in lower market price levels.

One of the most recent papers on investor attention is by Smales (2021), who examined investor attention and global market returns during the COVID-19 crisis. Smales (2021) showed that an increase in investor attention, measured by Google Search Volume with the term 'coronavirus', results in lower stock returns in the major G7 stock indices with Japan as an exception. Regarding the volatility of stocks, the results obtained have shown that increased investor attention is associated with greater volatility in all G7 stock markets. Similar results are obtained by Iyke and Ho (2021), who investigated the financial implications of the growing global investor attention related to the COVID-19 crisis in African stock markets and found that an increase in investor attention reduces stock returns.

2.1.4 Google Trends as a Measure of Attention

Investor attention has been measured by various proxies in earlier literature, such as news articles (Barber & Odean 2008; Yuan 2015), media coverage (Fang & Peress, 2019), and extreme returns (Barber & Odean, 2008). Other measures, like advertising expenditure (Chemmanur & Yan, 2010), consumer confidence (Schmeling, 2009), and trading volume (Hou, Xiong & Peng, 2009) have also been used in the past. Da, Engelberg, and Goa (2011) proposed a measure of investor attention using search frequency in Google Trends. They found that the Google Search Volume Index (GSVI) is representative of the internet search behaviour of the general population and that it is likely to measure the attention of retail investors. The advantage of using the GSVI is that it is likely to be a good representation of the search behaviour of the general population since 92% of all searches performed on search engine providers are done through Google (Oberlo, 2021).

Since the publication of Da et al. (2011), Google Trends have often been used as a proxy for investor attention in all areas of finance. Ji and Gu (2015), for example, examined the influence of investor attention on returns in the energy and commodity market, using Google search queries as a proxy. Han, Xu, and Yin (2018) examined whether investor attention matters for currency movements and found that the movements of exchange rates can at least partly be explained by investor attention. Research on the relationship between investor attention and cryptocurrencies also frequently makes use of Google Trends (Kristoufek, 2013; Urquhart, 2018; Philippas, Rijba & Guesmi, 2019; Zhu et al., 2021).

2.2. Cryptocurrencies

2.1.1 Characteristics

Cryptocurrencies are transferable digital assets secured by cryptography that are created by individuals or organizations rather than by governments (White, 2015). Lansky (2018) defined six conditions that a system must meet in order to comply with the formal definition of cryptocurrency:

(1) The system does not require a central authority, distributed to reach consensus on the state.
(2) The system maintains a record of cryptocurrency units and their ownership.
(3) The system determines whether new cryptocurrency units can be created. If new cryptocurrency units can be created, the system defines the circumstances of their origin and how ownership of these new units can be determined.
(4) Ownership of cryptocurrency units can only be proven cryptographically.

(5) The system makes it possible to carry out transactions that change the owner of the cryptographic units. A transaction statement can only be issued by an entity that demonstrates current ownership of these units.

(6) If two different instructions to change ownership of the same cryptographic units are entered simultaneously, the system will execute at most one.

2.1.2 Risks and Rewards

The main advantage and the key difference compared to traditional money is that cryptocurrencies have a peer-to-peer system, where online payments can be sent directly from one party to another without the intervention of a financial institution (Nakamoto, 2008). Another difference between cryptocurrencies and traditional financial assets is the lack of intrinsic value. Researchers argue that cryptocurrencies, with their research especially focussing on Bitcoin, essentially only function as a speculative phenomenon without intrinsic value as it cannot be incorporated into a productive process or consumed directly as a commodity and does not have the condition of currency or anything else that can give them an objective value (Yermack, 2015; Abboushi, 2017; Baur et al., 2018).

Trading in cryptocurrencies is an attractive option for many risk-seeking investors because it can be seen as a high-risk investment with high rewards. Chuen et al. (2018) highlighted this high reward aspect with their conclusion that the average daily return of most cryptocurrencies is higher than that of traditional investments. Even publicly listed companies with high exposure to cryptocurrencies outperform the traditional stock market. Identification of 19 US stocks with a market cap of more than $1 billion, that are the biggest based on their cryptocurrency exposure, showed that these companies achieved an average return of 43% this year, which is more than three times the gain of the S&P 500 of 13% over the same period (Ponciano, 2021).

As stated before, trading in cryptocurrencies is associated with relatively high risk. Several papers point out that cryptocurrencies, often with a specific focus on Bitcoin, can be characterized by high volatility (Chuen et al., 2017; Liu & Tsyvinski, 2018; Baur et al., 2018; Chaim & Laurini, 2019). This high volatility can be destructive for long-term investors since it can create fear and uncertainty and as a result lead to panic selling (Spaventa, 2020). Furthermore, several papers have found evidence that bubbles are more prone to emerge in the crypto market than in the stock markets (Cheah & Fry, 2015; Cheung, Roca & Su, 2015; Enoksen, Landsnes, Lučivjanská & Molnár, 2020). Besides these financial aspects of cryptocurrencies, regulators are also concerned about an increase in criminal action using cryptocurrencies for activities such as fraud and manipulation, tax evasion, hacking, and money laundering (Houben & Snyers, 2018).

2.1.3 Cryptocurrency Market

Many have argued that the cryptocurrency market is greatly interlinked, with strong dependencies between different coins. Balli, de Bruin, Chowdhury, and Naeem (2020) documented increasing connectivity of cryptocurrencies which in line probably limits the diversification opportunities in this asset class. Bitcoin is especially interconnected with other cryptocurrencies, possibly because it was the first to circulate or because it has the highest market capitalization. Boako, Tiwari, and Roubaud (2019) showed that there are strong dependencies between Bitcoin and Ethereum, the two most capitalized cryptocurrencies. Koutmos (2018) measured return and volatility spillovers among 18 major cryptocurrencies and found that Bitcoin is the main driver of shocks to the other cryptocurrencies. Consistent with this finding, Corbet et al. (2018) stated that Bitcoin is the main driver of the prices of other cryptocurrencies like Ripple and Litecoin. In contrast, Zięba, Kokoszczyński, and Śledziewska (2019) argued that Bitcoin's price changes do not cause price changes in other cryptocurrencies. The authors found that among three different cryptocurrencies (Bitcoin, Dogecoin, and Litecoin), Bitcoin has the least impact on other cryptocurrencies based on their VAR analysis. Their explanation for this is that the mechanisms of the smaller coins work differently compared to mechanisms of mining Bitcoin, and that demand shocks in Litecoin and Dogecoin therefore could potentially have a more impact as their supply shows a more even distribution.

2.1.4 Pricing

The lack of intrinsic value raises the question of the determination and drivers of the price of cryptocurrencies. While there is a large number of cryptocurrencies available, almost all research on this question has been done using data on Bitcoin. Bouoiyour and Selmi (2014) have found that investor attractiveness, measured by Google views, is a major driver of Bitcoin prices. More recent research by Bouoiyour, Selmi, Tiwari and Olayeni (2016) showed that the long-term fundamentals are likely to be a key driver of Bitcoin pricing. Results similar to these are also found by Kristoufek (2015), who documented that the standard fundamental factors like trade usage, money supply, and price level influence the price variation of Bitcoin. Van Wijk (2013) note that various financial indicators like the Dow Jones index, the euro-dollar exchange rate and even oil price measures like the WTI oil price can affect the long-term pricing of Bitcoin.

2.1.5 Bitcoin

The first and most well-known cryptocurrency is Bitcoin, which was launched in 2008. Bitcoin was invented by a person or persons using the pseudonym Satoshi Nakamoto (Dwyer, 2015). The main goal of the development of Bitcoin was to offer an alternative to traditional money and to be able to transfer digital currency (Feuer, 2013). The question today remains whether Bitcoin functions as a currency, in line with its original goal, or rather as an asset. While there are proponents and opponents on both sides, the prevailing argument is that Bitcoin's behaviour is similar to that of an emerging asset class, rather than that of a currency or security (Yermack, 2015; Baur et al., 2018; White, Marinakis, Islam, & Walsh, 2020).

Since Bitcoin was introduced, its price development can be characterized by a roller coaster, as it has seen many fluctuations. In 2010, the price of a Bitcoin was just $0.008 and a rapid rise in 2013 occurred, followed by a substantial decline in 2014 after one of the first cryptocurrency exchanges filed for bankruptcy. The reward for these though years followed in 2017, where Bitcoin saw a year-to-year increase of 947% (Sapuric, Kokkinaki & Georgiou, 2020). As of the 30th of April 2021, the price of one Bitcoin is $57,750, with a total market capitalization of just over 1 trillion dollars based on data from CoinMarketCap.

2.1.6 Ethereum

The second-biggest coin based on market capitalization is Ethereum, with a market cap of $320 billion as of April 30, 2021. Ethereum went live in July 2015 and is the value of one Ethereum coin is much more affordable compared to that of Bitcoin with a price of $2773 as of April 2021. While Ethereum and Bitcoin are both cryptocurrencies, they differ in their goal. Ethereum was created with the intention to become a global decentralized application platform, enabling users to write and run software that is immune to censorship, downtime and fraud. Another difference between Bitcoin and Ethereum is that Ethereum is programmable, which lending itself for several purposes like a marketplace for financial services, games, and apps that cannot steal your data or censor you (Ethereum, 2021). Together, Bitcoin and Ethereum account for over 60% of the cryptocurrency market capitalization and both have seen massive price swings over the years. They are increasingly being used for investing and speculating purposes, despite warnings from various financial institutions (Katsiampa, 2019).

In the last few months, the popularity of Ethereum has risen greatly. Asset manager VanEck is even seeking approval from US regulatory authorities to launch an Ethereum ETF (Mozée, 2021). Developments like these caused Ethereum to go up more than 450% over the past year to an all-time high of more than $4,100 on Monday the 10th of May 2021. Analysts from JPMorgan, however, suggest that the fair trading price of Ethereum should be around $1000 (Insider Inc., 2021).

2.1.7 Binance Coin

The youngest coin in this research is Binance Coin (BNB), which was launched in July 2017 through an initial coin offering (ICO). BNB is intrinsically linked to the Binance exchange, the world’s largest cryptocurrency exchange measured in volume (Corporate Finance Institute, 2020). Because of this, users receive a discount in transaction fees when they trade in BNB on Binance. Binance Coin showed impressive growth in a short period with a different price trend compared to Bitcoin. While the major currencies at that time fell rapidly and then moved around a falling average at the beginning of 2018, BNB grew at a steady pace (Duda, 2019). The huge price increase of Binance Coin this year is likely mainly because of the success of the Binance Smart Chain (BSC), a new blockchain, and the launch of decentralized financing on BSC. The rising transaction costs on Ethereum could also at least partly explain the price increase of BNB as of lately (Schijven, 2021).

2.2 Investor Attention and Cryptocurrencies

The paper of Kristoufek (2013) was one of the first where digital currencies were connected to search queries on Google Trends and Wikipedia. A dataset with data between May 1, 2011, and June 30, 2013, was analyzed using a vector autoregression method and a vector error-correction model. The results obtained showed that there is a strong correlation between search queries and the prices of Bitcoin. In addition, Kristoufek (2013) found a strong causal relationship that is bi-directional, meaning that the searches affect not only the prices, but the prices also affect the searches. The conclusion drawn from this is that it is in line with expectations for a financial asset with no underlying fundamentals and that speculation and trend hunting dominate Bitcoin's price dynamics.

Similar research has been done by Eom et al. (2019), who empirically investigated the effect of investor sentiment on changes in Bitcoin return and volatility in the period from October 2013 to May 2017 using the Google Trends index as a proxy for investor sentiment. Their reason for Google Trends as a proxy is because investors often use the Google search engine to research information about investment objects. The frequency of keyword searches can indicate the strength of investor interest, and this strength changes over time. Subsequently, Google Trends is the index created using the frequency with which investors search time series. The evidence found in their paper points toward the conclusion that investor sentiment can help to explain future changes in Bitcoin volatility. While they did not find statistically significant evidence that investor sentiment can predict Bitcoin prices, their findings do provide additional evidence to support previous studies that found Bitcoin to have the characteristics of speculative assets.

Nasir, Huynh, Nguyen, and Duong (2019) analyzed the predictability of Bitcoin volume and returns using Google search values. Their data set contains of weekly data from the first week of 2014 to the last week of 2017. Several empirical approaches are used including a VAR model and non-parametric drawings. The main results obtained lead to the conclusion that the frequency of Google searches lead to significant and positive Bitcoin returns, especially in the short run. They also look at shocks to search volumes and found that these shocks have an immediate positive effect on the returns that last for just a week. Regarding the trading volumes, they found that Google search volumes have some influence, but these results had a near-marginal significance.

Shen, Urquhart, and Wang (2019) also add to the literature on the relationship between investor attention and Bitcoin by looking at Bitcoin's return, trading volume, and volatility. Rather than using Google Trends as a proxy to measure attention, as the previously mentioned papers have done, the authors use the number of tweets from Twitter as a measure of attention. Their rationale behind this is as follows: knowledgeable investors, who are well-informed about cryptocurrencies, will not use the Google search engine to find information since they are already informed, but rather tweet about it with the knowledge that they have. These informed investors could tweet about news stories related to Bitcoin or make predictions about Bitcoin, making tweets a strong measure of investor attention for informed investors. Twitter data on tweets that include the term 'Bitcoin' from September 2014 to August 2018 have been used in this research. The findings of the authors indicate that the volume of tweets are significant drivers of both volatility and trading volume, but they do not find evidence for a causal relationship between tweets and returns of Bitcoin

More recent papers on cryptocurrency and investor attention are by Zhu, Zhang, Wu, Zheng, and Zhang (2021) and Al Guindy (2021). Zhu et al. (2021) analyze the relationship between investor attention and the return and volatility of Bitcoin and work with the most recent data, specifically from July 1, 2013, to May 31, 2020. Using a Granger causality test, they found that investor attention is the Granger cause of both the return and volatility of Bitcoin and that this shock can sustain for several weeks. The authors also conduct out-of-sample forecasts and these results show that investor attention improves appreciation accuracy in Bitcoin return. Al Guindy (2021) more specifically examines the relationship between the volatility of 23 large cryptocurrencies and investor attention, measured by the number of tweets. The vector autoregression framework shows that more investor attention leads to an increase in the volatility of the chosen cryptocurrencies.

2.3 Hypotheses

Previous literature, like that of Kristoufek (2013), has shown that there is a correlation between investor attention and the return on Bitcoin. More recent research adds to this literature. Dastgir, Demir, Downing, Gozgor, and Lau (2019) measured the relationship between Bitcoin attention with Google Trends search queries and Bitcoin returns and found that there is a bi-directional causal relationship between investor attention and Bitcoin returns with the exception of some central distributions from 40% to 80%. Subramaniam and Chakraborty (2020) also found that investor attention causes positive returns for several cryptocurrencies, and Zhu et al. (2021) documented a significant relationship between these two. The following hypothesis follows from these papers:

H1: Investor attention has a significant impact on returns for Bitcoin, Ethereum, and Binance Coin.

Shen et al. (2019) find that the volume of tweets is a significant driver of trading volume using tweets as a proxy for investor attention. Nasir et al. (2019), however, used Google search volumes and documented that these search volumes have some influence on the trading volume of Bitcoin, but these results were not statistically significant. Unlike returns and volatility, little research has been done on investor attention and cryptocurrencies regarding trading volume. Literature on the effect of investor attention on stock returns, however, has shown that the Google search intensity has a positive significant effect on trading volume (Preis, Reith & Stanley; 2010; Vlastakis & Markellos, 2012; Goddard, Kita & Wang, 2015). Based on these papers, the following hypothesis will be tested:

H2: Investor attention has a significant impact on trading volume for Bitcoin, Ethereum, and Binance Coin.

The volatility of cryptocurrency has also been researched often, among others by Eom et al. (2019) and Shen et al. (2019). The conclusions of these papers lead to a similar conclusion: investor attention, either measured by Google Trends or tweets on Twitter, can help to explain changes in the volatility of Bitcoin. Zhu et al. (2021) also demonstrated that for Bitcoin, investor attention shows an impact on volatility. Since previous research has shown that the cryptocurrency market is highly interlinked (Balli et al., 2020), this effect is expected not only for Bitcoin but also for the two other cryptocurrencies in this research. In addition, Al Guindy (2021) suggests that an increase in investor attention leads to an increase in the volatility of cryptocurrency prices. This leads to the following and last hypothesis:

H3: Investor attention has a significant impact on realized volatility for Bitcoin, Ethereum, and Binance Coin.

3 DATA

3.1 Cryptocurrency Data

3.1.1 Data Collection and Calculations

Information on the cryptocurrency market is obtained using the website CoinMarketCap (https://coinmarketcap.com/). This website provides daily information on the open, high, low, and close prices of coins as well as their market capitalization and the trading volume. CoinMarketCap is a widely used cryptocurrency pricing proxy that combines prices from a large number of exchanges, providing a more accurate and general value presentation which is independent of any stock price preference (Kraaijeveld & De Smedt, 2020). The cryptocurrencies are selected based on their market capitalization as of April 30, 2021, as can be seen in Table 1. The three chosen cryptocurrencies Bitcoin, Ethereum, and Binance coin account for just over 70% of the total cryptocurrency market capitalization.

Table 1

Market capitalization of cryptocurrencies as of April 30, 2021

Name	Symbol	Price	Market capitalization	Share
Bitcoin	BTC	$57,750.18	$1,079,669,884,320	51.2%
Ethereum	ETH	$2,773.21	$320,822,874,721	15.2%
Binance Coin	BNB	$624.08	$95,754,488,402	4.5%
Total market capitalization of the cryptocurrency market: $2,107,371,771,528				

Data on the closing prices of Bitcoin, Ethereum, and Binance Coin are used in this research from October 15, 2017, to April 30, 2021. This starting date is chosen since Equation 2 calls for data on the trading volume of the past 12 weeks, so this research cannot be conducted earlier than 12 weeks after the launch of Binance Coin in July 2017. The first few months of 2021 are included in this research since this period is characterized by major price changes in the chosen cryptocurrencies, which makes it an interesting period to further analyse. Since weekly data is used in the chosen period, a total of 185 observations are collected for the different cryptocurrency variables, as can be seen in Table 2.

Using this data, the average closing price in a week is calculated first to represent the weekly cryptocurrency prices. The returns for the three cryptocurrencies will be computed using the following equation:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where R_t is the return of the cryptocurrency (so either of Bitcoin, Ethereum, or Binance Coin) and P_t and P_{t-1} are the average weekly closing prices at respectively weeks *t* and *t – 1*.

Data on the trading volume of the cryptocurrencies is also made available by CoinMarketCap. Since data on the trading volume is also daily, it needs to be converted to weekly data for it can match the weekly Google Trends data. The weekly volumes are computed using the arithmetic mean for the same seven-day period as the Google Trends data. In the literature, a a strong relationship between volume and returns is reported (Glosten, Jagannathan& Runkle, 1993; Conrad, Hameed & Niden, 1994; Cooper, 2019), which is why a detrended volume is be used, based on the paper of Campbell, Grossman and Wang (1993). The additional advantage of using a logarithm is that it will avoid great skew and excessive kurtosis (Urquhart, 2018).

Similar research by Nasir et al. (2019) also makes use of the de-trended tool for log volume of the past 12 weeks as is shown in Equation 2:

$$VLM_t = \log(Volume_t) - \frac{1}{12}\sum_{i\,=t-11}^{t} \log(Volume_i) \tag{2}$$

where $\log(Volume_t)$ is the logarithm of the weekly trading volume.

The last variable needed is the weekly realized volatility (RV), which is calculated using the daily return, a method popularized by Andersen and Bollerslev (1997). To obtain the weekly realized volatility, daily returns of the 7 days in that week are calculated using Equation 1. These returns are squared and summed up and finally a root is extracted from this sum, which is shown in Equation 3:

$$RV_t = \sqrt{\sum_{i=1}^{N} {R_t}^2} \tag{3}$$

where ${R_t}^2$ is the squared logarithmic daily return of a cryptocurrency.

3.1.2 Figures and Descriptive Statistics

Figures 1 to 3 show the price developments of Bitcoin, Ethereum, and Binance Coin in the chosen period. Figures 1 and 2 show that the pricing of Bitcoin and Ethereum follows a noticeably similar path and that they are at least partially correlated. Both cryptocurrencies document a steep increase in price in the last month of 2017, followed by a strong correction at the beginning of 2018. Following this short bubble phase, prices of both Bitcoin and Ethereum are more stable and show less volatility. The end of 2020 marks the beginning of an even bigger price rise compared to the one observed in 2018, with both Bitcoin and Ethereum continuously reaching a new all-time high. The price development of Binance Coin, as can be observed in Figure 3, shows more stability compared to the previous two since this coin did not go through the 2018 bubble. Similar to Bitcoin and Ethereum, the real takeoff of Binance Coin happened around the turn of the year. An enormous price surge at the beginning of 2021 quickly resulted in a price drop in March, but ever since then, the price has risen on average.

Figure 1

Bitcoin's price development in US dollars

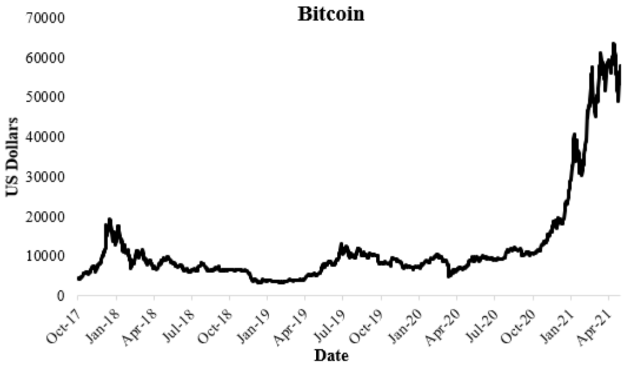


Figure 2

Ethereum's price development in US dollars

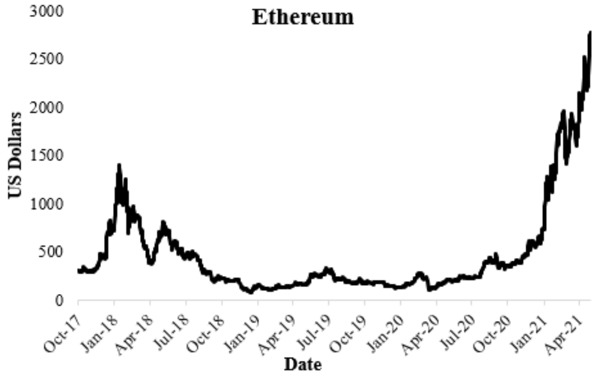


Figure 3

Binance Coin's price development in US dollars

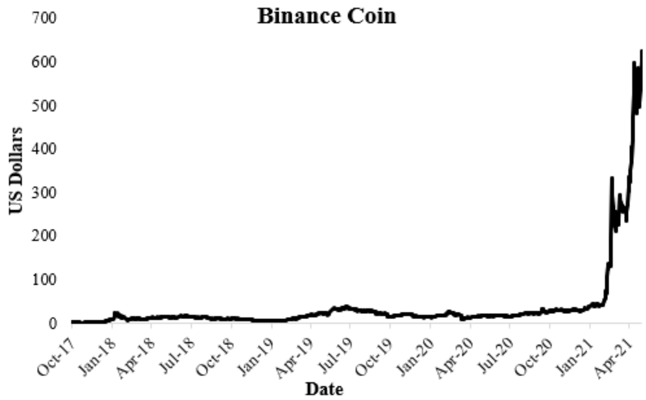


Table 2 shows the descriptive statistics of the cryptocurrency variables. The average weekly returns of the three chosen cryptocurrencies are all positive, with similar results for Bitcoin and Ethereum, which show average weekly returns of 1.3% and 1.2%, respectively Binance Coin has the highest average weekly return with 3.2% but is riskier as can be seen from the high kurtosis, high positive skewness, and more extreme values for the minimum and maximum weekly returns of respectively -36.6% and 68%. When comparing the returns, Bitcoin shows the most normality since Ethereum has a higher kurtosis, and the null hypothesis of the Jarque-Bera test that the data is normally distributed can be rejected at the 5% significant level, indicating that the data does not fit a normal distribution. Similar results can be seen for Binance Coin, with a high skew, high kurtosis, and a rejection of the null hypothesis of the Jarque-Bera test. The results for trading volume and the realized volatility show that Binance Coin is the most volatile of the three as Binance Coin has the highest skewness, highest kurtosis, and the most extreme values for the minimum and maximum values. For the trading volume and realized volatility, Bitcoin and Ethereum, the two oldest and more established coins, show similar results.

Table 2
Descriptive statistics of the cryptocurrency variables.

	Return			Volume			Volatility		
	BTC	ETH	BNB	BTC	ETH	BNB	BTC	ETH	BNB
Mean	0.013	0.012	0.032	0.046	0.049	0.083	0.094	0.119	0.136
Median	0.008	0.078	0.017	0.030	0.037	0.048	0.083	0.108	0.110
Minimum	-0.266	-0.337	-0.366	-0.308	-0.319	-0.496	0.005	0.010	0.012
Maximum	0.325	0.449	0.680	0.625	0.630	1.062	0.493	0.607	0.662
St. Dev.	0.092	0.119	0.142	0.156	0.171	0.268	0.059	0.067	0.097
Skewness	0.072	0.003	1.082	0.770	0.598	1.065	2.306	2.557	2.752
Kurtosis	1.002	1.201	3.864	1.648	1.122	1.773	11.396	14.551	10.662
Jarque-Bera	7.899	11.120	151.169	39.205	20.721	59.185	1164.968	1833.580	1109.794
Probability	0.019	0.004	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	185	185	185	185	185	185	185	185	185

3.2 Investor Attention Data

3.2.1 Data Collection and Calculations

Google Trends provides access to a largely unfiltered sample of searches made to Google. The search requests are anonymized, categorized, and aggregated, which makes it an ideal tool to show interest in a particular topic on a local or global level (Google, 2021). The Google Search Volume Index (GSVI) has a value between 0 and 100, based on the relative popularity of the Google search frequency. The value of 0 refers to a period in which search volume does not meet a designated threshold, whereas a value of 100 is a period in which the highest relative volume was observed (Bank et al., 2011). This search volume indicates how much interest a specific topic or search term is bringing about, which is used as a representation of the total attention to that topic.

Google Trends allows users to view search queries by country but also globally, which is used in this thesis since cryptocurrencies can be traded from all over the world. In addition, search queries can be categorized into different categories such as “games”, “arts and entertainment” and “pets and animals”. This category is set to “all categories” to make sure all the interest in the keywords used is shown. The following keywords will be used to measure the investor’s attention: “Bitcoin”, “Ethereum” and “Binance Coin”.

Following the paper of Da et al. (2011), the abnormal GSVI (AGSVI) is constructed with the following equation:

$$AGSVI_t = \log(GSVI_t) - log[Med(GSVI_{t-1}, \dots, GSVI_{t-8})] \quad (7)$$

where $\log(GSVI_t)$ is the logarithm of the Google Search Volume Index ($GSVI_t$) during week t and $log[Med(GSVI_{t-1}, \dots, GSVI_{t-8})]$ represents the logarithm of the $GSVI_t$ median in the previous 8 weeks.

The median is used since it can capture the "normal" level of attention in such a way that it can withstand recent jumps. Another advantage of this method is that of eliminating time trends and other low-frequency seasonalities (Da et al., 2011). In line with the method proposed by Da et al. (2011) and implemented by Swamy and Dharani (2019) and Nasir et al. (2019), the AGSVI is further standardized to make the indices more comparable. The standardized abnormal Google Search Volume Index is calculated using the following equation:

$$SAGSVI_t = \frac{AGSVI_t - \frac{1}{n}\sum_{i=1}^{n} AGSVI_i}{\sigma_{AGSVI}} \tag{8}$$

where σ_{AGSVI} is standard deviation of the AGSVI time series of the whole data set.

3.2.2 Figures and Descriptive Statistics

Figures 4 to 7 show Google Trends data for the search queries "Bitcoin", "Ethereum" and "Binance Coin". When compared to Figures 1 to 3, a correlation between the prices of cryptocurrencies and investor attention can be observed. The short bubble in 2018 also translates to high investor attention, with a increase in investor attention around the beginning of that year. Figure 7 shows that the investor attention of the 3 cryptocurrencies follows similar movements in the chosen period. It is interesting to note that Binance Coin's investor attention is lagging behind Bitcoin and Ethereum, which could indicate that it is tracking the two larger cryptocurrencies in terms of returns and investor attention.

Figure 4

Google Trends data for Bitcoin

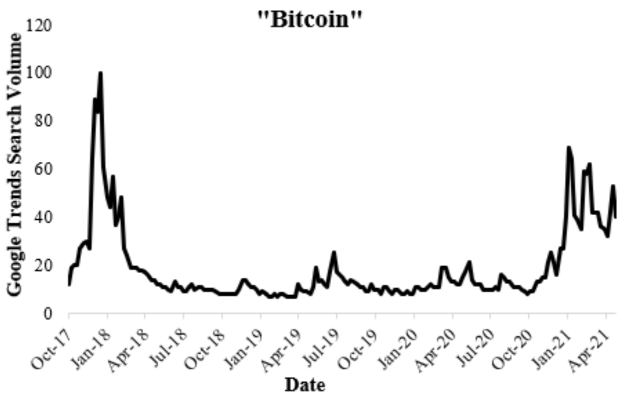


Figure 5

Google Trends data for Ethereum

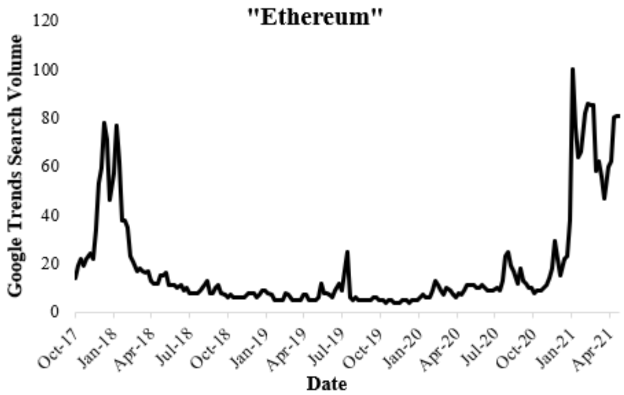


Figure 6

Google Trends data for Binance Coin

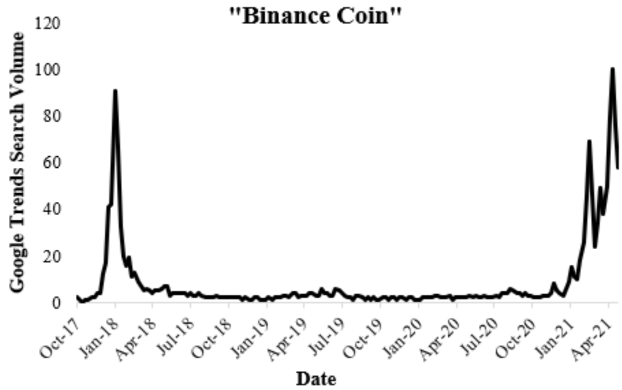


Figure 7

Google Trends data for Bitcoin, Ethereum and Binance Coin

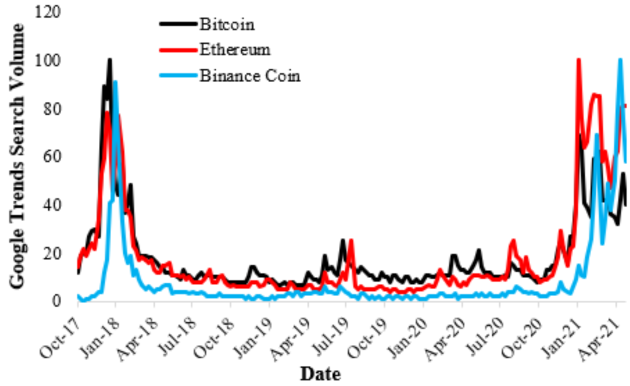


Table 3 shows the descriptive statistics of the standardized abnormal Google Search Volume Index (SAGSVI), which is used as a proxy for investor attention. Interestingly, investor attention on Bitcoin and Ethereum show similar results, with minimum and maximum values that are relatively close. Both show a slight positive skew and a positive kurtosis. Since the data is standardized, all variables have a zero mean and a standard deviation of 1. Bitcoin has a kurtosis of 1.513, which indicates that positive surges are present. Binance Coin on the other hand is highly skewed and has a higher dispersion between the minimum and maximum values compared to Bitcoin and Ethereum, which makes this investor's attention on Binance Coin the most volatile. For all the cryptocurrencies, the Jarque-Bera test statistic rejects the null hypothesis that investor attention has a normal distribution.

Table 3

Descriptive statistics of investor attention on "Bitcoin", "Ethereum" and "Binance Coin"

	$SASGSVI_t$ BTC	$SAGSVI_t$ ETH	$SAGSVI_t$ BNB
Mean	0.000	0.000	0.000
Median	-0.139	-0.132	-0.125
Minimum	-2.539	-2.157	-1.857
Maximum	3.398	3.684	4.430
St. Dev.	1.000	1.000	1.000
Skewness	0.884	0.817	1.272
Kurtosis	1.513	1.205	3.343
Jarque-Bera	41.741	31.787	136.036
Probability	0.000	0.000	0.000
Observations	185	185	185

4 METHOD

In order to establish the relationship between the variables, a vector autoregression (VAR) and a Granger causality test will be conducted.

4.1 Vector Autoregression Model

In line with the paper of Kristoufek (2013), the first step is to test if the data is stationary using the Augmented Dickey-Fuller test (ADF). The ADF test is a common method to test data for stationarity and has a null hypothesis of a unit root against the alternative of no unit root (Mushtaq, 2011). In the following equation, the ADF tests the null hypothesis that α = 1, where α is the coefficient of the first delay on Y:

$$y_t = c + \beta t + \alpha y_{t-1} + \emptyset \Delta y_{t-1} + \varepsilon_t \qquad (9)$$

$$H_0: \alpha = 1$$

$$H_a: \alpha < 1$$

Stationarity can be defined as a flat looking series, with no trend, constant variance and autocorrelation over time and without any periodic or seasonal fluctuations (Ghaffar, 2017). In series where data is stationary, no link between previous values is present, while series with non-stationary data can misleading and spurious results (Mushtaq, 2011). Therefore, it is of great importance that validate whether the data is stationary. The results of the ADF stationarity test are shown in Table 4. Based on these results, the null hypothesis of a unit root can be rejected for all variables, meaning that all series are stationary and therefore can be used in a vector autoregression model.

Table 4

Augmented Dickey-Fuller test on all variables.

		t-statistic
Return	Bitcoin	-7.775***
	Ethereum	-7.544***
	Binance Coin	-6.894***
Volume	Bitcoin	-3.609***
	Ethereum	-4.692***
	Binance Coin	-4.563***
Volatility	Bitcoin	-6.056***
	Ethereum	-7.810***
	Binance Coin	-5.506***
SAGSVI	Bitcoin	-4.984***
	Ethereum	-5.150***
	Binance Coin	-4.649***

*, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

After the stationarity has been checked, the relationship between investor attention, measured by the Google Search Volume Index, and the cryptocurrency variables can be examined. To do this, a vector autoregressive (VAR) model will be used. The VAR model is often used for multivariate time series analysis and has proven to be especially useful for describing the dynamic behavior of economic and financial time series and for forecasting (Zivot & Wang, 2006).

The general VAR model according to Zhu et al. (2021) can be characterized by the following equation:

$$X_t = c + \sum_{i=1}^{\rho} \beta_i X_{t-i} + \varepsilon_t \tag{10}$$

where X_t is a vector containing the variables of interest (return, volatility, trading volume, and the Google Trends index), c is a vector of constants, and ε_t is a vector of error terms. The lag length of the model is captured by ρ and β_i is the coefficient representing the effect of the lagged term X_{t-i} (Shen et al. 2019; Zhu et al., 2021).

An important aspect of the VAR model is the determination of the lag length based on information criteria. A VAR model using too few lags can lead to autocorrelated errors, while using too many lags leads to over-fitting, thereby increasing the mean-square-forecast errors of the model. Based on similar previous research, there is no clear consensus on one specific information criterion. Shen et al. (2019) determine the lag length by the Schwarz-Bayesian Information Criterion (BIC), while Nasir et al. (2019) select the lag order based on the Akaike Information Criteria (AIC) and Zhu et al. (2019) use the AIC in addition to the Final Prediction Error (FPE). Kristoufek (2013) uses three information criteria for the lag length selection: the AIC, BIC, and Hannan–Quinn information criterion (HQC). Since the AIC is the most commonly used criterion in the literature and Ivanov and Kilian (2005) find that the AIC tends to produce the most accurate structural and semi-structural impulse response estimates, the AIC will be used to determine the lag length in this research. The procedure to select the lag length for the VAR models is presented in Appendix A. Most of the models in this research have either one or two lags, but the AIC for Ethereum and Bitcoin volatility showed that four lags was the best option.

An important step after the VAR model has been established is to determine whether the model presents an acceptable description of the data. To do this, the residuals will be examined by assessing the potential autocorrelation of the residual values. If there is autocorrelation present in the residuals, this could indicate that there is information that has not been accounted for in the model and therefore another model might be better suited. (Bose, Hravnak & Sereika, 2017). Residual autocorrelation will be tested with the Lagrange Multiplier (LM) test. The null hypothesis of the LM test is that there is no residual autocorrelation while the alternative states that there is residual autocorrelation present (Lütkepohl, 2005).

Another way to assess the performance of the VAR model is by testing its stability. Stability refers to checking that the model accurately reflects how the time series has evolved over the period of the sampling window. An unstable VAR implies that the impact of a shock from one variable to another has a permanent effect, which is an unreasonable implication for most models (Bose et al., 2017). An unstable VAR model can be corrected by making the variables in the model stationary. The stability will be checked using the 'varstable' command in Stata.

4.2 Granger Causality Test

In addition to the VAR model, a Granger causality test will be conducted to test whether there is a linear causal relationship between the cryptocurrency variables and investor attention. Granger (1969) introduced a time series test to determine whether there is causality between variables and if one time series can predict another time series. The models used to test for a Granger causality are the following:

$$R_t = a_{01} + a_{11}R_{t-1} + \dots + a_{n1}R_{t-n} + \beta_{11}Att_{t-1} + \dots + \beta_{n1}Att_{t-n} + \varepsilon_t \tag{11}$$

$$Att_t = a_{02} + a_{12}R_{t-1} + \dots + a_{n2}R_{t-n} + \beta_{12}Att_{t-1} + \dots + \beta_{n2}Att_{t-n} + \epsilon_t \tag{12}$$

$$Va_t = a_{03} + a_{13}Va_{t-1} + \dots + a_{n3}Va_{t-n} + \beta_{13}Att_{t-1} + \dots + \beta_{n3}Att_{t-n} + \mu_t \tag{13}$$

$$Att_t = a_{04} + a_{14}Va_{t-1} + \dots + a_{n4}Va_{t-n} + \beta_{14}Att_{t-1} + \dots + \beta_{n4}Att_{t-n} + \upsilon_t \tag{14}$$

$$Vu_t = a_{05} + a_{15}Vu_{t-1} + \dots + a_{n5}Vu_{t-n} + \beta_{15}Att_{t-1} + \dots + \beta_{n5}Att_{t-n} + \nu_t \tag{15}$$

$$Att_t = a_{06} + a_{16}Vu_{t-1} + \dots + a_{n6}Vu_{t-n} + \beta_{16}Att_{t-1} + \dots + \beta_{n6}Att_{t-n} + \psi_t \tag{16}$$

R_t, Va_t and Vu_t, respectively, represent respectively the return, volatility, and volume of the cryptocurrencies while Att_t represents the investor attention at week t. The constants in these equations are a_{01}, $a_{02,}a_{03,}a_{04\,,}a_{05}$ and a_{06}. The error terms are represented by the following variables: ε_t, ϵ_t, μ_t, υ_t , ν_t and ψ_t. To determine the lag length, the AIC information criterion will be used, in line with the information criteria used for the vector autoregression models.

The null hypothesis for these tests above is that the relevant coefficient is zero. For example, for Equation 11, the null hypothesis states that investor attention (Att_t) does not Granger cause returns (R_t):

$$H_0: \beta_{11} = \dots = \beta_{n1} = 0$$

To test whether the null hypothesis should be rejected, an F-test will be used (Han, Wu & Yin, 2018).

5 Results

5.1 Vector Autoregression Test Results

5.1.1 Bitcoin

Tables 5 to 7 show the results of the vector autoregression models for the Bitcoin variables. Table 5 shows that investor attention does not significantly influence the future returns of Bitcoin. The return of the previous week, on the other hand, does have a positive significant effect on investor attention, indicating that investor attention in the following week increases with the return of the previous week. Intuitively, this would make sense, as people might expect that a previous positive return can also yield positive returns for them in the future, causing them to be more interested in that asset through, for example, more Google searches. Similar results were obtained by Urquhart (2018), who finds that higher returns of Bitcoin increase the search queries in Google. The results of more recent research by Subramaniam and Chakraborty (2020) also suggest that higher Bitcoin returns induce more attention from investors. Nasir et al. (2019), however, found that the lagged returns of Bitcoin did not lead to a surge in Google searches. This may be because Nasir et al. (2019) use a dataset which consist of four years, while Urquhart (2018) and Subramaniam and Chakraborty (2020) take six and almost six years, respectively, into account. In this shorter period, the effect of returns on investor attention might not be as pronounced compared to a longer period.

Table 5

Vector autoregression results for Bitcoin return and investor attention

	R_t	$SAGSVI_t$
Intercept	0.008	-0.027
	(0.006)	(0.043)
R_{t-1}	0.340***	1.969***
	(0.072)	(0.495)
$SAGSVI_{t-1}$	0.010	0.734***
	(0.007)	(0.046)
R^2	0.154	0.660

Note: This table reports the VAR estimation results of the analysis between Bitcoin returns (R_t) and investor attention ($SAGSVI_t$). The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

The VAR estimation results for Bitcoin volume and investor attention are displayed in Table 6. The expectations based on previous research on the effect of investor attention and stock returns were that the Google search intensity has a positive significant effect on trading volume. Surprisingly, Table 6 does not show any significant effect of investor attention on the trading volume of Bitcoin. These results are not in line with previous work from Nasir et al. (2019), who document that a shock to the Google search volume positively influences the trading volume of Bitcoin with a gradual increase in the first two weeks and a diminishing effect thereafter. There is also no significant coefficient found for past volume on investor attention, while Urquhart (2018) showed that a higher trading volume for Bitcoin leads to more Google searches. This might be because Urquhart (2018) uses daily data, while this research works with weekly data. In a small interval of just a day, past volume could influence investor attention, but it could be that weekly data does not capture this relationship.

Table 6

Vector autoregression results for Bitcoin volume and investor attention

	VLM_t	$SAGSVI_t$
Intercept	0.009	-0.001
	(0.007)	(0.049)
VLM_{t-1}	0.789***	-0.852
	(0.099)	(0.729)
VLM_{t-2}	-0.007	0.817
	(0.097)	(0.714)
$SAGSVI_{t-1}$	0.011	0.988***
	(0.013)	(0.097)
$SAGSVI_{t-2}$	0.005	-0.209**
	(0.013)	(0.096)
R^2	0.732	0.642

Note: This table reports the VAR estimation results of the analysis between Bitcoin volume (VLM_t) and investor attention ($SAGSVI_t$). The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 7 shows that the first lag of investor attention has strong significant predictive power for the volatility of the following week at the 1% significance level. This indicates that more investor attention results in higher volatility in Bitcoin in the next week. This finding is consistent with research by Eom et al. (2019), Shen et al. (2018), and Urquhart (2018), who all find that investor attention can help to explain changes in the volatility of Bitcoin. Shen et al. (2018) find that more investor attention leads to higher volatility, in line with the findings in this paper. However, it is important to note that Shen et al. (2018) use tweets on Twitter as a proxy for investor attention rather than Google searches. While both can be used as proxies for investor attention, the results cannot be compared directly. A statistically significant positive effect of the second lag of investor attention on realized volatility is also present, but only at a significance level of 10%, suggesting that investor attention affects the realized volatility of Bitcoin for several periods rather than just 1 week. Zhu et al. (2021) also documented a persisting effect of Bitcoin's realized volatility, but their coefficients of investor attention were significant at the third and four lags. The effect is also present the other way around, as the first lag of Bitcoin's realized volatility has a negative and significant effect on investor attention at a 5% significance level. Interestingly, this effect is not present for the second lag but the third lag does show a negative influence on investor attention at the 10% significance level. Urquhart (2018) also find that lagged volatility can significantly influence search queries, but his results show that an increase in volatility will lead to more investor attention rather than a decrease in search queries.

Table 7

Vector autoregression results for Bitcoin volatility and investor attention

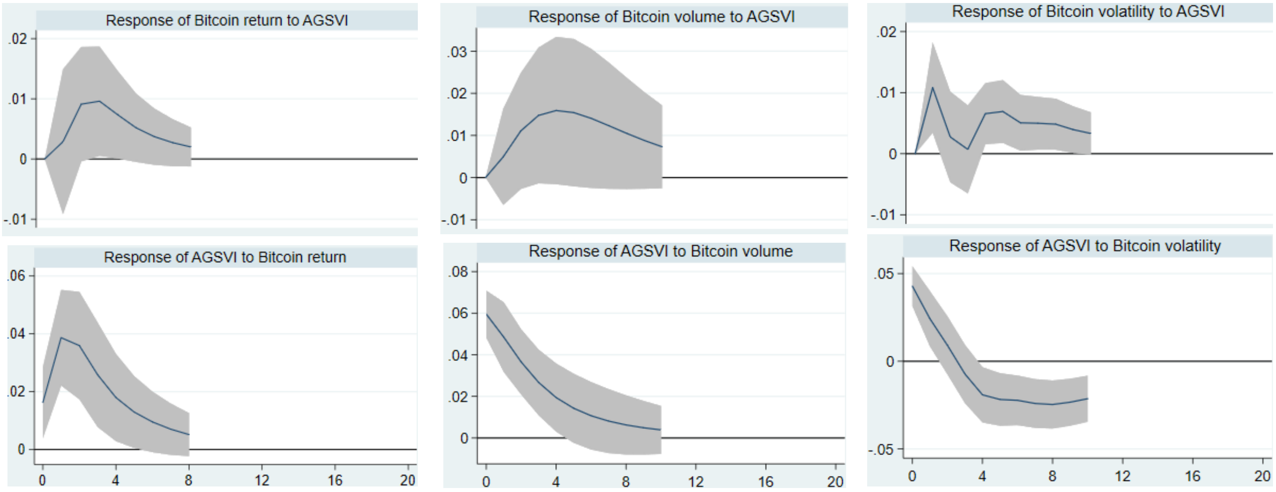
	RV_t	$SAGSVI_t$
Intercept	0.039***	0.439***
	(0.010)	(0.111)
RV_{t-1}	0.145*	-2.102**
	(0.085)	(0.958)
RV_{t-2}	0.188**	0.115
	(0.086)	(0.974)
RV_{t-3}	0.164*	-0.249*
	(0.088)	(0.878)
RV_{t-4}	0.084	-0.163
	(0.086)	(0.751)
$SAGSVI_{t-1}$	0.022***	0.932***
	(0.008)	(0.086)
$SAGSVI_{t-2}$	-0.183*	-0.236*
	(0.010)	(0.112)
$SAGSVI_{t-3}$	0.000	0.125
	(0.010)	(0.112)
$SAGSVI_{t-4}$	0.009	0.036
	(0.007)	(0.082)
R^2	0.275	0.678

Note: This table reports the VAR estimation results of the analysis between Bitcoin volatility (RV_t) and investor attention ($SAGSVI_t$). The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

To get a broader perspective on the relationship between the Bitcoin variables and investor attention, an impulse response function (IRF) analysis is also performed, as shown in Figure 8. Impulse response functions represent the responses of variables to shocks in the system, which makes it a useful tool to study the interactions between variables in a VAR model (Lütkepohl, 2010). The IRF analysis shows that there is a positive response of Bitcoin returns to a shock in investor attention, but this result lacks statistical significance, similar to the results obtained in the VAR model. The same can be said for the response of Bitcoin volume and Bitcoin volatility to SAGSVI, where the contribution is trivial due to insignificant results. A shock to Bitcoin volume and return both significantly lead to a surge in investor attention in the first few weeks, but this effect is completely faded by week 8. The response of investor attention to Bitcoin volatility starts positive in the first week, but decreases sharply hereafter and becomes negative after a few weeks. All in all, the IRF results from the VAR model show that shocks to Bitcoin return, volume, and volatility on investor attention can persist for several weeks.

Figure 8

Impulse response functions for VAR of the Bitcoin variables and the investor attention proxy



The blue line represents the impulse response to Cholesky one standard deviation innovations, while the gray area shows the ninety-five percent confidence interval. The duration of the shocks in week is represented on the X-axis, the Y-axis shows the magnitude of the shock.

5.1.2 Ethereum

Table 8 shows that current investor attention is positively impacted by the return of Ethereum over the past week, as the coefficient R_{t-1} is significant at the 1% significance level. This indicates that past returns have a positive effect on investor attention the following week. This follows the results found by Lin (2021), who documents that there is a temporary positive influence of returns on Google search queries. Past investor attention, however, soes not significantly influence the current return for Ethereum. These results are similar to the results obtained for Bitcoin, which is not surprising since research by Boako et al. (2019) showed that there are strong dependencies between Bitcoin and Ethereum, the two most capitalized and well-known cryptocurrencies. This makes it likely that the returns of these two coins are at least partly interlinked. In addition, Figure 7 showed that investor attention to Bitcoin and Ethereum follows a similar path. In line with these results, Bleher and Dimpfl (2019) also do not find a significant effect of investor attention on returns for Ethereum. Subramaniam and Chakraborty (2020), on the other hand, found that more investor attention increases the return of Ethereum using their quantile causality approach. This may be because a quantile regression approach generates a more detailed and flexible analysis of the conditional distribution compared to the conditional mean regression analysis (Troster, 2018). Lee and Yang (2012) for example find that the Granger causality between money and income is insignificant for the conditional mean, but significant using a quantile approach.

Table 8

Vector autoregression results for Ethereum return and investor attention

	R_t	$SAGSVI_t$
Intercept	0.008	-0.013
	(0.008)	(0.046)
R_{t-1}	0.316***	1.232***
	(0.074)	(0.417)
$SAGSVI_{t-1}$	0.012	0.713***
	(0.009)	(0.049)
R^2	0.133	0.617

Note: This table reports the VAR estimation results of the analysis between Ethereum returns (R_t) and investor attention ($SAGSVI_t$). The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

The vector autoregression results for Ethereum's trading volume and investor attention are shown in Table 9. Investor attention does not show any effect on the trading volume, since all the coefficients are not significant at the 10% level. Ethereum's investor attention on the other hand is negatively affected by the past trading volume only on the second lag. This indicates that there is not an immediate effect of trading volume of the last week on investor attention in the following week, but that trading volume two weeks ago negatively influences the investor attention for Ethereum. Based on previous literature, however, a positive relationship between trading volume and investor attention was expected, as Urquhart (2018) showed that a higher trading volume for Bitcoin leads to more Google searches rather than less. Urquhart (2018), however, used a dataset with daily return data, so it is difficult to compare his daily effect to the weekly data used in this paper as daily data is more volatile compared to weekly data.

Table 9

Vector autoregression results for Ethereum volume and investor attention

	VLM_t	$SAGSVI_t$
Intercept	0.013*	0.038
	(0.007)	(0.049)
VLM_{t-1}	0.986***	0.679
	(0.096)	(0.677)
VLM_{t-2}	-0.218**	-1.391**
	(0.095)	(0.666)
$SAGSVI_{t-1}$	-0.002	0.787***
	(0.014)	(0.096)
$SAGSVI_{t-2}$	0.014	0.010
	(0.013)	(0.093)
R^2	0.731	0.619

Note: This table reports the VAR estimation results of the analysis between Ethereum returns (VLM_t) and investor attention ($SAGSVI_t$). The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

The VAR estimation results for Ethereum's volatility and the investor attention are displayed in Table 10. Unlike the results for Bitcoins' realized volatility, the coefficients of the effect of past investor attention on current realized volatility are all insignificant. In contrast, the past realized volatility of Ethereum seems to negatively affect investor attention at a 1% significance level. This is similar to the VAR estimation results for the realized volatility of Bitcoin, which was also expected. Namely, Boako et al. (2019) showed that there are strong dependencies between the two most capitalized cryptocurrencies Bitcoin and Ethereum. Urquhart (2018) also concluded that previous volatility can significantly influence search queries, however, his results however show that an increase in volatility will lead to more investor attention rather than a decrease in search queries. High volatility on an asset is often associated with high rewards, but research by Baker and Haugen (2012) and Blitz, Van Vliet, and Baltussen (2019) shows that less volatile stocks have been outperforming stocks which show higher volatility across various markets. In addition, Spaventa (2020) noted that highly volatile assets can be destructive for investors as they can create fear and uncertainty and as a result lead to panic selling. These findings could serve as an explanation for the negative effect found between the volatility of cryptocurrencies and investor attention. If investors have a negative association with volatility based on their performance, an increase in volatility of in this case Ethereum would not be well received by those investors, and their attention decreases and potentially moves to a different cryptocurrency or asset.

Table 10

Vector autoregression results for Ethereum volatility and investor attention

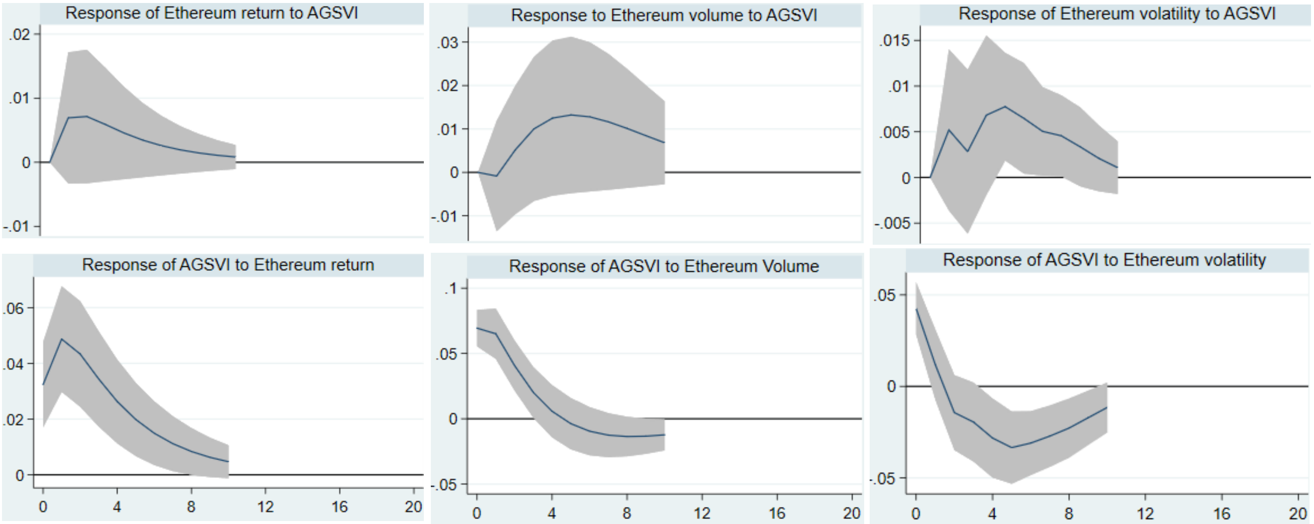
	RV_t	$SAGSVI_t$
Intercept	0.074***	0.109***
	(0.015)	(0.025)
RV_{t-1}	0.178**	-1.422***
	(0.079)	(0.745)
RV_{t-2}	0.022	-1.019
	(0.085)	(0.796)
RV_{t-3}	0.016	-0.869
	(0.085)	(0.800)
RV_{t-4}	0.168**	-0.637
	(0.082)	(0.664)
$SAGSVI_{t-1}$	0.010	0.890***
	(0.008)	(0.079)
$SAGSVI_{t-2}$	-0.005	-0.194*
	(0.011)	(0.106)
$SAGSVI_{t-3}$	0.011	0.210**
	(0.011)	(0.105)
$SAGSVI_{t-4}$	0.000	-0.119
	(0.008)	(0.078)
R^2	0.138	0.663

Note: This table reports the VAR estimation results of the analysis between Ethereum volatility (RV_t) and investor attention ($SAGSVI_t$). The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Figure 9 shows the impulse response functions for the Ethereum variables and the investor attention proxy SAGSVI. The responses of return, volume, and volatility of Ethereum to shocks of investor attention are all insignificant. This implies that investors who search for information on Ethereum do not necessarily act upon this information and enter into a transaction. When comparing Figure 9 to Figure 8, the response of Ethereum return to investor attention is almost the same as for Bitcoin's return and investor attention, with an increase that peaks in the first week and slowly declines in the following weeks. A shock to the trading volume of Ethereum triggered a slight increase in investor attention in the first four weeks, and thereafter the effects diminished. The response of investor attention to the realized volatility of Ethereum starts positive only in the first week and decreases sharply hereafter, but these results fall short of significance as can be seen in the wide confidence interval area.

Figure 9

Impulse response functions for VAR of the Ethereum variables and the investor attention proxy



The blue line represents the impulse response to Cholesky one standard deviation innovations, while the gray area shows the ninety-five percent confidence interval. The duration of the shocks in week is represented on the X-axis, the Y-axis shows the magnitude of the shock.

5.1.3 Binance Coin

Table 11 shows the VAR estimation results for the return and investor attention of Binance Coin. The Google Search Volume Index in the last period, so in this case the last week, had significant positive impacts on the current return for Binance Coin. This indicates that more investor attention in the past week results in a higher return in the subsequent week. An explanation for these results can be found in the attention-induced price pressure hypothesis of Barber and Odean (2008), who hypothesize that an increase in attention will lead to an increase in buying, which will push up the price and make the returns higher. Interestingly, the effect is also significant the other way around at the 5% level. The positive significant relationship between returns and investor attention indicates that a higher return in the last week results in higher investor attention in the following week. Since Binance Coin has not been a cryptocurrency often researched, these results cannot be compared to previous research on this coin, but these results are in line with previous Bitcoin research by Urquhart (2018) and Subramaniam and Chakraborty (2020).

Table 11

Vector autoregression results for Binance Coin return and investor attention

	R_t	$SAGSVI_t$
Intercept	0.022*	-0.023
	(0.009)	(0.050)
R_{t-1}	0.330***	0.908**
	(0.079)	(0.424)
$SAGSVI_{t-1}$	0.034***	0.668***
	(0.011)	(0.060)
R^2	0.260	0.571

Note: This table reports the VAR estimation results of the analysis between Binance Coin returns (R_t) and investor attention ($SAGSVI_t$). The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

The VAR results for Binance Coin's volume and the investor attention are displayed in Table 12. The statistically significant coefficient of 0.042 for the lagged investor attention shows that higher investor attention in the previous week entails that the trading volume will be higher in the following week. This effect is in line with the expectations based on previous literature, but Binance Coin is the only cryptocurrency in this research that confirms this hypothesis. Similar to the results of the return on Binance Coin, this effect can also be explained using the attention-induced price pressure hypothesis of Barber and Odean (2008), as they stated that more attention results in higher sales with a higher trading volume as a result. The trading volume does not show any influence on investor attention in the VAR model, since the coefficient VLM_{t-1} is not significant at the 10% significance level.

Table 12

Vector autoregression results for Binance Coin volume and investor attention

	VLM_t	$SAGSVI_t$
Intercept	0.022**	-0.004
	(0.010)	(0.052)
VLM_{t-1}	0.756***	0.118
	(0.046)	(0.236)
$SAGSVI_{t-1}$	0.042***	0.725***
	(0.012)	(0.063)
R^2	0.762	0.561

Note: This table reports the VAR estimation results of the analysis between Binance Coin volume (VLM_t) and investor attention ($SAGSVI_t$). The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

The first lag of investor attention seems to have a positive and significant effect on the realized volatility of Binance Coin at the 10% significance level, as can be seen from Table 13. This indicates that higher investor attention in the previous week results in a higher realized volatility for Binance Coin in the current week. However, this influence quickly fades as the second lag of investor attention is insignificant. These results follow the conclusion of Al Guindy (2021), who finds that investor attention predicts future price volatility as increased investor attention to cryptocurrencies leads to increased price volatility. Realized volatility also influences investor attention, but only for the second lag with a significantly negative coefficient of -1.453. This negative effect of past realized volatility on investor attention is also present for the other two cryptocurrencies in this research.

Table 13

Vector autoregression results for Binance Coin volatility and investor attention

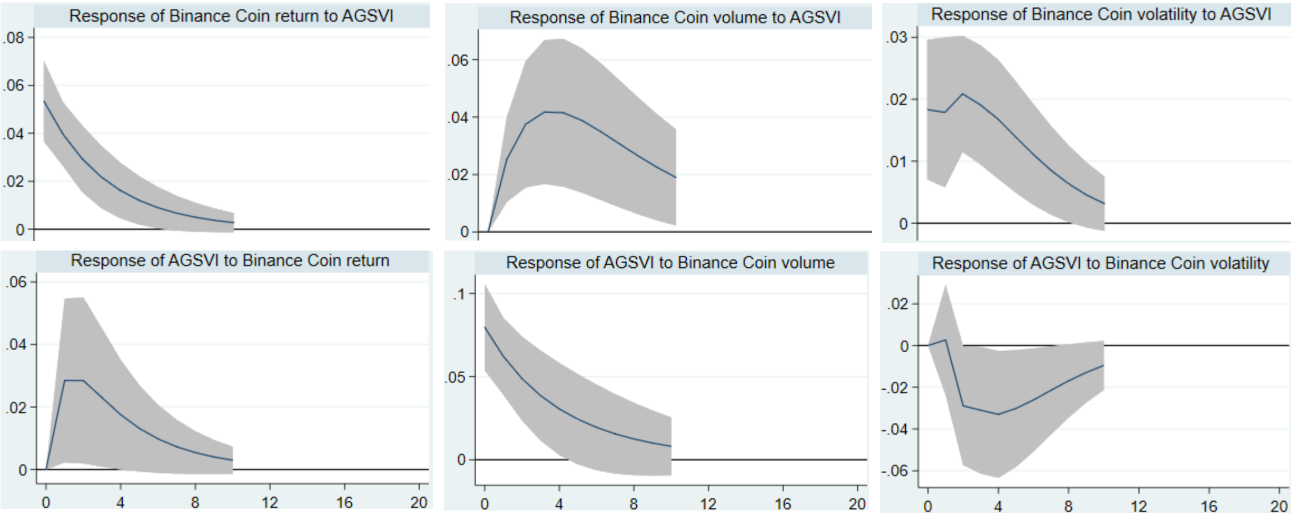
	RV_t	$SAGSVI_t$
Intercept	0.065***	0.186**
	(0.012)	(0.099)
RV_{t-1}	0.365***	0.123
	(0.075)	(0.616)
RV_{t-2}	0.137*	-1.453**
	(0.074)	(0.608)
$SAGSVI_{t-1}$	0.017*	0.707***
	(0.009)	(0.074)
$SAGSVI_{t-2}$	0.006	0.095
	(0.012)	(0.076)
R^2	0.346	0.575

Note: This table reports the VAR estimation results of the analysis between Binance Coin volatility (RV_t) and investor attention ($SAGSVI_t$). The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

The impulse response function for the VAR model of the Binance Coin variables and the investor attention proxy is shown in Figure 10. The returns of Binance Coin return respond positively to a shock to the SAGSVI, but this effect starts to decline every week. Binance Coin's volume and volatility both react positively to a shock to SAGSVI. This effect increased in the first few weeks and thereafter it starts to diminish, but it does remain positive. A shock to Binance Coin's volume and return both significantly lead to a surge in investor attention in the first few weeks, but this effect is completely faded by week 8. The response of investor attention to a shock of Binance Coin volatility is positive only in the first week and decreases sharply hereafter and becomes negative. Similar to the IRF results of the other cryptocurrencies, the IRF results from the VAR model show that shocks to Binance Coin return, volume, and volatility on investor attention can last for several weeks.

Figure 10

Impulse response functions for VAR of the Binance Coin variables and the investor attention proxy



The blue line represents the impulse response to Cholesky one standard deviation innovations, while the gray area shows the ninety-five percent confidence interval. The duration of the shocks in week is represented on the X axis, the Y axis shows the magnitude of the shock.

As stated in the Section 4.1, several performance tests on the VAR model are being conducted. The results of the Lagrange Multiplier are shown in Table 32 of Appendix B. For all the VAR models of the different cryptocurrencies, the null hypothesis that there is no residual autocorrelation cannot be rejected since the p-values are higher than 0.005. In addition, the results of the stability tests showed that all the VAR models satisfy the stability condition.

5.2 Granger Causality Test Results

Table 14 shows the Granger causality test estimation results between the Bitcoin variables and investor attention. The Granger causality test provides significant evidence that Bitcoin returns do Granger cause investor attention, which is in line with the findings of the VAR model of Urquhart (2018) and Subramaniam and Chakraborty (2020), who also find Granger causality. However, there is no significant relationship between previous returns and the Google Search Volume Index, which indicates that the relationship between returns and investor attention is unidirectional. There is no statistically significant evidence that Bitcoin trading volume Granger causes investor attention or that this effect is present the other way around. Nasir et al. (2019) also fail to reject the hypotheses that volume does not Granger cause investor attention and that investor attention does not show Granger causality with trading volume, which leads to the same conclusion found in this paper. Urquhart (2018), on the other hand, found that trading volume Granger-causes search queries for Bitcoin. Finally, the Granger causality tests show that a bidirectional Granger causality exists between Bitcoin volatility and investor attention, both at the 1% significance level.

Table 14

Granger causality test estimation results between the Bitcoin variables and investor attention

Equation	Excluded	P-value
Return	Investor attention	0.121
Investor attention	Return	0.000***
Volume	Investor attention	0.189
Investor attention	Volume	0.482
Volatility	Investor attention	0.010***
Investor attention	Volatility	0.000***

*, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Similar to the Granger causality test result for Bitcoin return, a unidirectional Granger causality from Ethereum return to investor attention is confirmed, which can be seen in Table 15, and was expected based on the paper of Subramaniam and Chakraborty (2020). Ethereum's volume Granger causes investor attention at the 5% significance level, while no statistical Granger causality can be observed from investor attention to volume. This suggests that there is a unidirectional flowing from trading volume to the investor attention proxy. The Granger results for volatility confirm the findings of the VAR model, where the results suggested that past realized volatility of Ethereum affects the current investor attention at a 1% significance level. There exists a statistically significant Granger causality running from realized volatility to investor attention at the 1% significance level and a Granger causality from investor attention to realized volatility at the 10% significance level, indicating that this relationship is a bilateral one.

Table 15

Granger causality test estimation results between the Ethereum variables and investor attention

Equation	Excluded	P-value
Return	Investor attention	0.183
Investor attention	Return	0.001***
Volume	Investor attention	0.282
Investor attention	Volume	0.029**
Volatility	Investor attention	0.095*
Investor attention	Volatility	0.000***

*, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Lastly, the Granger causality test estimation results between the Binance Coin variables and investor attention, which are shown in Table 16, are analyzed. The Granger causality relationship from Binance Coin investor attention to return is confirmed at a 1% significance level, while the Granger causality relationship of return to investor attention is statistically significant at the 5% significance level. This bidirectional relationship between the two variables confirms the findings of the VAR model of Table 11 and fits the expectations based on previous papers by Dastgir et al. (2019), Subramaniam and Chakraborty (2020), and Zhu et al. (2021). Regarding trading volume, a statistically significant unidirectional Granger causality can be observed from volume to investor attention at the 1% significance level. The last variable is realized volatility, for which the Granger causality test provides significant evidence that the proxy for investor attention Granger causes volatility as well as that volatility Granger causes investor attention, implying a bilateral relationship between the two variables.

Table 16

Granger causality test estimation results between the Binance Coin variables and investor attention

Equation	Excluded	P-value
Return	Investor attention	0.003***
Investor attention	Return	0.032**
Volume	Investor attention	0.615
Investor attention	Volume	0.001***
Volatility	Investor attention	0.003***
Investor attention	Volatility	0.034**

*, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

5.3 Robustness checks

5.3.1 Bubble Period

In order to test the robustness of the obtained results, the 'bubble' periods of Bitcoin and Ethereum are further analysed to see if the results found still hold during this period or if investor attention has a different impact on the Bitcoin and Ethereum variables during this period. Bitcoin and Ethereum both had a bubble period that started October 2017, with a peak in December 2017 and a 'burst' of the bubble that lasted until late April 2018. Another bubble period started in September last year, 2020, until the end of the analyzed data, so April 2021. A VAR model is conducted only during these periods, with the same process as discussed begore with stationarity tests, lag selection, and performance tests. The Augmented Dickey-Fuller test shows that not all variables are stationary, so all the variables are first-differenced.

The results of the vector autoregression models for the bubble periods are presented in Tables 33, 34 and 35 of Appendix C. During the bubble period, similar results are obtained for the relationship between the returns of Bitcoin and investor attention as for the whole period, but the effect of past return on current investor attention is slightly stronger present at the same confidence level. Bitcoin's volume has a significant effect on the investor attention only during a bubble period, as Table 6 showed that there were no significant coefficients present when considering the full sample period into account. Interestingly, a higher volume in the past week leads to less investor attention in the following week, but for the second lag of volume, this effect is positive.

Table 17 shows the results for Bitcoin volatility and investor attention during bubble periods and is more valuable for this research than the results in Tables 33, 34 and 35 of Appendix C, since the earlier obtained results showed that for the three different Bitcoin and Ethereum variables, investor attention only had a significant impact on the realized volatility of Bitcoin. Table 7 showed that the first lag of investor attention has strong significant predictive power for the volatility of the following week at the

1% significance level with a value of 0.022. Similar results are obtained during the bubble period, with a statistically significant positive effect of 0.019. This suggests that during a bubble period, the effect of investor attention does not have more explanatory power when it comes to the volatility of Bitcoin.

Table 17

Vector autoregression results for Bitcoin volatility and investor attention during bubble periods

	RV_t	$SAGSVI_t$
Intercept	0.002	-0.021
	(0.005)	(0.100)
RV_{t-1}	-0.831***	-3.240**
	(0.122)	(1.347)
RV_{t-2}	-0.490**	0.482
	(0.133)	(1.553)
$SAGSVI_{t-1}$	0.019***	0.271**
	(0.007)	(0.134)
$SAGSVI_{t-2}$	0.01	-0.168
	(0.007)	(0.143)
R^2	0.456	0.267

Note: This table reports the VAR estimation results of the analysis between Bitcoin volatility (RV_t) and investor attention ($SAGSVI_t$) in the two 'bubble periods' from October 15, 2017 to May 6, 2018 and September 6, 2020 to April 25, 2021. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

The VAR results for Ethereum's volatility and investor attention, shown in Table 10, had insignificant coefficients for the effect of past investor attention on current realized volatility. During a bubble, however, a positive significant effect can be observed in Table 18 at the 5% significance level. This indicates that during a bubble, an increase in investor attention results in higher volatility in Ethereum in the following week. This is in line with the findings of Rognone, Hyde, and Zhang (2020), who show that the volatility of cryptocurrency is usually unrelated is to more investor attention, measured by news, but that the impact of news is more pronounced during bubble periods. All in all, the main results obtained in this research do not change much when the focus is only on the bubble period. Therefore, this robustness check shows that most of the conclusions found still hold when compared to the full sample analysis.

Table 18

Vector autoregression results for Ethereum volatility and investor attention during bubble periods

	RV_t	$SAGSVI_t$
Intercept	0.001	0.034
	(0.007)	(0.081)
RV_{t-1}	-0.659***	-2.878***
	(0.135)	(1.175)
RV_{t-2}	-0.433***	-1.575*
	(0.139)	(1.230)
$SAGSVI_{t-1}$	0.026**	0.391***
	(0.012)	(0.136)
$SAGSVI_{t-2}$	0.0138	-0.096
	(0.013)	(0.140)
R^2	0.308	0.190

Note: This table reports the VAR estimation results of the analysis between Ethereum volatility (RV_t) and investor attention ($SAGSVI_t$) in the two 'bubble periods' from October 15, 2017 to May 6, 2018 and September 6, 2020 to April 25, 2021. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

5.3.2 Control Variables

As an additional robustness check, several control variables that could influence the return, volume, or volatility of cryptocurrency are included. Most of the research done on this subject focuses only on Bitcoin as a representative of the cryptocurrency market, with prior literature that has analyzed a link between Bitcoin and the S&P 500 return, gold, VIX, and WTI oil. It is important, however, to note that there are thousands of different cryptocurrencies and that the movement of Bitcoin might not fully represent the same development of these other cryptocurrencies.

Georgoula, Pournarakis, Bilanakos, Sotiropoulos, and Giaglis (2015) conducted a vector error correction model and found that Bitcoin price is negatively associated with the S&P 500 stock market index, which they use as a representation of the general state of the economy worldwide. In addition, Erdas and Caglar (2018) have found a causal relationship between Bitcoin price and the S&P 500 index and Kjærland, Khazal, Krogstad, Nordstrøm, and Oust (2018) obtained similar results, where their empirical findings show that Bitcoin's price is affected by the returns on the S&P 500.

Adebola, Gil-Alana, and Madigu (2019) find a limited connection between the gold market and the cryptocurrency market, but state that it is challenging to determine the changes in the gold market based on the changes in the cryptocurrency market and the other way around. Zeng, Yang, and Shen (2020) also find a connection between Bitcoin and gold, but they find that that connection is rather weak. For Ethereum however, there is a stronger link to gold compared to Bitcoin, but that connectedness is still low. The existence of a relationship between gold and cryptocurrency is still debatable though, as Kjærland et al. (2018) and Erdas and Caglar (2018) do not find a statistically significant relationship between the variables.

Shocks or fluctuations in oil prices can affect other markets (Zhang, 2017), which makes oil price an interesting variable to add to this research. As stated before, Van Wijk (2013) notes that various financial indicators can affect the long-term pricing of Bitcoin, one of those being the WTI oil price. The author concludes that in the long run, the WTI oil price can significantly influence the value of Bitcoin, where an increase in the WTI oil price would lead to a decrease in demand for Bitcoin with a lower value as a result. A relationship between oil and cryptocurrencies is also found by Okorie and Lin (2020), who show that there are both bidirectional and unidirectional volatility spillovers from the crude oil market to the cryptocurrency market and to the oil market from the cryptocurrency market. However, Kjærland et al. (2018) and Erdas and Caglar (2018) do not find any casual relations between Bitcoin and the oil price.

Another control variable to account for is the VIX index, which is one of the most recognized measures of volatility globally derived from call and put options of the S&P 500 Index published by the Chicago Board Options Exchange (CBOE) (CBOE, 2021). The VIX index reflects not only historical volatility information, but also the expectation that investors have about the potential future market circumstances (Liu, Ji & Fan, 2013). Bouri, Azzi, and Dyhrberg (2017) find that there exists a negative relationship between the implied volatility index (VIX) and the volatility of Bitcoin. In line with these findings, the results of López-Cabarcos, Pérez-Pico, Piñeiro-Chousa, and Šević (2019) indicate that the market volatility, measured by VIX returns, statistically significantly influence Bitcoin volatility. In contrast to these results, Kjærland et al (2018) do not find a relationship between Bitcoin and the VIX index. Malladi and Dheeriya (2021), on the other hand, find that measures of fear, like the VIX index, are factors that influence the price of Bitcoin.

Weekly data on the S&P 500 index, WTI oil spot prices, gold prices, and the VIX index are downloaded from Investing.com (Investing, 2021a, 2021b, 2021c, 2021d). The descriptive statistics of the control variables are shown in Appendix C. The returns of these variables are calculated using the weekly closing prices with the following equation, in line with the calculations of the returns of the cryptocurrencies:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{17}$$

The returns on the variables are added in the original VAR models and the same method is used which includes the stationarity tests, lag selection, and performance tests. The variables are stationary, as can be seen from Table 19.

Table 19
Augmented Dickey-Fuller test on the control variables.

	t-statistic
S&P 500	-14.816***
WTI Oil	-10.244***
Gold	-16.983***
VIX	-15.577***

*, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

The results of the VAR models where the control variables are added for Bitcoin are shown in Tables 20, 21, and 22. The return of the previous week still has a positive significant effect on investor attention, but compared to the original VAR model, the coefficient is just a bit higher with a value of 2.197 compared to the coefficient of 1.969 in the previous model. The original VAR model did not show a significant coefficient for the effect of investor attention on the volume of Bitcoin, but when controlling for the additional variables, there is a slight positive effect of investor attention of the previous week on the current volume, albeit only at the 10% level. Adding the control variables still does not yield a significant coefficient on the effect of trading volume on investor attention. The effect of adding the control variables on the relationship between investor attention and volatility is negligible, as the coefficient only changes slightly. The effect of the second lag of investor attention on Bitcoin volatility however is now significant at the 5% level with a value of -0.019 compared to -0.183 at a 10% significance level. All in all, this shows that the model does not react strongly to the addition of the control variables with only minor changes in the coefficients and significant levels and that the control variables do not drive the original results. In line with earlier literature of Malladi and Dheeriya (2021), Kjærland et al. (2018), and Erdas and Caglar (2018), there is no statistically significant relationship between the Bitcoin variables return, volume and volatility and the variables VIX, gold, WTI oil, and the S&P500.

Table 20

Vector autoregression results for Bitcoin return, investor attention and the control variables

	R_t	$SAGSVI_t$
Intercept	0.008	-0.029
	(0.006)	(0.043)
R_{t-1}	0.376***	2.197***
	(0.078)	(0.549)
$SAGSVI_{t-1}$	0.009	0.730***
	(0.007)	(0.047)
WTI_{t-1}	0.002	-0.474
	(0.101)	(0.704)
$Gold_{t-1}$	-0.389	-0.567
	(0.320)	(2.222)
VIX_{t-1}	-1.369	-2.086
	(0.921)	(3.358)
$SP500_{t-1}$	-0.062	-0.182
	(0.249)	(1.735)
$Adjusted\ R^2$	0.174	0.684

Note: This table reports the VAR estimation results of the analysis between Bitcoin return (R_t) and investor attention ($SAGSVI_t$), with control variables WTI oil, gold, VIX and the S&P500. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 21

Vector autoregression results for Bitcoin volume, investor attention and the control variables

	VLM_t	$SAGSVI_t$
Intercept	0.008	0.008
	(0.006)	(0.049)
VLM_{t-1}	0.792***	-0.312
	(0.053)	(0.401)
$SAGSVI_{t-1}$	0.015*	0.834
	(0.008)	(0.062)
WTI_{t-1}	0.034	0.152
	(0.095)	(0.714)
$Gold_{t-1}$	0.130	0.305
	(0.307)	(1.302)
VIX_{t-1}	-1.046	-2.59
	(0.842)	(3.814)
$SP500_{t-1}$	0.157	1.334
	(0.235)	(0.763)
$Adjusted\ R^2$	0.759	0.656

Note: This table reports the VAR estimation results of the analysis between Bitcoin volume and investor attention ($SAGSVI_t$) with control variables WTI oil, gold, VIX and the S&P500. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 22

Vector autoregression results for Bitcoin volatility, investor attention and the control variables

	RV_t	$SAGSVI_t$
Intercept	0.037***	0.509***
	(0.010)	(0.119)
RV_{t-1}	0.181**	-1.676
	(0.091)	(0.936)
RV_{t-2}	0.099	-0.050
	(0.092)	(0.955)
RV_{t-3}	0.099	-2.732***
	(0.095)	(0.976)
RV_{t-4}	0.216**	-1.189
	(0.095)	(1.089)
$SAGSVI_{t-1}$	0.023***	0.897***
	(0.007)	(0.087)
$SAGSVI_{t-2}$	-0.019**	-0.213*
	(0.009)	(0.110)
$SAGSVI_{t-3}$	0.004	0.138
	(0.010)	(0.111)
$SAGSVI_{t-4}$	0.007	0.072
	(0.007)	(0.084)
WTI_{t-1}	0.073	0.507
	(0.068)	(0.777)
WTI_{t-2}	-0.073	-1.379*
	(0.069)	(0.785)
WTI_{t-3}	0.006	-1.408*
	(0.066)	(0.754)
WTI_{t-4}	0.065	0.562
	(0.062)	(0.705)
$Gold_{t-1}$	0.198	0.061
	(0.210)	(1.393)
$Gold_{t-2}$	-0.269	-0.575
	(0.209)	(1.393)
$Gold_{t-3}$	0.465**	2.199
	(0.210)	(1.400)
$Gold_{t-4}$	0.270	2.195
	(0.215)	(1.458)
VIX_{t-1}	0.147	-5.189
	(0.777)	(4.021)
VIX_{t-2}	-0.682	-7.839
	(0.769)	(4.497)
VIX_{t-3}	-0.655	-6.568
	(0.764)	(4.444)
VIX_{t-4}	0.287	2.035
	(0.651)	(3.152)
$SP500_{t-1}$	-0.144	1.487
	(0.158)	(1.306)
$SP500_{t-2}$	0.271	1.103
	(0.157)	(1.293)
$SP500_{t-3}$	-0.002	-0.394
	(0.155)	(1.267)
$SP500_{t-4}$	0.106	-1.346
	(0.151)	(1.228)
$Adjusted\ R^2$	0.409	0.813

Note: This table reports the VAR estimation results of the analysis between Bitcoin volatility (RV_t) and investor attention ($SAGSVI_t$), with control variables WTI oil, gold, VIX and the S&P500. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

The vector autoregression results for the Ethereum variables, investor attention, and the four control variables are displayed in Tables 23, 24, and 25. Similar to the results obtained for the Bitcoin variables, adding the control variables does not influence the coefficients much when compared to the original model. Table 23 shows that the return of the past week positively influences investor attention in the following week with a coefficient of 1.201, which is consistent with the previous coefficient obtained of 1.232. Adding the control variables yields a negative significant effect of volume on investor attention, which indicates that a higher trading volume in the previous week leads to lower investor attention in the week thereafter. Realized volatility influences investor attention slightly stronger when the four control variables are added and the second lag is also significant, suggesting that the volatility affects investor attention for several weeks rather than just one week after controlling for the four financial instruments. Based on previous literature by Zeng, Yang, and Shen (2020), a link between Ethereum and gold could be expected. The results, however, do not show any influence of previous gold returns on either the return, the trading volume, or the realized volatility of Ethereum. Accordingly, the results obtained follow the results of Kjærland et al. (2018) and Erdas and Caglar (2018), who both do not find any relationship between gold and cryptocurrency characteristics. Global stock market returns, measured by returns on the S&P500 and VIX also do not show a significant effect on either the return, the volume, or the volatility of Ethereum, in agreement with literature by Kjærland et al (2018). As for WTI oil, the second lag has a statistically negative effect on the attention investors have on Ethereum. This suggests that an increase in return in oil in week 1 will result in fewer Google searches for Ethereum, but this effect only appears after two weeks in week 3. If oil prices increase, investors could switch to oil as an investment opportunity rather than cryptocurrency, which at least temporarily decreases the attention they have for coins like Ethereum.

Table 23

Vector autoregression results for Ethereum return, investor attention and the control variables

	R_t	$SAGSVI_t$
Intercept	0.008	-0.018
	(0.008)	(0.046)
R_{t-1}	0.309***	1.201***
	(0.082)	(0.460)
$SAGSVI_{t-1}$	0.117	0.726***
	(0.009)	(0.050)
WTI_{t-1}	-0.020	-0.282
	(0.133)	(0.738)
$Gold_{t-1}$	-0.029	1.619
	(0.426)	(1.367)
VIX_{t-1}	1.252	-2.413
	(1.525)	(2.052)
$SP500_{t-1}$	0.081	0.368
	(0.332)	(0.851)
$Adjusted\ R^2$	0.140	0.643

Note: This table reports the VAR estimation results of the analysis between Ethereum return (R_t) and investor attention ($SAGSVI_t$), with control variables WTI oil, gold, VIX and the S&P500. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 24

Vector autoregression results for Ethereum volume, investor attention and the control variables

	VLM_t	$SAGSVI_t$
Intercept	0.009	0.018
	(0.007)	(0.049)
VLM_{t-1}	0.811***	-0.546*
	(0.047)	(0.330)
$SAGSVI_{t-1}$	0.014*	0.832***
	(0.008)	(0.057)
WTI_{t-1}	0.038	-0.077
	(0.105)	0.739
$Gold_{t-1}$	0.541	1.427
	(0.337)	(1.370)
VIX_{t-1}	-1.333	-3.722
	(1.023)	(4.218)
$SP500_{t-1}$	0.129	1.570
	(0.258)	(0.811)
$Adjusted\ R^2$	0.756	0.635

Note: This table reports the VAR estimation results of the analysis between Ethereum volume (VLM_t) and investor attention ($SAGSVI_t$), with control variables WTI oil, gold, VIX and the S&P500. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 25

Vector autoregression results for Ethereum volatility, investor attention and the control variables

	RV_t	$SAGSVI_t$
Intercept	0.096***	0.556***
	(0.013)	(0.124)
RV_{t-1}	0.285***	-1.535***
	(0.085)	(0.797)
RV_{t-2}	-0.076	-1.162***
	(0.088)	(-0.826)
$SAGSVI_{t-1}$	0.003	0.886***
	(0.008)	(0.077)
$SAGSVI_{t-2}$	0.007	-0.040
	(0.008)	(0.079)
WTI_{t-1}	0.068	-0.721
	(0.080)	(0.753)
WTI_{t-2}	-0.084	-1.758**
	(0.078)	(0.732)
$Gold_{t-1}$	0.375	1.241
	(0.257)	(1.418)
$Gold_{t-2}$	-0.249	-0.162
	(0.252)	(1.366)
VIX_{t-1}	1.052	-3.812
	(1.527)	(4.360)
VIX_{t-2}	-1.315	-1.728
	(1.464)	(3.762)
$SP500_{t-1}$	-0.170	1.811
	(0.188)	(1.772)
$SP500_{t-2}$	-0.232	1.581
	(0.190)	(1.787)
$Adjusted\ R^2$	0.163	0.717

Note: This table reports the VAR estimation results of the analysis between Ethereum volatility (RV_t) and investor attention ($SAGSVI_t$), with control variables WTI oil, gold, VIX and the S&P500. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Lastly, the VAR results for the Binance Coin's variables and the control variables are displayed in Tables 26, 27, and 28. Adding the control variables does not change the coefficients for the effect of investor attention on the return and volume of Binance Coin, as Tables 26 and 27 show the same coefficients at the same confidence level. The effect of investor attention in the previous week on the volatility the following week is now stronger when controlling for the additional variables. The coefficient in the original model had a significance level of 10%, but now the effect is present at the 1% significance level. VIX returns negatively influence the returns of Binance Coin, but only on the 10% significance level. Table 26 shows that higher market volatility leads to lower returns for Binance Coin, but this is not a strong effect as the significant level is only 10%. Malladi & Dheeriya (2021) find similar results and state that VIX is one of the primary factors that can influence cryptocurrency, however, their focus is only on Bitcoin. While gold returns did not have any effect on Ethereum and Bitcoin, a higher gold return leads to lower Binance Coin returns at the 10% significance level. This is not surprising, as Malladi & Dheeriya (2021) report that smaller cryptocurrencies show more sensitivity to gold prices and also to general stock market volatility (VIX). Higher gold returns lead to more realized volatility for Binance Coin, however this effect is present only at the 10% significance level. The relationship between gold returns and the volatility of cryptocurrency is not often researched, which leads to few papers on this subject. An explanation for this relationship could be that when investors perceive higher gold returns, they are more likely to sell their cryptocurrencies and instead invest in gold in the following week, which leads to more price fluctuations on the cryptocurrency that is being sold.

Table 26

Vector autoregression results for Binance Coin return, investor attention and the control variables

	R_t	$SAGSVI_t$
Intercept	0.216	-0.023
	(0.009)	(0.050)
R_{t-1}	0.352***	0.920**
	(0.082)	(0.443)
$SAGSVI_{t-1}$	0.034***	0.665***
	(0.011)	(0.061)
WTI_{t-1}	-0.091	0.002
	(0.143)	(0.777)
$Gold_{t-1}$	-0.870*	-1.354
	(0.460)	(1.498)
VIX_{t-1}	-1.882*	0.216
	(0.725)	(1.787)
$SP500_{t-1}$	0.278	1.186
	(0.353)	(1.192)
$Adjusted\ R^2$	0.298	0.593

Note: This table reports the VAR estimation results of the analysis between Binance Coin return (R_t) and investor attention ($SAGSVI_t$), with control variables WTI oil, gold, VIX and the S&P500. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 27

Vector autoregression results for Binance Coin volume, investor attention and the control variables

	VLM_t	$SAGSVI_t$
Intercept	0.021**	-0.008
	(0.010)	(0.053)
VLM_{t-1}	0.756***	0.129
	(0.046)	(0.236)
$SAGSVI_{t-1}$	0.042***	0.718***
	(0.012)	(0.064)
WTI_{t-1}	0.000	0.200
	(0.152)	(0.781)
$Gold_{t-1}$	0.064	-1.566
	(0.488)	(1.501)
VIX_{t-1}	-2.245	-0.260
	(0.919)	(4.970)
$SP500_{t-1}$	0.466	1.774
	(0.012)	(1.919)
$Adjusted\ R^2$	0.793	0.583

Note: This table reports the VAR estimation results of the analysis between Binance Coin volume (VLM_t) and investor attention ($SAGSVI_t$), with control variables WTI oil, gold, VIX and the S&P500. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 28

Vector autoregression results for Binance Coin volatility, investor attention and the control variables

	RV_t	$SAGSVI_t$
Intercept	0.070***	0.070
	(0.011)	(0.094)
RV_{t-1}	0.477***	-0.480
	(0.069)	(0.580)
$SAGSVI_{t-1}$	0.021***	-0.761**
	(0.007)	(0.055)
WTI_{t-1}	-0.083	0.656
	(0.230)	(0.792)
$Gold_{t-1}$	0.576*	-2.000
	(0.304)	(2.540)
VIX_{t-1}	-1.033	-2.377
	(1.800)	(3.049)
$SP500_{t-1}$	-0.083	1.607
	(0.007)	(1.924)
$Adjusted\ R^2$	0.358	0.584

Note: This table reports the VAR estimation results of the analysis between Binance Coin volatility (RV_t) and investor attention ($SAGSVI_t$), with control variables WTI oil, gold, VIX and the S&P500. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

6 CONCLUSION

6.1 Summary

In this research, the relationship between investor attention and the return, realized volatility and trading volume of cryptocurrencies is explored, using the following research question: *"What is the effect of investor attention on the returns, volatility, and trading volume of the cryptocurrency market, specifically for Bitcoin, Ethereum, and Binance Coin, during the period October 2017 – April 2021?"*

To answer the research question mentioned above, three hypotheses are tested. The first hypothesis that was examined is: "*Investor attention has a significant impact on returns for Bitcoin, Ethereum, and Binance Coin".* The vector autoregression model results show that only for Binance Coin, investor attention is the Granger cause of returns with a significant positive effect, indicating that an increase in attention will lead to an increase in buying, which will push up the prices and returns. For Bitcoin and Ethereum, the results lack significance. The VAR results for all three coins show that a higher return leads to more investor attention in the next week, which is supported by the Granger causality tests.

The second hypothesis focuses on the volume and is as follows: "*Investor attention has a significant impact on trading volume for Bitcoin, Ethereum, and Binance Coin".* For Bitcoin and Ethereum, investor attention has no predictive powers to the trading volume, which is supported by both the VAR results and the Granger causality test results. Investor attention does influence the volume of Binance Coin, with a positive significant effect, that indicates that more Google searches Granger causes an increase in trading volume. Trading volume also exerts significant influence on investor attention for Ethereum, with the second lag of volume negatively impacting the attention investors have for Ethereum. However, there is no significant evidence that lagged trading volume significantly influences investors' attention for Bitcoin and Binance Coin.

Lastly, the third hypothesis will test the effect of investor attention on volatility: "*Investor attention has a significant impact on volatility for Bitcoin, Ethereum, and Binance Coin*". There is significant evidence of a relationship between investor attention and the volatility of both Bitcoin and Binance Coin, as an increase in investor attention leads to more volatile cryptocurrencies. These results are also confirmed by the Granger causality test results, as investor attention of Bitcoin and Binance Coin Granger causes volatility. For all three coins, the results demonstrate that volatility is also a significant driver of investor attention. From the VAR models and Granger causality tests, the conclusion follows that an increase in volatility of the cryptocurrencies leads to a decrease in investor attention in the following week.

Moreover, a robustness test is done in order to obtain more accurate results regarding the research question and the corresponding hypotheses. The ‘bubble’ periods of Bitcoin and Ethereum are further analysed to see if the results found still hold during this period or if a different impact can be found. The effect of the past return of investor attention and the bidirectional relationship of investor attention and volatility for Bitcoin show similar results, suggesting that during a bubble period, the effect of investor attention does not have more explanatory power regarding these relations. Bitcoin’s volume however now statistically significantly influences investor attention, with the first lag being negative and the second positive. As for Ethereum, during a bubble period, investor attention is positively associated with volatility, in line with findings of Rognone et al. (2020), who show that the impact of news is more pronounced during bubble periods. All in all, this robustness check shows that most of the obtained results found still hold.

As an additional robustness check, several control variables that could influence the return, volume, or volatility of cryptocurrencies are included in the VAR models, which are the S&P500 return, gold, VIX, and WTI oil. Adding the control variables results in a slightly higher coefficient of return on investor attention for Bitcoin and similar results are found for the bidirectional relation between volatility and Google searches. Investor attention does significantly influence trading volume for Bitcoin in this model, however only on the 10% significance level. Similar to Bitcoin, the original results do not change much after controlling for the additional variables for Ethereum. An increase in return of WTI oil though leads to less Google searches for Ethereum after two weeks. As for Binance Coin, the coefficients on the relation between return and investor attention do not alter with the control variables and similar results are present for volatility and trading volume. VIX returns negatively influence the returns of Binance Coin, albeit only on the 10% significance level. Higher gold returns lead to both lower returns and higher volatility for Binance Coin but only when the 10% significance level is taken into account. All in all, this shows that the model does not react strongly to the addition of the control variables with only minor changes in the coefficients and significant levels and that the control variables do not drive the original results.

6.2 Discussion

6.2.1 Limitations

There are some limitations to this study, which are discussed in this section. The first limitation concerns the availability of data. Over a longer period, Google Trends only provides weekly insights into their data. Since cryptocurrencies are known for their volatility, research on the effect of investor attention on cryptocurrencies using daily data is likely to give better and more complete results. Some coins have substantial price, volume, or volatility shocks in just a few hours or days, but this effect could not be analysed as only weekly data is available. Next to this, the period that is being researched is relatively short compared to previous literature, because Binance Coin was launched in July 2017. Consequently, the price history and its relation to investor attention of both Bitcoin and Ethereum, coins that exist since 2008 and 2015 respectively, are not fully being analysed. Most earlier literature only focussed on Bitcoin and did take Bitcoin's full existence into account, which can explain some of the different findings. Because one 'young' coin is added, a full analysis of Bitcoin and Ethereum however was not possible and potentially valuable data and information on the relationship between investor attention and cryptocurrency characteristics before October 2017 are not accounted for in this research.

Furthermore, Bitcoin, Ethereum, and Binance Coin are the only three coins taken into account to represent the cryptocurrency market. These cryptocurrencies are chosen based on their market capitalization so that they reflect an important share (over 70%) of the whole cryptocurrency market. It is important to note however that over 10.000 crypto coins exist and that the share of the market capitalization of the most established coins like Bitcoin and Ethereum decreases as more coins are being launched. Therefore, the three coins used in this paper might not necessarily reflect the relationship between cryptocurrency variables and investor attention on the whole cryptocurrency market, which is why is why the conclusions in this research should be treated with care.

As there is little research on Binance Coin, it makes this coin interesting to analyse. This lack of previous research, however, is also a limitation, since the results found in this thesis cannot be compared to previous work. The results found for Binance Coin are now compared to results found in the literature on Bitcoin or Ethereum, while the coins differ greatly in terms of market capitalization, infrastructure, and how well known and used they are. For this reason, the conclusions drawn for Binance Coin are not as well substantiated when compared to Bitcoin and Ethereum.

Several control variables are added in this research since previous research has shown a link between these variables and the pricing of cryptocurrencies. Regardless of this, these are not the only variables that could influence the return of cryptocurrencies and investor attention. Abboushi (2017) and Baur et al. (2018) pointed out the lack of intrinsic value of cryptocurrency, which makes it difficult how to determine the pricing. Research has shown that cryptocurrency prices also can be influenced by the returns of other cryptocurrencies (Ji, Bouri, Lau & Roubaud, 2019), uncertainty on the stock market (Bouri, Gupta, Tiwari & Roubaud, 2017), and fundamental factors like trade usage, money supply, and price (Kristoufek, 2015). Even governmental policy choices can determine cryptocurrency pricing, as Cheng & Yen (2020) show that economic policy uncertainty of a country and the Chinese government ban on cryptocurrency in September 2017 significantly affected the return on Bitcoin. It could be meaningful to add additional variables like these since they might influence the coefficients obtained in the vector autoregression models.

6.2.2 Recommendations for Future Research

Based on the limitations encountered in this research, there are several suggestions for future research. First of all, the analysis of the cryptocurrency market could be expanded by adding other notable cryptocurrencies like Cardano (ADA), Litecoin (LTC), and so-called 'meme coins'[1] like Dogecoin (DOGE). This gives a better representation of the whole cryptocurrency market, as there currently exist over thousands of crypto coins. Furthermore, research that focuses on a longer period could yield more insights into the trends of the early years of the cryptocurrencies, but since Binance Coin is a relatively new coin, this research could not also focus on the early years of Bitcoin.

In this research, Google Trends data was used as a proxy for investor attention, but there are various options to use as a measure for investor attention. Shen et al. (2019) for example use the number of tweets as a measure of investor attention when examining the relationship between attention and Bitcoin characteristics. They argue that this proxy of investor attention should be more informed than the use of Google Trends and therefore could reflect the attention Bitcoin is getting from more informed investors since well-informed investors will not use the Google search engine to find information but rather tweet about it with the knowledge that they have. As Google Trends have often been researched already, more research on Twitter as an investor attention proxy regarding cryptocurrencies could give more insights into the use of this proxy and add to the literature on the relationship between attention and Bitcoin. Since the attention of investors can also come from clicking on sources that do not have a direct link to Google but for example sources through a news site that carries more information than just cryptocurrency news, it might be interesting to look at more types of search queries.

As stated before, the relationship examined in this research could also be influenced by other behavioral factors including the risk tolerance of investors and the sentiment that they have. Especially the latter factor would be a good addition to research on investor attention, as sentiment tells us more about how an investor agent perceives the market and their feeling of the market (positive or negative or somewhere in between) (Naeem, Mbarki & Shahzad, 2021). Previous research has shown that investor sentiment, measured using the Twitter Happiness index or the Financial and Economic Attitudes Revealed by Search (FEARS) index, has shown a significant connection to the cryptocurrency market (Bucher, 2017; Chen, Després, Guo & Renault, 2019; Naeem, 2021). Hence, a combination of investor attention and investor sentiment deserves in-depth research in the future.

[1] A meme coin is a cryptocurrency often based on internet memes, which thank their popularity due to promotion by online influencers rather than by strong fundamentals (Hamacher, 2021).

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Appendix A: Lag Length Selection

Table 29

Lag length selection VAR model for the Bitcoin variables

Lag	LR	FPE	AIC	BIC
Lag length selection Bitcoin return				
1	211.650*	0.0025*	-0.315*	-0.209*
2	6.993	0.0025	-0.310	-0.133
3	2.554	0.0026	-0.280	-0.032
4	2.756	0.0027	-0.250	0.068
Lag length selection Bitcoin volume				
1	402.3	0.0015	-0.848	-0.742*
2	11.277*	0.0014*	-0.866*	-0.689
3	2.595	0.0015	-0.836	-0.589
4	3.486	0.0015	-0.811	-0.493
Lag length selection Bitcoin volatility				
1	235.62	0.0009	-1.387	-1.281
2	20.142	0.0008	-1.455	-1.278
3	21.457*	0.0007	-1.529	-1.281*
4	9.306	0.0007*	-1.536*	-1.218

Table 30

Lag length selection VAR model for the Ethereum variables

Lag	LR	FPE	AIC	BIC
Lag length selection Ethereum return				
1	189.2*	0.0046*	0.303*	0.346*
2	7.713	0.0046	0.305	0.376
3	2.794	0.0048	0.333	0.434
4	8.2645	0.0048	0.332	0.461
Lag length selection Ethereum volume				
1	427.66	0.0019	-0.565	-0.459*
2	8.103	0.0019*	-0.566*	-0.389
3	4.511	0.0020	-0.547	-0.299
4	10.495*	0.0020	-0.560	-0.242
Lag length selection Ethereum volatility				
1	203.73	0.0014	-0.887	-0.781*
2	13.126	0.0014	-0.915	-0.738
3	6.082	0.0014	-0.904	-0.657
4	15.506*	0.0013*	-0.946*	-0.628

Table 31

Lag length selection VAR model for the Binance Coin variables

Lag	LR	FPE	AIC	BIC
Lag length selection Binance Coin return				
1	169.37*	0.0054*	0.455*	0.562*
2	4.329	0.0055	0.476	0.653
3	1.244	0.0057	0.513	0.761
4	6.380	0.0058	0.522	0.840
Lag length selection Binance Coin volume				
1	356.23*	0.0059*	0.536*	0.642*
2	7.958	0.0059	0.536	0.713
3	2.246	0.0060	0.568	0.815
4	0.543	0.0063	0.609	0.927
Lag length selection Binance Coin volatility				
1	202.01	0.0028	-0.199	-0.093*
2	13.979*	0.0027*	-0.232*	-0.055
3	4.286	0.0028	-0.211	0.036
4	1.620	0.0029	-0.176	0.142

Appendix B: Lagrange Multiplier Test Results

Table 32

Lagrange Multiplier test results

Lag	Chi2	Df	Prob > chi2
Bitcoin return			
1	6.550	4	0.162
Bitcoin volume			
1	5.209	4	0.267
2	3.032	4	0.553
Bitcoin volatility			
1	1.776	4	0.777
2	2.912	4	0.573
3	4.283	4	0.369
4	7.601	4	0.107
Ethereum return			
1	7.587	4	0.108
Ethereum volume			
1	1.125	4	0.890
2	6.469	4	0.167
Ethereum volatility			
1	3.991	4	0.407
2	3.062	4	0.548
3	2.849	4	0.583
4	4.368	4	0.358
Binance Coin return			
1	3.619	4	0.460
Binance Coin volume			
1	6.921	4	0.140
Binance Coin volatility			
1	4.300	4	0.367
2	3.967	4	0.411

Appendix C: Robustness Tests Results

Table 33

Vector autoregression results for Bitcoin return and investor attention during bubble periods

	R_t	$SAGSVI_t$
Intercept	-0.003	-0.013
	(0.015)	(0.094)
R_{t-1}	-0.226*	2.201***
	(0.129)	(0.831)
R_{t-2}	-0.258*	1.418
	(0.136)	(0.877)
$SAGSVI_{t-1}$	-0.009	-0.042
	(0.019)	(0.121)
$SAGSVI_{t-2}$	-0.001	-0.029
	(0.015)	(0.117)
R^2	0.111	0.252

Note: This table reports the VAR estimation results of the analysis between Bitcoin return (R_t) and investor attention ($SAGSVI_t$) in the two 'bubble periods' from October 15, 2017 to May 6, 2018 and September 6, 2020 to April 25, 2021. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 34

Vector autoregression results for Bitcoin volume and investor attention during bubble periods

	VLM_t	$SAGSVI_t$
Intercept	-0.004	-0.015*
	(0.013)	(0.103)
VLM_{t-1}	-0.103	-1.323*
	(0.166)	(1.192)
VLM_{t-2}	0.107	1.305*
	(0.168)	(1.213)
$SAGSVI_{t-1}$	0.008	0.311*
	(0.021)	(0.165)
$SAGSVI_{t-2}$	0.009	-0.315*
	(0.021)	(0.167)
R^2	0.133	0.207

Note: This table reports the VAR estimation results of the analysis between Bitcoin volume (VLM_t) and investor attention ($SAGSVI_t$) in the two 'bubble periods' from October 15, 2017 to May 6, 2018 and September 6, 2020 to April 25, 2021. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 35

Vector autoregression results for Ethereum return and investor attention during bubble periods

	R_t	$SAGSVI_t$
Intercept	0.007	0.033
	(0.018)	(0.083)
R_{t-1}	-0.462***	-0.218
	(0.151)	(0.708)
R_{t-2}	-0.376***	-1.316**
	(0.133)	(0.623)
$SAGSVI_{t-1}$	-0.022	0.322**
	(0.032)	(0.150)
$SAGSVI_{t-2}$	0.002	-0.109
	(0.030)	(0.140)
R^2	0.282	0.156

Note: This table reports the VAR estimation results of the analysis between Ethereum return (R_t) and investor attention ($SAGSVI_t$) in the two 'bubble periods' from October 15, 2017 to May 6, 2018 and September 6, 2020 to April 25, 2021. The lag length is chosen based on the AIC. The standard errors are presented in the brackets. *, ** and *** represent the significance of the t-statistics at 10%, 5% and 1%, respectively.

Table 36

Descriptive statistics of the control variables

	WTI	Gold	VIX	S&P500
Mean	0.001	0.001	0.000	0.002
Median	0.006	0.002	0.000	0.006
Minimum	-0.347	-0.099	-0.041	-0.162
Maximum	0.276	0.101	0.016	0.114
St. Dev.	0.068	0.020	0.003	0.029
Skewness	-0.814	0.013	-9.810	-1.289
Kurtosis	9.344	8.747	132.690	11.189
Jarque-Bera	351.650	271.909	1398.988	602.323
Probability	0.000	0.000	0.000	0.000
Observations	185	185	185	185

Appendix D: Stata Do-file

Step 1: Time set
tsset Date, weekly
tsset Date, delta(7)
format %td Date
tsset Date, delta(7)

Step 2: Test for stationarity using the Augmented Dickey-Fuller test
dfuller BTC_Return , lags(1)
dfuller ETH_Return , lags(1)
dfuller BNB_Return , lags(1)
dfuller BTC_Volume , lags(1)
dfuller ETH_Volume , lags(1)
dfuller BNB_Volume , lags(1)
dfuller BTC_Volatility , lags(1)
dfuller ETH_Volatility , lags(1)
dfuller BNB_Volatility , lags(1)
dfuller BTC_SAGSVI , lags(1)
dfuller ETH_SAGSVI , lags(1)
dfuller BNB_SAGSVI , lags(1)
//Data is stationary

Step 3: Determine the optimal lag length with the information criteria (this do-file only shows Bitcoin Return and AGSVI as an example)
varsoc BTC_Return BTC_SAGSVI
//Optimal lag length for this model is 1 based on AIC

Step 4: Estimate the VAR model with the optimal lag length
var BTC_Return BTC_SAGSVI, lags(1/1)

Step 5: Perform diagnostic test
varlmar, mlag(1)
varstable

Step 6: The Granger-Causality test
vargranger

Step 7: Create the Impulse Response Function (IRF)
irf create order1, step(10) set(myirf1) replace
irf graph oirf, impulse(BTC_Return BTC_GSVI) response(BTC_Return BTC_SAGSVI) yline (0,lcolor(black)) xlabel(0(4)20) byopts(yrescale)
//A test for significance of the IRF
irf table irf, std