ESSAYS ON CRYPTOCURRENCIES AND INVESTOR ATTENTION

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ABSTRACT

This thesis presents three chapters related to cryptocurrency and investor attention measures. Examining investor behaviour in the cryptocurrency market is important for understanding cryptocurrency market dynamics.

The first chapter examines the impact of investor attention measures on cryptocurrency market returns between 2017 and 2022. Using the Google search volume index (GSVI) and Wikipedia (WIKI) searches for investor attention measures, we find no association between Bitcoin and Ethereum returns in up to eight periods and investor attention measures in the most recent period, 2020 to 2022. This new finding enriches the literature by revealing that the association between investor attention and Bitcoin and Ethereum returns has recently weakened.

In the second chapter, we analyse the effect of the GSVI and WIKI investor attention measures on cryptocurrency return volatility. In particular, we build on the work of Figà-Talamanca et al. (2019), which studies the effect of GSVI on Bitcoin volatility, extending in terms of cryptocurrencies considered, sample period, and investor attention measures. Employing GARCH and EGARCH, we find that both GSVI and WIKI have a negative impact on the volatility of Ripple returns in the mean equation, also significantly increasing its volatility. Furthermore, these measures of investor attention significantly increase the volatility of all cryptocurrency returns.

In the third and final chapter of the thesis, we study herding behaviour in the cryptocurrency market during bearish and bullish conditions by employing cross-sectional absolute deviation (CSAD) (Chang et al., 2000), and during extreme sentiment conditions based on GSVI and WIKI sentiment measures 2017 to 2024. Including WIKI as a sentiment proxy is a novel contribution to the extant literature on herding in the cryptocurrency market. In line

with our previous chapters, we find significant results related to WIKI. We find herding behaviour in the cryptocurrency market and herding predominantly occurring during bearish markets. However, we find less evidence of herding during extreme positive days in the recent period.

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Declaration

I declare that this PhD thesis is my own work and was result of my studies. The work has not been submitted, in whole or in part, for any other degree or qualification at this or any other university or institution.

I used the following tools for language editing (grammar, spelling and clarity of expression): Claude (Anthropic, 2026), Gemini (Google, 2026), ChatGPT (OpenAI, 2026), DeepL (DeepL, 2026) and Grammarly (Grammarly, 2026). All outputs were reviewed and verified by me.

Signature: Meryem Öncül Oral

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List of Abbreviations

AAPL	Apple Inc
ADA	Cardano
ADF	Augmented Dickey-Fuller
ADR	American Depositary Receipts
AR-CGARCH	Autoregressive Component Generalized Autoregressive Conditional Heteroskedasticity
ARMAX	Autoregressive Moving Average with exogenous inputs
AVAX	Avalanche
BSE	Bombay Stock Exchange
BTC	Bitcoin
BTCUSD	Bitcoin/United States Dollar
CBOE	Chicago Board Options Exchange
CGCD	Copula-quantile causality approach
CMSI	Cryptocurrency Market Sentiment Indicator
CRIX	Cryptocurrency Index
CSAD	Cross-sectional absolute deviation
DASH	Digital cash cryptocurrency
DHS	Daily Happiness Sentiment
DOGE	Dogecoin
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
EPU	Economic policy uncertainty
ETF	Exchange traded funds
ETH	Ethereum

FTX	FTX Trading Limited
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GSVI	Google search volume index
ICO	Initial Coin Offering
LTC	Litecoin
MCS	Model confidence set
MSCI	Morgan Stanley Capital International
MSFT	Microsoft Corporation
NEM	New Economy Movement cryptocurrency
NFT	Non-Fungible Token
OLS	Ordinary Least Squares
PoS	Proof of Stake
PP	Phillips–Perron
RV	Realized Volatility
SEC	Securities and Exchange Commission
SFDR	Sustainable Finance Disclosure Regulation
SOL	Solana
STOXX	STOXX LIMITED
SYS	Systematic risk
T-GARCH	Threshold Generalized Autoregressive Conditional Heteroskedasticity
US	United States
USD	United States Dollar
VAR	Vector Autoregression
VECM	Vector Error Correction Model
VIX	Chicago Board Options Exchange’s Volatility Index

WIKI	Wikipedia
XLM	Stellar
XRP	Ripple

INTRODUCTION

Background to the study

Modern finance theory emphasises that all investors are rational decision makers and that behaviours play no part in their investment decisions. Instead, this theory argues that competition among rational investors who diversify their portfolios to optimise statistical properties will lead to an equilibrium in which prices reflect the rationally discounted value of expected cash flows. In such an equilibrium, the variation in expected returns across different assets depends solely on their exposure to systematic risks (Baker et al., 2006). However, Kahneman and Tversky (1979) demonstrated that investors evaluate gains and losses differently, based on their reference point. In fact, when investors lose, it feels twice as bad as when they gain an equivalent amount, and thus they are more willing to take risks when they lose. Brown et al. (2004) and Baker et al. (2006) examined the role of investor behaviours in stock prices and demonstrated their power in financial markets.

Currencies are standard economic goods whose prices are determined by the interaction of supply and demand in the market. Supply and demand depend on the macroeconomic variables of an issuing country or institution. Cryptocurrencies are arguably an alternative form of currency that exists entirely digitally. Furthermore, since these are not issued by a particular country's central bank or government, they are practically independent of the real economy. However, while cryptocurrencies are relatively isolated from the real economy, their prices have generally been quite volatile (Kristoufek, 2013).

Cryptocurrencies lack macroeconomic fundamentals; their supply is either fixed or evolves through a publicly available algorithm. Demand is driven by the expected profit from holding and then selling the currency; therefore, cryptocurrencies are now essentially speculative, compared to the traditional asset classes such as equities and bonds (Gurdgiev, 2020). Baker et al. (2007) argue that some stocks are more speculative than others due to the

difficulty and subjectivity of determining their true value supports the assumption that cryptocurrencies are speculative assets due to their high volatility (Katsiampa, 2017; Güler, 2023).

The promise of technological transformation in facilitating payments and transactions was originally the primary driver for cryptocurrency demand. However, speculative and investor attention has become the primary driver from 2017 onwards. Relatedly, in late 2017 and early 2018, well-known media organisations published several articles relating to the abnormal financial gains gathered by early investors, encouraging a sizeable inflow of new capital. In general, although there is some institutional investment (e.g., MicroStrategy, BlackRock), the cryptocurrency market is often argued to be dominated by short-term investors, trend followers, noise traders, and speculators. Under these circumstances, the fundamental elements that allow fair pricing to be set in the market are absent. Consequently, the price of currencies is driven by investors' (speculative) belief in the continuous growth (or not) of a particular cryptocurrency. Investor interest becomes critically important at this point (Kristoufek, 2013; Gurdgiev et al., 2020).

It is challenging to find a good tool to measure investor interest in cryptocurrencies. Two sets of indicators have typically been used by researchers in the extant literature to measure the concept: variables measuring either investor interest/attention or investor moods/emotions (Dias et al., 2022). Attention is a limited resource, and when investors have options, assets with higher attention tend to be more frequently traded (Barber and Odean, 2008). This suggests that investor attention influences asset prices and that decisions made in response to this attention are important and worth studying (Dias et al., 2022). Thus, studies in the literature have considered proxies such as the Google search volume index (GSVI) and Wikipedia page views (WIKI) to measure investor attention in cryptocurrencies (Liu et al., 2021; Urquhart, 2018; Kristoufek, 2013; Al Guindy, 2021; Bleher et al., 2019). Moreover, researchers have studied

investor moods and emotions from news headlines, indexes, and social media platforms such as Twitter, Reddit, and StockTwits (Dias et al., 2022; Güler, 2023; Gurdgiev et al., 2020; Kraaijeveld et al., 2020). Recently, GSVI and WIKI have been employed as variables in empirical studies ranging from explaining herding in financial markets through to volatility forecasting and portfolio and trading strategy construction (Da et al., 2011; Kristoufek, 2013; Focke et al., 2020; Koch et al., 2023; Philippas et al., 2019; Swamy et al., 2019).

Objectives and contributions of the thesis

This thesis consists of three essays that investigate investor interest measures, with an emphasis on cryptocurrency markets. The first chapter of the thesis examines the impact of GSVI and WIKI investor attention measures on cryptocurrency market returns. In the second chapter, we analyse the effect of the same investor attention measures on cryptocurrency return volatility. Finally, in the third chapter of the thesis, we study herding behaviour in the cryptocurrency market during bearish and bullish conditions, and extreme sentiment conditions based on investor sentiment measures. We examine the extent to which the cryptocurrency market supports traditional behavioural finance theories by analysing recent periods in the market in relation to investor attention. Our aim is to shed light on how investors can manage risk when constructing their portfolios and how policymakers can consider the psychological aspects of investors' behaviour in the cryptocurrency market when formulating regulations.

The first chapter makes three main contributions to the literature. First, we extend the sample period to include 2019 and beyond. This is important for investigating the cryptocurrency-investor attention nexus after 2020, as COVID-19, MicroStrategy's and Tesla's substantial Bitcoin purchases[1], the FTX failure, the authorisation of ETFs, and the start of the crypto winter all occurred after this date and contributed to greatly increased price volatility

[1] These have led investors to perceive the cryptocurrency market as an institutional asset class.

(Arner et al., 2023). To the best of our knowledge, no study covering 2021 and beyond examines the relationship between cryptocurrency returns and the GSVI and WIKI. Second, while most studies in the extant literature provide empirical evidence that there is a positive association between cryptocurrency returns and investor attention measures, the work in Chapter 1 shows that this result does not hold for Bitcoin and Ethereum in the subperiod from 2020 to 2022. This new finding suggests that the cryptocurrency–investor attention nexus weakened after 2020 with events such as the pandemic, monetary policy responses, and the crypto winter leading to greater volatility in price dynamics. It should be noted that this weakening, although still present, happens lesser extent less for cryptocurrencies such as Ripple, Stellar, and Dash. Third, we do not typically find a significant impact of WIKI on cryptocurrency returns, especially for Bitcoin and Stellar returns, which is an important contribution since the literature shows a significant association between Wikipedia searches and cryptocurrency returns. While GSVI may represent an initial search, WIKI likely represents a deeper interest in the subject (Kämpf et al., 2015). Of course, by 2020, Bitcoin was by far the most well-known cryptocurrency, and plausibly, many investors had already progressed to more specialised information sources than GSVI or WIKI. This new finding enriches the literature by revealing that the association between investor attention and Bitcoin and Ethereum returns has recently weakened. Considering these findings, cryptocurrency investors can build their portfolios more informedly by knowing which cryptocurrency returns are more sensitive to investor attention.

The second chapter also makes three contributions to the literature. First, we employ WIKI, which is rarely used in the literature to explain cryptocurrency return volatility, and employing the GARCH (1,1) and EGARCH (1,1) frameworks, we show empirically that this measure of investor attention is positively and significantly associated with such volatility. Second, we consider seven cryptocurrencies: Bitcoin, Ethereum, Ripple, Litecoin, Dash, Stellar, and Solana to provide a wider, market-based view of the effect of investor attention on

cryptocurrency return volatility. Moreover, aspects such as differences in technological infrastructure and launch times among cryptocurrencies have become important considerations in current studies, and consequently, the examination of a variety of cryptocurrencies is necessary. Third, we consider between the sample period from 2017 to 2023 and thus, again, extend the sample period typically used in the extant literature to 2020 and beyond, allowing results to reflect more recent events. Our findings demonstrate that the volatility of cryptocurrencies depends on investor attention, thereby providing guidance for investors considering including these cryptocurrencies in their portfolios. At the same time, these findings confirm that cryptocurrencies are volatile, consistent with the literature, and we encourage further research into Ripple returns, which provide particularly interesting results.

Finally, the third chapter makes three novel contributions to the literature. First, we analyse herding in both bull and bear conditions in the cryptocurrency market and find herding primarily in the bear market. Second, we include WIKI as a sentiment proxy, which has not been employed by the extant literature in the herding context for cryptocurrency markets. In line with our previous chapters, we find significant results related to the Wikipedia search measure. During extreme positive days based on WIKI, investors do not tend to herd in the cryptocurrency market. The GSVI results are in line with WIKI as well. The finding that days when investors are extremely positive in Google and Wikipedia searches do not lead to herd behaviour in the cryptocurrency market is instructive for investors. Third, we create a market portfolio by selecting the top ten cryptocurrencies and consider a seven-year period from 2017 to 2024, which is an important point since the literature mainly covers the period until 2022, and major events such as the collapse of FTX, the crypto winter in 2022, and the launch of ETFs occurred after 2022. Moreover, as the selected cryptocurrencies are the top ten by market capitalisation, including Bitcoin and Ethereum, which account for approximately 70 per cent of the market, our sample reflects the market well.

Structure of the thesis

This thesis consists of three chapters that investigate investor interest measures, with an emphasis on cryptocurrency markets. The first chapter examines the impact of investor attention measures on cryptocurrency market returns. We consider the top six weekly cryptocurrency returns in terms of market capitalisation from 2017 to 2022. Using GSVI and Wikipedia (WIKI) searches as investor attention measures, we find that no association between Bitcoin and Ethereum returns and the GSVI in the full sample period, while Ripple, Dash, Stellar, and Litecoin returns show a positive association with both investor attention measures, suggesting newer cryptocurrencies still attracted by investors on Google and Wikipedia. The Bitcoin and Ethereum results contrast with the work of Liu et al. (2021), who found an association between Bitcoin returns and the GSVI from 2011 to 2018. Moreover, we divide our period before and after 2020 and find that Bitcoin and Ethereum returns show significant results for the period from 2017 to 2020, in line with Liu et al. (2021); however, we do not find any significant results in the latter period. By 2020, Bitcoin was by far the most well-known cryptocurrency, and plausibly, many investors had already progressed to more specialised information sources than GSVI or WIKI. Our results newly reveal that Bitcoin returns and WIKI do not have any significant association in the period from 2017 to 2022, and this result contrasts with Kristoufek (2013). In contrast, although Ethereum returns are not significantly associated with GSVI, they present significant and positive coefficients, with WIKI as an explanatory variable for the full sample period from 2017 to 2022. Ripple, Stellar, Dash, and Litecoin returns have a stronger association with GSVI than WIKI in terms of p-value.

In the second chapter, we analyse the effect of GSVI and WIKI investor attention measures on cryptocurrency return volatility. Specifically, we build on the work of Figà-Talamanca et al. (2019), who examined the effect of GSVI on Bitcoin return volatility and found

that volatility is positively and significantly affected by GSVI, by extending their work in terms of cryptocurrencies, sample period, and investor attention measures. We select the seven largest cryptocurrencies by market capitalisation at the end of 2023 and employ the same attention proxies as in the first chapter of the thesis. Furthermore, we estimate both GARCH (1,1) and EGARCH (1,1) models using daily data and find that both GSVI and WIKI have a significant impact on the volatility of each cryptocurrency, irrespective of which model is used. One striking finding is that GSVI and WIKI have a negative impact on Ripple returns in the mean equation, and also significantly increase its volatility. In our first chapter, we find a positive effect of GSVI and WIKI on Ripple returns from 2017 to 2022. However, we reveal the negative impact of these investor attention measures on Ripple's returns between 2017 and 2023 in the second chapter analysis.

Finally, in the third chapter of the thesis, we study herding behaviour in the cryptocurrency market from the perspective of both bearish and bullish conditions, and extreme sentiment conditions. In this analysis, we consider the top ten cryptocurrencies by market capitalisation. Investor sentiment proxies are GSVI and WIKI, and we apply dummy variables for 1 per cent and 5 per cent extreme positive and negative days based on these sentiment measures. To compute and detect herding, we employ the popular measure of CSAD by Chang et al. (2000). We find herding behaviour in the cryptocurrency market from 2017 to 2024. Moreover, we find asymmetric herding, with herding predominantly occurring during bearish markets. We find less evidence of herding during extreme positive days in the recent period.

Chapter 1

Cryptocurrencies: The Role of Investor Attention

1.1. Introduction

Return and volatility prediction is a key topic in finance literature. While classical finance argues that asset prices in efficient markets are determined by fundamental information, behavioural finance theory emphasises the relevance of investor emotions, interests, and moods in predicting financial market prices. Behavioural finance views investors as ordinary people who may be rational based on their emotions and interests. As a result, it can explain market abnormalities that traditional finance cannot. Investor interest derived from expert media, social media, search engines, and market indexes has demonstrated considerable predictive power on cryptocurrency prices, volatility, and return movements in the literature (Dias et al., 2022). For example, studies of investor behaviour in the cryptocurrency market have shown that investor attitudes taken from social networks such as Twitter and Wikipedia (Kraaijeveld et al., 2020; Kristoufek, 2013; Dias et al., 2022) or investor interest extracted from Google Trends (Liu and Tsyvinski, 2021; Urquhart, 2018; Dastgir et al., 2019) have an impact on Bitcoin returns (Almeida et al., 2023; López-Cabarcos et al., 2021).

In this paper, we build on seminal work by Liu and Tsyvinski (2021) and study the role of investor attention on an extended set of cryptocurrencies, including not only Bitcoin, Ethereum, and Ripple, but also more recently launched cryptocurrencies such as Litecoin, Stellar, and Dash. Studying a broader set of currencies allows us to consider aspects such as differences in popularity, technological infrastructure, adoption rate, and launch times. The combined effect of these differences may moderate the effect of investor attention; for example, the prices of newer cryptocurrencies may be, ceteris paribus, more sensitive to changes in attention as investors ‘learn’ about their dynamics. In addition to the GSVI, we also consider

an alternative measure for investor attention based on Wikipedia (WIKI) searches. While GSVI may represent an initial search, WIKI likely represents a deeper interest in the subject (Kämpf et al., 2015). Finally, we extend previous work to the most recent period, post 2020. This is relevant because it allows us to explore the role of the COVID period and the subsequent "crypto winter". Ex ante, both important 'events' may also have moderated the effect of investor attention on cryptocurrency returns. To the best of our knowledge, we are the first to explore this set of cryptocurrencies in this recent period.

The market for cryptocurrencies was first described by Nakamoto (2008). Cryptocurrencies are digital currencies, and they use blockchain technology, which is both decentralised and trustworthy (Almeida et al., 2023; López-Cabarcos et al., 2021; Kraaijeveld et al. 2020). Blockchain is a transparent and immutable technology that can encourage confidence among consumers while fostering financial integration by promoting digital trade (El Hajj et al., 2024). The growing cryptocurrency market has received remarkable attention from researchers, governments, and investors.

Bitcoin is the pioneer and the largest cryptocurrency in terms of market capitalisation, with a market share exceeding 85 per cent of the total cryptocurrency market value from 2010 to 2016. This noticeable growth has led many researchers to study the characteristics of Bitcoin and its relationship with different index and financial assets (Yen et al., 2023). Following the crash in mid-December 2017, more than USD 200 billion of Bitcoin's total market capitalisation vanished within six weeks, resulting in cumulative losses of 41 per cent from the peak. It was during this period that the term 'crypto winter' was first coined.[2] Market analysts have identified high inflation, rising interest rates, and the financial turmoil following Russia's invasion of Ukraine as the main contributing factors to this crypto winter. This large crash followed an

[2] "A 'crypto winter' basically means that prices have dropped a long way and then stayed low for weeks or months. There have been five crypto winters since 2017 and three since 2021." weforum.org/stories/2022/06/cryptocurrency-crash-crypto-winter

equally startling 43-fold price increase (Gerlach, 2019) (see Figure 1.1). Another episode of "crypto winter" took place at the end of 2021 and throughout 2022, partly due to the United States (US) Federal Reserve tightening monetary policy after a lax stance in response to the COVID-19 pandemic.[3] A series of cryptocurrency platform collapses and panic selling caused a downturn in the cryptocurrency market in 2022. Investors' internet searches during this period may indicate panic selling.[4]

As a result of garnering interest from the media, retail investors, institutional investors, and regulators, cryptocurrencies have developed quickly and have emerged as popular assets in financial markets around the world. For this reason, they attract more attention from those who want to understand the factors that influence the price dynamics of cryptocurrencies (Akyildirim et al., 2021). Bitcoin has emerged as a "trending topic" in financial research, especially when it comes to investor interest, particularly after its futures launched on the CBOE at the end of 2017 (Almeida et al., 2023; López-Cabarcos et al., 2021; Kraaijeveld et al., 2020). This allows investors to leverage and speculate in both directions without having to own Bitcoin (Akyildirim et al., 2021). Therefore, researching Bitcoin returns and volatility, particularly in terms of predictability, is both academically and practically significant (Eom et al., 2019).

In this paper, we consider the six largest cryptocurrencies by market capitalisation for the period 2017–2022. These cryptocurrencies are Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and Dash. Building on Liu and Tsyvinski (2021), we study the effect of investor attention on cryptocurrency returns by employing GSVI and WIKI. Initial results show that Bitcoin and Ethereum are not associated with GSVI in our full sample period from 2017 to 2022; this contrasts with Liu and Tsyvinski (2021), who found a positive association for the period 2011

[3] weforum.org/stories/2022/06/cryptocurrency-crash-crypto-winter
[4] chicagofed.org/publications/chicago-fed-letter/2023/479

to 2018. Conversely, we find a positive association between the returns of Ripple, Dash, Litecoin, and Stellar, and investor attention as measured by GSVI.

Splitting the sample into two subperiods, 2017–2020 and 2020–2022, we shed some light on our findings. We show that Bitcoin and Ethereum returns *are associated* with GSVI for the period from 2017 to 2020, in line with previous work, such as Liu and Tsyvinski (2021), Dias et al. (2022), and Raza et al. (2022); however, we do not find any significant effect from 2020 to 2022. These results suggest that the association between investor attention and cryptocurrency returns, which weakened after 2020 with events such as the pandemic, monetary policy responses, and the crypto winter, leading to greater volatility in price dynamics. It should be noted that this weakening, although still present, happens less for cryptocurrencies such as Ripple, Stellar, and Dash.

Finally, we employ an alternative measure for investor attention based on WIKI. This reveals that, in general, WIKI presents less predictability for cryptocurrency returns as compared to GSVI. However, there are also exceptions. For example, WIKI is significantly associated with Litecoin over the second subsample period from 2020 to 2022, whereas it was not for GSVI. This suggests that the WIKI attention measure is a stronger predictor of Litecoin, potentially reflecting the 'deeper interest' character of WIKI searches by investors. Of course, by 2020, Bitcoin was by far the most well-known cryptocurrency, and plausibly, many investors had already progressed to more specialised information sources than GSVI or WIKI.

We contribute to the literature on the effect of investor attention on cryptocurrency returns. In the literature, studies have shown that there is a significant association between GSVI and cryptocurrency returns, and that the GSVI can be employed to predict cryptocurrency returns. Furthermore, the literature has documented a positive association between GSVI and Bitcoin returns (e.g., Liu and Tsyvinski, 2021; Kristoufek, 2013; Dias et al., 2022; and Raza et al., 2022). We contribute to this literature by extending the analysis to the period post-2020.

This is important for investigating a period when important events affected crypto markets. While most studies find that there is a relationship between cryptocurrency returns and investor attention, we show that this result does not hold in the most recent period since 2020, especially for Bitcoin and Ethereum returns. As a consequence, GSVI measures of attention provide less or no return predictability, a key practical implication for investors.

The remainder of the chapter is organised as follows. The next section provides a review of the literature and develops the hypotheses. Section 1.3 presents the data and the methodology employed for analysing the relationship between the returns of the selected cryptocurrencies and GSVI and WIKI. The results are discussed in Section 1.4, while Section 1.5 concludes.

1.2. Literature Review and Hypothesis Development

1.2.1. Cryptocurrency Return Predictability

Since Bitcoin was launched by Nakamoto (2008), Bitcoin and other cryptocurrencies have been studied by academic researchers. Bouri et al. (2019b) extended Granger causality understanding on cryptocurrencies returns. They investigated Granger causality from extreme trading volume to cryptocurrency returns and volatility, using the copula-quantile causality approach (CGCD). They examined Bitcoin, Ethereum, Ripple, Litecoin, NEM, Dash, and Stellar daily returns and found that trading volume Granger leads to extreme negative and positive returns for all cryptocurrencies. According to this conclusion, trading volume includes some significant information about the returns of cryptocurrencies.

Another research area on cryptocurrency returns is return dependence. In this topic, Yen et al. (2023) studied the association between the return of the top 20 cryptocurrencies by market capitalisation from 2016 to 2022. They also considered the effect of economic policy uncertainty on these associations by using the economic policy uncertainty (EPU) Index. They

revealed that an increase in the EPU index makes the dependency effect of the other cryptocurrency returns on Bitcoin returns stronger. Malladi and Dheeriya (2021) considered the returns and volatility of Bitcoin, Ripple, stock markets, gold prices, and fear measures (VIX and US EPU Index) returns and volatilities and applied some time series analyses such as ARMAX, GARCH, and VAR to find associations between returns and volatilities. For the period between 2013 and 2019, they found that stock market returns and gold prices have no causal effect on Bitcoin returns, while they are associated with Ripple returns. The main drivers of Bitcoin returns were VIX and US EPU Index fear measures and Ripple returns.

Finally, the use of machine learning to predict cryptocurrency returns has recently become popular. One of the papers that studies this issue is Akyildirim et al. (2021). They considered the returns of the 12 most liquid cryptocurrencies returns and examined their predictability using state-of-the-art methods such as support vector machines, logistic regression, artificial neural networks, and random forest classification algorithms from 2013 to 2018. They found that cryptocurrency returns can be predicted at the daily and intra-daily (five minute) frequencies, justifying the use of machine learning methods for short-term predictions of cryptocurrency returns.

1.2.2. Investor Attention

Traditional asset pricing models, which assume that information is reflected in prices as soon as it becomes available, expect investors to dedicate the necessary attention to assets. However, in reality, attention is a scarce cognitive resource, and investors have limited attention spans (Da et al., 2011). Studies in the literature have used various alternatives to measure investor attention. For example, Da et al. (2011) used the GSVI as a direct measurement to gauge investor attention. Barber and Odean (2008), on the other hand, used stock news, abnormal trading volume, and extreme daily returns as indicators of investor attention in their study.

Several studies use the GSVI as a measure of investor attention, starting with Da et al. (2011). In their study, they presented a novel measurement for investor interest based on the frequency of Google searches (e.g., “AAPL” for Apple Computer and “MSFT” for Microsoft). Subsequently, they examined the relationship between investor interest and the Russell 3000 index stock returns, using weekly data from January 2004 to June 2008, and found that an increase in GSVI predicts higher stock returns in the following two weeks and returns reversal within a year. This pioneering study argued that GSVI is an appropriate measure of investor interest, measuring the attention of individual investors, particularly retail investors.

Tang and Zhu (2017) studied the impact of growing investor interest on security returns in the US stock markets across a four-week investment horizon. They created a daily dummy variable based on GSVI to measure the rise in investor attention and focused on a sample of American Depositary Receipts (ADRs) traded in the US stock markets between 2004 and 2015. They found that an increase in investor interest is positively associated with same-day positive excess returns. However, the positive relationship between investor interest and stock returns weakens or even reverses shortly after. Developing and developed market ADRs seem to respond equally to increased investor interest.

Another study by Swamy et al. (2019) investigated whether GSVI can forecast stock returns. They used weekly closing price and turnover data from the S&P BSE 500 index from September 2012 to August 2017. Applying a quantile regression approach, they found that a higher GSVI predicts positive and significant returns in the first and second weeks. Moreover, higher GSVI quantiles predicted higher excess returns.

Halousková et al. (2022) investigated the impact of event-specific attention indices based on GSVI in predicting stock returns before and during Russia's invasion of Ukraine in February 2022. They used daily data from the MSCI stock market indices and GSVI for a total of 51 countries from 22/06/2021 to 08/03/2022 and found that GSVI was useful in forecasting

stock returns during Russia's invasion of Ukraine in February 2022. Lastly, Birindelli et al. (2023) studied whether investors' interest in the Sustainable Finance Disclosure Regulation (SFDR) drives European stock markets. They used weekly GSVI data from January 2019 to April 2022, as well as the closing prices of European financial sector stock market indexes (namely, S&P Europe Financials, MSCI Europe Financials, and Euro STOXX Financials) and sub-indices representative of single financial industries (namely, Euro STOXX Banks and Euro STOXX Insurance) and analysed them using the non-parametric causality method of Balcilar et al. (2017). According to the study's findings, investor attention has considerable predictive power for stock markets, particularly in bearish and normal market conditions.

1.2.3. Cryptocurrency Returns and Investor Attention

Simultaneously, studies in the literature have investigated the relationship between returns/volatility/prices/volume of cryptocurrencies and investor attention. Considering that the popularity of cryptocurrencies has increased in the past few years, we noted that most of the studies have been published in the last five years. This quote from the *Financial Times* suggests one of the reasons for this:

> *"Crypto is a vibes-based financial market. The lack of fundamental anchors such as earnings or interest rates mean that crypto trades overwhelmingly on sentiment. But the proximate cause of the recent return of 'good vibes' to the crypto market appears to be the Securities and Exchange Commission's decision to allow direct crypto exchange traded funds (ETFs) run by investment institutions to enter the US market.[5]"*

[5] ft.com/content/10fe3070-c739-495c-941d-fd57f1daafa9

Kristoufek (2013) carried out pioneering work in this field. In their research, for the period 01/05/2011 to 30/06/2013, and considering weekly data for GSVI, daily data for WIKI, and applying a VECM, they studied the relationship between attention measures and Bitcoin prices, and found a positive correlation. Another study by Urquhart (2018) investigated the role of GSVI on the volume and volatility of Bitcoin. They estimated a VAR model, ran Granger causality tests for weekly data between 01/08/2010 and 31/07/2017, and showed that when searches for the term "Bitcoin" on the GSVI increase, Bitcoin experiences significantly higher trading volume and volatility. The volatility and volume from the previous day and from the previous two days are important sources of interest in Bitcoin according to the VAR model; however, attention does not have the capacity to predict volatility or returns. Bitcoin returns affect search queries with a two-day lag, and high returns lead to increased search queries. However, by dividing the data into two subsamples, they found that this only applies to the period after October 2013, indicating that investors' focus on Bitcoin followed significant rises in its volatility and trading volume. In conclusion, their paper showed that while the next day's investor attention is significantly influenced by realised volatility and volume, investor attention has little predictive capacity when it comes to predicting realised volatility, volume, or returns.

Since these two seminal studies, the literature related to the relationship between the GSVI and cryptocurrencies has grown over time. For example, considering 12 cryptocurrencies and GSVI for the period from launch date of each cryptocurrency to 30/09/2018, Bleher and Dimpfl (2019) used a VAR model and concluded that GSVI can forecast cryptocurrency volatility but cannot forecast returns. Another study by Eom et al. (2019) examined the relationship between Bitcoin returns, volatility, and GSVI for the period 03/10/2011 to 31/05/2017, and found that volatility can be explained by past changes in investor attention; however, again, returns cannot be predicted. The findings of these papers contrast with Urquhart

(2018), who found that investor attention has little ability to predict actual volatility, volume, or returns.

Only a few studies have focus on the relationship between GSVI and cryptocurrencies other than Bitcoin. Liu and Tsyvinski (2021) assessed the relationship between Bitcoin, Ethereum, and Ripple weekly returns and the GSVI for the period 01/01/2011 to 31/12/2018. They found that cryptocurrency returns are unconditionally positively predicted by investor attention. There is also strong negative return predictability resulting from the use of negative investor attention measures; these are 20 negative phrases including ‘Bitcoin down’, ‘Bitcoin bearish’, and ‘Bitcoin dump’. Other work includes Lin (2021) investigating the relationship between the GSVI and the weekly returns of Bitcoin, Ethereum, Ripple, Litecoin, and Tether cryptocurrencies. They concluded that although their effects are short-lived, the returns of the cryptocurrencies Bitcoin, Ethereum, and Litecoin certainly affect investor interest; however, there is only weak evidence that past GSVI affect future returns. Similarly, Li et al. (2021a) tested the relation between these same cryptocurrencies' weekly returns (except for Tether) and the GSVI. They found a bidirectional Granger causal relationship between investor attention and the returns of Bitcoin, Ethereum, Ripple, and Litecoin. Interestingly, in short-term bearish markets, investor attention was more influential on cryptocurrency returns than on bullish ones.

More contemporary studies include new cryptocurrencies, such as Dash and NEM. For example, Aslanidis et al. (2022) used the daily returns and volatility of Bitcoin, Ethereum, Litecoin, Ripple, and Dash over the period from 07/08/2015 to 22/04/2021. Using the Shannon Transfer Entropy method, they found that for up to six days, there was a bidirectional transfer between GSVI and cryptocurrency returns. Additionally, there was an important tail dependency between Google searches and cryptocurrency returns. Shannon transfer entropy is a flexible, non-parametric approach designed to overcome some of Granger causality's restrictions (such as the linearity assumption). Transfer entropy is a metric based on the

Kullback–Liebler distance of transition probabilities that allows directional identification and the quantification of the strength of information flows (see Aslanidis et al., 2022). Furthermore, Raza et al. (2022) added NEM returns using nonlinear causality-in-quantile methodology and concluded that apart from Dash, GSVI drives the prices of Bitcoin, Ripple, Ethereum, and NEM in a large number of quantiles. This indicates that GSVI can be an effective predictor of cryptocurrency pricing. It also implies that as more investors seek Bitcoin knowledge, trading volumes and returns will increase.

Overall, this literature review shows there is mixed empirical evidence for whether there is a significant association between GSVI and cryptocurrency returns, and whether GSVI can be employed to predict cryptocurrency returns. According to some literature, there is a positive association between GSVI and Bitcoin prices (e.g., Liu and Tsyvinski, 2021; Kristoufek, 2013; Dias et al., 2022; and Raza et al., 2022). However, it also needs to be noted that, while realised volatility and volume have a considerable influence on the following day's investor attention, some studies find only weak predictive ability when it comes to predicting realised volatility, volume, or returns (e.g., Urquhart, 2018 and Bleher and Dimpfl 2019).

To contribute to this literature, we examine whether the returns of the six largest cryptocurrencies by market capitalisation can be predicted by GSVI and WIKI investor attention measures. Very few papers take such a combined multi-currency, multi-investor attention approach. To do so, first consider the following hypothesis:

H_1: There is a positive association between the GSVI and WIKI attention measures, and selected cryptocurrency weekly returns from 2017 to 2022.

In particular, given that recent empirical research has found a positive association between investor attention and cryptocurrency returns (e.g., Liu and Tsyvinski, 2021), H_1 seems to be a

reasonable hypothesis for our full 2017 to 2022 sample period. However, ex ante, there are compelling arguments for suggesting that splitting the sample into two subperiods, 2017 to 2020 and 2020 to 2022, may produce different results. As noted earlier, the period before 2020 presented relatively smooth price movements, whereas subsequently, and concurrent with the COVID-19 pandemic, monetary policy changes, and a crypto 'winter', dynamics were more volatile. This may lessen the effect of investor attention on cryptocurrency returns, leading to the second hypothesis:

H_2: The positive association between the GSVI and Wikipedia searches and selected cryptocurrency weekly returns has weakened in the period from 2020 to 2022.

1.3. Empirical Analysis

1.3.1. Data and Methodology

Our dependent variable is the returns of the six largest cryptocurrencies by market capitalisation. The USD exchange rates for Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Dash, Litecoin (LTC), and Stellar (XLM) are obtained from coinbase.com. Daily cryptocurrency prices are converted to weekly values by taking a seven-day average. Following Liu and Tsyvinski (2021), cumulative future log-returns for one-week to eight-week horizons are calculated using this formula:

$$r_t = p_t - p_{t-1} \tag{1.1}$$

We employ GSVI to build our first investor attention measure by using the terms "Bitcoin", "Ethereum", "Ripple", "Dash", "Litecoin", and "Stellar" in worldwide searches for each

cryptocurrency, respectively, from trends.google.co.uk. The most popular engine for searching, with more than 70 per cent of the global market share, GSVI is widely used in the literature to measure cryptocurrency investors' internet search behaviour for public information (Zhang and Wang, 2020). Da et al. (2011) was the first paper to apply GSVI as a measure of investor attention, testing the reliability of Google searches by using terms such as “recession” and “bankruptcy”. For example, they examined the term “recession” and the related GSVI showed a dramatic increase from mid-2007 to early 2008. This was just before the global economic crisis occurred in December 2008. They also examined the term “bankruptcy”, and the related GSVI revealed peaks (once) in 2005 and (once) in 2009. According to the American Bankruptcy Institute, real bankruptcies in the US have similar patterns.

It is important to mention that Google Trends does not provide raw search numbers for a subject. Instead, it calculates the proportion of subject searches to total searches and adjusts the proportion in relation to the highest value in the series (which is 100) before normalising the series. The index is calculated by Google Trends using a sample from its database. Processing the vast quantity of all search data would be too demanding computationally, and therefore Google Trends examines a dataset representative of all Google searches. Thus, refreshing the website will result in somewhat different index values. This prevents exact replication, even though the basic conclusions are unlikely to vary as a result of sampling (Yelowitz and Wilson, 2015). Additionally, if Google Trends is unable to collect enough data, it gives a result of 0 (Yelowitz and Wilson, 2015). As a last important detail, historical data for more than five years is only available at monthly frequency, as opposed to weekly. For this reason, we employ five years as the study's time span. Hence, we use weekly data from 26/06/2017 to 26/06/2022. We then apply the normalisation formula used by Liu and Tsyvinski (2021), essentially normalising the GSVI data by using the average of the previous four weeks so that the series has a mean of zero and a standard deviation of one.

The second investor attention measure used in the study is Wikipedia searches (WIKI), and for this we rely on raw count data from wikishark.com. Analogously to extraction of GSVI, we use the terms “Bitcoin”, “Ethereum”, “Ripple”, “Dash”, “Litecoin” and “Stellar” for worldwide searches. The same normalisation steps followed for GSVI are also carried out for WIKI.

We examine the association of our investor attention measures with cryptocurrency returns using multiple regression analysis. To begin, we assess each series for stationarity via the popular Augmented Dickey–Fuller (ADF) test. Notably, since the null hypothesis of non-stationary is rejected for all series, we confirm that the series are stationary and include it in the model in levels (see Table 1.1).

To determine the effect of investor attention on cryptocurrency returns, we estimate the following regression equations:

$$R_{t,t+i} = \alpha + \beta GSVI_t + u_t \tag{1.2}$$

$$R_{t,t+i} = \alpha + \beta WIKI_t + u_t \tag{1.3}$$

where R are the returns of the cryptocurrencies between t and $t + i$, where i is 1 to 8 weeks, while α is the constant coefficient and β is the coefficient of investor attention. Investor attention is measured with the *GSVI* in Equation (1.2) and with the *WIKI* in Equation (1.3).

The equations are estimated by OLS. We estimate the models for the full sample period 2017–2022, and two subperiods from 26/06/2017 to 10/03/2020 and 11/03/2020 to 26/06/2022, to enable the testing of our two earlier hypotheses posited in Section 1.2.3.

The models include typical control variables, such as the returns of gold, the USD index, and the S&P 500 index (Dyhberg, 2016; Kjærland et al., 2018; López-Cabarcos et al., 2021).

There is a need for data construction at this point. Since these variables are daily and the period used in the analysis is weekly, we convert the control variables to weekly form, but they are 5-day average data as they only have weekday data. However, the problem with the GSVI data is that the Google volume index gives 7-day averages data on a weekly basis. To get 5-day averages data, we first need five years of daily data. However, to download daily data, we are able to only download only 90 days at a time. Similarly, if we want to download weekly data, we can download only a maximum of five years. This is why we first considered a 5-year period in this chapter. Also, Google only provides annual data if we want to have more than five years of data, and for each download Google calculates the ratio of keyword searches to total searches, adjusts all other values in relation to the highest value in the series (which is 100), and normalises the series (Yelowitz and Wilson, 2015). Therefore, we have to find a construction method. After analysing many papers, methods, and constructions, we decided on our construction method and have data to analyse. We download the daily data at seven times from Google Trends for each cryptocurrency search term. We construct the data using this formula:

$$\left[\left(\frac{Daily\ data - Previous\ day}{Previous\ day} \right) * Weekly\ data \right) + Weekly\ data \right] \tag{1.4}$$

for each day, and then we standardise the data by using the method of Liu and Tsyvinski (2021). As a final step, we remove weekend observations and the first day of each series we downloaded to obtain series without spikes.

To determine the effect of the control variables on cryptocurrency returns, we estimate the following regression equations:

$$R_{t,t+i} = \alpha + \beta_1 GSVI_t + \beta_2 Gold_t + \beta_3 USDindex_t + \beta_4 S\&P500index_t + u_t \quad (1.5)$$

$$R_{t,t+i} = \alpha + \beta_1 WIKI_t + \beta_2 Gold_t + \beta_3 USDindex_t + \beta_4 S\&P500index_t + u_t \quad (1.6.)$$

where R are the returns of the cryptocurrencies between t and $t + i$, where i is one to eight weeks, while α is the constant coefficient and β is the coefficient of investor attention, $Gold$ is gold returns, $USDindex$ is USD index returns, and $S\&P500index$ is S&P500index returns.

1.3.2. Descriptive Statistics

Table 1.2 presents the descriptive statistics of all cryptocurrencies returns, GSVI, and WIKI searches, and control variables. When the data are separated into two subperiods, it can be observed that skewness and kurtosis values change from the first to the second period. Specifically, in the first period, the returns of cryptocurrencies are positively skewed between 2017 and 2020, indicating a greater potential for larger gains on the buy side. However, returns are typically negatively skewed in the second subperiod between 2020 and 2022, suggestive of a greater risk of larger negative outcomes.

Tables 1.3, 1.4 and 1.5 report the correlation analysis for each cryptocurrency return series, GSVI, WIKI, and the control variables for the three periods (i.e., one full sample and the two subperiods) separately. There is a negative correlation between Bitcoin returns and GSVI in each sample period. Similarly, Bitcoin returns and WIKI have a negative correlation, except for the subperiod from 2020 to 2022. While Bitcoin, Ethereum, and Litecoin returns do not have significant correlations with their relevant GSVI measures, Dash, Ripple, and Stellar returns show high positive correlations in all three periods. Moreover, the correlations between the GSVI and WIKI searches for Bitcoin, Ethereum, and Litecoin are positive.

1.3.3. Results

Table 1.6 reports the results of the estimation of the regression Equation (1.2) without controls, whereas Table 1.8 reports the results with the controls (regression Equation 1.5). Applying a level of significance of 5 per cent or less, we find no significant association between Bitcoin returns and the GSVI for the full sample period 2017–2022. This rejection of H_1 contrasts with the results in earlier literature, such as Liu and Tsyvinski (2021). The lack of significance also applies to the association between all Ethereum return series and GSVI. However, strikingly, for Ripple, Dash, Litecoin, and Stellar returns, GSVI presents positive and significant coefficients at different horizons for the full sample period. This non-rejection of H_1 suggests that the GSVI presents some predictability for their returns and raises an intriguing question. Why might the less well-known cryptocurrencies have more predictability? One explanation might be that newer cryptocurrencies are subject to a greater degree of learning by investors, where easily available sources of information, such as Google, are more frequently used.

Turning to the subsample analysis provides some equally arresting results. In particular, for some forecast horizons, GSVI is now positively and significantly associated with Bitcoin and Ethereum returns in the 2017–2020 period, but not in the most recent 2020–2022 period. Our results for the period between 2017 and 2020 are consequently in line with the literature (Liu and Tsyvinski, 2021; Kristoufek, 2013). However, the results for the latter sample period are different; we cannot reject H_2, indicating that investor attention (as measured by GSVI) does not predict Bitcoin or Ethereum over the 8-week forecast horizon in the most recent period. As we noted earlier in our hypotheses development, the rationale for H_2 is based on the observation that while the period before 2020 presented relatively smooth price movements, the period after, and concurrent with the COVID-19 pandemic, monetary policy changes, and a crypto ‘winter’, dynamics were more volatile, lessening the effect of investor attention on cryptocurrency returns. Our results here for Bitcoin and Ethereum provide evidence of this mechanism.

Turning to the other cryptocurrencies also produces interesting results when considering the subsample analysis. Taken as a whole, even though the other cryptocurrencies produce more significance (i.e., more positive and significant coefficients, at more forecast horizons) in the 2017–2020 period, relative to the 2020–2022, we still find several positive and significant coefficients in the later period (aside from Litecoin). Therefore, although H_2 appears to hold for the newer cryptocurrencies, the positive association between the GSVI and returns weakened much less than for Bitcoin and Ethereum.

The regression results for WIKI are reported in Table 1.7 without controls, and in Table 1.9 with controls. Examining the full sample clearly indicates different results from GSVI, with H_1 being rejected for more cryptocurrencies (i.e., there are fewer positive and significant associations between WIKI and returns). Indeed, only Ethereum and Ripple present positive and significant coefficients at some forecast horizons over the full sample. Turning to H_2, overall, one might argue that again, in contrast to GSVI, this can be rejected. In particular, Dash Litecoin present some significant and positive coefficients in 2020–2022, whereas they did not in the full sample. Overall, the results of Tables 1.7 and 1.9 show that WIKI has less predictability for cryptocurrency returns than the GSVI and that, notably, WIKI does not affect Bitcoin returns across any period.

The above results are robust to other approaches and further analyses. To examine whether a bidirectional relationship exists between cryptocurrency returns and our measures of investor attention, we employ a bivariate VAR (with up to eight lags) and Granger causality tests. The results both support and extend our prior work. For example, in the case of Bitcoin, GSVI does not Granger Cause returns over the full sample 2017–2022 or the latter sample period 2020–2022, but GSVI does Granger Cause returns in the early sample period 2017–2020. Interestingly, Bitcoin returns Granger Cause GSVI in the full sample and the early subsample (see Tables 1.10–12).

1.4. Conclusion

The purpose of this study is to examine the relation between investor attention measured by GSVI and Wikipedia (WIKI) searches, and selected cryptocurrency returns: Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and Dash. Studying a broader set of currencies than typical allows the us to consider whether differences (in popularity, technological infrastructure, adoption rate, and launch times) moderate the effect of investor attention. We consider two measures of investor attention, as they may capture different investor information needs. In any case, some extant literature, including the empirical work by Liu and Tsyvinski (2021) and Kristoufek (2013), documents a positive and significant relation between investor attention and returns, particularly for Bitcoin. This indicates that investor attention measures may present some predictability for cryptocurrency returns—an important practical implication for investors.

Employing weekly data from 2017 to 2022, we consider both full sample results, and results from two subsamples: 2017 to 2020, and 2020 to 2022. We justify the subsample analysis by noting that the period before 2020 presented relatively smooth price movements, whereas subsequently, and concurrent with the COVID-19 pandemic, monetary policy changes and a crypto 'winter', dynamics were more volatile. Overall, we show empirically that GSVI commonly presents more predictability (with forecast horizons up to eight weeks) than Wikipedia searches, and one could argue that this reflects that GSVI may capture more *frequent* initial searches, rather than the *slower*, deeper interest gleaned from Wikipedia pages.

Focusing on GSVI then, we show that for Bitcoin and Ethereum, returns are positively and significantly associated with this measure of investor attention over the period 2017 to 2020 but not 2020 to 2022. This striking result implies that the association between investor attention and the most well-known cryptocurrency returns has substantially weakened after 2020, indicating less predictability from GSVI—potentially as a result of greater volatility in price

dynamics and/or that investors have already progressed to more specialised information sources.

It should be noted that this weakening of the predictability relation, although still present, happens less for cryptocurrencies such as Ripple, Stellar, and Dash. The fact that Ripple provides more significant results for the GSVI in the latter sample period, when compared to other cryptocurrency returns, might be due to differences in infrastructure in its system and the attention it has received, as well as some legal issues it has been experiencing with the SEC since December 2020. The SEC & Ripple lawsuits, which lasted three years and ended on 13 July 2023, affected Ripple's reputation in both positive and negative ways. The SEC claimed that Ripple raised more than USD 1.4 billion from investors in an unauthorised security sale in 2013, but their claim was denied. Judge Analisa Torres, for the United States District Court for the Southern District of New York, determined that “Ripple did not violate federal securities law by selling XRP.” The XRP (Ripple) coin, which had reached billions of USD in market value in 2017, lost value as a result of the 2020 lawsuit. The fact that the lawsuit occurred at the same time as Bitcoin's all-time high of USD 64,000 was bad news for Ripple. However, after the court case was resolved, the price of the XRP (Ripple) coin was expected to rise. According to the price statistics, the XRP (Ripple) token, which was USD 0.36 on 12 July 2023, increased to USD 0.62 on the day of the conclusion of the lawsuit, 13 July 2023. Incidentally, the reason why Google searches had an impact on Dash and Stellar returns from the 2020 to 2022 period may be that these terms have meanings beyond their use as cryptocurrency names, unlike the other cryptocurrencies.

Finally, as with all research work, there are limitations. Future work could consider more sophisticated modelling approaches (e.g., allowing explicitly for the time-varying variance of returns) and/or both in-sample and out-of-sample forecasting evaluation methods. Moreover, there are a large number of cryptocurrencies that have not been considered in this chapter. For

future research, more cryptocurrencies, particularly those much less traded and where investors may have different information requirements, should be examined.

Chapter 2

Cryptocurrencies' Volatility and Investor Attention

2.1 Introduction

Since Nakamoto first introduced Bitcoin in 2008, various virtual currencies have emerged around the world. In addition to Bitcoin, there are around 10,000 virtual currencies in the world (source: coinmarketcap.com), such as Ethereum, Ripple, and Solana. Depending on the reason for being created, each virtual money performs a specific purpose. Uncertainty about the financial stability of existing currencies is leading to growing interest in cryptocurrencies (Yu et al., 2019). Investors use volatility as a key indicator to determine future value, risk management and hedging, and portfolio composition. Price fluctuations are driven by various pieces of real-time market information, and as the value of information increases, so do price changes. In other words, new knowledge influences investors' expectations of future value, one of the reasons for volatile prices. Cryptocurrencies' price volatility is significantly higher than that of stocks, bonds, and traditional currencies (Yu et al., 2019). Bitcoin's use as a speculative investment is one of the reasons for this high volatility in the cryptocurrency market (Güler, 2023). Measuring the components that influence price volatility has significant effects on cryptocurrency investors (Yu et al., 2019). As a result, the study of cryptocurrency returns and volatility, particularly predictability, is an academic and practical research topic (Eom et al., 2019).

We build on the work of Figà-Talamanca and Patacca (2019), who studied the effect on GSVI on Bitcoin volatility and found that the volatility of Bitcoin is significantly affected by the GSVI, and extend the extant literature in terms of data, time period considered, and investor attention measures. The aim of this chapter is to examine the effect of selected investor attention measures on the selected cryptocurrency volatility. For this purpose, we select the seven largest

cryptocurrencies by market capitalisation at the time, namely Bitcoin (BTC), ETH (Ethereum), Ripple (XRP), Dash, Litecoin (LTC), Stellar (XLM), and Solana (SOL). We consider two different investor attention measures, namely, the GSVI and Wikipedia searches (WIKI), since we use the same attention proxies in the first chapter of the thesis and to maintain the flow among the chapters. We apply GARCH (1,1) and EGARCH (1,1) models on a daily basis between 26/06/2017 to 02/11/2023, according to data availability. Then, as in the first chapter of the thesis, we split the data before and after 11/03/2020.

We find that both the GSVI and Wikipedia searches have an impact on the volatility of each cryptocurrency from 2017 to 2023 on both the GARCH (1,1) and EGARCH (1,1) analyses. Even though the coefficients are small, EGARCH analysis results show that the coefficients are larger than those of the GARCH analysis. The interesting point of the analysis results is that we find that the GSVI and Wikipedia searches affect the returns of Ripple negatively. This may show that when investors search for Ripple on Google and Wikipedia, the returns of Ripple decrease.

This chapter makes several contributions to the literature. First, we use WIKI, which is rarely used in the literature to relate cryptocurrency volatility. Instead, emotion-based sentiment measures derived from social media platforms such as Twitter and Reddit are mainly used to predict the volatility of cryptocurrencies. We use WIKI to find volatility in the cryptocurrency market, and we conclude that WIKI increases cryptocurrency returns volatility. Second, we consider seven cryptocurrencies, including Bitcoin, since not only Bitcoin, but also the other cryptocurrencies affect market volatility. Third, we consider 2020 and beyond, a period that is not considered in many papers, making our chapter up to date. Considering 2020 and beyond is important to see the effect of COVID-19 and the 2021 crypto winter on the cryptocurrency market.

The rest of the chapter is structured as follows. Section 2.2 provides a review of the literature on investor attention measures such as the GSVI and WIKI. Section 2.3 presents the data and methodology, Section 2.4 presents the results, and the last section (2.5) is the conclusion.

2.2 Literature Review and Hypothesis Development

2.2.1 Cryptocurrency Volatility and Investor Attention

A pioneering study in this research field is Urquhart (2018), who investigated the role of attention data from the GSVI on the volume and volatility of Bitcoin. For this purpose, they applied the VAR model and Granger causality test to weekly data between 01/08/2010 and 31/07/2017. They revealed that when Google searches for the Bitcoin term increase, it faces more significant trading volume and volatility. The volatility and volume from the previous day and from the previous two days are important points of interest in Bitcoin. However, they divided the data into two subsamples using Bai and Perron's (2003) test, since the findings may not be stable over time. They found that this only applies to the period after October 2013, indicating that investors begin to get interested in Bitcoin following significant rises in its volatility and trading volume. Another study by Eom et al. (2019) considered the relationship between Bitcoin returns and volatility, and the GSVI for the period between 03/10/2011 to 31/05/2017. The results of their paper showed that, similarly Urquhart (2018), Bitcoin volatility can be explained by past changes in investor attention towards the cryptocurrency. Bystrom and Krygier (2018) also considered the GSVI to examine the volatility of Bitcoin in their studies. Using daily, weekly, and monthly data for the period 2011 to 2017, they applied VAR analysis and impulse response functions. They used the GSVI as well as gold returns, S&P500 index, USD currency index, EPU index, and the systemic risk (SYS) measure from the Federal

Reserve Bank of Cleveland. They found that there is an extremely significant and positive association between Bitcoin volatility and the GSVI. Furthermore, they applied benchmark predictive models to analyse whether the GSVI can predict Bitcoin volatility. Their analysis showed that past volatility fluctuations have predictive power on Bitcoin volatility on a daily and monthly data basis, similarly to Urquhart (2018) and Eom et al. (2019). Bleher and Dimpfl (2019) used a VAR model, and examined the association between 12 cryptocurrencies and the GSVI for the period from the start date of each cryptocurrency to 16 September 2018. They concluded that the GSVI can forecast cryptocurrency volatility, but it cannot forecast returns. Mittal et al. (2019) investigated predicting short-term Bitcoin price changes. For this purpose, they used the GSVI, tweets from Twitter and tweet volume data as dependant variables and applied machine learning techniques. Considering daily data, the time period between 09/04/2014 to 07/01/2019, the paper concluded that while there is a correlation between the GSVI and tweets from Twitter, and Bitcoin price changes, tweet volume data and the price of Bitcoin have a weak association.

Wang et al. (2023) studied the effect of macroeconomic and technical indicators on Bitcoin volatility. They used monthly data for the period December 2011 to April 2021 and considered 17 macroeconomic indicators, such as the GSVI, S&P 500 returns and RV, CBOE implied volatility index, CBOE oil volatility index, emerging market index return and RV, global commodity index return and RV, global economic uncertainty index, China economic uncertainty index, global real economic activity index, USD index return and RV, geopolitical risk index, geopolitical threats index, geopolitical acts index, and 18 technical indicators. The results suggest that macroeconomic indicators are stronger than technical indicators in predicting Bitcoin volatility. Al Guindy (2021) investigated the relationship between the 23 largest cryptocurrencies' volatility and investor interest in their study. They considered tweets from Twitter as a measure of investor attention, considered daily data between 16/11/2017 to

05/11/2018, and applied VAR analysis and Granger causality test. The study revealed that there is a causal association between investor attention and volatility.

2.2.2 Cryptocurrency Volatility and GARCH Modelling

In a pioneering study on this topic, Katsiampa (2017) examined the volatility of Bitcoin, highlighting its role as a speculative asset. Their research considered daily Bitcoin returns between July 2010 and October 2016 using an autoregressive model for the mean and a first-order GARCH-type model for the variance. Their study concluded that the AR-CGARCH model is the most effective in explaining Bitcoin price volatility. Apergis (2022) aimed to explore the relationship between COVID-19 metrics and eight major cryptocurrency returns and their volatility, using an asymmetric volatility model. The analysis considered daily data from February 2020 to October 2021, focusing on transaction volumes and COVID-19 metrics, such as confirmed cases and deaths. A TGARCH (1,1) model was used to assess the impact of COVID-19 on cryptocurrency returns and volatility, including liquidity and market sentiment as additional variables. Their results indicated that COVID-19 metrics negatively affected the average returns of cryptocurrencies, with a more pronounced impact observed when death counts were used as a proxy. Their analysis showed that negative shocks lead to larger increases in conditional volatility, highlighting the significant impact of the pandemic on cryptocurrency market dynamics.

Köchling et al. (2020) investigated out-of-sample forecasting of return volatility in cryptocurrencies using various GARCH-type models and robust loss functions. Importantly, their study highlighted the challenge of model selection, showing that many models yield statistically equivalent forecasting accuracy, making it difficult to identify superior models. Their research used daily and high-frequency intraday Bitcoin return data to construct volatility proxies, covering the period from November 2015 to August 2018. A comprehensive set of 172

GARCH-type models was constructed, using a model confidence set (MCS) approach to evaluate and compare forecasting performance, which iteratively eliminates inferior models, allowing for statistically sound identification of models with equal predictive ability. The results indicated that the intraday volatility proxy outperforms the daily proxies, particularly during periods of high volatility, and that asymmetric loss functions enhance model discrimination. Venter and Maré (2020) aimed to estimate the volatility indices of the Bitcoin and Cryptocurrency Index (CRIX), using daily data from 01/01/2016 to 03/01/2019. The CRIX was introduced as a statistically robust measure of the cryptocurrency market, comparable to the S&P 500 index, and was determined by the explanatory power of its constituents. The GARCH (1,1) model showed strong performance in pricing Bitcoin/USD (BTCUSD) options, with results closely aligned with market prices, validating its use in volatility index calculations. The term structure of volatility was analysed, showing that short-term indices tend to rise sharply during market jumps, while longer-term indices remain lower, reflecting market uncertainty. Their research confirmed the effectiveness of the symmetric GARCH volatility index in capturing the dynamics of BTCUSD and CRIX, with both indices responding similarly to market shocks. Their findings support the use of GARCH models to capture the dynamics of cryptocurrency volatility, reinforcing their relevance in financial modelling.

2.2.3 Cryptocurrency Volatility, GARCH Models, and Investor Attention

Figà-Talamanca and Patacca (2019) applied nonlinear econometric models and investigated the effectiveness of the investor attention measure on the mean, and the variance of Bitcoin returns. Using daily data of Bitcoin returns and adapting the GSVI, they considered the period between 01/01/2012 and 31/12/2017. Then they divided the dataset into 01/01/2012 to 31/12/2014 and 01/01/2015 to 31/12/2017, since they considered the second period to be the beginning of the

new phase of Bitcoin history. They found that the GSVI largely impacts the volatility of Bitcoin returns.

Figà-Talamanca and Patacca (2020) also published a complementary paper to their research and that of Urquhart (2018). In this paper, they used a VAR-EGARCH model expanding the earlier approach and considered the time period January 2012–December 2018. They applied Bitcoin daily prices and the GSVI to investigate the association between Bitcoin and the GSVI and trading volume. Moreover, using dummy variables, they added significant events that may affect the relationship between the GSVI and Bitcoin volatility and Bitcoin returns. The results showed that there was no direct association between the two market attention measures and Bitcoin returns. In contrast, both the trading volume and the GSVI intensity positively affected Bitcoin volatility. However, Bitcoin returns affected both trading volume and the GSVI intensity positively, which means they have reverse causality.

To analyse the relationship between Bitcoin returns volatility and user opinion difference and user interest, Yu et al. (2019) applied the GJR-GARCH model in their studies. As a measurement of the interest of users, the GSVI and Wikipedia page views were used. They used daily data, and the time period for the study was 01/01/2015–31/10/2017. They found that while the GSVI affects Bitcoin volatility, Wikipedia does not influence Bitcoin volatility. Since Yu et al. (2019) tested the impact of Wikipedia only on Bitcoin returns volatility and we have significant Wikipedia results in the first chapter of the thesis, we aim to examine other cryptocurrencies, including Bitcoin, and consider Wikipedia in this chapter.

López-Cabarcos et al. (2021) investigated the influence of social network sentiment from StockTwits and stock market variables on Bitcoin volatility using EGARCH models. The aim was to clarify the association between Bitcoin, investor sentiment and its behaviour in financial markets, particularly in relation to the S&P 500 index and the volatility index (VIX). Data were collected from 4 January 2016 to 30 September 2019, including daily returns for

Bitcoin, S&P 500, and VIX, along with sentiment analysis from StockTwits. The study used a GARCH (1,1) model to assess the impact of S&P 500 returns, VIX returns, and investor sentiment on Bitcoin returns. The model showed that both market returns and sentiment have a significant impact on Bitcoin volatility, with S&P 500 returns having a larger impact. The results supported the suitability of the GARCH (1,1) model to capture the volatility dynamics of Bitcoin. In addition, an E-GARCH (1,1) model was used to further explore the influence of market variables and sentiment on Bitcoin volatility, confirming similar results to the GARCH model. The results showed that both S&P 500 returns and social network sentiment significantly influenced Bitcoin volatility, with sentiment having a stronger effect than VIX returns. The study concluded that Bitcoin investors may prioritise social network sentiment over traditional market volatility when making investment decisions. Güler (2023) considered the COVID-19 pandemic and multiple investor sentiment measures such as Bitcoin trading volume, daily Crypto Fear & Greed Index, and weekly American Association of Individual Investors Index. They analysed the effect of investor sentiment on Bitcoin returns and conditional volatility. For this purpose, they applied the EGARCH model and divided their data into three parts: all periods, before March 2020, and from March 2020. Their results indicated that interest has a positive impact on both Bitcoin returns and the conditional volatility of Bitcoin returns. Moreover, the Bitcoin market is affected by emotions more than rationality; therefore, investor attention measures are important features and need to be taken seriously when trading in the crypto market.

Dempere (2019) aimed to explain the prediction capability of variables such as GSVI, exchange rate of major currencies, S&P 500 index, and gold and oil prices on Bitcoin, Ethereum, and Ripple returns. In this regard, they applied GARCH models and took the period between each dependent variable's beginning dates (Bitcoin: 29/04/2013, Ethereum: 10/08/2015, Ripple: 06/08/2013) to 31/07/2019 as daily data. Their study showed that the daily

GSVI had a significant and positive effect on both Bitcoin and Ripple returns. On the other hand, the GSVI had no significant association with Ethereum returns.

Overall, this literature shows that there is a significant association between the GSVI and cryptocurrency volatility, and that GSVI can be applied to predict cryptocurrency volatility. However, there is limited literature on the association between WIKI and Bitcoin and the volatility of other cryptocurrencies. According to the studies included in the review, the GSVI has an impact on Bitcoin volatility (e.g., Eom et al., 2019; Yu et al., 2019; Urquhart, 2018; Bleher and Dimpfl, 2019; Wang et al., 2023). Finally, the Bitcoin market is affected by interest more than rationality; therefore, investor attention measures are important features and need to be taken seriously when trading in the crypto market (Güler, 2023).

Looking at the literature, it is remarkable that relatively few studies have used GARCH models to examine the association between cryptocurrency volatility and investor attention, especially WIKI. However, Venter and Maré (2020) concluded that GARCH models are suitable for capturing the volatility of cryptocurrencies. Following this suggestion and based on the rarity of the application of GARCH models in the literature, we apply such models in our study to understand the association between investor attention measures and the daily volatility of cryptocurrencies from 26/06/2017 to 02/11/2023. Then, as in the first chapter of the thesis, we split the data before and after 11/03/2020 to see the COVID and crypto winter effects on the selected cryptocurrency volatility. Moreover, our study is, to the best of our knowledge, the first to analyse the association between WIKI and cryptocurrency volatility using GARCH (1,1) and EGARCH (1,1). This is what we aim to investigate in our paper. In light of this goal, the following hypothesis is established:

H_1: Google search volume index data and Wikipedia searches affect the volatility of the selected cryptocurrencies from 2017 to 2023.

Furthermore, while most studies only examine Bitcoin, we consider seven different cryptocurrency volatility and extend the results. One of our contributions to the literature is including GSVI and WIKI in the same paper. Studies often consider only GSVI or WIKI, or more recently, sentiment variables such as VIX or Twitter. We aim to determine whether GSVI and WIKI retain their effectiveness as attention variables when the effects of sentiment variables are evident.

2.3 Empirical Analysis

2.3.1 Data and Methodology

The data for this study are collected from three different sources. The USD exchange rate of cryptocurrencies, which are Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Dash, Litecoin (LTC), Stellar (XLM) and Solana (SOL), are obtained from binance.com, the GSVI is collected from trends.google.co.uk/trends/, and WIKI data are from wikishark.com.

In the analysis, we use daily data from 26/06/2017 to 02/11/2023 due to data availability and to be consistent with the first chapter of the thesis. We apply a construction method to the GSVI data to obtain a proper dataset for analysis. The GSVI gives a maximum of five years of daily data; for longer periods it provides only monthly data. Because our sample period is longer than five years, we develop a construction method to convert the monthly data into daily data.

We download the daily data at nine times from Google Trends for each cryptocurrency search term. We convert the data using this formula:

$$\left\{\left[\frac{(Daily\ data - Daily\ average\ of\ the\ month)}{Daily\ average\ of\ the\ month} * Monthly\ data) + Monthly\ data\right]\right\} \quad (2.1.)$$

for each day, and then we standardise the data applying the normalisation formula, which is data to have a mean of zero and a standard deviation of 1 to the GSVI data. We remove weekends, and first day of each series which we download to have the series without spikes. As a final step, all cryptocurrencies are listed from smallest to largest to find the smallest value, and then this value is subtracted from all the datasets to have positive attention variables for GARCH analysis. Then the data are split into two subperiods from 26/06/2017 to 10/03/2020 and from 11/03/2020 to 02/11/2023 to see the effects of crypto winter and COVID-19 more clearly.

Daily cryptocurrency prices taken from binance.com and their returns are calculated using this formula:

$$rt \ = pt \ - pt - 1 \tag{2.2}$$

where r is returns of cryptocurrencies, p is prices of cryptocurrencies, and t is at a time. The launch dates of each cryptocurrency vary. While the historical price data used in the study for Bitcoin, Ethereum, Litecoin, Stellar, and Dash are from 26/06/2017, the data for Ripple are from 04/05/2018, and the data for Solana are from 17/06/2021. We use the GSVI and WIKI to build the investor attention measures by using the search terms “Bitcoin”, “Ethereum”, “Ripple”, “Dash”, “Litecoin”, “Stellar”, and “Solana” for worldwide searches.

We use the GARCH (1,1) and EGARCH (1,1) models as our methodology. GARCH is a statistical model used for volatility. The model assumes that a time series variance is a function of the previous term variance and error terms (Bollerslev, 1986). The aim of the EGARCH model is to address positive certainty problems and to effectively handle asymmetric shocks by using a logarithmic function of conditional variability in financial time series (Nelson, 1991).

To determine the effect of investor attention on cryptocurrency return volatility, we estimate the following GARCH (1,1) and EGARCH (1,1) equations:

$$Rb_{returns} = \mu + \beta GSVI_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha_{returns}\varepsilon_{t-1}^2 + \beta_{returns}\sigma_{t-1}^2 + \gamma GSVI_{t-1} \quad (2.3.)$$

$$Rb_{returns} = \mu + \beta WIKI_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha_{returns}\varepsilon_{t-1}^2 + \beta_{returns}\sigma_{t-1}^2 + \gamma WIKI_{t-1} \quad (2.4.)$$

$$Rb_{returns} = \mu + \beta_1 GSVI_{t-1} + \beta_2 WIKI_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha_{returns}\varepsilon_{t-1}^2 + \beta_{returns}\sigma_{t-1}^2 + \gamma_1 GSVI_{t-1} + \gamma_2 WIKI_{t-1} \quad (2.5.)$$

These are GARCH (1,1) model equations, and where Rb represents the returns of each cryptocurrency, μ is the constant coefficient, and β is the coefficient of investor attention on the mean equations. Moreover, where ω is constant coefficent, σ_t^2 is conditional variance, α is the effect of the square of the previous period's error term, ε_{t-1}^2 is squared error term of the previous period, β is the effect of the previous period's conditional variance, and γ is the lagged effect of the investor attention measure on the variance equations.

$$\mathcal{Y}returns_t = \mu + \beta GSVI_{t-1} + \epsilon_t$$

$$\mathcal{I}n(\sigma_t^2) = \omega + \alpha\frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta\, In(\sigma_{t-1}^2) + \gamma GSVI_{t-1} \quad (2.6.)$$

$$\mathcal{Y}returns_t = \mu + \beta WIKI_{t-1} + \epsilon_t$$

$$\mathcal{I}n(\sigma_t^2) = \omega + \alpha\frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta\, In(\sigma_{t-1}^2) + \gamma WIKI_{t-1} \quad (2.7.)$$

$$\mathcal{Y}returns_t = \mu + \beta_1 GSVI_{t-1} + \beta_2 WIKI_{t-1} + \epsilon_t$$

$$\mathcal{I}n(\sigma_t^2) = \omega + \alpha\frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta\, In(\sigma_{t-1}^2) + \gamma_1 GSVI_{t-1} + \gamma_2 WIKI_{t-1} \quad (2.8.)$$

These are EGARCH (1,1) model equations, and where $\mathcal{Y}$ shows each cryptocurrency returns, μ is the constant coefficient, and β is the lagged impact of investor attention measure on the mean equations. On the other hand, $\mathcal{I}n(\sigma_t^2)$ shows conditional variance, where ω is the constant coefficient, α is effect of the previous period's error term, ϵ_{t-1} is error term of the previous period, σ_{t-1} is the conditional standard deviation of the previous period, β is the effect of previous period's conditional variance, and γ is the lagged impact of investor attention measure on the variance equations.

The series are tested for stationarity by using the Augmented Dickey–Fuller (ADF) test and the Phillips–Perron (PP) test. Since all series are stationary at the level, we include the variables in the model levels (see Table 2.1).

2.3.2 Descriptive Statistics

Table 2.2 (descriptive statistics) indicates that Bitcoin and Ethereum daily returns are generally stable with minor changes between 2017 and 2023, occasional major losses can occur, and return movements are prone to large spikes and downs. On the other hand, while the highest volatility is on XLM daily returns from 2017 to 2023 and from 2017 to 2020, Ripple returns are the most volatile crypto returns for the 2020–2023 period.

Table 2.3 (correlation) show the returns of each cryptocurrency, alongside GSVI and WIKI, for the 2017–2023 term. All cryptocurrencies have high positive correlations with each other and high t-statistics, which means that they act synchronically in the crypto market. In examining the correlation between cryptocurrency returns and GSVI, only Bitcoin returns show a positive relationship. In contrast, the correlations between other cryptocurrencies and GSVI are negative. The coefficient of the correlation between Ripple and GSVI is -0.06, indicating that the correlation is negative, although not statistically significant; it is the closest to being a significant relationship among the others with a t-statistic value of -1.53. Given that between Ripple and SEC case was on the agenda during the selected period, it may be expected that this relationship is negative. In comparison, while Dash and Solana returns show a positive correlation with WIKI, the Bitcoin, Ethereum, Litecoin, Ripple, and Stellar returns have a negative correlation with WIKI. However, none of these correlations are statistically significant according to their t-statistic values. The correlation between investor attention measures is positive and high in Bitcoin, Ethereum, Litecoin, Ripple, and Solana. However, between investor attention measures for the Dash correlation is negative.

2.3.3 Results

When we run the GARCH (1,1) equation with GSVI (Table 2.4.) for each cryptocurrency return from 2017 to 2023, all cryptocurrency returns show insignificant coefficients in the mean equations. This means that the lagged GSVI has no significant effect on the returns. On the other hand, all cryptocurrency returns apart from GSVI Ethereum returns lagged variance coefficient, and Ripple returns constant coefficient are significant according to their p-values in the variance equations. The results show that the returns are sensitive to market shocks. That is, unexpected movements in the previous period increase volatility in the current period. At the same time, these volatilities are long term. While the lagged GSVI effect on Bitcoin, Ripple,

and Litecoin returns are positive on Dash and Stellar returns are negative. As GSVI increases, volatility tends to increase in the positive coefficients. This may indicate that GSVI increases volatility, and this may be a sign that influences investor behaviour.

The GARCH (1,1) results with WIKI for each cryptocurrency return from 2017 to 2023 are similar to GSVI GARCH (1,1) results (Table 2.5). The constant term and the lagged WIKI both have insignificant coefficients in the mean equations, except for Ripple returns. In addition, the lagged WIKI have a negative impact on the Ripple returns, meaning that when Wikipedia searches increase Ripple returns decrease. According to the variance equations, the attention measure of GSVI slightly increases the volatility on the Ripple returns (0.004) more than Wikipedia searches (0.0003). Moreover, both GSVI and WIKI investor attention measures can be considered as playing a speculative role due to their negative impact on Ripple returns.

Furthermore, all cryptocurrency returns are significant according to their p-values in the variance equations. According to these results, returns are sensitive to market shocks. That is, unexpected movements in the previous period increase volatility in the current period. At the same time, these volatilities are long term, similar to the Google GARCH (1,1) results. The lagged effect of WIKI on all cryptocurrency returns is positive. This means that when WIKI increases, volatility tends to increase. As their coefficients are lower than GSVI, their effect is also not as strong as GSVI on volatility.

These results show that both GSVI and WIKI attention measures on Bitcoin returns search have no significant effect on the mean equations. This result is consistent with Figà-Talamanca and Patacca (2019), implying that the explanatory power of GSVI on Bitcoin returns is the same in both their period and our period that we consider. These attention measures are not efficient in explaining Bitcoin mean returns. One of the results consistent with this paper is that GSVI on Bitcoin affects Bitcoin volatility. However, WIKI attention on Bitcoin also affects

Bitcoin volatility, which is our contribution to the literature, as they do not consider WIKI as a measure of investor attention.

When the data are divided to see the effects more clearly, no notable results could be obtained. To interpret the results that come to the fore here:

Since Solana data started in 2021, this cryptocurrency return is considered in the period between 2020 and 2023. Neither GSVI nor WIKI are not significant in the mean equations. The Solana returns are sensitive to market shocks, and volatility is long term for both scenarios. However, although the coefficients are very small, while GSVI does not affect the volatility of Solana returns as its p-value is insignificant, WIKI positively affects Solana volatility. Moreover, the lagged GSVI attention and the lagged WIKI attention both positively drive Ripple returns volatility in the period from 2017 to 2020. This may suggest that these attention measures are almost equally an indicator of cryptocurrency return volatility, since their coefficients are very small.

Figà-Talamanca and Patacca (2019) investigated the effect of GSVI on Bitcoin return volatility using GARCH (1,1) and EGARCH (1,1). They found that the EGARCH (1,1) model generally outperformed the GARCH (1,1) model, capturing GSVI effects more strongly in volatility equations. It was also more successful in capturing asymmetric shocks, which makes it more advantageous for the cryptocurrency market (Figà-Talamanca and Patacca, 2019). In light of this paper, we apply the EGARCH (1,1) model.

The EGARCH (1,1) mean equations results with GSVI for each return from 2017 to 2023 are insignificant, except for Ripple returns. While Ripple has long-term returns (0.007), the lagged GSVI affects Ripple returns negatively (-0.022), which means that if the interest in GSVI rises, Ripple returns may be affected negatively. According to the volatility analysis results, the volatility degrees in the returns are low, as their constant values are negative. Moreover, all returns are sensitive to the last term shocks, and the last term shocks increase

volatility. These shocks raise volatility negatively for Bitcoin, Ethereum, and Litecoin returns, but Ripple, Dash, and Stellar returns are positive. Since all GARCH (-1) coefficients of the returns are close to 1, their volatility is long term. While GSVI affects Bitcoin, Ripple, and Litecoin returns volatility positively, its effect is negative on Dash and Stellar returns. This explains that when investors search for Dash and Stellar returns on Google, the volatility of these returns may decrease.

Similarly, the EGARCH (1,1) results with WIKI on returns from 2017 to 2023 are not significant, apart from Ripple returns. Ripple returns have long-term returns (0.062), and the lagged WIKI have a negative effect (-0.010) on Ripple returns. Furthermore, all cryptocurrency returns are sensitive to recent market shocks, and these shocks increase the volatility positively on Stellar returns; however, Bitcoin, Ethereum, and Litecoin returns volatility increase negatively. WIKI affects all cryptocurrency volatility except for Stellar returns positively. This means that when investors search for these cryptocurrencies on Wikipedia, their volatility may increase.

When the data is split, Bitcoin and Ethereum returns show long-term returns between 2020 and 2023 term on the GARCH (1,1) framework with GSVI. The sensitivity of returns to past shocks persists across periods. The lagged GSVI are more effective between 2017 and 2020, as their coefficients are higher than the whole period coefficients. Moreover, WIKI have a negative effect on Ripple returns between 2020 and 2023 in the EGARCH (1,1) framework. While the volatility levels are similar throughout the whole period, lagged WIKI still affects cryptocurrency returns even when the periods are split.

We apply the GSVI and WIKI investor attention measures in the same equation to detect the real effect of each measure on cryptocurrency returns clearly (Tables 2.7 and 2.8). We test it using the GARCH (1,1) and EGARCH (1,1) frameworks. Although the results of GARCH (1,1) analysis are significant, we discuss EGARCH (1,1) results since the coefficient of the

investor attention measures are greater in this framework. This result shows us that WIKI is a more reliable attention measure than the GSVI on cryptocurrency volatility. The selected cryptocurrency searches on WIKI increase each cryptocurrency volatility from 2017 to 2023.

When the data is split from 2017 to 2020, Ethereum and Stellar searches on WIKI does not affect their volatility. However, Ethereum searches on GSVI increase Ethereum returns volatility. The Ethereum ICO boom between 2017 and 2018 might have increase searches about Ethereum on Google and increased the volatility of the Ethereum returns. Furthermore, Ripple and Litecoin searches on WIKI increase their return volatility with 0.324 and 0.385 coefficients, respectively. Ripple collaborated with large companies, and Litecoin had a second halving event in that period. These events might increase investor attention to these coins, and thus, Ripple and Litecoin return volatility.

After the COVID-19 pandemic, all crypto markets had shocks and long-term volatility. All selected cryptocurrency searches on WIKI increase their return volatility from 2020 to 2023. In contrast, we conclude that Bitcoin, Ethereum, and Solana on GSVI decrease their return volatility. The news about Ethereum's PoS transition and Solana's integration with large institutions might help to stabilise these cryptocurrencies.

2.4 Conclusion

This chapter aims to investigate the effect of investor attention measures, such as GSVI and WIKI, on selected cryptocurrency volatility.

There are only a few papers that investigate the effect of investor attention measures on cryptocurrency using the GARCH (1,1) and EGARCH (1,1) frameworks. Most of the papers in the literature use the VAR model to study investor attention measures effects (Urquhart, 2018; Bleher and Dimpfl, 2019). Moreover, while most of the papers use GSVI as an investor attention measure (Eom et al., 2019; Wang et al., 2023), there are fewer papers investigating WIKI effects

on cryptocurrency volatility (Ciaian, 2016; Focke et al., 2020). Some papers investigate the effect of GSVI on Bitcoin volatility using GARCH models (Figà-Talamanca and Patacca, 2019; López-Cabarcos et al., 2021) and find that this investor attention measure can drive Bitcoin's volatility. However, to the best of our knowledge, there are no papers that investigate the effect of the GSVI and WIKI investor attention measures on cryptocurrency volatility in the same paper. Moreover, as far as we know, there is also no paper that uses the GARCH framework to find WIKI effects on cryptocurrency volatility.

Given these gaps, we decide to select seven cryptocurrencies: Bitcoin, Ethereum, Litecoin, Dash, Stellar, and Solana. This is one of our contributions to the literature, since this is the first study to use this set of cryptocurrencies to investigate their volatility in the same paper. We use daily data and consider the period between 26/06/2017 and 02/11/2023. This is also one of our contributions, as most of the papers do not consider the period after 2020. We then divide our data before 11/03/2020 and after. As a methodology, we replicate the study by Figà-Talamanca and Patacca's (2019) and use first GARCH (1,1) and then EGARCH (1,1) models. We apply a construction method for using GSVI appropriately in the analysis. We also calculate the logarithmic version of WIKI and calculate the returns of cryptocurrencies. According to the GARCH (1,1) results, both GSVI and WIKI can drive the volatility of cryptocurrencies between 2017 and 2023. This result is consistent with Figà-Talamanca and Patacca's (2019) paper regarding Bitcoin and GSVI association. What is interesting at this point is that we find that WIKI have a negative impact on Ripple returns. Similarly, we find that both GSVI and WIKI have a negative impact on Ripple returns according to the EGARCH (1,1) results. There could be many reasons for this, such as the fall in Ripple prices in 2020, because of the lawsuit initiated by the SEC on whether Ripple is a security, and as a result of the analysis, we can see that Wikipedia searches also negatively affected the returns. The subsequent COVID pandemic also reinforced this situation. In July 2023, Ripple won a partial victory in this case,

but as a result of our EGARCH (1,1) analysis, we can see that WIKI negatively affected Ripple returns between 2020 and 2023. These findings are our contribution to the literature, since they show the relationship between WIKI and Ripple returns up to date. This could show that as investor interest in Ripple on WIKI increases, its returns decrease.

Furthermore, we find interesting results on the relationship between Solana and WIKI. While GSVI does not affect Solana volatility, WIKI affects the Solana volatility according to both GARCH (1,1) and EGARCH (1,1) results. There may be many reasons for these results, such as Solana having low transaction fees, so it attracted investors around 2021 and its price rose. In addition, Solana had a huge NFT ecosystem during 2022. However, when FTX, which is one of the major supporters of Solana, collapsed at the end of 2022, the price of Solana crashed and this caused volatility.

Moreover, the results of tests where we use both the GSVI and WIKI investor attention measure in the same equation conclude that WIKI is a more reliable investor attention measure on the selected cryptocurrency volatility than GSVI.

Consequently, our study implies that the relation between WIKI and selected cryptocurrency returns volatility is stronger than the relation between GSVI and selected cryptocurrency returns volatility (in terms of coefficients and p-values). This study can be extended by using data after 2023 and selecting more cryptocurrencies and other investor attention measures.

Chapter 3

Cryptocurrencies: Herding Behaviour and Extreme Sentiment Conditions

3.1 Introduction

Behavioural finance suggests that psychological factors and biases influence investors' financial decisions (Kyriazis, 2020). Herding occurs when investors imitate the decisions or movements of others in the market rather than basing their own actions on their own beliefs and information (Hwang and Salmon, 2004). Kellard et al. (2017) defined herding as follows:

> *"In the context of markets, herding commonly refers to several actors making the same investment decision either at the same time or in close succession, leading to a high concentration of similar market orders and higher risks."*[6]

This phenomenon has been widely observed in both traditional financial markets and the cryptocurrency market (Jia et al., 2022). The opposite scenario shows that anti-herding exists in the market. Cryptocurrencies are alternative forms of assets with significant differences in asset creation, transaction process, and ownership relative to traditional financial assets. Their decentralised infrastructure and lack of regulatory oversight can make them attractive to both speculators and investors. The significant level of illiteracy about the infrastructure of cryptocurrencies has made the market very sensitive to the collective actions of the market. In addition, the risk-return trade-off in the context of cryptocurrency volatility has been the focus of academic research (Kyriazis, 2020).

In this chapter, we build on and extend two studies by Kaiser et al. (2020) and Jia et al. (2022), which investigated herding behaviour in the cryptocurrency market during bearish and

[6] Kellard, N., Millo, Y., Simon, J., and Engel, O., 2017. Close communications: Hedge funds, brokers and the emergence of herding. *British Journal of Management*, *28*(1), pp.84–101.

bullish conditions, and extreme sentiment conditions. Their findings suggest that herding behaviour occurs in the cryptocurrency market, especially on negative extreme days and bearish market conditions. We consider the returns of the top ten cryptocurrencies by market capitalisation, namely Bitcoin, Ethereum, Ripple, Litecoin, Dash, Stellar, Solana, Dogecoin, Cardano, and Avalanche from 01/07/2017 to 30/11/2024. The sample period reflects data availability. We use the Google search volume index (GSVI) and Wikipedia searches (WIKI) as investor sentiment proxies, and we apply dummy variables for 1 per cent and 5 per cent extreme positive and negative days based on these sentiment measures. We decide to apply Google and Wikipedia searches as investor sentiment measures since Google Trends and Wikipedia search queries have proved to be a useful information source on financial applications, including explanations of the home bias, the traded volume explanations, earnings announcements, portfolio diversification, and trading strategies (Kristoufek, 2013). Furthermore, the need for consistency among the chapters of this thesis and the significant results from the first and second chapters are the other reasons for selecting these investor sentiment measures. The methodology we used is cross-sectional absolute deviation (CSAD) by Chang et al. (2000), which measures the diversion of asset returns from market returns to detect herding behaviour.

Overall, while we find herding behaviour in the cryptocurrency market, we also find that this is asymmetric, with herding predominantly occurring during bearish markets. Moreover, we find less evidence of herding during the extreme positive days. Although these findings are in line with the literature (Vidal-Tomás et al., 2019; Kallinterakis et al., 2019; Gyamerah 2021), there are other studies that find herding in bullish markets (Kaiser, 2020; Ballis et al., 2020).

This chapter makes two novel contributions to the literature. First, we include WIKI as a sentiment proxy, which has not been employed before in the herding context for

cryptocurrency markets. We apply WIKI in our first and second chapters and find significant results on cryptocurrency returns and volatility context. This lead us to apply and investigate it in the third chapter. In line with our previous chapters, we find significant results related to the Wikipedia search measure. Second, we select the top ten cryptocurrencies and consider the seven-year period from 2017 to 2024, which is an important point, since the papers in the literature mainly study the period until 2022. This time period is important because major events such as the collapse of FTX, the crypto winter, and the launch of ETFs occurred after 2022. These events affect herding behaviour in the cryptocurrency market.

The remainder of the chapter is organised as follows. Section 3.2 provides a review of the literature on herding behaviour and, in particular, the nexus between cryptocurrencies and herding. Section 3.3. outlines the data and empirical methodology. The results are discussed in Section 3.4. Finally, Section 3.5 presents the conclusion.

3.2 Literature Review and Hypothesis Development

Behavioural finance has shown that investment choices are heavily influenced by changes in investor sentiment, which is a key area of research in finance. Papers employ different sources such as Google search data and the VIX Market Fear Index for the extraction of investor sentiment (Gurdgiev et al., 2020; Moat et al., 2013). Studies have shown herding behaviour in different contexts. From the perspective of institutional herding, Guo et al. (2024) found herding behaviour especially predominant in high sentiment periods. Xing et al. (2024) revealed the herding behaviour mainly driven by sentiment in the Chinese stock market during the COVID-19 pandemic; however, there is no evidence of this in the US market. On the other hand, Filip et al. (2023) found herding in the US market, and moreover, there is evidence of herding behaviour under extreme positive and negative sentiment days in the American and European stock markets. Turning to cryptocurrencies, Philippas et al. (2020) examined the impact of

herding intensity, which demonstrates how powerful herd behaviour is in the cryptocurrency market. Using daily data from 100 cryptocurrencies between 01/01/2016 and 31/05/2018, they applied the well-known cross-sectional absolute deviation (CSAD) method for herding detection. Their analysis incorporated market variables, media attention, and indicators of risk and uncertainty to assess the role of exogenous factors on the herding behaviour of the selected cryptocurrencies. Employing the GSVI as a proxy for media attention, they showed that the GSVI causes herding behaviour in cryptocurrency returns. Koch et al. (2023) also used the GSVI to measure investor attention and investigate herding behaviour in cryptocurrencies. Unlike previous studies, they calculated realised correlations to capture price co-movements and detect herding patterns. Their findings indicated that increased attention was associated with the increased price synchronicity of cryptocurrencies. However, this effect was not persistent for more than one day and was primarily concentrated on Bitcoin. Bashir et al. (2021) utilised the GSVI as a measure of investor sentiment and applied CSAD to capture herding dynamics in cryptocurrencies. Their study focused on the impact of the COVID-19 pandemic, revealing that investor attention is associated with anti-herding in the cryptocurrency market, especially during the COVID-19 period, since the pandemic led to increased attention from individual investors, resulting in a greater focus on market operations and more information being made available (Bashir et al., 2021). Overall, these findings on the association between the GSVI sentiment and cryptocurrencies are mixed in the literature.

Some studies show evidence of cryptocurrency herding in both bull and bear markets. Kaiser et al. (2020) investigated herding behaviour in the cryptocurrency market and examined the role of Bitcoin as a transfer currency. In other words, Bitcoin served as a transmission mechanism for the entire cryptocurrency market (Kaiser et al., 2020). Using daily data from 2015 to 2019, they covered all available cryptocurrencies from the CoinmarketCap, aiming to extend the sample and reduce bias. They applied both CSAD and the beta herding methodology

proposed by Hwang and Salmon (2009), which captures the convergence of asset betas over time and analysed herding by using two benchmarks: market-cap weighted portfolio and Bitcoin returns. Their results showed herding, especially when Bitcoin was used as the benchmark, and there was herding in both bear and bull markets, but more strongly in downturns in the cryptocurrency market. The beta herding results indicate lower beta dispersion among cryptocurrencies, supporting the idea of Bitcoin as a transfer currency in the cryptocurrency market, since there is stronger co-movement and systematic alignment in the market. Following Kaiser et al. (2020), we establish our first and second hypotheses:

H_1: In the cryptocurrency market, herding behaviour is observed when the CSAD measure is calculated using both the cap-weighted market portfolio and the Bitcoin benchmark.

We test the recent period from 2017 to 2024 and expect to find herding behaviour in the cryptocurrency market consistent with the literature.

H_2: There is herding in the cryptocurrency market during bearish and bullish market conditions.

We consider the period from 2017 to 2024 as a sample period different from Kaiser et al. (2020) and we expect to find herding in both market conditions result for our second hypothesis, since the major events that occurred after 2019 in the cryptocurrency market might have affected the herding behaviour.

Gurdgiev et al. (2020) examined herding behaviour in the top ten cryptocurrencies by market capitalisation between 2017 and 2019, especially under fear and uncertainty conditions such as the VIX fear index, the US Equity Market Uncertainty Index, which is a news-based

measure of uncertainty in US stock markets developed by Baker et al. (2013), and the CBOE put/call ratio, and applied generalised least squares and generalised method of moments methodology. The results indicated that there is statistically significant herding behaviour, especially in the bear market conditions. Kallinterakis et al. (2019) examined herding in the cryptocurrency market from 2013 to 2018. They analysed 296 cryptocurrencies and applied CSAD. They found herding in the cryptocurrency market, and also during bull markets, low volatility, and high-volume days. Gyamerah (2021) examined the effect of COVID-19 on cryptocurrency herding, considering the returns of the top five cryptocurrencies returns from 2019 to 2021. They also investigated herding behaviour under bear and bull market conditions and applied CSAD. Their results indicated the presence of herding in the cryptocurrency market, particularly during bull markets, and that the COVID-19 pandemic increased herding in the cryptocurrency market. Likewise, Ballis et al. (2020) applied the CSAD to examine the effect of herd behaviour on the top six cryptocurrencies; their results showed that there was herding in the cryptocurrency market, and especially in bullish markets. Haryanto et al. (2020) investigated the disposition effect and herding in the cryptocurrency market from 2011 to 2013. The disposition effect is observed when investors are more reluctant to realise their losses and more eager to realise their gains (Haryanto et al., 2020). According to the CSAD application, there was evidence of herding in both bearish and bullish markets; however, it was greater in the bullish market. These findings contrast with Vidal-Tomás et al. (2019), who analysed the returns of 65 cryptocurrencies between 2015 and 2017 and identified herd behaviour in bear markets; however, the differences in the cryptocurrencies and the sample periods in the studies should be considered. Overall, the findings do not all point in the same direction, given the context of bearish/bullish market conditions in the cryptocurrency market.

Other studies consider alternative sentiment measures on the herding behaviour of cryptocurrencies. For instance, Bouri et al. (2019a) applied the Economy Policy Uncertainty

Index (EPU) of the US to examine the sentiment effect on cryptocurrencies. Using CSAD, they analysed herding in Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash, NEM, Monero, Bytecoin, Verge, Siacoin, BitShares, Decred, and Dogecoin between 28/04/2013 and 02/05/2018. Their results indicated significant herding in the cryptocurrency market, fluctuating over time and driven by uncertainty, when rising uncertainty leads to increased herding. Youssef (2022) investigated the herding intensity by employing the EPU index and CSAD. They found that an increase in the EPU index led to a decrease in herding behaviour in the cryptocurrency market. Additionally, Jia et al. (2022) considered 1,000 cryptocurrencies and applied the Cryptocurrency Market Sentiment Indicator (CMSI). This novel methodology uses daily returns and historical volatility data from cryptocurrencies to construct a sentiment proxy through trading. Also, they built a daily happiness sentiment (DHS) extracted from Twitter to measure investor sentiment. Proposing extremely positive (euphoria) and negative (dysphoria) sentiment, their findings revealed that dysphoria days (negative sentiment) significantly amplified herding behaviour, particularly for larger cryptocurrencies such as Bitcoin and Ethereum, with stronger herding tendencies observed during periods of dysphoria. Following Jia et al. (2022), we create our third hypothesis:

H_3: Herding behaviour increases in the cryptocurrency market during extreme investor sentiment periods.

We use WIKI as an investor sentiment measure in this hypothesis, instead of using CMSI or DHS, and this is our contribution to the literature. To the best of our knowledge, this is the first study to apply WIKI in the context of euphoria/dysphoria days in the cryptocurrency market.

3.3 Data and Empirical Methodology

The cryptocurrency data are obtained from binance.com for Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Dash, Litecoin (LTC), Stellar (XLM), Solana (SOL), Dogecoin (DOGE), Cardano (ADA), and Avalanche (AVAX) daily prices. We use daily data between 01/07/2017 to 30/11/2024 due to data availability.[7] Due to differences in launch dates, the earliest historical price data available for Solana is 11/04/2020, for Cardano 02/10/2017, and for AVAX 23/09/2020. Also, WIKI data does not cover the last month of the main data period, since the data source provides limited availability. Daily cryptocurrency returns are calculated as follows:

$$R_t = p_t - p_{t-1} \tag{3.1}$$

where R is returns, t is time, and p are log prices for cryptocurrencies.

Chang et al. (2000) proposed a widely used method for detecting herding. This approach suggests that asset pricing models predict a linear relation between the distribution of asset returns and the absolute value of market returns. The linear model predicts that individual asset returns will vary from market returns during extreme market movements and, consequently, that individual returns tend to be closer to the market returns during periods of stability. To assess this linearity, the cross-sectional absolute deviation (CSAD) measures the diversion of asset returns from market returns and has become a standard methodology used in the analysis of herd behaviour in the literature. This measurement is calculated as follows (Chang et al., 2000):

[7] As with many studies, a potential technical limitation of this work is the survivorship bias in the data. However, this sample comprises the top ten cryptocurrencies by market capitalisation that were listed and remained in circulation throughout the study period.

$$CSAD_t(x) = \sum_{t=1}^{N_t} w_{x,t}\left|R_{x,t} - R_{m,t}\right| \text{ with } \sum_{t=1}^{N_t} w_{x,t} = 1 \quad (3.2)$$

where $R_{x,t}$ is the return of the cryptocurrencies on day *t*, $w_{x,t}$ is its market-cap weight as $w_{x,t} = \frac{MW_{x,t}}{\sum_{t=1}^{Nt} MW_{x,t}}$, $MW_{x,t}$ is the market cap of each cryptocurrency directly obtained from CoinmarketCap, and $R_{m,t}$ is either the return of a cap-weighted portfolios of the top ten cryptocurrency returns at time t or the return of Bitcoin on that.

To detect herding, we run regressions of the form:

$$CSAD_t(x) = \gamma_0 + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad (3.3)$$

where $R_{m,t}$ is the return of a market-cap-weighted average of the top ten cryptocurrency returns. If, during periods of relatively large price fluctuations, market participants do indeed follow indicators such as the average consensus of all market constituents, the relationship between $CSAD_t$ and the average market return would be nonlinear. This nonlinearity would be captured by a negative and statistically significant γ_2 coefficient. In other words, as $R_{m,t}$ increases, $CSAD_t$ is trending up (or down) over the range where realised average daily returns are less (or greater) than $R_{m,t}$ (Chang et al., 2000). If γ_2 is significantly larger than zero; we would find statistical evidence for anti-herding.

Moreover, to test whether herding takes place in bull or bear markets, we follow Kaiser and Stöckl (2020) and run a similar regression, including a dummy variable D that is equal to 1 when $R_{m,t}$< 0 and 0 otherwise:

$$CSAD_t(x) = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3 (1-D)R_{m,t}^2 + \gamma_4 DR_{m,t}^2 \quad (3.4)$$

Following Jia et al. (2022), to determine whether herding behaviour is related to extreme investor sentiment conditions, we include both an interaction term and main effects in our model:

$$CSAD_t = \alpha_0 + \alpha_1 D R_{m,t}^2 + \alpha_2 R_{m,t}^2 + \alpha_3 D + \alpha_4 \left|R_{m,t}\right| + \alpha_5 R_{m,t}^2 \qquad (3.5)$$

where D is a dummy variable for extreme positive (euphoria) days or extreme negative (dysphoria) days according to levels in the GSVI and Wikipedia sentiment measure. Since we look for the long-term herding behaviour in the cryptocurrency market and believe our sentiment proxies will show more consistent findings, we consider the levels of the sentiment variables. For instance, other sentiment variables such as Twitter or Reddit may give better results if we use them based on their changes rather than their levels, since these sentiment measures capture short-term reactions of the cryptocurrency market more strongly (Georgoula et al., 2015; Kraaijeveld et al., 2020; Li et al., 2021b; Zhang et al., 2022).

We build 1 per cent and 5 per cent to define extreme sentiment conditions, where the upper 1 per cent and 5 per cent are euphoria, and the lower 1 per cent and 5 per cent are dysphoria. $D_{euphoria(dysphoria)}$ is equal to 1 if the GSVI/WIKI is euphoria (dysphoria), 0 otherwise.

Using the same variables as Equation (3.5), following the study of Christie and Huang (1995), who tested whether the average level of dispersion excluding the outermost market returns in the extreme tails of the market return distribution differ significantly, we build an alternative regression model to test both the effects of euphoria and dysphoria tails, and make clearer comparisons with neutral days:

$$CSAD_t = \alpha_0 + \alpha_1 D_{euphoria} R_{m,t}^2 + \alpha_2 D_{dysphoria} R_{m,t}^2 + \alpha_3 D_{euphoria} + \alpha_4 D_{dysphoria} + \alpha_5 \left|R_{m,t}\right| + \alpha_6 R_{m,t}^2 \qquad (3.7)$$

While we use “bitcoin” as a search term on Wikipedia (wikishark.com) data as raw data in our analysis, we apply a construction method to the GSVI variable, since the GSVI raw data is not suitable for analysis. Google Trends does not provide raw search numbers for a subject. Instead, Google Trends calculates the proportion of subject searches to total searches, adjusts the proportion in relation to 100, and normalises the series. The index is calculated by Google Trends using a sample from its database. Thus, refreshing the website results in somewhat different index values. This prevents exact replication, even though the basic conclusions are unlikely to vary as a result of sampling. Additionally, if Google Trends is unable to collect enough data, it gives a result of 0 (Yelowitz et al., 2015). We use “bitcoin” search term on Google Trends and download the data 11 times because the historical data for more than five years is only available at monthly frequency; however, we use daily data in our study. We formulate monthly data for the construction of the daily data with this formula:

$$\left(\frac{(Daily\ data - Daily\ average\ of\ the\ month)}{Daily\ average\ of\ the\ month} * Monthly\ data\right) + Monthly\ data) \qquad (3.6)$$

We extract the daily average for each search term from the daily search term data and then divide it by the daily average for each search term. We then multiply the output by the monthly search term data and add the monthly data to find the constructed data.

Then, we standardise the constructed data applying normalisation, resulting in a mean of zero and a standard deviation of 1 following Liu et al.’s (2021) normalisation formula. We remove the first day of each series we downloaded to obtain series without spikes, because each time we downloaded the data in parts, we refreshed the source page and refreshed the website, resulting in different index values.

All the variables are tested for non-stationarity by employing the Augmented Dickey–Fuller (ADF) test and, rejecting the null, we detect stationary at the 5 per cent significance level for all the series (see Table 3.1).

3.4 Empirical Results

Table 3.2 reports the descriptive statistics of the variables. All the variables have close to zero mean coefficients, except for Wikipedia, since we use the proxy of sentiment as raw data. All the variables are predominantly skewed to the right and are considered risky variables. The similarity in means between the benchmark and cap-weighted market returns is evidence that Bitcoin is the largest cryptocurrency, as it accounts for approximately 60 per cent of the market. Figures 3.4. and 3.5 show CSAD calculations based on market cap-weighted portfolios and Bitcoin returns. The similarity in the graphs indicates that Bitcoin returns dominate the market.

Table 3.3 shows the correlation matrix of the variables. Between the sentiment proxies GSVI BTC and WIKI BTC, and CSAD, there is positive correlation at 0.44 and 0.54, respectively, which shows significant co-movement between them. Similarly, the sentiment proxies have positive correlation coefficients of 0.40 and 0.53, with the CSAD benchmark as well. The correlations between the benchmark and cap-weighted market returns are higher than 90 per cent, which means the cap-weighted returns are driven by Bitcoin returns as the largest cryptocurrency in the market. Moreover, the relationship between GSVI and WIKI is positive and strong with a 0.66 coefficient, which might be a sign that these measures capture similar investor sentiment. Figures 3.6 and 3.7 demonstrate that the Bitcoin search term on the GSVI and WIKI and the increases observed in 2017 and 2021 in these graphs are similar.

Table 3.4 presents regression results for cap-weighted CSAD in relation to the market portfolio in Panel A and regression results for cap-weighted CSAD (referenced to Bitcoin) in relation to the market portfolio in Panel B. Table 3.4 shows the results for Equations (3.3) and

(3.4) in terms of the cap-weighted market return and Bitcoin as the reference currency for the construction of the CSAD measure, respectively. First, in Panel A, we report a statistically significant negative coefficient (i.e., -0.265) for squared market returns ($R_{m,t}^2$) in Column 3, with CSAD measured against the market portfolio and, as such, confirm the existence of herding in the crypto market. This result is in line with Kaiser and Stöckl (2020), who argued that earlier studies such as Bouri et al. (2019a) and Vidal-Tomás et al. (2018), finding no evidence of herding in cryptocurrencies, suffered from a small samples and survivorship bias. They accounted for this by constructing their measures of dispersion based on a large cross-section of available coins at every point in time t. There exists herding in the bear market ($DR_{m,t}^2$) with a coefficient of -0.184, which contrasts with Kaiser and Stöckl (2020), who found herding in both bull and bear markets. These results can be explained by the certainty effect, which is a preference for a loss that is merely probable over a smaller certain loss, as proposed by Kahneman et al. (1979), who argued that a person who has not come to terms with their losses will take risks that would otherwise be unacceptable to them (Kahneman et al., 1979; Tversky et al., 1992).

Similarly, we find statistical evidence of herding when deriving CSAD based on Bitcoin returns. The results presented in Panel B reports a statistically significant negative coefficient (-0.277) for the ($R_{m,t}^2$) and there is herding in bear ($DR_{m,t}^2$) markets (-0.345) in Panel B. This result contrasts with Kaiser and Stöckl (2020), who found herding in both bull and bear markets.

Table 3.5 shows regression results when we apply 1per cent and 5 per cent thresholds to capture euphoria and dysphoria days, separately, both with the cap-weighted market portfolio and Bitcoin benchmark in relation to the market portfolio. We confirm the existence of herding both in all extreme sentiment conditions and the cap-weighted market portfolio and Bitcoin benchmark in Column $R_{m,t}^2$. We show a statistically significant and positive coefficient (0.562) for only euphoria days on 5 per cent extreme sentiment conditions in Panel A, which shows a

sign of anti-herding on the cryptocurrency market and is consistent with the findings of Bashir et al. (2021).

Table 3.6 shows regression results when we apply 1 per cent and 5 per cent thresholds to capture euphoria and dysphoria days in the same equation, both with the cap-weighted market portfolio and Bitcoin benchmark in relation to the market portfolio. The findings are in line with those of Table 3.5.

Table 3.7 shows regression results when we apply 1 per cent and 5 per cent thresholds for euphoria and dysphoria days and use the Wikipedia search levels, both with the cap-weighted market portfolio and Bitcoin benchmark in relation to the market portfolio. Similar to the GSVI results, we confirm the existence of herding both in all extreme sentiment conditions and the cap-weighted market portfolio and Bitcoin benchmark. Furthermore, the significant coefficients (0.747 and 0.418) on euphoria days in 1 per cent and 5 per cent extreme sentiment conditions in Panel A support the GSVI results.

Table 3.8 shows regression results when we apply 1 per cent and 5 per cent thresholds for euphoria and dysphoria days sentiment and use the Wikipedia search levels in the same equation, both with cap-weighted market portfolio and Bitcoin benchmark in relation to the market portfolio. The findings are in line with those of Table 3.7.

This shows that investors who consider either Google or Wikipedia searches on their investment decisions have a similar decision pattern, and this is our contribution to the literature.

Overall, our findings support our first and second hypotheses. We find herding behaviour in the cryptocurrency market when the CSAD measure is calculated using both the cap-weighted market portfolio and the Bitcoin benchmark. We confirm that Bitcoin still dominates the cryptocurrency market by calculating benchmarks for CSAD, and herding behaviour exists in the cryptocurrency market from 2017 to 2024. This result is consistent with

the literature (Philippas et al., 2020; Koch et al., 2023). Secondly, we find herding in the cryptocurrency market during bearish market conditions, which is consistent with the studies by Vidal-Tomás et al. (2019), Kallinterakis et al. (2019), Gyamerah (2021), and Gurdgiev et al. (2020). We do not find herding behaviour in the bull market, unlike Kaiser et al. (2020), who found herding in both bear and bull markets, predominantly in the bearish market from 2015 to 2019. Our findings reveal that herding behaviour only occurs in the bear market from 2017 to 2024; thus, we update recent findings in this context.

We follow Jia et al. (2022) when formulating our third hypothesis. In their study, using CMSI and DHS investor sentiment measures to find herding behaviour in extreme positive (euphoria) and negative (dysphoria) sentiment days, Jia et al. (2022) found that dysphoria days significantly affected herding behaviour. However, our results reveal that there is only anti-herding behaviour is observed in both the GSVI and WIKI sentiment-based positive extreme days. The results highlight our contribution that we find anti-herding behaviour on extreme days from 2017 to 2024.

3.5 Conclusion

This study aims to investigate herding and asymmetric herding behaviour in the cryptocurrency market.

There is a growing body of literature studying herding behaviour in cryptocurrency markets (Bouri et al., 2019a; Ballis et al. 2020). Some of these studies examined asymmetric herding behaviour on cryptocurrencies as well (Gurdgiev et al., 2020; Kaiser et al., 2020). Some papers focused on the impact of extreme sentiment conditions on cryptocurrencies, such as the GSVI, Twitter tweets, and daily happiness sentiment proxies (Jia et al. 2022, Philippas et al. 2020). All these studies rely on the CSAD framework to detect herding behaviour, which is widely used in the literature. However, to the best of our knowledge, there are as yet no papers

on this topic that study 2022 and beyond. This is important because major events such as the collapse of FTX, the crypto winter in 2022, and the launch of ETFs occurred after 2022. These events affected herding behaviour in the cryptocurrency market. Furthermore, there are no papers that consider Wikipedia search data as a proxy for sentiment in the herding behaviour of cryptocurrencies. This chapter contributes to the literature by showing how Wikipedia searches affect herding behaviour in the cryptocurrency market. Our contribution to the literature is that we are the first study to test Wikipedia searches, previously used as a variable in relation to cryptocurrency returns and volatility in limited studies (Kristoufek 2013; Yu et al. 2019), in the herding context.

Given these gaps, we consider the top ten cryptocurrencies (Bitcoin, Ethereum, Ripple, Dash, Litecoin, Stellar, Solana, Dogecoin, Cardano, Avalanche) and create a market portfolio with their daily return of a market-cap weighted average of them. We apply CSAD methodology to the variables between 01/07/2017 and 30/11/2024. Using dummy variables, we test the bearish and bullish markets as well, similar to Kaiser et al. (2020). Our test results show the existence of herding behaviour in the cryptocurrency market and also asymmetric herding when the market is decreasing. Since the cryptocurrency market is more volatile than other markets, such as the stock market, investors may show more herd behaviour during bearish market conditions.

Furthermore, we investigate extreme sentiment conditions. We create 1 per cent and 5 per cent euphoria and dysphoria dummy variables that capture the extreme positive and negative days on the sentiment, respectively. We find that investors do not tend to show herding behaviour during euphoria days. The GSVI and Wikipedia sentiment proxies show similar results, which indicates that investors searching for the term "Bitcoin" on Google and Wikipedia on positive sentiment days did not tend to herd in the cryptocurrency market.

In conclusion, our study indicates that herding behaviour exists in the cryptocurrency market, especially during a bearish market. Moreover, when the investors are positive to the market based on Google and Wikipedia (euphoria days), they show more independent investment decisions. This study can be extended by using data after 2024 and selecting more cryptocurrencies and investor sentiment measures.

CONCLUSION

Cryptocurrencies have emerged as popular digital assets in global markets over the last decade. As a consequence, investors and researchers have turned their attention to cryptocurrencies in part due to their independence from any authority or country, such as the government or central bank, as well as their typical high volatility and potential for significant profit or loss. Relatedly, investor attention has become important for the cryptocurrency market, as investors embrace cryptocurrencies as an alternative investment instrument.

In our first chapter, we investigate the association between the Google Search Volume Index (GSVI) and Wikipedia (WIKI) page searches (as proxies for investor attention) and cryptocurrency returns in three different periods, from 2017 to 2022, from 2017 to 2020, and from 2020 to 2022, respectively. We justify the subsample analysis by noting that the period before 2020 presented relatively smooth price movements, whereas subsequently, and concurrent with the COVID-19 pandemic, monetary policy changes and a crypto 'winter', dynamics were more volatile. Overall, we show empirically that GSVI commonly presents more predictability (with forecast horizons up to eight weeks) than Wikipedia searches, and one could argue that this reflects that GSVI may capture more *frequent* initial searches, rather than the *slower*, deeper interest gleaned from WIKI.

Building on Liu et al. (2021), who found a positive and significant relationship between Bitcoin and Ethereum returns and GSVI investor attention, we also find this association from 2017 to 2020; however, we do not find it in the latter sample period. This striking result implies that the association between investor attention and the most well-known cryptocurrency returns has substantially weakened after 2020, indicating less predictability from GSVI—potentially as a result of greater volatility in price dynamics and/or the possibility that investors have already progressed to more specialised information sources. It should be noted that this weakening of the predictability relation, although still present, happens less for

cryptocurrencies such as Ripple, Stellar, and Dash. The fact that Ripple provides more significant results for the GSVI in the latter sample period, when compared to other cryptocurrency returns, might be due to differences in infrastructure in its system and the attention it has received, as well as some legal issues it has been experiencing with the SEC since December 2020. Furthermore, the reason why Google searches have an impact on Dash and Stellar returns from 2020 to 2022 may be that these terms have meanings beyond their use as cryptocurrency names, unlike other cryptocurrencies.

The first chapter makes three main contributions to the literature. First, we extend the sample period to include 2019 and beyond. This is important for investigating the cryptocurrency-investor attention nexus after 2020 as COVID-19, the FTX failure, and the start of the crypto winter all occurred after this date and contributed to greatly increased price volatility (Arner et al., 2023). To the best of our knowledge, there is currently no study covering 2021 and beyond examining the relationship between cryptocurrency returns and the GSVI and WIKI. Second, while most studies in the extant literature provide empirical evidence that there is a positive association between cryptocurrency returns and investor attention measures, the work in Chapter 1 shows that this result does not hold for Bitcoin and Ethereum in the subperiod from 2020 to 2022. This new finding suggests that the cryptocurrency–investor attention nexus weakened after 2020 with events such as the COVID-19 pandemic, monetary policy responses, and the crypto winter leading to greater volatility in price dynamics. This indicates that investor attention measures predictability for cryptocurrency returns is weakening—an important practical implication for investors. This weakening, although still present, happens less for cryptocurrencies such as Ripple, Stellar, and Dash. Third, we do not typically find a significant impact of WIKI on cryptocurrency returns, especially for Bitcoin and Stellar returns, which is an important contribution since the literature shows a significant association between Wikipedia searches and cryptocurrency returns. While GSVI may represent an initial search, WIKI likely

represents a deeper interest in the subject (Kämpf et al., 2015). Of course, by 2020, Bitcoin was by far the most well-known cryptocurrency, and plausibly, many investors had already progressed to more detailed information sources than GSVI or WIKI. This new finding enriches the literature by revealing that the association between investor attention and Bitcoin and Ethereum returns has recently weakened. Considering these findings, cryptocurrency investors will be able to build their portfolios more informedly by knowing which cryptocurrency returns are more sensitive to investor attention.

In our second chapter, we aim to investigate the effect of the same attention measures used above on cryptocurrency return volatility. To the best of our knowledge, there are no other studies that investigate the effect of the GSVI and the WIKI investor attention measures on the second moment within a single framework. Moreover, as far as we know, our study is the first to employ a GARCH-type framework, consider data after the 2020 period, and examine the effects of WIKI on cryptocurrency return volatility, namely, Bitcoin, Ethereum, Ripple, Litecoin, Dash, Stellar, and Solana, the largest cryptocurrencies by market capitalisation in 2024. Importantly, we find that both the GSVI and WIKI commonly positively drive the volatility of cryptocurrencies over the full sample period, from 2017 to 2023. This result extends work such as Figà-Talamanca et al. (2019), who only examined Bitcoin and GSVI. What is interesting at this point is that we find that both GSVI and WIKI have a negative impact on Ripple returns. These new findings contribute to the literature by suggesting that as investor attention in Ripple on Wikipedia increases, its returns decrease. There could be many reasons for this, such as the lawsuit initiated in 2020 by the SEC on whether Ripple is a security, as a result of which the Ripple price fell. The subsequent COVID pandemic also reinforced this situation. In July 2023, Ripple won a partial victory in this case, but our analysis shows that WIKI negatively affected Ripple returns between 2020 and 2023. Furthermore, we find interesting results related to Solana. Specifically, while GSVI affects Solana volatility

negatively, WIKI presents a positive association in the latter sample period. Negative experiences in Solana between 2020 and 2023 may have had a detrimental effect on returns, as investment decisions are based on their initial searches on Google. Finally, in the results of GARCH-type regressions where we include both the GSVI and WIKI investor attention measures together in the same equation, we conclude that the association of WIKI and cryptocurrency return volatility is often stronger than the association between GSVI and cryptocurrency return volatility, in terms of p-value. This reflects that WIKI may affect volatility by providing deeper information than initial Google searches.

In our third chapter, we combine and extend the work of Kaiser et al. (2020), which investigated herding behaviour in the cryptocurrency market, and Jia et al. (2022), which studied the effects of extreme sentiment conditions (also in the cryptocurrency market). Specifically, we investigate extreme sentiment conditions (i.e., based on the GSVI and WIKI measures used in earlier chapters); to do so, we follow Jia et al. (2022) by creating 1 per cent and 5 per cent euphoria and dysphoria dummy variables, which captured the extreme positive and negative days for sentiment, respectively. In addition, to the best of our knowledge, our study is the first to cover 2022 and beyond when considering herding in the cryptocurrency market. Furthermore, no other studies have considered WIKI search data as a proxy for sentiment in the herding behaviour of cryptocurrencies. Employing CSAD by Chang et al. (2000), we consider Bitcoin, Ethereum, Ripple, Litecoin, Dash, Stellar, Solana, Dogecoin, Cardano and Avalanche from 2017 to 2024. Our study indicates that herding behaviour exists in the cryptocurrency market, especially during the bearish market. These results can be explained by the certainty effect, which is a preference for a loss that is merely probable over a smaller certain loss, as proposed by Kahneman et al. (1979). Relatedly, we find that investors do not tend to herd during euphoria days. Both GSVI and WIKI sentiment proxies show similar results.

Overall, this thesis provides significant contributions to the literature in the field of cryptocurrency markets and investor attention research by examining the impact of investor attention measures on cryptocurrency returns, volatility, and herd behaviour. In the first chapter, we find evidence of a weakening association in the recent period between attention measures and cryptocurrency returns. Moreover, our findings on the association between Ripple returns and investor attention measures differ from those in the literature. In the second chapter, we find significant results between attention measures and cryptocurrency returns volatility. Furthermore, we demonstrate that WIKI drives investor attention positively, whereas GSVI commonly drives cryptocurrency volatility negatively. In the third chapter, we use both GSVI and WIKI as sentiment proxies to detect herding behaviour in the cryptocurrency market, and as far as we know, ours is the first study to do so. These analyses of the impact of sentiment measures on cryptocurrencies contribute to existing literature on the subject. In addition, by examining the period of the recent past in our thesis, we provide insights for future research.

Finally, as with all research work, there are limitations. One potential limitation of this study is the presence of endogeneity issues, which relate to the composition of the error term. In the context of cryptocurrency markets, the error term inevitably captures various unobservable or difficult-to-measure factors, such as informal social media hype or unrecorded regulatory rumours. These unobserved factors are likely to be correlated with the independent variables included in the model, thereby introducing the risk of omitted variable bias. Due to data constraints, it was not possible to fully isolate the causal impact of this model. Future studies could address this by identifying strictly exogenous instrumental variables and considering more sophisticated modelling approaches and/or both in-sample and out-of-sample forecasting evaluation methods. Moreover, there are many cryptocurrencies not considered in this thesis. For future research, more cryptocurrencies, particularly those much less traded and where investors may have different information requirements, should be examined. Finally, to

provide more up-to-date information, the period under consideration could be extended to the present day.

Appendix

Table 1.1 Augmented Dickey-Fuller (ADF) test results

Panel A. ADF Unit Root Test	**Intercept - Level**	
	t-Statistics	**p-Value**
BTC	-11.06	0.000 (H_0 is rejected)
ETH	-11.58	0.000 (H_0 is rejected)
LTC	-11.97	0.000 (H_0 is rejected)
DASH	-11.78	0.000 (H_0 is rejected)
XRP	-11.17	0.000 (H_0 is rejected)
XLM	-12.55	0.000 (H_0 is rejected)
GSVI-BTC	-10.14	0.000 (H_0 is rejected)
GSVI-ETH	-8.85	0.000 (H_0 is rejected)
GSVI-LTC	-10.14	0.000 (H_0 is rejected)
GSVI-DASH	-9.15	0.000 (H_0 is rejected)
GSVI-XRP	-9.88	0.000 (H_0 is rejected)
GSVI-XLM	-10.28	0.000 (H_0 is rejected)
WIKI-BTC	-11.13	0.000 (H_0 is rejected)
WIKI-ETH	-10.10	0.000 (H_0 is rejected)
WIKI-LTC	-6.82	0.000 (H_0 is rejected)
WIKI-DASH	-10.62	0.000 (H_0 is rejected)
WIKI-XRP	-5.06	0.000 (H_0 is rejected)
WIKI-XLM	-6.82	0.000 (H_0 is rejected)
GOLD	-12.49	0.000 (H_0 is rejected)
USDOLLAR INDEX	-13.80	0.000 (H_0 is rejected)
S&P500 INDEX	-14.84	0.000 (H_0 is rejected)

Notes: Table 1.1. shows that the ADF test results of the variables.

Table 1.2 Descriptive statistics

Panel A. 2017 – 2022 term					Panel B. 2017 – 2020 term				Panel C. 2020 – 2022 term			
Weekly	**Mean**	**SD**	**Skewness**	**Kurtosis**	**Mean**	**SD**	**Skewness**	**Kurtosis**	**Mean**	**SD**	**Skewness**	**Kurtosis**
BTC	0.00%	0.09%	-0.05%	4.10%	0.00%	0.09%	0.21%	3.57%	0.00%	0.09%	-0.42%	4.74%
ETH	0.00%	0.11%	-0.11%	4.24%	-0.00%	0.12%	0.09%	3.40%	0.01%	0.11%	-0.37%	5.48%
LTC	0.00%	0.12%	1.18%	11.28%	0.00%	0.13%	2.04%	14.52%	-0.00%	0.11%	-0.38%	3.87%
DASH	-0.00%	0.13%	0.45%	5.49%	-0.00%	0.13%	0.92%	5.34%	-0.00%	0.13%	-0.08%	5.72%
XRP	-0.00%	0.13%	0.95%	7.90%	-0.01%	0.10%	1.31%	7.88%	0.00%	0.15%	0.74%	6.80%
XLM	0.00%	0.16%	1.82%	10.11%	0.00%	0.17%	1.79%	9.28%	0.00%	0.14%	1.78%	10.83%
GSVI – BTC	1.02%	1.00%	1.43%	11.31%	-0.02%	0.98%	1.44%	15.44%	0.02%	1.01%	1.42%	7.06%
GSVI – ETH	-1.28%	1.00%	1.03%	15.18%	-0.05%	0.53%	0.85%	10.12%	0.05%	1.34%	0.74%	9.55%
GSVI – LTC	0.00%	1.00%	7.06%	101.03%	-0.00%	1.33%	5.53%	59.33%	0.00%	0.31%	1.01%	9.15%
GSVI – DASH	-0.00%	1.00%	1.91%	16.38%	-0.00%	1.04%	1.08%	12.22%	0.01%	0.94%	3.18%	23.01%
GSVI – XRP	-0.00%	0.23%	2.58%	19.41%	-0.01%	0.12%	1.44%	11.54%	-0.00%	0.29%	2.23%	13.84%
GSVI – XLM	0.00%	1.00%	4.66%	62.05%	-0.00%	1.21%	4.56%	51.89%	0.00%	0.67%	2.02%	15.56%
WIKI – BTC	0.00%	1.00%	3.38%	41.55%	-0.01%	1.30%	2.84%	26.87%	0.02%	0.44%	1.28%	8.21%
WIKI – ETH	0.00%	1.00%	2.87%	31.00%	-0.04%	1.27%	2.66%	22.50%	0.04%	0.55%	0.89%	10.58%
WIKI – LTC	0.00%	1.00%	2.71%	36.99%	-0.01%	1.25%	2.59%	28.13%	0.02%	0.60%	0.64%	12.10%
WIKI – DASH	0.00%	1.00%	-0.85%	7.83%	0.02%	0.98%	-0.97%	8.66%	-0.02%	1.02%	-0.72%	7.04%
WIKI – XRP	-0.00%	1.08%	0.67%	32.98%	-0.00%	0.04%	2.16%	15.98%	0.00%	1.44%	0.50%	18.65%
WIKI – XLM	222.25%	280.35%	6.57%	58.09%	210.28%	266.13%	5.71%	43.73%	235.89%	296.24%	7.23%	67.45%
USDOLLAR INDEX	-0.00%	0.15%	-0.21%	4.76%	-0.00%	0.15%	-0.21%	4.13%	-0.00%	0.16%	-0.20%	5.48%
GOLD	0.00%	0.17%	-0.23%	13.21%	0.00%	0.18%	-1.19%	14.04%	0.00%	0.17%	0.89%	12.13%
S&P500	0.00%	0.12%	0.01%	3.10%	0.00%	0.13%	0.04%	3.05%	0.00%	0.12%	0.00%	3.19%

Notes: Table 1.2. reports the weekly summary statistics of returns for each cryptocurrency, the GSVI and Wikipedia for each cryptocurrency searches, gold, US dollar index and S&P500index.

Table 1.3 Correlation matrix of the variables from 2017 to 2022

Panel A. 2017-2022	BTC	ETH	LTC	DASH	XRP	XLM	GSVI-BTC	GSVI-ETH	GSVI-LTC	GSVI-DASH	GSVI-XRP	GSVI-XLM	GOLD	USDOLLAR INDEX	S&P 500	WIKI-BTC	WIKI-ETH	WIKI-LTC	WIKI-DASH	WIKI-XRP	WIKI-XLM
BTC	1																				
ETH	0.81 (20.65)	1																			
LTC	0.81 (20.73)	0.81 (20.85)	1																		
DASH	0.23 (3.53)	0.28 (4.34)	0.27 (4.19)	1																	
XRP	0.12 (1.78)	0.20 (3.07)	0.20 (3.03)	0.62 (11.69)	1																
XLM	0.16 (2.45)	0.19 (2.97)	0.15 (2.30)	0.68 (13.72)	0.77 (17.93)	1															
GSVI-BTC	-0.00 (-0.13)	0.04 (0.61)	-0.03 (-0.44)	-0.07 (-1.13)	-0.14 (-2.09)	0.02 (0.43)	1														
GSVI-ETH	-0.06 (-1.02)	0.08 (1.23)	0.03 (0.46)	0.11 (1.70)	0.10 (1.47)	0.26 (4.04)	0.60 (11.17)	1													
GSVI-LTC	-0.01 (-0.21)	0.06 (0.94)	-0.01 (-0.23)	0.33 (5.13)	0.16 (2.44)	0.34 (5.39)	0.62 (11.65)	0.69 (14.16)	1												
GSVI-DASH	0.04 (0.60)	-0.02 (-0.38)	0.08 (1.20)	0.42 (6.79)	0.15 (2.28)	0.24 (3.60)	0.26 (3.97)	0.30 (4.63)	0.46 (7.76)	1											
GSVI-XRP	0.17 (2.60)	0.19 (2.83)	0.21 (3.20)	0.23 (3.59)	0.41 (6.65)	0.31 (4.92)	0.24 (3.61)	0.27 (4.13)	0.51 (8.78)	0.23 (3.53)	1										
GSVI-XLM	-0.02 (-0.35)	0.02 (0.42)	-0.01 (-0.26)	0.32 (5.02)	0.38 (6.06)	0.56 (10.00)	0.44 (7.17)	0.64 (12.35)	0.75 (16.76)	0.35 (5.49)	0.49 (8.41)	1									
GOLD	-0.08 (-1.20)	-0.14 (-2.13)	-0.07 (-1.02)	-0.00 (-0.09)	0.08 (1.17)	0.12 (1.78)	0.16 (2.41)	0.15 (2.26)	0.16 (2.38)	0.03 (0.46)	-0.02 (-0.30)	0.25 (3.92)	1								
USDOLLAR INDEX	0.01 (0.18)	0.03 (0.54)	0.05 (0.83)	-0.06 (-0.99)	-0.03 (-0.54)	-0.09 (-1.45)	0.02 (0.34)	0.02 (0.37)	0.00 (0.10)	-0.03 (-0.58)	-0.03 (-0.54)	0.01 (0.26)	0.32 (5.02)	1							
S&P 500	-0.00 (-0.01)	0.02 (0.39)	0.05 (0.85)	0.02 (0.32)	0.07 (1.08)	0.03 (0.45)	-0.03 (-0.52)	0.01 (0.24)	0.02 (0.32)	-0.04 (-0.66)	0.03 (0.58)	0.09 (1.44)	0.29 (4.52)	0.75 (16.72)	1						
WIKI-BTC	-0.02 (-0.40)	0.00 (0.02)	-0.07 (-1.05)	0.05 (0.86)	-0.05 (-0.95)	0.00 (0.01)	0.32 (4.99)	0.24 (3.66)	0.21 (3.27)	0.15 (2.22)	0.01 (0.21)	0.09 (1.35)	0.04 (0.68)	-0.08 (-1.23)	-0.07 (-1.10)	1					
WIKI-ETH	0.02 (0.30)	-0.01 (-0.26)	-0.00 (-0.06)	0.17 (2.62)	0.01 (0.23)	0.08 (1.18)	0.26 (4.02)	0.32 (5.06)	0.22 (3.39)	0.19 (2.95)	0.03 (0.44)	0.21 (3.16)	0.15 (2.25)	0.01 (0.21)	-0.02 (-0.42)	0.48 (8.08)	1				
WIKI-LTC	0.10 (1.58)	0.10 (1.56)	0.07 (1.02)	0.06 (0.92)	0.03 (0.51)	0.09 (1.44)	0.31 (4.81)	0.21 (3.28)	0.23 (3.53)	0.09 (1.34)	0.17 (2.55)	0.20 (3.13)	0.02 (0.41)	-0.03 (-0.56)	-0.00 (-0.03)	0.45 (7.41)	0.32 (5.03)	1			
WIKI-DASH	0.01 (0.19)	-0.00 (-0.02)	0.00 (0.01)	-0.01 (-0.23)	0.07 (1.08)	-0.07 (-1.11)	-0.10 (-1.51)	-0.12 (-1.85)	-0.15 (-2.24)	0.02 (0.29)	-0.09 (-1.44)	-0.09 (-1.39)	-0.05 (-0.76)	-0.10 (-1.50)	-0.09 (-1.44)	0.09 (1.44)	-0.14 (-2.13)	0.10 (1.52)	1		

WIKI-XRP	0.15 (2.29)	0.08 (1.31)	0.10 (1.60)	0.00 (0.05)	0.03 (0.47)	0.04 (0.71)	0.05 (0.80)	-0.01 (-0.18)	-0.05 (-0.73)	-0.04 (-0.63)	0.03 (0.50)	0.00 (0.06)	-0.00 (-0.03)	-0.01 (-0.21)	0.00 (0.11)	0.18 (2.81)	0.17 (2.53)	0.81 (20.67)	0.06 (0.93)	1
WIKI-XLM	0.02 (0.33)	0.02 (0.36)	-0.02 (-0.39)	0.03 (0.47)	-0.05 (-0.81)	-0.06 (-0.90)	0.17 (2.66)	0.11 (1.64)	0.06 (0.95)	0.04 (0.60)	-0.07 (-1.03)	-0.02 (-0.38)	-0.02 (-0.36)	0.01 (0.19)	-0.05 (-0.82)	0.13 (1.98)	0.10 (1.47)	0.04 (0.72)	-0.00 (-0.10)	-0.03 (-0.46)	1

Notes: Table 1.3. reports the correlations between each cryptocurrency returns, the search query "name of cryptocurrency" from the GSVI and Wikipedia searches, gold, US dollar index and S&P500 index for the period 2017 - 2022.

Table 1.4 Correlation matrix of the variables from 2017 to 2020

Panel B. 2017-2020	BTC	ETH	LTC	DASH	XRP	XLM	GSVI-BTC	GSVI-ETH	GSVI-LTC	GSVI-DASH	GSVI-XRP	GSVI-XLM	GOLD	USDOLLAR INDEX	S&P 500	WIKI-BTC	WIKI-ETH	WIKI-LTC	WIKI-DASH	WIKI-XRP	WIKI-XLM
BTC	1																				
ETH	0.80 (12.94)	1																			
LTC	0.75 (11.00)	0.80 (13.12)	1																		
DASH	0.22 (2.22)	0.31 (3.14)	0.23 (2.26)	1																	
XRP	0.17 (1.68)	0.34 (3.54)	0.19 (1.93)	0.59 (7.06)	1																
XLM	0.13 (1.28)	0.21 (2.12)	0.08 (0.80)	0.68 (8.85)	0.74 (10.68)	1															
GSVI-BTC	-0.03 (-0.33)	-0.01 (-0.14)	-0.05 (-0.48)	0.14 (1.40)	0.05 (0.56)	0.06 (0.64)	1														
GSVI-ETH	-0.12 (-1.23)	-0.04 (-0.45)	-0.03 (-0.33)	0.00 (0.08)	0.00 (0.09)	0.10 (1.04)	0.39 (4.10)	1													
GSVI-LTC	0.10 (1.00)	0.20 (1.96)	0.07 (0.75)	0.35 (3.64)	0.29 (2.98)	0.23 (2.34)	0.54 (6.17)	0.24 (2.37)	1												
GSVI-DASH	-0.02 (-0.21)	-0.03 (-0.36)	-0.03 (-0.33)	0.53 (6.07)	0.11 (1.10)	0.27 (2.72)	0.42 (4.43)	0.16 (1.59)	0.35 (3.65)	1											
GSVI-XRP	0.12 (1.24)	0.15 (1.51)	0.15 (1.45)	0.22 (2.23)	0.56 (6.45)	0.31 (3.17)	0.28 (2.82)	0.16 (1.59)	0.33 (3.40)	0.13 (1.31)	1										
GSVI-XLM	0.05 (0.54)	0.10 (0.99)	0.04 (0.47)	0.31 (3.11)	0.30 (3.09)	0.49 (5.45)	0.18 (1.83)	0.11 (1.14)	0.11 (1.06)	0.21 (2.05)	0.24 (2.39)	1									
GOLD	0.00 (0.00)	-0.09 (-0.94)	0.03 (0.32)	0.04 (0.46)	-0.00 (-0.09)	0.00 (0.02)	0.05 (0.54)	-0.00 (-0.06)	-0.01 (-0.17)	0.00 (0.01)	-0.03 (-0.31)	0.09 (0.88)	1								
USDOLLAR INDEX	0.14 (1.36)	0.13 (1.31)	0.24 (2.38)	0.03 (0.29)	-0.01 (-0.10)	-0.12 (-1.22)	-0.05 (-0.49)	0.01 (0.18)	0.00 (0.06)	-0.02 (-0.19)	0.01 (0.10)	0.00 (0.07)	0.40 (4.20)	1							
S&P 500	0.07 (0.70)	0.09 (0.86)	0.18 (1.75)	0.09 (0.89)	-0.00 (-0.01)	-0.06 (-0.64)	-0.10 (-0.97)	0.03 (0.35)	-0.02 (-0.25)	-0.03 (-0.34)	0.03 (0.30)	0.16 (1.55)	0.37 (3.81)	0.77 (11.88)	1						
WIKI-BTC	-0.14 (-1.39)	-0.11 (-1.09)	-0.10 (-1.04)	0.05 (0.55)	-0.10 (-1.02)	-0.13 (-1.29)	0.10 (1.00)	0.06 (0.63)	0.05 (0.56)	0.20 (1.99)	0.04 (0.40)	-0.02 (-0.26)	0.14 (1.36)	-0.00 (-0.04)	-0.01 (-0.16)	1					
WIKI-ETH	0.06 (0.61)	-0.05 (-0.55)	0.04 (0.39)	0.25 (2.53)	0.00 (0.05)	0.01 (0.11)	-0.00 (-0.04)	-0.04 (-0.40)	-0.04 (-0.46)	0.41 (4.34)	0.01 (0.15)	0.05 (0.49)	0.19 (1.89)	0.07 (0.72)	-0.02 (-0.19)	0.50 (5.62)	1				
WIKI-LTC	0.05 (0.50)	0.09 (0.92)	0.07 (0.72)	0.05 (0.52)	0.13 (1.32)	0.04 (0.42)	0.16 (1.61)	0.21 (2.10)	0.26 (2.58)	0.04 (0.43)	0.53 (6.02)	0.21 (2.10)	-0.03 (-0.30)	0.01 (0.13)	0.02 (0.20)	0.44 (4.74)	0.05 (0.50)	1			
WIKI-DASH	-0.11 (-1.07)	0.00 (0.04)	-0.04 (-0.42)	-0.01 (-0.12)	0.03 (0.31)	-0.02 (-0.23)	0.06 (0.60)	-0.07 (-0.75)	0.01 (0.13)	-0.02 (-0.22)	0.01 (0.10)	0.10 (1.01)	-0.15 (-1.47)	-0.12 (-1.21)	-0.11 (-1.14)	-0.04 (-0.46)	-0.37 (-3.89)	0.05 (0.54)	1		

WIKI-XRP	-0.01 (-0.10)	0.04 (0.38)	-0.00 (-0.02)	-0.15 (-1.53)	-0.07 (-0.72)	-0.08 (-0.79)	0.02 (0.26)	-0.05 (-0.54)	0.05 (0.51)	0.01 (0.13)	-0.03 (-0.31)	-0.12 (-1.23)	0.01 (0.15)	-0.03 (-0.31)	-0.06 (-0.60)	0.04 (0.43)	0.02 (0.27)	-0.06 (-0.58)	0.09 (0.88)	1
WIKI-XLM	-0.29 (-2.94)	-0.31 (-3.14)	-0.24 (-2.41)	-0.16 (-1.56)	0.03 (0.33)	-0.04 (-0.46)	0.08 (0.84)	-0.01 (-0.18)	0.00 (0.08)	0.04 (0.38)	0.16 (1.61)	-0.00 (-0.07)	-0.07 (-0.67)	-0.03 (-0.32)	-0.05 (-0.48)	-0.01 (-0.11)	-0.05 (-0.55)	0.02 (0.23)	0.17 (1.69)	0.03 (0.35)	1

Notes: Table 1.4. reports the correlations between each cryptocurrency returns, the search query "name of cryptocurrency" from the GSVI and Wikipedia searches, gold, US dollar index and S&P500 index for the period 2017 – 2020.

Table 1.5 Correlation matrix of the variables from 2020 to 2022

Panel C. 2020-2022	BTC	ETH	LTC	DASH	XRP	XLM	GSVI-BTC	GSVI-ETH	GSVI-LTC	GSVI-DASH	GSVI-XRP	GSVI-XLM	GOLD	USDOLLAR INDEX	S&P 500	WIKI-BTC	WIKI-ETH	WIKI-LTC	WIKI-DASH	WIKI-XRP	WIKI-XLM
BTC	1																				
ETH	0.82 (16.03)	1																			
LTC	0.85 (17.94)	0.82 (16.17)	1																		
DASH	0.23 (2.67)	0.26 (2.95)	0.29 (3.40)	1																	
XRP	0.09 (1.04)	0.13 (1.49)	0.20 (2.25)	0.64 (9.23)	1																
XLM	0.17 (1.96)	0.17 (1.97)	0.18 (2.04)	0.68 (10.37)	0.78 (13.84)	1															
GSVI-BTC	-0.00 (-0.07)	0.05 (0.58)	-0.03 (-0.35)	-0.13 (-1.47)	-0.18 (-2.00)	0.02 (0.23)	1														
GSVI-ETH	-0.07 (-0.85)	0.10 (1.19)	0.04 (0.46)	0.14 (1.63)	0.11 (1.25)	0.30 (3.54)	0.61 (8.56)	1													
GSVI-LTC	-0.04 (-0.47)	0.03 (0.40)	-0.04 (-0.44)	0.35 (4.20)	0.14 (1.62)	0.38 (4.56)	0.63 (8.86)	0.73 (11.42)	1												
GSVI-DASH	0.05 (0.62)	-0.02 (-0.31)	0.11 (1.24)	0.44 (5.40)	0.16 (1.81)	0.24 (2.77)	0.25 (2.84)	0.31 (3.56)	0.47 (5.95)	1											
GSVI-XRP	0.19 (2.20)	0.21 (2.36)	0.24 (2.76)	0.25 (2.93)	0.39 (4.63)	0.33 (3.81)	0.23 (2.67)	0.28 (3.24)	0.53 (6.95)	0.24 (2.77)	1										
GSVI-XLM	-0.04 (-0.48)	0.01 (0.15)	-0.03 (-0.38)	0.36 (4.29)	0.41 (4.92)	0.61 (8.48)	0.45 (5.62)	0.67 (9.87)	0.80 (14.89)	0.36 (4.24)	0.52 (6.78)	1									
GOLD	-0.13 (-1.53)	-0.17 (-1.97)	-0.14 (-1.58)	-0.04 (-0.49)	0.13 (1.46)	0.19 (2.20)	0.21 (2.39)	0.21 (2.34)	0.23 (2.59)	0.04 (0.48)	-0.01 (-0.19)	0.34 (3.94)	1								
USDOLLAR INDEX	-0.07 (-0.77)	-0.02 (-0.30)	-0.06 (-0.66)	-0.12 (-1.37)	-0.04 (-0.43)	-0.07 (-0.79)	0.04 (0.47)	0.03 (0.36)	0.01 (0.11)	-0.04 (-0.51)	-0.05 (-0.63)	0.02 (0.26)	0.26 (2.99)	1							
S&P 500	-0.04 (-0.54)	-0.01 (-0.16)	-0.02 (-0.23)	-0.01 (-0.20)	0.12 (1.39)	0.10 (1.10)	-0.02 (-0.30)	0.01 (0.20)	0.03 (0.43)	-0.05 (-0.57)	0.04 (0.51)	0.09 (1.08)	0.23 (2.63)	0.72 (11.63)	1						
WIKI-BTC	0.02 (0.29)	0.05 (0.59)	-0.05 (-0.58)	0.06 (0.72)	-0.04 (-0.53)	0.05 (0.61)	0.37 (4.41)	0.28 (3.21)	0.25 (2.91)	0.15 (1.67)	0.00 (0.07)	0.11 (1.28)	-0.00 (-0.05)	-0.13 (-1.53)	-0.11 (-1.28)	1					
WIKI-ETH	-0.03 (-0.32)	0.02 (0.25)	-0.06 (-0.71)	0.09 (1.06)	0.02 (0.28)	0.16 (1.83)	0.51 (6.63)	0.63 (8.95)	0.47 (5.83)	0.20 (2.33)	0.05 (0.55)	0.39 (4.67)	0.10 (1.17)	-0.07 (-0.78)	-0.04 (-0.49)	0.57 (7.66)	1				
WIKI-LTC	0.12 (1.41)	0.11 (1.20)	0.07 (0.77)	0.06 (0.74)	0.00 (0.10)	0.11 (1.21)	0.32 (3.81)	0.22 (2.53)	0.23 (2.61)	0.09 (1.06)	0.11 (1.27)	0.21 (2.34)	0.05 (0.58)	-0.06 (-0.67)	-0.01 (-0.12)	0.46 (5.68)	0.63 (8.89)	1			
WIKI-DASH	0.09 (1.08)	0.00 (0.07)	0.04 (0.44)	-0.00 (-0.00)	0.11 (1.21)	-0.08 (-0.94)	-0.14 (-1.63)	-0.15 (-1.70)	-0.20 (-2.31)	0.03 (0.40)	-0.13 (-1.53)	-0.15 (1.67)	0.02 (0.21)	-0.10 (-1.14)	-0.09 (-1.06)	0.17 (1.89)	0.14 (1.63)	0.13 (1.43)	1		
WIKI-XRP	0.19 (2.18)	0.11 (1.26)	0.13 (1.52)	0.00 (0.09)	0.03 (0.42)	0.06 (0.65)	0.05 (0.61)	-0.01 (-0.13)	-0.05 (-0.57)	-0.04 (-0.48)	0.03 (0.40)	0.00 (0.06)	-0.00 (-0.03)	-0.01 (-0.20)	0.01 (0.13)	0.22 (2.48)	0.32 (3.74)	0.88 (20.51)	0.08 (0.88)	1	

WIKI-XLM	0.04 (0.53)	0.03 (0.38)	-0.02 (-0.22)	0.04 (0.51)	-0.08 (-0.91)	-0.09 (-1.06)	0.17 (1.98)	0.10 (1.19)	0.06 (0.72)	0.04 (0.45)	-0.09 (-1.01)	-0.03 (-0.33)	-0.02 (-0.26)	0.02 (0.27)	-0.07 (-0.76)	0.15 (1.71)	0.19 (2.19)	0.04 (0.46)	-0.01 (-0.14)	-0.03 (-0.36)	1

Notes: Table 1.5. reports the correlations between each cryptocurrency returns, the search query "name of cryptocurrency" from the GSVI and Wikipedia searches, gold, US dollar index and S&P500 index for the period 2020 – 2022.

Table 1.6 Regression results for the GSVI

	Panel A. 2017 – 2022 term						Panel B. 2017 – 2020 term						Panel C. 2020 – 2022 term					
Bitcoin (BTC)																		
Weekly	$R_{t, t+1}$ (1)	$R_{t, t+2}$ (2)	$R_{t, t+3}$ (3)	$R_{t, t+4}$ (4)	$R_{t, t+6}$ (5)	$R_{t, t+8}$ (6)	$R_{t, t+1}$ (1)	$R_{t, t+2}$ (2)	$R_{t, t+3}$ (3)	$R_{t, t+4}$ (4)	$R_{t, t+6}$ (5)	$R_{t, t+8}$ (6)	$R_{t, t+1}$ (1)	$R_{t, t+2}$ (2)	$R_{t, t+3}$ (3)	$R_{t, t+4}$ (4)	$R_{t, t+6}$ (5)	$R_{t, t+8}$ (6)
$GSVI_t$	0.01	0.02*	0.02*	0.03*	0.03	0.02	0.02***	0.04***	0.04***	0.05***	0.05**	0.02	-0.00	0.00	0.00	0.00	0.00	0.02
	(1.57)	(1.74)	(1.82)	(1.90)	(1.16)	(0.55)	(2.90)	(3.08)	(2.79)	(2.79)	(2.16)	(0.69)	(-0.08)	(0.03)	(0.35)	(0.58)	(0.07)	(0.58)
R^2	0.01	0.01	0.01	0.01	0.00	-0.00	0.05	0.05	0.04	0.04	0.02	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
Ethereum (ETH)																		
$GSVI_t$	0.01	0.01	0.02	0.03	0.02	0.01	0.02	0.04	0.09**	0.13***	0.22***	0.19***	0.00	0.00	0.01	0.01	-0.01	-0.02
	(1.43)	(0.93)	(1.19)	(1.18)	(0.68)	(0.23)	(1.16)	(1.45)	(2.31)	(2.72)	(3.91)	(2.91)	(1.11)	(0.51)	(0.63)	(0.58)	(-0.26)	(-0.80)
R^2	0.00	0.00	0.00	0.00	0.00	-0.00	0.00	0.00	0.03	0.04	0.09	0.05	0.00	-0.00	-0.00	-0.00	-0.00	0.00
Ripple (XRP)																		
$GSVI_t$	0.23***	0.29***	0.30***	0.26**	0.13	0.15	0.44***	0.52***	0.44**	0.35**	0.65***	0.89***	0.20**	0.25**	0.28**	0.24	0.04	0.04
	(2.91)	(2.80)	(2.97)	(1.98)	(0.73)	(0.88)	(3.81)	(3.06)	(2.48)	(2.07)	(4.48)	(6.62)	(2.27)	(2.27)	(2.49)	(1.64)	(0.23)	(0.22)
R^2	0.17	0.10	0.07	0.04	0.00	0.00	0.29	0.17	0.07	0.03	0.09	0.15	0.14	0.08	0.06	0.03	-0.00	-0.00
Dash																		
$GSVI_t$	0.06***	0.09***	0.10***	0.11***	0.12***	0.10***	0.06***	0.10***	0.13***	0.16***	0.18***	0.15***	0.06***	0.07***	0.05**	0.04*	0.03	0.01
	(5.79)	(5.55)	(4.60)	(4.21)	(3.52)	(2.68)	(5.79)	(5.92)	(6.47)	(6.80)	(4.64)	(3.03)	(2.88)	(2.62)	(2.09)	(1.77)	(1.15)	(0.30)
R^2	0.23	0.17	0.13	0.12	0.08	0.04	0.26	0.23	0.23	0.23	0.18	0.10	0.19	0.09	0.02	0.01	0.00	-0.00
Litecoin (LTC)																		
$GSVI_t$	0.02***	0.02*	0.03*	0.03*	0.00	-0.00	0.02***	0.03*	0.03	0.03*	0.01	-0.00	-0.01	-0.05	-0.02	-0.01	-0.05	-0.05
	(2.99)	(1.74)	(1.69)	(1.74)	(0.35)	(-0.35)	(2.90)	(1.73)	(1.64)	(1.67)	(0.49)	(-0.19)	(-0.47)	(-0.83)	(-0.25)	(-0.22)	(-0.40)	(-0.42)
R^2	0.03	0.01	0.01	0.00	-0.00	-0.00	0.06	0.03	0.02	0.01	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00
Stellar (XLM)																		
$GSVI_t$	0.09***	0.10***	0.10***	0.12***	0.12**	0.12**	0.08***	0.09***	0.10***	0.12***	0.12*	0.13*	0.13***	0.13***	0.11***	0.11***	0.13**	0.11*
	(5.59)	(4.68)	(3.69)	(3.50)	(2.24)	(2.29)	(5.30)	(4.24)	(3.05)	(2.82)	(1.82)	(1.88)	(5.61)	(4.39)	(3.08)	(3.06)	(1.99)	(1.66)
R^2	0.32	0.16	0.10	0.09	0.05	0.04	0.31	0.16	0.10	0.10	0.05	0.04	0.37	0.16	0.08	0.06	0.05	0.02

Notes: Table 1.6. reports the results of the regression equation (1.2.) for Google searches for all three periods.

Table 1.7 Regression results for WIKI

Panel A. 2017 – 2022 term							Panel B. 2017 – 2020 term						Panel C. 2020 – 2022 term					
Bitcoin (BTC)																		
Weekly	$R_{t, t+1}$	$R_{t, t+2}$	$R_{t, t+3}$	$R_{t, t+4}$	$R_{t, t+6}$	$R_{t, t+8}$	$R_{t, t+1}$	$R_{t, t+2}$	$R_{t, t+3}$	$R_{t, t+4}$	$R_{t, t+6}$	$R_{t, t+8}$	$R_{t, t+1}$	$R_{t, t+2}$	$R_{t, t+3}$	$R_{t, t+4}$	$R_{t, t+6}$	$R_{t, t+8}$
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
$WIKI_t$	0.01	0.01	0.02	0.03	0.02	0.00	0.01	0.01	0.02	0.02	0.01	-0.01	0.00	0.03	0.05	0.06	0.07	0.10
	(1.60)	(1.12)	(1.20)	(1.18)	(0.56)	(0.01)	(1.55)	(0.99)	(1.00)	(0.99)	(0.33)	(-0.24)	(0.23)	(0.79)	(1.35)	(1.28)	(1.09)	(1.14)
R^2	0.00	0.00	0.01	0.01	0.00	-0.00	0.01	0.00	0.01	0.01	-0.00	-0.00	-0.00	0.00	0.01	0.00	0.00	0.00
Ethereum (ETH)																		
$WIKI_t$	-0.00	0.00	0.02	0.04**	0.08***	0.07***	-0.00	-0.00	0.01	0.04	0.08**	0.07*	0.00	0.02	0.05	0.06	0.03	0.03
	(-0.68)	(0.24)	(1.28)	(2.23)	(3.00)	(2.71)	(-0.85)	(-0.09)	(0.66)	(1.65)	(2.33)	(1.93)	(0.16)	(0.64)	(1.16)	(1.00)	(0.41)	(0.35)
R^2	-0.00	-0.00	0.00	0.02	0.04	0.02	0.00	-0.00	-0.00	0.01	0.07	0.03	-0.00	-0.00	0.01	0.01	-0.00	-0.00
Ripple (XRP)																		
$WIKI_t$	0.00	0.01*	0.01**	0.02***	0.03***	0.02	-0.17	-0.34	-0.63	-0.85	0.24	-0.13	0.00	0.01*	0.02*	0.02**	0.03**	0.02
	(1.37)	(1.93)	(2.19)	(3.08)	(2.91)	(1.47)	(-0.66)	(-0.62)	(-0.96)	(-1.15)	(0.28)	(-0.16)	(1.22)	(1.71)	(1.88)	(2.37)	(1.99)	(1.11)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	0.01	0.02	-0.00	-0.01	-0.00	-0.00	0.00	0.00	0.00	-0.00
Dash																		
$WIKI_t$	-0.00	-0.00	-0.00	0.00	0.02	-0.01	-0.00	-0.01	-0.02	-0.03	-0.03	-0.05	-0.00	0.00	0.02	0.06**	0.09**	0.05
	(-0.73)	(-0.58)	(-0.29)	(0.33)	(0.52)	(-0.28)	(-0.67)	(-0.88)	(-0.73)	(-0.68)	(-0.45)	(-0.73)	(-0.00)	(0.37)	(0.95)	(2.19)	(2.19)	(0.76)
R^2	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	0.03	0.05	0.01
Litecoin (LTC)																		
$WIKI_t$	0.01	0.03*	0.04*	0.04	0.03	0.03	0.02	0.03	0.03	0.03	0.01	0.01	0.01	0.02	0.06*	0.10**	0.12***	0.12*
	(1.57)	(1.70)	(1.96)	(1.61)	(0.79)	(0.75)	(1.37)	(1.46)	(1.61)	(1.23)	(0.37)	(0.36)	(0.88)	(1.00)	(1.91)	(3.05)	(2.77)	(1.81)
R^2	0.01	0.01	0.02	0.02	0.00	0.00	0.02	0.02	0.02	0.01	-0.00	-0.00	-0.00	0.00	0.02	0.06	0.04	0.02
Stellar (XLM)																		
$WIKI_t$	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	0.00	-0.00	-0.00*	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.08)	(-0.13)	(-0.06)	(-0.12)	(-0.46)	(-0.78)	(0.73)	(0.38)	(0.40)	(0.13)	(-0.24)	(-0.89)	(-1.92)	(-1.21)	(-1.09)	(-0.53)	(-0.46)	(-0.39)
R^2	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00

Notes: Table 1.7. reports the results of the regression equation (1.3.) for Wikipedia searches for all three periods.

Table 1.8 Regression results for the GSVI with controls

Panel A. 2017 – 2022 term							Panel B. 2017 – 2020 term						Panel C. 2020 – 2022 term					
Bitcoin (BTC)																		
Weekly	$R_{t, t+1}$ (1)	$R_{t, t+2}$ (2)	$R_{t, t+3}$ (3)	$R_{t, t+4}$ (4)	$R_{t, t+6}$ (5)	$R_{t, t+8}$ (6)	$R_{t, t+1}$ (1)	$R_{t, t+2}$ (2)	$R_{t, t+3}$ (3)	$R_{t, t+4}$ (4)	$R_{t, t+6}$ (5)	$R_{t, t+8}$ (6)	$R_{t, t+1}$ (1)	$R_{t, t+2}$ (2)	$R_{t, t+3}$ (3)	$R_{t, t+4}$ (4)	$R_{t, t+6}$ (5)	$R_{t, t+8}$ (6)
$GSVI_t$	0.01	0.02*	0.03*	0.03*	0.03	0.02	0.02**	0.04**	0.04*	0.05*	0.05	0.02	0.00	0.00	0.01	0.00	0.00	0.02
	(1.64)	(1.82)	(1.88)	(1.87)	(1.13)	(0.54)	(2.03)	(2.19)	(1.92)	(1.66)	(1.10)	(0.34)	(0.23)	(0.35)	(0.53)	(0.41)	(0.09)	(0.57)
$Gold_t$	-0.04	-0.08*	-0.07	-0.02	-0.01	-0.03	-0.01	-0.00	-0.02	-0.01	0.04	-0.01	-0.06	-0.13	-0.09	0.04	-0.02	-0.05
	(-1.31)	(-1.72)	(-1.40)	(-0.39)	(-0.18)	(-0.38)	(-0.41)	(-0.19)	(-0.48)	(-0.30)	(0.60)	(-0.26)	(-1.05)	(-1.45)	(-1.02)	(0.36)	(-0.26)	(-0.35)
USDollar	0.00	0.04	0.01	0.02	0.05	-0.02	0.04	0.08	0.06	0.07	0.07	-0.00	-0.02	0.02	-0.01	-0.02	0.06	-0.02
$index_t$	(0.10)	(0.71)	(0.13)	(0.25)	(0.52)	(-0.21)	(0.75)	(1.31)	(0.69)	(0.68)	(0.61)	(-0.06)	(-0.41)	(0.28)	(-0.09)	(-0.23)	(0.33)	(-0.12)
$S\&P\ 500_t$	0.02	0.02	0.08	0.04	0.00	0.04	0.02	-0.03	0.04	-0.04	0.00	0.10	0.01	0.05	0.06	0.06	-0.03	-0.07
	(0.56)	(0.36)	(0.92)	(0.40)	(0.02)	(0.33)	(0.29)	(-0.32)	(0.34)	(-0.25)	(0.03)	(0.59)	(0.20)	(0.54)	(0.52)	(0.59)	(-0.20)	(-0.33)
R^2	0.00	0.01	0.01	0.00	-0.00	-0.01	0.03	0.04	0.03	0.02	0.00	-0.02	-0.01	-0.00	-0.02	-0.03	-0.03	-0.03
Ethereum (ETH)																		
$GSVI_t$	0.01	0.01	0.03	0.03	0.03	0.01	0.02	0.04	0.09*	0.13*	0.22**	0.20**	0.01	0.01	0.01	0.01	-0.00	-0.02
	(1.54)	(1.00)	(1.21)	(1.16)	(0.70)	(0.29)	(0.89)	(1.07)	(1.67)	(1.72)	(2.40)	(2.00)	(1.35)	(0.68)	(0.68)	(0.48)	(-0.17)	(-0.71)
$Gold_t$	-0.08	-0.11*	-0.12	-0.06	-0.10	-0.13	-0.03	-0.06	-0.11	-0.10	-0.06	-0.22**	-0.14*	-0.17	-0.12	0.04	-0.10	-0.02
	(-1.52)	(-1.66)	(-1.59)	(-0.63)	(-0.94)	(-1.14)	(-0.57)	(-0.71)	(-1.24)	(-1.09)	(-0.51)	(-2.09)	(-1.73)	(-1.44)	(-0.87)	(0.26)	(-0.56)	(-0.11)
USDollar	0.02	0.03	0.00	0.03	0.11	-0.01	0.05	0.13	0.10	0.17	0.20	0.08	0.00	-0.04	-0.06	-0.09	0.02	-0.13
$index_t$	(0.39)	(0.44)	(0.01)	(0.33)	(0.85)	(-0.10)	(0.70)	(1.44)	(0.90)	(1.23)	(1.24)	(0.49)	(0.00)	(-0.48)	(-0.64)	(-0.83)	(0.12)	(-0.65)
$S\&P\ 500_t$	0.04	0.07	0.14	0.06	0.00	0.07	0.05	-0.04	0.05	-0.10	-0.07	-0.07	0.02	0.17	0.17	0.17	0.01	0.11
	(0.71)	(0.84)	(1.35)	(0.49)	(0.01)	(0.44)	(0.51)	(-0.30)	(0.33)	(-0.52)	(-0.38)	(-0.33)	(0.29)	(1.40)	(1.32)	(1.05)	(0.06)	(0.48)
R^2	0.01	0.00	0.00	0.00	-0.00	-0.01	-0.00	-0.00	0.01	0.02	0.08	0.04	0.02	0.00	-0.01	-0.02	-0.03	-0.02
Ripple (XRP)																		
$GSVI_t$	0.22***	0.28***	0.30***	0.25**	0.13	0.15	0.44***	0.52***	0.45***	0.36**	0.66***	0.90***	0.19**	0.25**	0.28**	0.23	0.04	0.03
	(3.00)	(2.82)	(2.97)	(1.97)	(0.74)	(0.84)	(3.84)	(3.08)	(2.66)	(2.18)	(4.52)	(6.36)	(2.39)	(2.34)	(2.45)	(1.62)	(0.24)	(0.19)
$Gold_t$	0.07	0.03	0.03	0.07	0.13	-0.00	0.01	-0.04	0.07	-0.01	0.01	-0.10	0.12	0.10	0.01	0.17	0.27	0.08
	(0.82)	(0.28)	(0.33)	(0.68)	(0.92)	(-0.01)	(0.26)	(-0.72)	(0.91)	(-0.23)	(0.14)	(-0.91)	(0.93)	(0.56)	(0.10)	(0.99)	(1.37)	(0.55)
USDollar	-0.14**	0.01	0.00	-0.14	0.04	-0.02	-0.00	0.05	0.04	0.00	0.07	0.00	-0.22**	-0.00	0.00	-0.20	0.03	-0.04
$index_t$	(-2.12)	(0.17)	(0.03)	(-0.96)	(0.30)	(-0.19)	(-0.09)	(0.47)	(0.33)	(0.02)	(0.57)	(0.03)	(-2.51)	(-0.02)	(0.02)	(-0.91)	(0.14)	(-0.17)
$S\&P\ 500_t$	0.16*	0.12	0.10	0.25	0.09	0.11	-0.01	0.09	-0.05	0.07	-0.01	0.00	0.30**	0.13	0.19	0.33	0.16	0.16
	(1.86)	(1.04)	(0.61)	(1.56)	(0.52)	(0.73)	(-0.09)	(0.62)	(-0.28)	(0.33)	(-0.09)	(0.03)	(2.35)	(0.76)	(0.71)	(1.44)	(0.60)	(0.65)
R^2	0.17	0.09	0.06	0.02	-0.00	-0.00	0.28	0.17	0.06	0.01	0.08	0.15	0.17	0.07	0.04	0.02	-0.01	-0.03
Dash																		
$GSVI_t$	0.06***	0.09***	0.10***	0.11***	0.12***	0.10***	0.06***	0.10***	0.13***	0.16***	0.18***	0.15***	0.06***	0.07**	0.05**	0.05*	0.03	0.01
	(5.83)	(5.47)	(4.60)	(4.26)	(3.52)	(2.66)	(5.79)	(5.70)	(6.25)	(6.51)	(4.53)	(3.00)	(2.90)	(2.56)	(2.08)	(1.77)	(1.14)	(0.31)
$Gold_t$	0.01	0.03	-0.02	-0.06	0.01	-0.05	0.05	0.13	0.13	0.02	0.03	-0.08	-0.03	-0.04	-0.16*	-0.11	0.05	-0.04
	(0.31)	(0.46)	(-0.22)	(-0.75)	(0.08)	(-0.43)	(0.97)	(1.04)	(0.91)	(0.20)	(0.21)	(-0.49)	(-0.72)	(-0.45)	(-1.90)	(-1.35)	(0.35)	(-0.25)
USDollar	-0.16***	-0.11	0.00	-0.05	-0.01	-0.07	-0.12**	-0.07	0.02	-0.08	-0.00	-0.12	-0.18**	-0.15*	-0.00	-0.03	-0.05	-0.05
$index_t$	(-3.48)	(-1.78)	(0.00)	(-0.41)	(-0.09)	(-0.48)	(-2.19)	(-0.83)	(0.15)	(-0.45)	(-0.00)	(-0.53)	(-2.59)	(-1.76)	(-0.04)	(-0.18)	(-0.31)	(-0.23)
$S\&P\ 500_t$	0.16**	0.22**	0.15	0.25*	0.18	0.19	0.12	0.12	0.00	0.16	0.06	0.14	0.19*	0.27**	0.25	0.25	0.25	0.11
	(2.41)	(2.54)	(1.21)	(1.84)	(1.15)	(1.16)	(1.40)	(0.94)	(0.04)	(0.83)	(0.29)	(0.56)	(1.84)	(2.31)	(1.49)	(1.33)	(1.09)	(0.50)
R^2	0.23	0.17	0.12	0.12	0.08	0.03	0.26	0.23	0.22	0.22	0.16	0.08	0.19	0.08	0.02	0.00	-0.01	-0.03
Litecoin (LTC)																		
$GSVI_t$	0.02***	0.02*	0.03*	0.03*	0.00	-0.00	0.02***	0.03*	0.03	0.03	0.01	-0.00	-0.00	-0.03	-0.00	-0.02	-0.05	-0.04
	(2.94)	(1.70)	(1.67)	(1.72)	(0.34)	(-0.36)	(2.86)	(1.68)	(1.60)	(1.65)	(0.50)	(-0.23)	(-0.11)	(-0.58)	(-0.08)	(-0.25)	(-0.37)	(-0.33)
$Gold_t$	-0.04	-0.09	-0.10*	-0.00	0.00	-0.09	0.00	-0.03	-0.05	0.01	0.05	-0.12	-0.09	-0.12	-0.12	0.01	-0.03	-0.06
	(-0.91)	(-1.64)	(-1.84)	(-0.09)	(0.04)	(-1.00)	(0.09)	(-0.56)	(-0.81)	(0.14)	(0.46)	(-1.05)	(-1.13)	(-1.23)	(-1.52)	(0.17)	(-0.29)	(-0.37)
USDollar	0.02	0.08	0.05	0.06	0.06	-0.00	0.10	0.16*	0.11	0.21	0.13	0.10	-0.05	0.01	0.02	-0.08	0.01	-0.10
$index_t$	(0.37)	(1.07)	(0.66)	(0.58)	(0.43)	(-0.05)	(1.44)	(1.79)	(1.16)	(1.25)	(0.64)	(0.45)	(-0.55)	(0.10)	(0.18)	(-0.65)	(0.06)	(-0.52)
$S\&P\ 500_t$	0.04	0.07	0.09	0.00	0.05	0.10	0.01	-0.03	0.01	-0.16	0.01	0.05	0.05	0.16	0.13	0.13	0.09	0.09
	(0.64)	(0.74)	(0.95)	(0.01)	(0.38)	(0.61)	(0.13)	(-0.23)	(0.11)	(-0.75)	(0.07)	(0.22)	(0.58)	(1.34)	(0.96)	(0.90)	(0.43)	(0.42)
R^2	0.02	0.01	0.00	-0.00	-0.01	-0.01	0.05	0.02	0.00	-0.00	-0.02	-0.02	-0.01	-0.00	-0.01	-0.03	-0.03	-0.03
Stellar (XLM)																		
$GSVI_t$	0.09***	0.11***	0.11***	0.13***	0.13***	0.14***	0.08***	0.10***	0.11***	0.13***	0.14**	0.15**	0.12***	0.14***	0.13***	0.12***	0.14*	0.14
	(5.42)	(5.05)	(4.00)	(3.73)	(2.57)	(2.70)	(4.88)	(4.51)	(3.37)	(3.19)	(2.27)	(2.39)	(5.89)	(4.30)	(2.88)	(2.64)	(1.87)	(1.62)
$Gold_t$	0.00	-0.18	-0.26	-0.25	-0.30	-0.35**	-0.02	-0.23	-0.28	-0.34	-0.46	-0.47*	0.00	-0.15*	-0.26**	-0.14	-0.09	-0.26
	(0.08)	(-1.51)	(-1.64)	(-1.59)	(-1.51)	(-2.03)	(-0.36)	(-1.11)	(-0.96)	(-1.24)	(-1.43)	(-1.67)	(0.12)	(-1.97)	(-2.20)	(-1.03)	(-0.48)	(-1.11)
USDollar	-0.14**	-0.03	-0.04	-0.08	0.13	0.06	-0.03	-0.07	0.04	0.08	0.16	0.16	-0.22**	0.02	-0.09	-0.24	0.13	-0.01
$index_t$	(-2.01)	(-0.32)	(-0.30)	(-0.57)	(0.80)	(0.27)	(-0.39)	(-0.53)	(0.22)	(0.38)	(0.58)	(0.45)	(-2.54)	(0.15)	(-0.46)	(-1.11)	(0.67)	(-0.06)
$S\&P\ 500_t$	0.13*	0.16	0.18	0.21	0.13	0.01	0.01	0.18	0.08	0.09	0.15	-0.04	0.25***	0.11	0.25	0.30	0.11	0.02
	(1.78)	(1.48)	(1.11)	(1.24)	(0.69)	(0.04)	(0.16)	(1.18)	(0.34)	(0.35)	(0.50)	(-0.10)	(2.77)	(0.71)	(1.10)	(1.47)	(0.51)	(0.08)
R^2	0.32	0.17	0.11	0.09	0.05	0.04	0.30	0.17	0.10	0.10	0.05	0.03	0.38	0.16	0.09	0.05	0.03	0.00

Notes: Table 1.8. reports the results of the regression equation (1.5.) for Google searches and control variables for all three periods.

Table 1.9 Regression results for WIKI with controls

Panel A. 2017 – 2022 term							Panel B. 2017 – 2020 term						Panel C. 2020 – 2022 term					
Bitcoin (BTC)																		
Weekly	$R_{t, t+1}$	$R_{t, t+2}$	$R_{t, t+3}$	$R_{t, t+4}$	$R_{t, t+6}$	$R_{t, t+8}$	$R_{t, t+1}$	$R_{t, t+2}$	$R_{t, t+3}$	$R_{t, t+4}$	$R_{t, t+6}$	$R_{t, t+8}$	$R_{t, t+1}$	$R_{t, t+2}$	$R_{t, t+3}$	$R_{t, t+4}$	$R_{t, t+6}$	$R_{t, t+8}$
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
$WIKI_t$	0.01	0.01	0.02	0.03	0.02	0.00	0.01	0.01	0.02	0.02	0.01	-0.01	0.00	0.03	0.06	0.06	0.07	0.10
	(1.52)	(1.07)	(1.17)	(1.17)	(0.56)	(0.00)	(1.48)	(0.95)	(0.97)	(0.96)	(0.33)	(-0.25)	(0.19)	(0.91)	(1.41)	(1.32)	(1.12)	(1.10)
$Gold_t$	-0.03	-0.07	-0.05	0.00	0.00	-0.02	-0.01	-0.02	-0.03	-0.02	0.01	-0.05	-0.06	-0.12	-0.08	0.04	-0.03	-0.03
	(-1.12)	(-1.51)	(-1.13)	(0.04)	(0.11)	(-0.38)	(-0.59)	(-0.51)	(-0.74)	(-0.54)	(0.24)	(-0.67)	(-1.11)	(-1.49)	(-0.94)	(0.41)	(-0.33)	(-0.25)
USDollar $index_t$	0.00	0.05	0.01	0.03	0.06	-0.01	0.04	0.09	0.07	0.08	0.09	0.00	-0.02	0.04	0.01	-0.00	0.08	0.01
	(0.20)	(0.89)	(0.24)	(0.37)	(0.61)	(-0.14)	(0.77)	(1.31)	(0.73)	(0.72)	(0.73)	(0.05)	(-0.38)	(0.45)	(0.10)	(-0.03)	(0.47)	(0.06)
S&P 500_t	0.02	0.02	0.08	0.04	-0.00	0.04	0.02	-0.02	0.05	-0.02	0.00	0.09	0.01	0.05	0.06	0.07	-0.03	-0.07
	(0.48)	(0.26)	(0.88)	(0.38)	(-0.01)	(0.28)	(0.35)	(-0.24)	(0.42)	(-0.17)	(0.06)	(0.54)	(0.17)	(0.53)	(0.52)	(0.61)	(-0.16)	(-0.34)
R^2	0.00	0.00	0.00	0.00	-0.00	-0.01	0.00	-0.00	-0.00	-0.00	-0.02	-0.02	-0.01	0.00	-0.00	-0.01	-0.01	-0.01
Ethereum (ETH)																		
$WIKI_t$	-0.00	0.00	0.02	0.05**	0.08***	0.08***	-0.00	-0.00	0.01	0.04	0.09***	0.08**	0.00	0.03	0.06	0.06	0.04	0.03
	(-0.60)	(0.31)	(1.45)	(2.42)	(3.18)	(2.99)	(-0.91)	(-0.25)	(0.65)	(1.61)	(2.65)	(2.13)	(0.33)	(0.80)	(1.24)	(0.95)	(0.48)	(0.36)
$Gold_t$	-0.07	-0.10	-0.10	-0.03	-0.09	-0.13	-0.03	-0.05	-0.11	-0.09	-0.03	-0.17	-0.12	-0.16	-0.11	0.04	-0.13	-0.09
	(-1.40)	(-1.58)	(-1.51)	(-0.43)	(-0.94)	(-1.21)	(-0.57)	(-0.70)	(-1.31)	(-1.21)	(-0.42)	(-1.56)	(-1.62)	(-1.52)	(-0.98)	(0.26)	(-0.80)	(-0.43)
USDollar $index_t$	0.03	0.02	-0.04	-0.06	-0.05	-0.17	0.09	0.15	0.05	0.01	-0.17	-0.25	0.00	-0.03	-0.04	-0.07	0.03	-0.11
	(0.66)	(0.32)	(-0.51)	(-0.55)	(-0.36)	(-1.05)	(1.46)	(1.47)	(0.35)	(0.08)	(-0.70)	(-0.98)	(0.04)	(-0.34)	(-0.43)	(-0.65)	(0.20)	(-0.56)
S&P 500_t	0.03	0.08	0.21*	0.20	0.23	0.29	0.01	-0.05	0.14	0.12	0.41	0.39	0.02	0.16	0.17	0.17	0.01	0.10
	(0.52)	(0.94)	(1.86)	(1.35)	(1.27)	(1.53)	(0.11)	(-0.36)	(0.76)	(0.56)	(1.38)	(1.38)	(0.25)	(1.39)	(1.34)	(1.06)	(0.05)	(0.45)
R^2	-0.00	-0.00	0.00	0.01	0.04	0.02	-0.00	-0.02	-0.01	0.00	0.05	0.01	0.00	0.00	-0.00	-0.01	-0.02	-0.03
Ripple (XRP)																		
$WIKI_t$	0.00	0.01*	0.01**	0.02***	0.03***	0.02	-0.16	-0.28	-0.59	-0.76	0.33	-0.06	0.00	0.01*	0.01*	0.02**	0.03**	0.02
	(1.25)	(1.91)	(2.17)	(2.94)	(2.93)	(1.45)	(-0.62)	(-0.54)	(-0.92)	(-1.04)	(0.39)	(-0.07)	(0.94)	(1.65)	(1.84)	(2.20)	(1.99)	(1.10)
$Gold_t$	0.06	0.02	0.02	0.07	0.13	-0.00	-0.00	-0.06	0.06	-0.02	-0.01	-0.14	0.11	0.09	0.01	0.17	0.27	0.08
	(0.88)	(0.25)	(0.31)	(0.71)	(0.94)	(-0.06)	(-0.04)	(-0.96)	(0.76)	(-0.29)	(-0.09)	(-1.14)	(1.06)	(0.64)	(0.09)	(1.15)	(1.40)	(0.56)
USDollar $index_t$	-0.19**	-0.04	-0.05	-0.19	0.02	-0.05	-0.01	0.04	0.04	0.00	0.05	-0.00	-0.29**	-0.08	-0.08	-0.27	0.03	-0.03
	(-2.27)	(-0.41)	(-0.40)	(-1.20)	(0.17)	(-0.37)	(-0.19)	(0.51)	(0.38)	(0.03)	(0.51)	(-0.02)	(-2.36)	(-0.50)	(-0.38)	(-1.15)	(0.14)	(-0.17)
S&P 500_t	0.23**	0.20	0.18	0.31*	0.11	0.15	0.01	0.12	-0.04	0.07	0.03	0.06	0.38**	0.23	0.30	0.42*	0.17	0.16
	(2.08)	(1.43)	(1.18)	(1.88)	(0.68)	(0.99)	(0.10)	(0.89)	(-0.27)	(0.36)	(0.21)	(0.32)	(2.36)	(1.12)	(1.25)	(1.74)	(0.63)	(0.68)
R^2	0.01	-0.00	-0.00	0.00	-0.00	-0.01	-0.03	-0.01	-0.01	-0.01	-0.04	-0.04	0.04	-0.01	-0.01	-0.00	-0.00	-0.02
Dash																		
$WIKI_t$	-0.00	-0.00	-0.00	0.00	0.02	-0.01	-0.00	-0.01	-0.02	-0.03	-0.03	-0.05	-0.00	0.00	0.02	0.06**	0.09**	0.05
	(-0.78)	(-0.50)	(-0.25)	(0.36)	(0.57)	(-0.27)	(-0.54)	(-0.77)	(-0.71)	(-0.67)	(-0.45)	(-0.74)	(-0.18)	(0.39)	(1.13)	(2.29)	(2.24)	(0.77)
$Gold_t$	0.00	0.03	-0.02	-0.06	0.01	-0.06	0.02	0.08	0.07	-0.05	-0.05	-0.17	-0.01	-0.02	-0.15*	-0.12	0.04	-0.05
	(0.23)	(0.41)	(-0.26)	(-0.74)	(0.10)	(-0.48)	(0.44)	(0.68)	(0.48)	(-0.33)	(-0.30)	(-0.89)	(-0.29)	(-0.23)	(-1.82)	(-1.54)	(0.26)	(-0.28)
USDollar $index_t$	-0.15***	-0.10	0.01	-0.03	0.00	-0.06	-0.09	-0.02	0.08	-0.00	0.08	-0.05	-0.20**	-0.16*	-0.00	-0.01	-0.01	-0.02
	(-3.23)	(-1.56)	(0.11)	(-0.29)	(0.06)	(-0.42)	(-1.53)	(-0.26)	(0.53)	(-0.03)	(0.39)	(-0.22)	(-2.56)	(-1.75)	(-0.02)	(-0.07)	(-0.06)	(-0.10)
S&P 500_t	0.14**	0.19**	0.12	0.22	0.15	0.16	0.12	0.10	-0.01	0.14	0.04	0.11	0.16	0.25**	0.25	0.26	0.29	0.14
	(2.01)	(2.19)	(0.97)	(1.58)	(0.98)	(0.97)	(1.28)	(0.81)	(-0.05)	(0.70)	(0.20)	(0.48)	(1.47)	(2.10)	(1.42)	(1.37)	(1.28)	(0.57)
R^2	0.00	-0.00	-0.01	-0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	-0.01	-0.00	-0.02	-0.00	0.02	0.04	-0.01
Litecoin (LTC)																		
$WIKI_t$	0.01	0.02	0.04*	0.04	0.03	0.03	0.02	0.03	0.03	0.03	0.01	0.01	0.01	0.03	0.07**	0.10***	0.13***	0.12*
	(1.50)	(1.59)	(1.86)	(1.62)	(0.81)	(0.72)	(1.40)	(1.40)	(1.56)	(1.24)	(0.42)	(0.30)	(1.02)	(1.19)	(2.16)	(3.06)	(2.98)	(1.83)
$Gold_t$	-0.03	-0.08	-0.08	0.01	0.02	-0.07	0.01	-0.01	-0.02	0.03	0.07	-0.10	-0.09	-0.15	-0.14*	-0.02	-0.09	-0.12
	(-0.72)	(-1.37)	(-1.38)	(0.28)	(0.26)	(-0.76)	(0.30)	(-0.24)	(-0.35)	(0.44)	(0.59)	(-0.84)	(-1.26)	(-1.54)	(-1.78)	(-0.21)	(-0.83)	(-0.82)
USDollar $index_t$	0.02	0.08	0.06	0.07	0.06	-0.00	0.10	0.17*	0.12	0.22	0.13	0.10	-0.04	0.03	0.05	-0.02	0.08	-0.03
	(0.43)	(1.15)	(0.74)	(0.67)	(0.47)	(-0.02)	(1.50)	(1.90)	(1.18)	(1.28)	(0.64)	(0.44)	(-0.48)	(0.30)	(0.44)	(-0.21)	(0.40)	(-0.18)
S&P 500_t	0.03	0.06	0.09	-0.00	0.05	0.09	0.00	-0.03	0.00	-0.17	0.01	0.04	0.05	0.15	0.11	0.09	0.04	0.05
	(0.59)	(0.69)	(0.87)	(-0.05)	(0.33)	(0.57)	(0.08)	(-0.28)	(0.04)	(-0.80)	(0.05)	(0.20)	(0.53)	(1.20)	(0.82)	(0.66)	(0.21)	(0.23)
R^2	0.01	0.01	0.01	0.01	-0.00	-0.00	0.02	0.01	0.00	-0.00	-0.02	-0.02	-0.00	0.00	0.02	0.03	0.02	0.00
Stellar (XLM)																		
$WIKI_t$	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.13)	(-0.09)	(-0.02)	(-0.08)	(-0.44)	(-0.77)	(0.62)	(0.33)	(0.35)	(0.07)	(-0.33)	(-0.97)	(-1.12)	(-1.00)	(-0.92)	(-0.37)	(-0.39)	(-0.37)
$Gold_t$	0.15	-0.00	-0.07	-0.03	-0.06	-0.09	0.13	-0.04	-0.07	-0.08	-0.19	-0.15	0.17	0.03	-0.08	0.04	0.12	-0.05
	(1.54)	(-0.04)	(-0.70)	(-0.30)	(-0.39)	(-0.74)	(1.05)	(-0.32)	(-0.40)	(-0.53)	(-0.98)	(-0.86)	(1.17)	(0.26)	(-0.67)	(0.32)	(0.55)	(-0.22)
USDollar $index_t$	-0.20**	-0.10	-0.12	-0.17	0.05	-0.01	-0.08	-0.12	-0.01	0.00	0.07	0.07	-0.31**	-0.06	-0.17	-0.32	0.05	-0.09
	(-2.27)	(-0.93)	(-0.84)	(-1.07)	(0.31)	(-0.06)	(-0.76)	(-1.09)	(-0.08)	(0.02)	(0.30)	(0.20)	(-2.40)	(-0.29)	(-0.80)	(-1.39)	(0.24)	(-0.34)
S&P 500_t	0.18**	0.22**	0.24	0.28	0.20	0.06	0.03	0.20	0.10	0.12	0.19	0.03	0.33***	0.19	0.31	0.38**	0.20	0.10
	(2.02)	(1.98)	(1.54)	(1.62)	(0.98)	(0.28)	(0.26)	(1.25)	(0.45)	(0.47)	(0.63)	(0.09)	(2.72)	(1.29)	(1.56)	(2.04)	(0.87)	(0.39)
R^2	0.02	-0.00	-0.01	-0.01	-0.01	-0.01	-0.00	-0.02	-0.02	-0.02	-0.02	-0.02	0.07	-0.01	-0.00	-0.01	-0.01	-0.03

Notes: Table 1.9. reports the results of the regression equation (1.6.) for Wikipedia searches and control variables for all three periods.

Table 1.10 Granger test results (2017 – 2022)

This table indicates the estimation results of the vector autoregressive models for log six cryptocurrency returns (X), and investor attention measures (GSVI_X, WIKI_X). Panel A shows the coefficient estimates while Panel B displays the test statistics of the VAR based Granger causality test.

Panel A. VAR Estimation		
	BTC	**GSVI_BTC**
BTC_{t-1}	0.362***	-0.222
BTC_{t-2}	-0.028	2.745***
BTC_{t-3}	-0.032	0.773
BTC_{t-4}	-0.005	-1.060
BTC_{t-5}	0.045	0.468
BTC_{t-6}	0.103	0.065
BTC_{t-7}	-0.097	0.827
BTC_{t-8}	0.135*	-0.092
$GSVI_BTC_{t-1}$	0.009	0.630***
$GSVI_BTC_{t-2}$	-0.010	-0.137*
$GSVI_BTC_{t-3}$	0.006	-0.196**
$GSVI_BTC_{t-4}$	-0.003	-0.032
$GSVI_BTC_{t-5}$	0.006	0.127
$GSVI_BTC_{t-6}$	-0.019**	-0.120
$GSVI_BTC_{t-7}$	0.001	0.080
$GSVI_BTC_{t-8}$	0.005	-0.074
Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_BTC does not Granger Cause BTC	9.942	
BTC does not Granger Cause GSVI_BTC	33.727***	
Panel A. VAR Estimation	**ETH**	**GSVI_ETH**
ETH_{t-1}	0.360***	1.423***
ETH_{t-2}	-0.056	0.868**
ETH_{t-3}	0.035	-0.535
ETH_{t-4}	-0.014	1.001**

ETH_{t-5}	-0.043	-0.034
ETH_{t-6}	0.011	-0.068
ETH_{t-7}	-0.033	-0.031
ETH_{t-8}	0.137**	0.154
$GSVI_ETH_{t-1}$	-0.005	0.731***
$GSVI_ETH_{t-2}$	0.012	-0.276***
$GSVI_ETH_{-3}$	0.006	0.020
$GSVI_ETH_{t-4}$	-0.016	-0.303***
$GSVI_ETH_{t-5}$	0.025*	0.342***
$GSVI_ETH_{t-6}$	-0.035**	-0.319***
$GSVI_ETH_{t-7}$	0.010	0.139
$GSVI_ETH_{t-8}$	0.001	-0.251***
Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_ETH does not Granger Cause ETH	12.20	
ETH does not Granger Cause GSVI_ETH	31.79***	
Panel A. VAR Estimation	**LTC**	**GSVI_LTC**
LTC_{t-1}	0.299***	3.741***
LTC_{t-2}	-0.060	-0.805*
LTC_{t-3}	0.040	0.333
LTC_{t-4}	0.043	0.289
LTC_{t-5}	0.004	-0.322
LTC_{t-6}	-0.043	-0.055
LTC_{t-7}	-0.055	0.068
LTC_{t-8}	0.122	-0.474
$GSVI_LTC_{t-1}$	-0.004	0.520***
$GSVI_LTC_{t-2}$	0.003	-0.165**
$GSVI_LTC_{t-3}$	0.001	-0.102
$GSVI_LTC_{t-4}$	-0.012	-0.138*
$GSVI_LTC_{t-5}$	0.008	0.101
$GSVI_LTC_{t-6}$	-0.008	-0.130*
$GSVI_LTC_{t-7}$	-0.014	0.064

GSVI_LTC$_{t-8}$	0.022**	-0.043
Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_LTC does not Granger Cause LTC	9.07	
LTC does not Granger Cause GSVI_LTC	106.03***	
Panel A. VAR Estimation	**DASH**	**GSVI_DASH**
DASH$_{t-1}$	0.326***	1.143**
DASH$_{t-2}$	-0.145*	-0.912*
DASH$_{t-3}$	0.064	0.441
DASH$_{t-4}$	-0.108	-0.778
DASH$_{t-5}$	0.022	0.385
DASH$_{t-6}$	-0.080	-0.178
DASH$_{t-7}$	0.011	-0.329
DASH$_{t-8}$	-0.001	0.083
GSVI_DASH$_{t-1}$	0.004	0.392***
GSVI_DASH$_{t-2}$	0.0003	0.124
GSVI_DASH$_{t-3}$	0.015	0.017
GSVI_DASH$_{t-4}$	0.013	-0.082
GSVI_DASH$_{t-5}$	-0.011	-0.033
GSVI_DASH$_{t-6}$	-0.001	-0.079
GSVI_DASH$_{t-7}$	-0.016	-0.046
GSVI_DASH$_{t-8}$	0.024**	0.014
Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_DASH does not Granger Cause DASH	11.10	
DASH does not Granger Cause DASH_LTC	10.17	
Panel A. VAR Estimation	**XRP**	**GSVI_XRP**
XRP$_{t-1}$	0.319***	0.295**
XRP$_{t-2}$	-0.174**	-0.142
XRP$_{t-3}$	0.109	0.208
XRP$_{t-4}$	-0.033	0.146
XRP$_{t-5}$	-0.112	-0.099

XRP_{t-6}	-0.111	-0.104
XRP_{t-7}	-0.106	-0.130
XRP_{t-8}	0.129	-0.083
$GSVI_XRP_{t-1}$	-0.047	0.472***
$GSVI_XRP_{t-2}$	0.110**	-0.210**
$GSVI_XRP_{t-3}$	-0.101*	-0.054
$GSVI_XRP_{t-4}$	0.036	-0.218**
$GSVI_XRP_{t-5}$	-0.099*	0.118
$GSVI_XRP_{t-6}$	0.123**	0.001
$GSVI_XRP_{t-7}$	0.002	0.002
$GSVI_XRP_{t-8}$	-0.107**	-0.082
Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_XRP does not Granger Cause XRP	17.05**	
XRP does not Granger Cause GSVI_XRP	16.63**	
Panel A. VAR Estimation	**XLM**	**GSVI_XLM**
XLM_{t-1}	0.395***	1.064**
XLM_{t-2}	-0.024	0.113
XLM_{t-3}	0.103	0.612
XLM_{t-4}	-0.028	0.156
XLM_{t-5}	0.053	1.342***
XLM_{t-6}	0.053	0.249
XLM_{t-7}	-0.046	-0.682
XLM_{t-8}	0.109	0.202
$GSVI_XLM_{t-1}$	-0.031**	0.249***
$GSVI_XLM_{t-2}$	0.001	0.010
$GSVI_XLM_{t-3}$	0.009	-0.091
$GSVI_XLM_{t-4}$	-0.0003	-0.144*
$GSVI_XLM_{t-5}$	-0.025*	-0.143
$GSVI_XLM_{t-6}$	0.019	0.009
$GSVI_XLM_{t-7}$	-0.012	-0.049
$GSVI_XLM_{t-8}$	-0.019	-0.176**

Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_XLM does not Granger Cause XLM	10.71	
XLM does not Granger Cause GSVI_XLM	20.19***	
Panel A. VAR Estimation	**BTC**	**WIKI_BTC**
BTC_{t-1}	0.355***	0.836*
BTC_{t-2}	-0.018	1.156**
BTC_{t-3}	-0.013	0.412
BTC_{t-4}	0.015	-0.007
BTC_{t-5}	0.019	-0.374
BTC_{t-6}	0.096	0.870
BTC_{t-7}	-0.062	-0.200
BTC_{t-8}	0.124*	0.026
$WIKI_BTC_{t-1}$	-0.004	0.913***
$WIKI_BTC_{t-2}$	0.007	-0.417***
$WIKI_BTC_{t-3}$	0.002	-0.102
$WIKI_BTC_{t-4}$	-0.010	-0.008
$WIKI_BTC_{t-5}$	0.005	0.122
$WIKI_BTC_{t-6}$	-0.011	-0.169*
$WIKI_BTC_{t-7}$	-0.007	0.044
$WIKI_BTC_{t-8}$	0.011	-0.022
Panel B. VAR based Granger Causality test		
	Chi-sq	
WIKI_BTC does not Granger Cause BTC	10.10	
BTC does not Granger Cause WIKI_BTC	17.18**	
Panel A. VAR Estimation	**ETH**	**WIKI_ETH**
ETH_{t-1}	0.280***	-0.022
ETH_{t-2}	-0.078	1.347**
ETH_{t-3}	0.033	0.072
ETH_{t-4}	0.006	-0.283
ETH_{t-5}	-0.033	0.352
ETH_{t-6}	0.034	0.032

ETH_{t-7}	-0.050	0.776
ETH_{t-8}	0.074	-1.455***
$WIKI_ETH_{t-1}$	0.012	0.270***
$WIKI_ETH_{t-2}$	0.012	0.005
$WIKI_ETH_{-3}$	0.014*	-0.119*
$WIKI_ETH_{t-4}$	0.013*	-0.279***
$WIKI_ETH_{t-5}$	0.006	0.027
$WIKI_ETH_{t-6}$	0.006	-0.023
$WIKI_ETH_{t-7}$	-0.006	-0.098
$WIKI_ETH_{t-8}$	-0.001	-0.011*
Panel B. VAR based Granger Causality test		
	Chi-sq	
WIKI_ETH does not Granger Cause ETH	23.49***	
ETH does not Granger Cause WIKI_ETH	15.26*	
Panel A. VAR Estimation	**LTC**	**WIKI_LTC**
LTC_{t-1}	0.310***	0.762**
LTC_{t-2}	-0.089	2.562***
LTC_{t-3}	0.054	-1.458***
LTC_{t-4}	-0.006	-0.123
LTC_{t-5}	-0.064	-0.017
LTC_{t-6}	0.003	0.071
LTC_{t-7}	-0.092	0.061
LTC_{t-8}	0.130*	-0.012
$WIKI_LTC_{t-1}$	-0.004	0.632***
$WIKI_LTC_{t-2}$	0.013	-0.168**
$WIKI_LTC_{t-3}$	0.002	-0.031
$WIKI_LTC_{t-4}$	-0.001	-0.271***
$WIKI_LTC_{t-5}$	0.002	0.141*
$WIKI_LTC_{t-6}$	-0.016	-0.045
$WIKI_LTC_{t-7}$	0.021*	-0.036
$WIKI_LTC_{t-8}$	-0.005	-0.064
Panel B. VAR based Granger Causality test		

	Chi-sq	
WIKI_LTC does not Granger Cause LTC	6.07	
LTC does not Granger Cause WIKI_LTC	66.65***	
Panel A. VAR Estimation	**DASH**	**WIKI_DASH**
DASH$_{t-1}$	0.328***	-0.087
DASH$_{t-2}$	-0.090	-0.094
DASH$_{t-3}$	0.112*	-0.201
DASH$_{t-4}$	-0.057	0.474
DASH$_{t-5}$	0.001	-0.431
DASH$_{t-6}$	-0.081	0.296
DASH$_{t-7}$	-0.054	-0.380
DASH$_{t-8}$	0.049	-0.648
WIKI_DASH$_{t-1}$	0.006	0.759***
WIKI_DASH$_{t-2}$	-0.016	-0.332***
WIKI_DASH$_{t-3}$	0.015	-0.014
WIKI_DASH$_{t-4}$	0.011	-0.065
WIKI_DASH$_{t-5}$	-0.00003	0.114
WIKI_DASH$_{t-6}$	-0.029**	-0.136
WIKI_DASH$_{t-7}$	0.009	0.082
WIKI_DASH$_{t-8}$	0.013	-0.089
Panel B. VAR based Granger Causality test		
	Chi-sq	
WIKI_DASH does not Granger Cause DASH	17.43**	
DASH does not Granger Cause WIKI_DASH	6.64	
Panel A. VAR Estimation	**XRP**	**WIKI_XRP**
XRP$_{t-1}$	0.270***	0.096
XRP$_{t-2}$	-0.138*	0.228
XRP$_{t-3}$	0.078	-0.275
XRP$_{t-4}$	-0.039	0.228
XRP$_{t-5}$	-0.129*	-0.085
XRP$_{t-6}$	-0.101	0.557
XRP$_{t-7}$	-0.050	0.276

XRP_{t-8}	0.033	0.110
$WIKI_XRP_{t-1}$	0.004	0.493***
$WIKI_XRP_{t-2}$	0.005	0.351***
$WIKI_XRP_{t-3}$	0.009	0.396***
$WIKI_XRP_{t-4}$	-0.011	-0.980***
$WIKI_XRP_{t-5}$	-0.004	-0.025
$WIKI_XRP_{t-6}$	0.005	0.107
$WIKI_XRP_{t-7}$	0.012	0.405***
$WIKI_XRP_{t-8}$	-0.007	-0.322***
Panel B. VAR based Granger Causality test		
	Chi-sq	
WIKI_XRP does not Granger Cause XRP	1.94	
XRP does not Granger Cause WIKI_XRP	4.55	
Panel A. VAR Estimation	**XLM**	**WIKI_XLM**
XLM_{t-1}	0.277***	351.16***
XLM_{t-2}	-0.051	157.63
XLM_{t-3}	0.128*	51.30
XLM_{t-4}	-0.033	130.79
XLM_{t-5}	-0.002	245.62**
XLM_{t-6}	0.089	300.33***
XLM_{t-7}	-0.085	111.76
XLM_{t-8}	0.090	57.02
$WIKI_XLM_{t-1}$	-0.00002	0.180***
$WIKI_XLM_{t-2}$	0.00005	0.112*
$WIKI_XLM_{t-3}$	0.00001	0.066
$WIKI_XLM_{t-4}$	-0.00006	0.019
$WIKI_XLM_{t-5}$	0.00005	0.013
$WIKI_XLM_{t-6}$	0.00008	0.032
$WIKI_XLM_{t-7}$	-0.00004	0.016
$WIKI_XLM_{t-8}$	-0.00003	0.040
Panel B. VAR based Granger Causality test		
	Chi-sq	

WIKI_XLM does not Granger Cause XLM	6.80
XLM does not Granger Cause WIKI_XLM	48.71***

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

Table 1.11 Granger test results (2017 – 2020)

This table indicates the estimation results of the vector autoregressive models for log six cryptocurrency returns (X), and investor attention measures (GSVI_X, WIKI_X). Panel A shows the coefficient estimates while Panel B displays the test statistics of the VAR based Granger causality test.

Panel A. VAR Estimation		
	BTC	**GSVI_BTC**
$\mathbf{BTC_{t-1}}$	0.435***	2.205***
$\mathbf{BTC_{t-2}}$	-0.038	1.534**
$\mathbf{BTC_{t-3}}$	-0.067	-0.005
$\mathbf{BTC_{t-4}}$	-0.044	-1.188
$\mathbf{BTC_{t-5}}$	0.045	1.765**
$\mathbf{BTC_{t-6}}$	0.175*	0.077
$\mathbf{BTC_{t-7}}$	-0.178*	0.307
$\mathbf{BTC_{t-8}}$	0.256***	0.128
$\mathbf{GSVI_BTC_{t-1}}$	0.020*	0.739***
$\mathbf{GSVI_BTC_{t-2}}$	-0.026*	-0.144
$\mathbf{GSVI_BTC_{t-3}}$	0.006	-0.045
$\mathbf{GSVI_BTC_{t-4}}$	0.016	-0.258**
$\mathbf{GSVI_BTC_{t-5}}$	0.005	0.056
$\mathbf{GSVI_BTC_{t-6}}$	-0.055***	-0.025
$\mathbf{GSVI_BTC_{t-7}}$	0.025*	0.274**
$\mathbf{GSVI_BTC_{t-8}}$	-0.001	-0.057
Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_BTC does not Granger Cause BTC	24.928***	
BTC does not Granger Cause GSVI_BTC	28.907***	
Panel A. VAR Estimation	**ETH**	**GSVI_ETH**
$\mathbf{ETH_{t-1}}$	0.341***	1.130***
$\mathbf{ETH_{t-2}}$	-0.080	-0.463
$\mathbf{ETH_{t-3}}$	-0.042	-0.023
$\mathbf{ETH_{t-4}}$	-0.048	0.873***

ETH_{t-5}	-0.128	-0.615**
ETH_{t-6}	0.089	-0.169
ETH_{t-7}	-0.030	-0.233
ETH_{t-8}	0.100	-0.019
$GSVI_ETH_{t-1}$	0.010	1.091***
$GSVI_ETH_{t-2}$	0.023	-0.923***
$GSVI_ETH_{-3}$	0.046	0.740***
$GSVI_ETH_{t-4}$	-0.043	-0.474***
$GSVI_ETH_{t-5}$	0.120**	0.344**
$GSVI_ETH_{t-6}$	-0.112**	-0.218
$GSVI_ETH_{t-7}$	0.046	0.048
$GSVI_ETH_{t-8}$	-0.021	-0.089
Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_ETH does not Granger Cause ETH	19.350**	
ETH does not Granger Cause GSVI_ETH	31.801***	
Panel A. VAR Estimation	**BTC**	**WIKI_BTC**
BTC_{t-1}	0.416***	1.390
BTC_{t-2}	-0.013	3.080***
BTC_{t-3}	-0.033	-0.367
BTC_{t-4}	-0.018	-0.133
BTC_{t-5}	-0.046	-0.476
BTC_{t-6}	0.247**	1.903**
BTC_{t-7}	-0.127	-0.358
BTC_{t-8}	0.181*	-1.227
$WIKI_BTC_{t-1}$	-0.006	0.992***
$WIKI_BTC_{t-2}$	0.005	-0.559***
$WIKI_BTC_{t-3}$	0.009	0.028
$WIKI_BTC_{t-4}$	-0.018	-0.079
$WIKI_BTC_{t-5}$	-0.002	0.117
$WIKI_BTC_{t-6}$	0.002	-0.137
$WIKI_BTC_{t-7}$	-0.019	0.105

WIKI_BTC$_{t-8}$	0.015*	-0.038
Panel B. VAR based Granger Causality test		
	Chi-sq	
WIKI_BTC does not Granger Cause BTC	12.614	
BTC does not Granger Cause WIKI_BTC	23.858***	
Panel A. VAR Estimation	**ETH**	**WIKI_ETH**
ETH$_{t-1}$	0.253***	-0.054
ETH$_{t-2}$	-0.078	1.689
ETH$_{t-3}$	-0.025	-0.845
ETH$_{t-4}$	-0.019	-0.546
ETH$_{t-5}$	-0.144	0.407
ETH$_{t-6}$	0.218**	-0.021
ETH$_{t-7}$	0.013	0.991
ETH$_{t-8}$	-0.001	-2.811***
WIKI_ETH$_{t-1}$	0.014*	0.203**
WIKI_ETH$_{t-2}$	0.013	-0.003
WIKI_ETH$_{-3}$	0.022***	-0.149
WIKI_ETH$_{t-4}$	0.021**	-0.303***
WIKI_ETH$_{t-5}$	0.010	-0.030
WIKI_ETH$_{t-6}$	0.009	-0.046
WIKI_ETH$_{t-7}$	0.002	-0.119
WIKI_ETH$_{t-8}$	-0.001	-0.123
Panel B. VAR based Granger Causality test		
	Chi-sq	
WIKI_ETH does not Granger Cause ETH	23.141***	
ETH does not Granger Cause WIKI_ETH	9.909	

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

Table 1.12 Granger test results (2020 – 2022)

This table indicates the estimation results of the vector autoregressive models for log six cryptocurrency returns (X), and investor attention measures (GSVI_X, WIKI_X). Panel A shows the coefficient estimates while Panel B displays the test statistics of the VAR based Granger causality test.

Panel A. VAR Estimation		
	BTC	**GSVI_BTC**
$\mathbf{BTC_{t-1}}$	0.319***	-1.667
$\mathbf{BTC_{t-2}}$	-0.041	2.950***
$\mathbf{BTC_{t-3}}$	-0.034	1.433
$\mathbf{BTC_{t-4}}$	0.177	-0.589
$\mathbf{BTC_{t-5}}$	0.065	-0.830
$\mathbf{BTC_{t-6}}$	0.009	0.089
$\mathbf{BTC_{t-7}}$	0.079	0.892
$\mathbf{BTC_{t-8}}$	0.025	-0.456
$\mathbf{GSVI_BTC_{t-1}}$	-0.006	0.488***
$\mathbf{GSVI_BTC_{t-2}}$	-0.001	-0.120
$\mathbf{GSVI_BTC_{t-3}}$	0.010	-0.250**
$\mathbf{GSVI_BTC_{t-4}}$	-0.018	0.044
$\mathbf{GSVI_BTC_{t-5}}$	0.007	0.173
$\mathbf{GSVI_BTC_{t-6}}$	0.008	-0.143
$\mathbf{GSVI_BTC_{t-7}}$	-0.015	0.066
$\mathbf{GSVI_BTC_{t-8}}$	0.016	-0.049
Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_BTC does not Granger Cause BTC	5.029	
BTC does not Granger Cause GSVI_BTC	15.455*	
Panel A. VAR Estimation	**ETH**	**GSVI_ETH**
$\mathbf{ETH_{t-1}}$	0.260***	1.980**
$\mathbf{ETH_{t-2}}$	-0.015	2.065**
$\mathbf{ETH_{t-3}}$	0.149	-0.697
$\mathbf{ETH_{t-4}}$	0.162	0.889

ETH_{t-5}	0.186	-0.380
ETH_{t-6}	-0.094	0.339
ETH_{t-7}	-0.071	-0.309
ETH_{t-8}	0.259**	0.482
$GSVI_ETH_{t-1}$	-0.014	0.669***
$GSVI_ETH_{t-2}$	-0.003	-0.191
$GSVI_ETH_{-3}$	0.005	-0.022
$GSVI_ETH_{t-4}$	-0.017	-0.353***
$GSVI_ETH_{t-5}$	0.010	0.363***
$GSVI_ETH_{t-6}$	-0.027*	-0.302**
$GSVI_ETH_{t-7}$	0.0004	0.144
$GSVI_ETH_{t-8}$	0.0006	-0.275***
Panel B. VAR based Granger Causality test		
	Chi-sq	
GSVI_ETH does not Granger Cause ETH	12.463	
ETH does not Granger Cause GSVI_ETH	15.638**	
Panel A. VAR Estimation	**BTC**	**WIKI_BTC**
BTC_{t-1}	0.336***	0.013
BTC_{t-2}	-0.044	-0.300
BTC_{t-3}	-0.044	0.643
BTC_{t-4}	0.140	0.211
BTC_{t-5}	0.078	-0.208
BTC_{t-6}	-0.015	0.201
BTC_{t-7}	0.060	-0.055
BTC_{t-8}	0.019	1.162**
$WIKI_BTC_{t-1}$	0.021	0.416***
$WIKI_BTC_{t-2}$	0.012	0.039
$WIKI_BTC_{t-3}$	-0.017	-0.247**
$WIKI_BTC_{t-4}$	0.020	-0.135
$WIKI_BTC_{t-5}$	0.021	0.130
$WIKI_BTC_{t-6}$	-0.052**	-0.096
$WIKI_BTC_{t-7}$	0.053**	-0.098

WIKI_BTC$_{t-8}$	-0.006	-0.083
Panel B. VAR based Granger Causality test		
	Chi-sq	
WIKI_BTC does not Granger Cause BTC	10.206	
BTC does not Granger Cause WIKI_BTC	9.683	
Panel A. VAR Estimation	**ETH**	**WIKI_ETH**
ETH$_{t-1}$	0.285***	0.267
ETH$_{t-2}$	-0.021	1.681***
ETH$_{t-3}$	0.148	0.301
ETH$_{t-4}$	0.092	-0.312
ETH$_{t-5}$	0.140	0.038
ETH$_{t-6}$	-0.167	0.072
ETH$_{t-7}$	-0.114	0.591
ETH$_{t-8}$	0.217*	0.093
WIKI_ETH$_{t-1}$	-0.027	0.662***
WIKI_ETH$_{t-2}$	0.034	-0.306**
WIKI_ETH$_{-3}$	-0.023	0.180
WIKI_ETH$_{t-4}$	0.030	-0.512***
WIKI_ETH$_{t-5}$	-0.043	0.311***
WIKI_ETH$_{t-6}$	0.007	-0.257**
WIKI_ETH$_{t-7}$	-0.008	0.156
WIKI_ETH$_{t-8}$	0.003	-0.173*
Panel B. VAR based Granger Causality test		
	Chi-sq	
WIKI_ETH does not Granger Cause ETH	3.339	
ETH does not Granger Cause WIKI_ETH	30.806***	

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

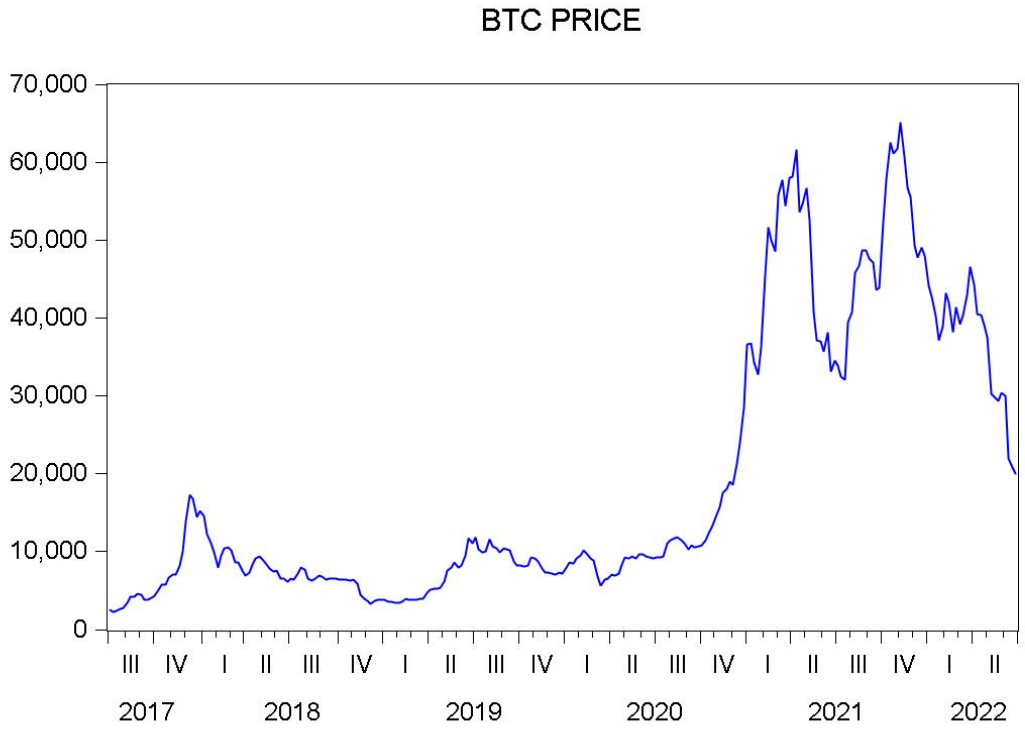


Figure 1.1 Bitcoin prices

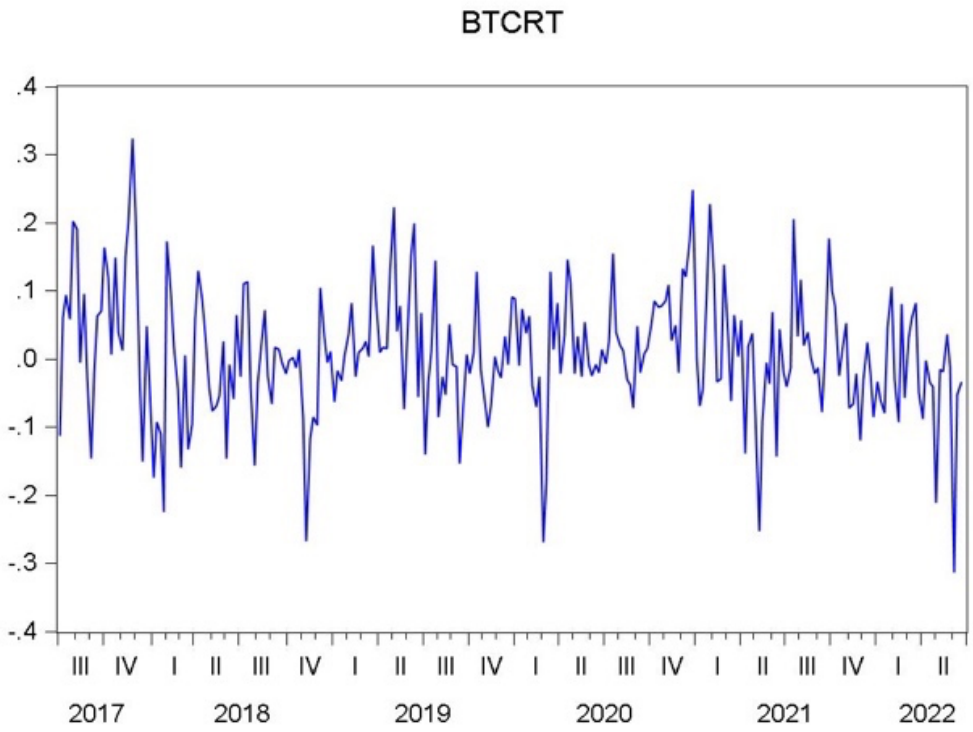


Figure 1.2 Bitcoin returns

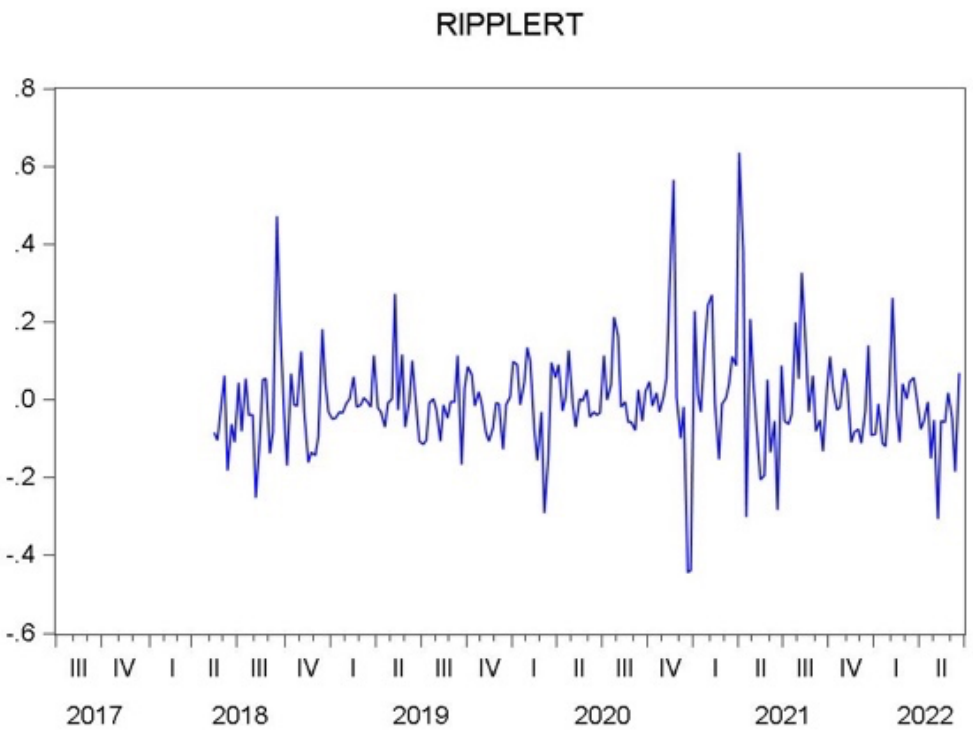


Figure 1.3 Ripple returns

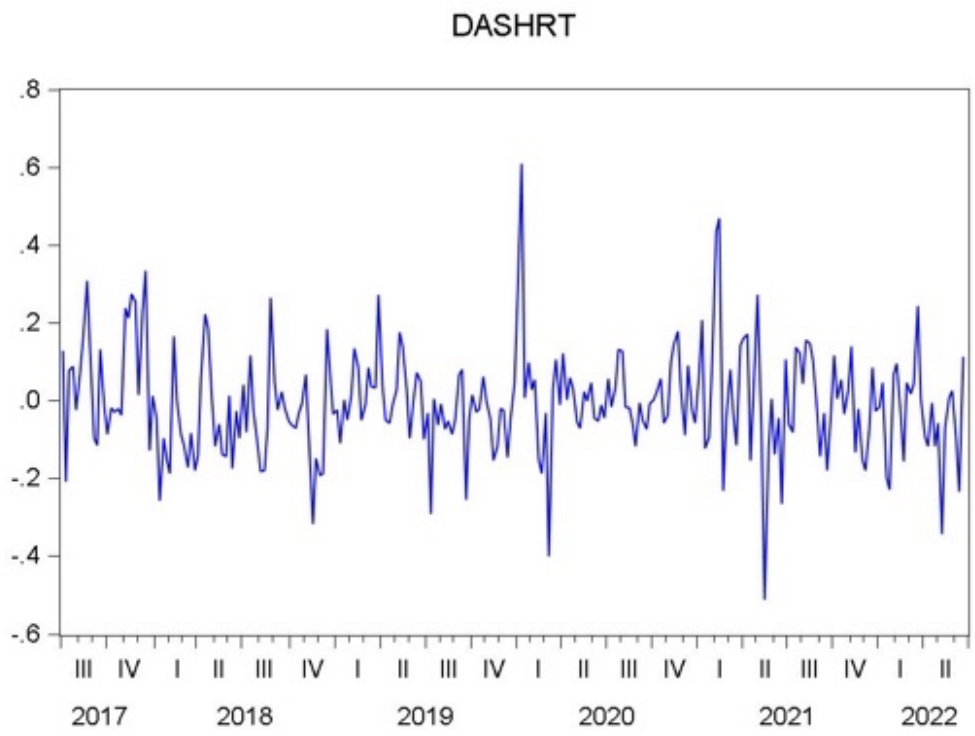


Figure 1.4 Dash returns

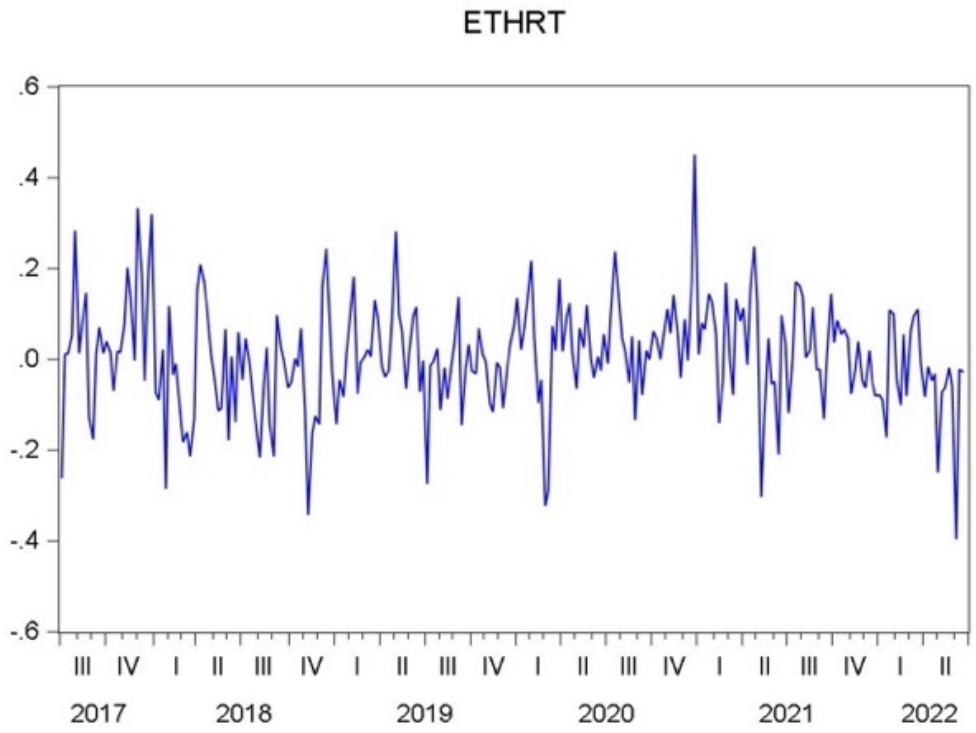


Figure 1.5 Ethereum returns

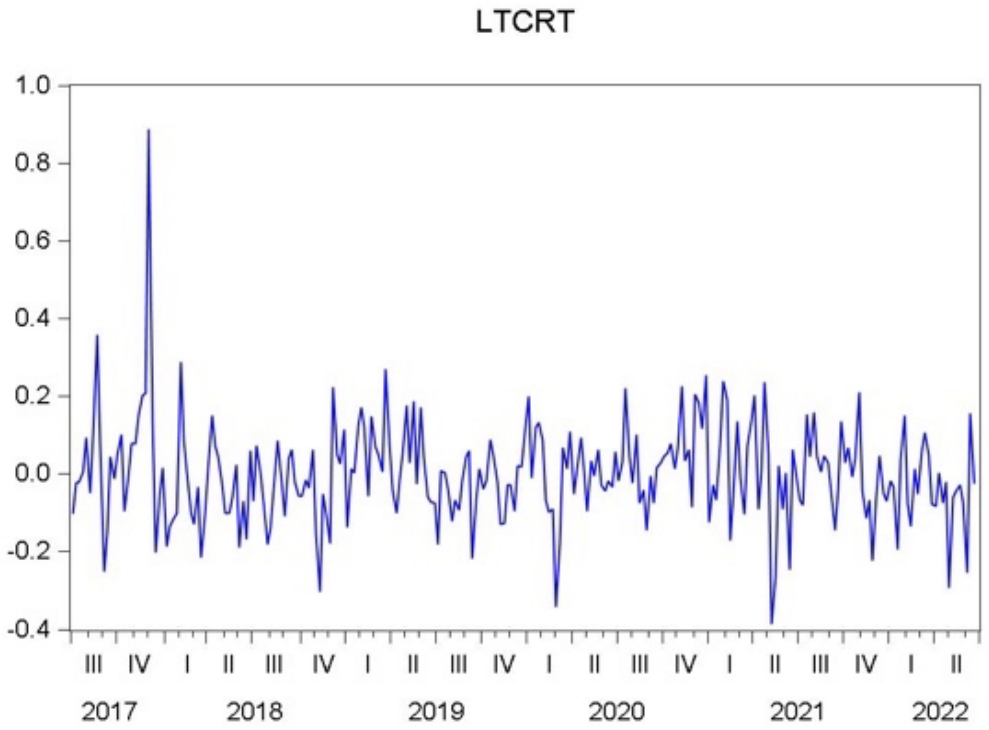


Figure 1.6 Litecoin returns

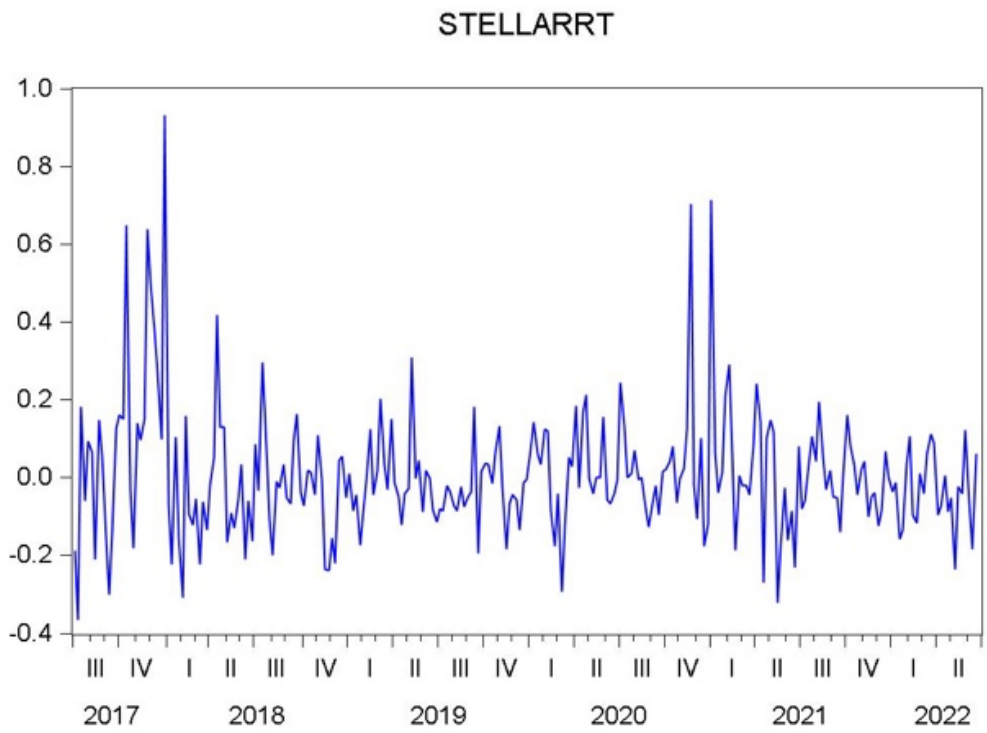


Figure 1.7 Stellar returns

Table 2.1 Augmented Dickey-Fuller (ADF) test

Panel A. ADF Unit Root Test	Intercept - Level	
	t-Statistics	p-Value
BTC	-41.73	0.000 (H_0 is rejected)
ETH	-42.85	0.000 (H_0 is rejected)
LTC	-40.17	0.000 (H_0 is rejected)
DASH	-41.41	0.000 (H_0 is rejected)
XRP	-38.45	0.000 (H_0 is rejected)
XLM	-39.13	0.000 (H_0 is rejected)
SOL	-22.70	0.000 (H_0 is rejected)
GSVI-BTC	-4.87	0.000 (H_0 is rejected)
GSVI-ETH	-4.01	0.001 (H_0 is rejected)
GSVI-LTC	-6.77	0.000 (H_0 is rejected)
GSVI-DASH	-3.86	0.013 (H_0 is rejected)
GSVI-XRP	-5.11	0.000 (H_0 is rejected)
GSVI-XLM	-8.56	0.000 (H_0 is rejected)
GSVI-SOL	-3.81	0.002 (H_0 is rejected)
WIKI-BTC	-3.28	0.015 (H_0 is rejected)
WIKI-ETH	-3.40	0.010 (H_0 is rejected)
WIKI-LTC	-3.05	0.030 (H_0 is rejected)
WIKI-DASH	-4.17	0.000 (H_0 is rejected)
WIKI-XRP	-3.64	0.005 (H_0 is rejected)
WIKI-XLM	-3.78	0.003 (H_0 is rejected)
WIKI-SOL	-4.03	0.001 (H_0 is rejected)

Notes: Table 2.1. shows the unit root test results of the variables.

Table 2.2 Descriptive statistics

Panel A. 2017 - 2023 term					Panel B. 2017 – 2020 term				Panel C. 2020 – 2023 term			
Daily	**Mean**	**SD**	**Skewness**	**Kurtosis**	**Mean**	**SD**	**Skewness**	**Kurtosis**	**Mean**	**SD**	**Skewness**	**Kurtosis**
Bitcoin (BTC)	0.001%	0.046%	-0.704%	13.70%	0.001%	0.049%	0.226%	6.48%	0.001%	0.044%	-1.687%	21.93%
Ethereum (ETH)	0.001%	0.059%	-0.605%	11.46%	-0.000%	0.062%	-0.042%	5.48%	0.002%	0.057%	-1.116%	17.43%
Ripple (XRP)	-0.000%	0.065%	0.732%	20.50%	-0.003%	0.054%	0.646%	7.61%	0.001%	0.070%	0.714%	21.75%
Dash	-0.001%	0.066%	-0.170%	10.16%	-0.001%	0.066%	0.614%	7.60%	-0.000%	0.065%	-0.774%	12.16%
Litecoin (LTC)	0.000%	0.063%	0.153%	12.95%	0.000%	0.068%	1.323%	12.72%	0.000%	0.059%	-1.175%	12.67%
Stellar (XLM)	0.000%	0.076%	1.308%	15.27%	0.000%	0.088%	1.351%	12.47%	0.000%	0.066%	1.126%	17.91%
Solana (SOL)									0.0000%	0.070%	-0.741%	10.81%
GSVI – BTC	0.96%	1.04%	3.13%	18.51%	0.70%	1.14%	4.15%	25.34%	1.14%	0.90%	2.35%	11.64%
GSVI – ETH	0.95%	1.02%	2.18%	10.27%	0.45%	0.59%	2.82%	12.35%	1.32%	1.12%	1.92%	8.93%
GSVI – XRP	0.54%	1.03%	8.14%	85.11%	0.79%	1.52%	5.56%	39.50%	0.36%	0.28%	4.10%	27.32%
GSVI – DASH	0.00%	0.27%	-0.57%	25.62%	1.60%	0.69%	2.21%	15.04%	2.82%	0.96%	0.85%	5.32%
GSVI – LTC	0.44%	1.09%	14.30%	294.61%	0.62%	1.62%	10.07%	140.87%	0.30%	0.32%	2.41%	9.27%
GSVI - XLM	1.53%	1.03%	6.97%	85.69%	1.45%	1.36%	6.67%	65.57%	1.59%	0.68%	3.45%	27.80%
GSVI - SOL	0.87%	1.02%	2.50%	11.24%	0.31%	0.06%	3.71%	44.94%	1.29%	1.18%	1.77%	7.51%
WIKI – BTC	8.64%	0.69%	1.16%	4.46%	8.87%	0.81%	0.93%	3.30%	8.47%	0.52%	0.66%	2.89%
WIKI – ETH	7.45%	0.75%	0.56%	2.48%	7.46%	0.81%	0.83%	2.81%	7.45%	0.70%	0.25%	1.92%
WIKI – XRP	6.25%	0.80%	1.34%	5.20%	6.69%	0.87%	1.15%	3.97%	5.92%	0.54%	0.95%	3.70%
WIKI – DASH	7.40%	0.21%	-0.52%	4.40%	7.40%	0.19%	-1.16%	8.48%	7.40%	0.22%	-0.22%	2.71%
WIKI - LTC	5.92%	0.92%	0.81%	3.26%	6.11%	0.98%	0.92%	3.08%	5.77%	0.83%	0.56%	2.68%
WIKI - XLM	4.99%	0.68%	1.07%	5.69%	5.16%	0.65%	1.96%	10.05%	4.87%	0.68%	0.68%	2.82%
WIKI - SOL	2.20%	0.89%	0.46%	3.57%	1.75%	0.53%	-0.68%	4.42%	2.53%	0.96%	0.05%	3.07%

Notes: Table 2.2. reports the daily summary statistics of returns for each cryptocurrency, the GSVI and Wikipedia for each cryptocurrency searches for all three periods.

Table 2.3 Correlation matrix

Panel A. 2017-2023	BTC	ETH	LTC	DASH	XRP	XLM	SOL	GSVI-BTC	GSVI-ETH	GSVI-LTC	GSVI-DASH	GSVI-XRP	GSVI-XLM	GSVI-SOL	WIKI-BTC	WIKI-ETH	WIKI-LTC	WIKI-DASH	WIKI-XRP	WIKI-XLM	WIKI-SOL
BTC	1																				
ETH	0.87 (44.03)	1																			
LTC	0.78 (31.93)	0.80 (33.21)	1																		
DASH	0.71 (25.34)	0.73 (26.54)	0.80 (33.72)	1																	
XRP	0.66 (22.15)	0.68 (23.12)	0.68 (23.57)	0.63 (20.28)	1																
XLM	0.70 (24.88)	0.71 (25.04)	0.72 (25.86)	0.68 (23.00)	0.84 (40.01)	1															
SOL	0.67 (22.69)	0.73 (26.96)	0.65 (21.37)	0.61 (19.42)	0.60 (18.92)	0.63 (20.31)	1														
GSVI-BTC	0.00 (0.22)	0.02 (0.58)	0.04 (1.16)	0.03 (0.91)	0.03 (0.95)	0.04 (1.01)	0.04 (1.15)	1													
GSVI-ETH	-0.01 (-0.45)	-0.00 (-0.15)	0.02 (0.70)	0.02 (0.65)	0.04 (1.04)	0.02 (0.71)	0.05 (1.41)	0.78 (31.15)	1												
GSVI-LTC	-0.03 (-0.75)	-0.01 (-0.36)	-0.03 (-0.87)	-0.02 (-0.52)	-0.02 (-0.50)	-0.02 (-0.69)	0.02 (0.61)	0.59 (18.46)	0.71 (25.28)	1											
GSVI-DASH	0.02 (0.64)	-0.02 (-0.51)	-0.01 (-0.33)	-0.01 (-0.41)	0.00 (0.21)	-0.01 (-0.42)	0.01 (0.33)	-0.16 (-4.16)	-0.29 (-7.56)	-0.27 (-7.07)	1										
GSVI-XRP	-0.02 (-0.53)	-0.01 (-0.35)	-0.01 (-0.41)	-0.01 (-0.44)	-0.06 (-1.53)	-0.08 (-2.01)	0.06 (1.52)	0.24 (6.21)	0.29 (7.62)	0.46 (13.06)	0.07 (-1.84)	1									
GSVI-XLM	-0.03 (-0.90)	-0.06 (-1.66)	-0.07 (-1.96)	-0.08 (-1.99)	-0.04 (-1.00)	-0.05 (-1.31)	-0.00 (-0.04)	0.01 (0.36)	0.05 (1.28)	0.17 (4.44)	0.18 (4.56)	0.29 (7.73)	1								
GSVI-SOL	-0.05 (-1.38)	-0.02 (-0.68)	-0.00 (-0.04)	-0.03 (-0.90)	-0.04 (-1.10)	-0.03 (-0.78)	-0.02 (-0.57)	0.53 (15.62)	0.61 (19.13)	0.54 (16.01)	-0.14 (-3.68)	0.23 (6.05)	0.06 (1.54)	1							
WIKI-BTC	-0.02 (-0.63)	-0.00 (-0.14)	-0.00 (-0.05)	-0.01 (-0.31)	-0.02 (-0.52)	-0.02 (-0.65)	0.00 (0.06)	0.73 (27.22)	0.79 (32.64)	0.68 (23.36)	-0.28 (-7.50)	0.25 (6.66)	-0.12 (-3.00)	0.59 (18.17)	1						
WIKI-ETH	-0.03 (-0.77)	-0.02 (-0.53)	-0.01 (-0.35)	-0.01 (-0.31)	-0.00 (-0.16)	-0.02 (-0.60)	-0.00 (-0.16)	0.66 (22.24)	0.86 (42.34)	0.69 (24.03)	-0.28 (-7.37)	0.24 (6.31)	-0.07 (-1.81)	0.64 (21.10)	0.90 (51.53)	1					
WIKI-LTC	-0.01 (-0.25)	-0.00 (-0.01)	-0.00 (-0.22)	-0.00 (-0.24)	-0.01 (-0.47)	-0.01 (-0.33)	0.00 (0.19)	0.61 (19.58)	0.74 (27.39)	0.70 (24.46)	-0.27 (-7.03)	0.28 (7.31)	-0.04 (-1.23)	0.61 (19.51)	0.86 (42.96)	0.91 (55.93)	1				
WIKI-DASH	0.01 (0.33)	0.02 (0.69)	0.01 (0.35)	0.02 (0.54)	0.05 (1.26)	0.02 (0.56)	0.04 (0.99)	0.45 (12.61)	0.64 (21.04)	0.59 (18.27)	-0.13 (-3.35)	0.28 (7.34)	-0.01 (-0.35)	0.42 (11.65)	0.76 (29.46)	0.78 (31.22)	0.74 (27.39)	1			

WIKI-XRP	-0.01 (-0.40)	-0.00 (-0.12)	-0.01 (-0.25)	-0.01 (-0.39)	-0.04 (-1.14)	-0.06 (-1.50)	0.02 (0.64)	0.55 (16.33)	0.65 (21.59)	0.70 (24.32)	-0.22 (-5.78)	0.63 (20.34)	0.16 (4.12)	0.54 (16.13)	0.72 (26.02)	0.72 (25.86)	0.71 (25.32)	0.68 (23.41)	1		
WIKI-XLM	-0.02 (-0.50)	0.00 (0.03)	-0.00 (-0.14)	0.00 (0.03)	-0.02 (-0.70)	-0.03 (-0.82)	0.02 (0.58)	0.62 (19.89)	0.79 (32.49)	0.76 (29.70)	-0.30 (-7.84)	0.40 (11.07)	0.04 (1.17)	0.60 (18.71)	0.83 (37.43)	0.88 (46.62)	0.84 (39.23)	0.75 (28.14)	0.82 (35.84)	1	
WIKI-SOL	-0.03 (-0.97)	-0.00 (-0.23)	0.00 (0.10)	-0.01 (-0.26)	-0.01 (-0.41)	-0.02 (-0.67)	0.02 (0.60)	0.55 (16.50)	0.66 (22.36)	0.61 (19.48)	-0.18 (-4.66)	0.26 (6.84)	-0.07 (-1.77)	0.73 (27.17)	0.71 (25.23)	0.76 (29.40)	0.70 (24.79)	0.59 (18.15)	0.62 (19.95)	0.73 (27.04)	1

Notes: Table 2.3. reports the correlations between each cryptocurrency returns, the search query "name of cryptocurrency" from the GSVI and Wikipedia searches for the period 2017 – 2023.

Table 2.4 GARCH (1,1) test for GSVI

GARCH (1,1)

Periods	**2017 - 2023**						**2017 - 2020**						**2020 - 2023**						
$Rb_{returns}$	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**SOL**
μ	0.002 (0.001)	0.001 (0.001)	0.004 (0.003)	-0.003 (0.003)	0.000 (0.001)	0.001 (0.003)	-0.0004 (0.002)	-0.001 (0.002)	0.008 (0.007)	-0.005 (0.006)	-0.001 (0.003)	-0.0006 (0.014)	0.003* (0.002)	0.004** (0.002)	0.001 (0.003)	-0.0008 (0.004)	0.002 (0.002)	0.004 (0.005)	0.003 (0.004)
$\beta GSVI_{t-1}$	-0.0003 (0.001)	-0.0006 (0.001)	-0.017* (0.009)	0.0006 (0.001)	0.0006 (0.004)	-0.001 (0.002)	0.003 (0.003)	0.002 (0.006)	-0.031 (0.019)	0.001 (0.004)	0.000 (0.004)	-0.003 (0.012)	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.010)	-0.0009 (0.001)	-0.003 (0.008)	-0.002 (0.003)	-0.002 (0.002)
ω	0.0001*** (0.0002)	0.0006*** (0.0001)	0.0002* (0.0001)	0.0007*** (0.0001)	0.0005*** (0.0008)	0.0002*** (0.0003)	0.0006*** (0.0002)	0.001*** (0.0004)	0.0002 (0.0002)	0.0003*** (0.0001)	0.003*** (0.000)	0.002** (0.0009)	0.0003*** (0.0006)	0.0005*** (0.0001)	-0.0001 (0.0001)	0.0006*** (0.0001)	0.0005*** (0.0001)	0.000** (0.000)	0.0008*** (0.0001)
$\alpha_{returns}\varepsilon_{t-1}^2$	0.118*** (0.010)	0.092*** (0.005)	0.325*** (0.022)	0.193*** (0.017)	0.100*** (0.015)	0.095*** (0.009)	0.024 (0.027)	0.085** (0.035)	0.186*** (0.049)	0.173*** (0.028)	0.124*** (0.033)	0.299*** (0.058)	0.052*** (0.016)	0.121*** (0.016)	0.449*** (0.033)	0.146*** (0.019)	0.083*** (0.023)	0.291*** (0.032)	0.243*** (0.027)
$\beta_{returns}\sigma_{t-1}^2$	0.781*** (0.025)	0.896*** (0.007)	0.307*** (0.022)	0.718*** (0.025)	0.654*** (0.046)	0.883*** (0.009)	0.379* (0.211)	0.440** (0.187)	0.171 (0.151)	0.717*** (0.038)	-0.224* (0.129)	0.128 (0.134)	0.532*** (0.090)	0.832*** (0.016)	0.105** (0.049)	0.768*** (0.031)	0.569*** (0.107)	0.305*** (0.060)	0.560*** (0.064)
$\gamma GSVI_{t-1}$	0.0005** (0.0002)	0.0005 (0.0008)	0.004*** (0.0005)	-0.0001*** (0.0002)	0.001*** (0.0002)	-0.0005*** (0.0001)	0.001*** (0.0004)	0.001*** (0.0005)	0.004*** (0.001)	0.0001 (0.0007)	0.002*** (0.0006)	-0.0006 (0.0008)	0.0003*** (0.0008)	0.0008*** (0.0002)	0.008*** (0.000)	-0.0001*** (0.0002)	0.002*** (0.000)	0.0009*** (0.0001)	0.0001 (0.0001)

Notes: Table 2.4. reports the results of the equation 2.3 for Google searches for all three periods.

Table 2.5 GARCH (1,1) test for WIKI

GARCH (1,1)																			
Periods	**2017 – 2023**						**2017 - 2020**						**2020 - 2023**						
$Rb_{returns}$	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**SOL**
μ	0.010 (0.016)	-0.002 (0.013)	0.054*** (0.014)	-0.033 (0.043)	0.003 (0.009)	0.009 (0.012)	-0.006 (0.022)	-0.012 (0.023)	0.003 (0.030)	-0.000 (0.083)	0.001 (0.016)	0.003 (0.032)	0.015 (0.022)	-0.001 (0.017)	0.097*** (0.017)	-0.058 (0.056)	0.004 (0.012)	0.024* (0.013)	-0.002 (0.009)
$\beta WIKI_{t-1}$	-0.001 (0.001)	0.000 (0.001)	-0.009*** (0.002)	0.004 (0.005)	-0.000 (0.001)	-0.002 (0.002)	0.000 (0.002)	0.001 (0.003)	-0.001 (0.004)	-0.000 (0.011)	-0.000 (0.002)	-0.001 (0.006)	-0.001 (0.002)	0.000 (0.002)	-0.016*** (0.002)	0.007 (0.007)	-0.000 (0.002)	-0.004* (0.002)	0.000 (0.003)
ω	-0.001*** (0.000)	-0.000*** (0.000)	-0.0009** (0.0004)	-0.003*** (0.000)	-0.001*** (0.000)	-0.0002*** (0.0007)	-0.002** (0.000)	-0.002** (0.001)	-0.004*** (0.001)	-0.001 (0.001)	-0.003*** (0.001)	0.000*** (0.0007)	-0.004*** (0.000)	-0.006*** (0.001)	-0.001 (0.000)	-0.006*** (0.001)	-0.002*** (0.000)	-0.002*** (0.000)	0.000 (0.000)
$\alpha_{returns}\varepsilon_{t-1}^2$	0.134*** (0.017)	0.087*** (0.005)	0.431*** (0.026)	0.206*** (0.018)	0.116*** (0.015)	0.098*** (0.009)	0.090*** (0.030)	0.105*** (0.033)	0.180*** (0.039)	0.202*** (0.032)	0.143*** (0.026)	0.021*** (0.004)	0.020 (0.014)	0.066*** (0.019)	0.742*** (0.048)	0.202*** (0.030)	0.087*** (0.027)	0.276*** (0.034)	0.226*** (0.027)
$\beta_{returns}\sigma_{t-1}^2$	0.698*** (0.038)	0.868*** (0.011)	0.337*** (0.020)	0.674*** (0.028)	0.629*** (0.044)	0.867*** (0.010)	0.616*** (0.126)	0.522*** (0.142)	0.301** (0.138)	0.673*** (0.043)	-0.162 (0.117)	0.975*** (0.005)	0.590*** (0.070)	0.514*** (0.089)	0.168*** (0.023)	0.576*** (0.055)	0.572*** (0.095)	0.300*** (0.062)	0.553*** (0.061)
$\gamma WIKI_{t-1}$	0.0002*** (0.0004)	0.0001*** (0.0002)	0.0003*** (0.00008)	0.0005*** (0.0001)	0.0004*** (0.0006)	0.0001*** (0.0001)	0.0003** (0.0001)	0.0005*** (0.0002)	0.0009*** (0.0003)	0.0002 (0.0001)	0.001*** (0.000)	-0.0007*** (0.0001)	0.0006*** (0.0001)	0.0009*** (0.0001)	0.0004*** (0.0001)	0.001*** (0.0002)	0.0005*** (0.0001)	0.0007*** (0.0001)	0.0003*** (0.0001)

Notes: Table 2.5. reports the results of the equation 2.4 for Wikipedia searches for all three periods.

Table 2.6 EGARCH (1,1) test for GSVI

EGARCH (1,1)

periods	**2017 - 2023**						**2017 - 2020**						**2020 - 2023**						
$\mathcal{Y}returns_t$	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**SOL**
μ	0.0005	0.001	0.007**	-0.003	-0.000	0.001	-0.0003	-0.001	0.007	-0.005	-0.001	0.002	0.004**	0.004**	0.007*	0.0005	0.001	0.005	0.004
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)	(0.002)	(0.003)	(0.007)	(0.006)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.006)	(0.004)
$\beta GSVI_{t-1}$	-0.0003	-0.000	-0.022**	0.0005	0.001	-0.000	0.002	0.001	-0.029	0.001	0.003	0.000	-0.001	-0.002	-0.016	-0.0004	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.009)	(0.001)	(0.002)	(0.002)	(0.003)	(0.005)	(0.019)	(0.004)	(0.004)	(0.003)	(0.001)	(0.001)	(0.012)	(0.001)	(0.007)	(0.003)	(0.002)
ω	-1.074***	-0.286***	-3.183***	-0.692***	-1.332***	-0.290***	-1.275***	-4.594***	-4.893***	-1.011***	-7.968***	0.040***	-1.136***	-0.415***	-3.252***	-0.534***	-1.505***	-0.501***	-1.336***
	(0.121)	(0.031)	(0.265)	(0.074)	(0.173)	(0.022)	(0.340)	(1.499)	(1.293)	(0.169)	(0.777)	(0.005)	(0.205)	(0.042)	(0.295)	(0.073)	(0.340)	(0.055)	(0.285)
$\alpha\frac{\epsilon_{t-1}}{\sigma_{t-1}}$	0.280***	0.188***	0.447***	0.328***	0.258***	0.211***	0.160***	0.203***	0.352***	0.339***	0.225***	0.002	0.150***	0.200***	0.474***	0.259***	0.167***	0.229***	0.410***
	(0.021)	(0.012)	(0.029)	(0.021)	(0.021)	(0.015)	(0.043)	(0.060)	(0.075)	(0.042)	(0.047)	(0.008)	(0.029)	(0.021)	(0.035)	(0.027)	(0.037)	(0.020)	(0.040)
RESID SIGN	-0.077***	-0.014*	0.040**	0.002	-0.036**	0.057***	-0.017	-0.098**	0.098**	0.024	0.094***	0.031***	-0.034**	0.018*	0.057***	0.031**	-0.066***	0.092***	-0.016
	(0.009)	(0.007)	(0.016)	(0.010)	(0.014)	(0.007)	(0.018)	(0.043)	(0.048)	(0.021)	(0.034)	(0.007)	(0.015)	(0.011)	(0.019)	(0.014)	(0.022)	(0.013)	(0.024)
$\beta\, In(\sigma^2_{t-1})$	0.861***	0.972***	0.530***	0.911***	0.801***	0.970***	0.816***	0.242	0.311*	0.867***	-0.376***	1.004***	0.851***	0.958***	0.520***	0.933***	0.778***	0.941***	0.812***
	(0.016)	(0.004)	(0.040)	(0.012)	(0.028)	(0.002)	(0.050)	(0.251)	(0.174)	(0.027)	(0.137)	(0.0001)	(0.028)	(0.005)	(0.044)	(0.012)	(0.052)	(0.008)	(0.046)
$\gamma GSVI_{t-1}$	0.024***	-0.001	0.683***	-0.013**	0.073***	-0.009***	0.065***	0.404***	1.392**	0.024	0.351***	-0.012***	0.055***	0.013***	0.789***	-0.009	0.296***	0.006	0.004
	(0.008)	(0.002)	(0.104)	(0.005)	(0.015)	(0.003)	(0.023)	(0.152)	(0.654)	(0.017)	(0.058)	(0.001)	(0.016)	(0.004)	(0.126)	(0.008)	(0.077)	(0.010)	(0.019)

Notes: Table 2.6. reports the results of the equation 2.6. for Google searches for all three periods.

Table 2.7 EGARCH (1,1) test for WIKI

EGARCH (1,1)																			
periods	**2017 - 2023**						**2017 - 2020**						**2020 - 2023**						
$\mathcal{Y}returns_t$	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**SOL**
μ	0.006	-0.004	0.062***	-0.029	0.003	-0.000	-0.009	-0.014	0.002	0.005	-0.006	0.015	0.018	0.000	0.083***	-0.053	0.003	0.012	-0.001
	(0.015)	(0.012)	(0.015)	(0.041)	(0.009)	(0.009)	(0.023)	(0.022)	(0.031)	(0.076)	(0.016)	(0.026)	(0.023)	(0.016)	(0.022)	(0.052)	(0.012)	(0.013)	(0.009)
$\beta WIKI_{t-1}$	-0.000	0.000	-0.010***	0.003	-0.000	0.000	0.001	0.001	-0.000	-0.001	0.001	-0.003	-0.001	0.000	-0.014***	0.007	-0.000	-0.002	0.000
	(0.001)	(0.001)	(0.002)	(0.005)	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)	(0.010)	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)	(0.007)	(0.002)	(0.002)	(0.003)
ω	-2.334***	-0.530***	-3.481***	-1.555***	-2.375***	-0.363***	-2.885***	-1.712***	-5.743***	-1.838***	-9.531***	0.109***	-2.697**	-0.788***	-4.826***	-1.054***	-2.024***	-0.629***	-1.690***
	(0.343)	(0.067)	(0.366)	(0.237)	(0.355)	(0.033)	(0.921)	(0.629)	(1.415)	(0.439)	(1.220)	(0.011)	(0.484)	(0.092)	(0.568)	(0.276)	(0.481)	(0.076)	(0.332)
$\alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}}$	0.293***	0.187***	0.466***	0.327***	0.258***	0.215***	0.210***	0.151***	0.369***	0.364***	0.224***	-0.000	0.123***	0.174***	0.486***	0.257***	0.170***	0.222***	0.385***
	(0.029)	(0.013)	(0.032)	(0.021)	(0.025)	(0.016)	(0.054)	(0.039)	(0.069)	(0.040)	(0.049)	(0.013)	(0.031)	(0.021)	(0.045)	(0.028)	(0.040)	(0.021)	(0.042)
RESID SIGN	-0.105***	-0.028***	0.021	-0.001	-0.064***	0.054***	-0.007	-0.016	0.078*	0.028	0.081**	0.012**	-0.041***	0.011	0.004	0.027*	-0.056**	0.089***	-0.026
	(0.013)	(0.008)	(0.016)	(0.010)	(0.017)	(0.007)	(0.022)	(0.025)	(0.044)	(0.023)	(0.036)	(0.006)	(0.016)	(0.011)	(0.023)	(0.014)	(0.023)	(0.013)	(0.025)
$\beta\, In(\sigma^2_{t-1})$	0.805***	0.954***	0.613***	0.904***	0.731***	0.963***	0.743***	0.803***	0.439***	0.857***	-0.231	1.004***	0.809***	0.943***	0.532***	0.929***	0.784***	0.931***	0.776***
	(0.027)	(0.006)	(0.035)	(0.013)	(0.041)	(0.003)	(0.080)	(0.074)	(0.136)	(0.028)	(0.159)	(0.0002)	(0.032)	(0.006)	(0.048)	(0.012)	(0.052)	(0.009)	(0.050)
$\gamma WIKI_{t-1}$	0.106***	0.018***	0.166***	0.107***	0.114***	0.003	0.131***	0.067**	0.337***	0.107**	0.419***	-0.016***	0.161***	0.043***	0.322***	0.063**	0.110***	0.018**	0.064**
	(0.019)	(0.004)	(0.030)	(0.025)	(0.019)	(0.003)	(0.046)	(0.027)	(0.099)	(0.049)	(0.068)	(0.001)	(0.033)	(0.008)	(0.054)	(0.030)	(0.028)	(0.007)	(0.029)

Notes: Table 2.7. reports the results of the equation 2.7. for Wikipedia searches for all three periods.

Table 2.8 GARCH (1,1) test both GSVI and WIKI

GARCH (1,1)

Period	2017 – 2023						2017 - 2020						2020 - 2023						
$Rb_{returns}$	BTC	ETH	XRP	DASH	LTC	XLM	BTC	ETH	XRP	DASH	LTC	XLM	BTC	ETH	XRP	DASH	LTC	XLM	SOL
μ	0.012 (0.020)	-0.008 (0.017)	0.014 (0.019)	-0.047 (0.046)	0.001 (0.0126)	0.012 (0.013)	0.016 (0.025)	-0.007 (0.027)	-0.020 (0.030)	-0.005 (0.089)	-0.001 (0.020)	0.001 (0.030)	0.005 (0.037)	-0.042* (0.024)	0.073** (0.030)	-0.062 (0.065)	-0.003 (0.016)	0.019 (0.016)	-0.007 (0.009)
$\beta GSVI_{t-1}$	0.0002 (0.001)	-0.001 (0.001)	-0.013 (0.011)	0.0008 (0.001)	-0.0002 (0.005)	-0.0008 (0.002)	0.003 (0.004)	0.001 (0.007)	-0.038* (0.020)	0.001 (0.004)	0.0003 (0.005)	-0.0008 (0.004)	-0.001 (0.002)	-0.006** (0.002)	0.023* (0.013)	0.0005 (0.001)	-0.007 (0.011)	-0.0004 (0.004)	-0.005 (0.003)
$\beta WIKI_{t-1}$	-0.001 (0.002)	0.001 (0.002)	-0.001 (0.003)	0.005 (0.006)	-0.0002 (0.002)	-0.002 (0.002)	-0.001 (0.003)	0.0008 (0.003)	0.004 (0.005)	-0.00006 (0.012)	0.00002 (0.003)	-0.0007 (0.006)	-0.0003 (0.004)	0.007* (0.003)	-0.013** (0.005)	0.008 (0.008)	0.001 (0.003)	-0.003 (0.003)	0.006 (0.004)
ω	-0.002*** (0.0003)	-0.001*** (0.0002)	0.0005 (0.0003)	-0.003*** (0.0009)	-0.0004 (0.0002)	-0.0001* (0.00009)	-0.002** (0.0009)	0.0003 (0.0009)	-0.004** (0.001)	-0.001 (0.001)	-0.0005 (0.001)	0.0001** (0.00005)	-0.006*** (0.001)	-0.006*** (0.001)	0.004*** (0.0008)	-0.005*** (0.001)	-0.0006* (0.0003)	-0.002*** (0.0006)	0.00005 (0.0002)
$\alpha_{returns}\varepsilon_{t-1}^2$	0.135*** (0.017)	0.082*** (0.006)	0.334*** (0.023)	0.206*** (0.020)	0.105*** (0.016)	0.097*** (0.009)	0.016 (0.027)	0.089** (0.036)	0.182*** (0.040)	0.185*** (0.032)	0.127*** (0.030)	0.005*** (0.0009)	0.020 (0.015)	0.073*** (0.020)	0.594*** (0.039)	0.174*** (0.029)	0.076*** (0.024)	0.263*** (0.034)	0.217*** (0.026)
$\beta_{returns}\,\sigma_{t-1}^2$	0.710*** (0.039)	0.867*** (0.012)	0.303*** (0.022)	0.653*** (0.033)	0.625*** (0.049)	0.871*** (0.010)	0.244 (0.223)	0.439** (0.181)	0.189 (0.179)	0.696*** (0.042)	-0.221** (0.121)	1.004*** (0.00005)	0.607*** (0.069)	0.532*** (0.089)	0.072** (0.039)	0.604*** (0.061)	0.556*** (0.114)	0.285*** (0.067)	0.578*** (0.066)
$\gamma GSVI_{t-1}$	-0.00005** (0.00002)	-0.00009*** (0.00001)	0.004*** (0.0005)	-0.0001*** (0.00002)	0.0007*** (0.0001)	-0.00007*** (0.00002)	0.001*** (0.0004)	0.001*** (0.0005)	0.002 (0.001)	0.00007 (0.00008)	0.001** (0.0007)	-0.0001*** (0.00001)	-0.0001*** (0.00005)	-0.0001*** (0.00005)	0.008*** (0.0007)	-0.0001*** (0.00004)	0.001** (0.0006)	0.0007*** (0.0001)	-0.0001 (0.0001)
$\gamma WIKI_{t-1}$	0.0003*** (0.00005)	0.0002*** (0.00003)	-0.00006 (0.00007)	0.0005*** (0.0001)	0.0002*** (0.00006)	0.00009*** (0.00001)	0.0003** (0.0001)	0.0001 (0.0001)	0.0007** (0.0003)	0.0002 (0.0001)	0.0007*** (0.0002)	0.00004 (0.00001)	0.0008*** (0.0001)	0.001*** (0.0002)	-0.0008*** (0.0001)	0.0009*** (0.0002)	0.0002*** (0.00008)	0.0007*** (0.0001)	0.0004*** (0.0001)

Notes: Table 2.8. reports the results of the equation 2.5. for all three periods

Table 2.9 EGARCH (1,1) test for both GSVI and WIKI

EGARCH (1,1)

periods	**2017 - 2023**						**2017 - 2020**						**2020 - 2023**						
$\mathcal{Y}returns_t$	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**BTC**	**ETH**	**XRP**	**DASH**	**LTC**	**XLM**	**SOL**
μ	0.009 (0.019)	-0.007 (0.015)	0.0466*** (0.017)	-0.053 (0.043)	0.003 (0.013)	0.001 (0.009)	-0.002 (0.026)	-0.013 (0.027)	-0.011 (0.034)	0.007 (0.080)	-0.002 (0.020)	-0.040* (0.022)	0.006 (0.040)	-0.043* (0.026)	0.098*** (0.033)	-0.064 (0.059)	-0.007 (0.016)	0.021 (0.015)	-0.006 (0.009)
$\beta GSVI_{t-1}$	0.0004 (0.001)	-0.001 (0.001)	-0.008 (0.012)	0.0008 (0.001)	0.0002 (0.004)	-0.0005 (0.002)	0.002 (0.003)	-0.0008 (0.007)	-0.037* (0.019)	0.001 (0.004)	0.002 (0.005)	-0.001 (0.003)	-0.001 (0.002)	-0.007*** (0.002)	0.015 (0.019)	0.0004 (0.001)	-0.007 (0.010)	0.0001 (0.004)	-0.006* (0.003)
$\beta WIKI_{t-1}$	-0.001 (0.002)	0.001 (0.002)	-0.007** (0.003)	0.006 (0.005)	-0.0005 (0.002)	-0.00005 (0.002)	0.0002 (0.003)	0.001 (0.004)	0.003 (0.006)	-0.001 (0.011)	0.0001 (0.003)	0.009* (0.004)	-0.00003 (0.005)	0.007* (0.003)	-0.017*** (0.006)	0.008 (0.007)	0.001 (0.003)	-0.004 (0.003)	0.006 (0.004)
ω	-2.386*** (0.350)	-0.572*** (0.081)	-3.636*** (0.350)	-1.488*** (0.246)	-2.375*** (0.363)	-0.381*** (0.035)	-2.744*** (0.930)	-4.865*** (1.579)	-6.668*** (1.896)	-1.729*** (0.434)	-10.632*** (1.141)	0.041** (0.017)	-3.169*** (0.566)	-0.961*** (0.126)	-4.037*** (0.500)	-1.022*** (0.285)	-1.857*** (0.426)	-3.015*** (0.456)	-1.689*** (0.395)
$\alpha\frac{\epsilon_{t-1}}{\sigma_{t-1}}$	0.300*** (0.029)	0.184*** (0.013)	0.457*** (0.032)	0.331*** (0.022)	0.251*** (0.028)	0.213*** (0.016)	0.194*** (0.055)	0.208*** (0.059)	0.373*** (0.069)	0.351*** (0.042)	0.191*** (0.048)	0.001 (0.010)	0.136*** (0.034)	0.174*** (0.022)	0.530*** (0.049)	0.260*** (0.028)	0.151*** (0.038)	0.409*** (0.041)	0.381*** (0.046)
RESID SIGN	-0.103*** (0.014)	-0.025*** (0.008)	0.021 (0.017)	-0.001 (0.010)	-0.069*** (0.019)	0.059*** (0.008)	-0.009 (0.022)	-0.097** (0.043)	0.071 (0.047)	0.024 (0.022)	0.071** (0.034)	0.044*** (0.008)	-0.039** (0.016)	0.0001 (0.013)	0.015 (0.023)	0.026* (0.015)	-0.072*** (0.023)	0.016 (0.026)	-0.047* (0.026)
$\beta\, In(\sigma^2_{t-1})$	0.812*** (0.027)	0.958*** (0.006)	0.538*** (0.041)	0.900*** (0.014)	0.723*** (0.042)	0.964*** (0.003)	0.737*** (0.087)	0.264 (0.243)	0.316 (0.196)	0.861*** (0.027)	-0.454*** (0.161)	1.004*** (0.00003)	0.822*** (0.032)	0.942*** (0.007)	0.507*** (0.045)	0.926*** (0.014)	0.765*** (0.054)	0.657*** (0.049)	0.786*** (0.058)
$\gamma GSVI_{t-1}$	-0.017 (0.012)	-0.013*** (0.004)	0.490*** (0.115)	-0.010* (0.005)	0.024 (0.021)	-0.013*** (0.003)	0.026 (0.025)	0.338** (0.156)	0.678 (0.554)	0.017 (0.019)	0.144** (0.068)	-0.012*** (0.003)	-0.055** (0.024)	-0.018*** (0.006)	0.602*** (0.187)	-0.004 (0.009)	0.213*** (0.066)	0.044 (0.030)	-0.053** (0.021)
$\gamma WIKI_{t-1}$	0.118*** (0.022)	0.028*** (0.007)	0.092*** (0.031)	0.097*** (0.026)	0.105*** (0.021)	0.012*** (0.003)	0.110** (0.043)	0.055 (0.064)	0.324*** (0.106)	0.093* (0.050)	0.385*** (0.072)	-0.0001 (0.003)	0.233*** (0.050)	0.068*** (0.013)	0.123* (0.071)	0.058* (0.032)	0.053** (0.021)	0.148*** (0.036)	0.116*** (0.032)

Notes: Table 2.9. reports the results of the equation 2.8. for all three periods.

Table 3.1 Augmented Dickey-Fuller (ADF) test

Panel A. ADF Unit Root Test	**Intercept - Level**	
	t-Statistics	**p-Value**
BTC	-53.40	0.000 (H_0 is rejected)
ETH	-54.48	0.000 (H_0 is rejected)
LTC	-53.02	0.000 (H_0 is rejected)
DASH	-54.61	0.000 (H_0 is rejected)
XRP	-51.17	0.000 (H_0 is rejected)
XLM	-50.51	0.000 (H_0 is rejected)
SOL	-42.77	0.000 (H_0 is rejected)
DOGE	-27.52	0.000 (H_0 is rejected)
CARDANO	-30.86	0.000 (H_0 is rejected)
AVAX	-38.22	0.000 (H_0 is rejected)
GSVI-BTC	-6.12	0.000 (H_0 is rejected)
WIKI-BTC	-3.38	0.011 (H_0 is rejected)
CSAD	-5.03	0.000 (H_0 is rejected)
CSAD benchmark	-6.58	0.000 (H_0 is rejected)
$R_{m,t}$	-54.63	0.000 (H_0 is rejected)
$R_{m,t}$ benchmark	-53.54	0.000 (H_0 is rejected)
$R^2_{m,t}$	-14.30	0.000 (H_0 is rejected)
$R^2_{m,t}$ benchmark	-14.82	0.000 (H_0 is rejected)

Notes: This table shows that unit root test results.

Table 3.2 Descriptive statistics

	MEAN	STD.DEV.	SKEWNESS	KURTOSIS
CSAD	0.010	0.011	4.733	44.51
CSAD benchmark	0.012	0.014	5.093	48.32
$\|R_{m,t}\|$	0.025	0.027	2.639	16.60
$\|R_{m,t}\|benchmark$	0.024	0.028	2.831	18.51
$R_{m,t}^2$	0.001	0.004	14.88	407.75
$R_{m,t}^2$ $benchmark$	0.001	0.004	15.01	389.04
GSVI BTC	0.0005	1.000	3.007	17.92
WIKI BTC	6611.75	8429.81	6.569	67.69

Notes: While CSAD calculated by market cap-weighted portfolios, CSAD benchmark calculated by Bitcoin returns.

Table 3.3 Correlation matrix

	CSAD	CSAD benchmark	$\|R_{m,t}\|$	$\|R_{m,t}\|$ *benchmark*	$R^2_{m,t}$	$R^2_{m,t}$ *benchmark*	GSVI BTC	WIKI BTC
CSAD	1.00							

CSAD benchmark	0.94	1.00						
	(156.52)	---						
$\|R_{m,t}\|$	0.21	0.16	1.00					
	(11.19)	(8.853)	---					
$\|R_{m,t}\|$*benchmark*	0.13	0.092	0.96	1.00				
	(6.793)	(4.810)	(189.27)	---				
$R^2_{m,t}$	0.32	0.30	-0.046	-0.034	1.00			
	(17.75)	(16.76)	(-2.424)	(-1.792)	---			
$R^2_{m,t}$ *benchmark*	0.27	0.24	-0.0046	0.037	0.95	1.00		
	(14.83)	(13.25)	(-0.239)	(1.955)	(161.27)	---		
GSVI BTC	0.44	0.40	0.023	-3.0008	0.26	0.26	1.00	
	(25.51)	(22.83)	(1.220)	(-0.0019)	(14.29)	(14.33)	---	
WIKI BTC	0.54	0.52	0.073	0.053	0.22	0.25	0.66	1.00
	(33.30)	(31.46)	(3.825)	(2.743)	(11.70)	(13.60)	(45.43)	---

Notes: t-statistics are in the parentheses.

Table 3.4 Regression results of herding

Panel A **Estimation of Equations:**	**(3.3)**	**(3.4)**
Constant	0.005***	0.005***
$\|R_{m,t}\|$	0.203***	
$R_{m,t}^2$	-0.265***	
$DR_{m,t}$		-0.130***
$(1-D)R_{m,t}$		0.216***
$DR_{m,t}^2$		-0.184**
$(1-D)R_{m,t}^2$		0.111
R^2	0.18	0.21
Panel B		
Constant	0.007***	0.007***
$\|R_{m,t}\|$	0.208***	
$R_{m,t}^2$	-0.277**	
$DR_{m,t}$		-0.187***
$(1-D)R_{m,t}$		0.202***
$DR_{m,t}^2$		-0.345***
$(1-D)R_{m,t}^2$		-0.033
R^2	0.11	0.11

Note: *p<0.1, **p<0.05, ***p<0.01

Table 3.5 Regression results for GSVI

	c	$DR^2_{m,t}$	$R^2_{m,t}$	D	$\lvert R_{m,t}\rvert$	R^2
1% extreme sentiment conditions						
Panel A: cap-weighted market portfolio						
Euphoria	0.005***	0.032	-0.299***	0.018***	0.196***	0.20
	(18.20)	(0.175)	(-3.475)	(7.662)	(15.51)	
Dysphoria	0.005***	0.474	-0.263***	-0.002	0.203***	0.18
	(17.72)	(0.255)	(-3.057)	(-1.007)	(15.79)	
Panel B: Bitcoin benchmark						
Euphoria	0.007***	-0.141	-0.277**	0.019***	0.197***	0.12
	(18.64)	(-0.658)	(-2.456)	(6.074)	(11.54)	
Dysphoria	0.007***	1.729	-0.272**	-0.002	0.207***	0.11
	(18.29)	(0.840)	(-2.480)	(-1.000)	(12.08)	
5% extreme sentiment conditions						
Panel A: cap-weighted market portfolio						
Euphoria	0.005***	0.562***	-0.339***	0.010***	0.176***	0.24
	(18.87)	(4.53)	(-4.01)	(10.33)	(14.21)	
Dysphoria	0.005***	-0.478	-0.268***	-0.0002	0.204***	0.18
	(17.18)	(-0.79)	(-3.10)	(-0.23)	(15.72)	
Panel B: Bitcoin benchmark						
Euphoria	0.007***	-0.122	-0.227**	0.015***	0.176***	0.16
	(18.67)	(-0.79)	(-2.04)	(11.46)	(10.51)	
Dysphoria	0.007***	0.251	-0.270**	-0.0009	0.206***	0.11
	(17.86)	(0.29)	(-2.45)	(-0.71)	(11.90)	

Notes: *p<0.1, **p<0.05, ***p<0.01 and t-statistics are in parentheses.

Table 3.6 Regression results for GSVI within both emotions

c	$D_{euphoria}R^2_{m,t}$	$D_{dysphoria}R^2_{m,t}$	$R^2_{m,t}$	$D_{euphoria}$	$D_{dysphoria}$	$\lvert R_{m,t}\rvert$	R^2
1% extreme sentiment conditions							
Panel A: cap-weighted market portfolio							
0.005***	0.033	0.625	-0.296***	0.018***	-0.002	0.195***	0.20
(18.19)	(0.179)	(0.342)	(-3.439)	(7.657)	(-1.024)	(15.40)	
Panel B: Bitcoin benchmark							
0.007***	-0.140	1.872	-0.272**	0.019***	-0.002	0.196***	0.12
(18.64)	(-0.656)	(0.918)	(-2.405)	(6.078)	(-1.012)	(11.42)	
5% extreme sentiment conditions							
Panel A: cap-weighted market portfolio							
0.005***	0.562***	-0.068	-0.339***	0.010***	-0.0001	0.176***	0.24
(18.27)	(4.531)	(-0.117)	(-3.994)	(10.31)	(-0.154)	(14.00)	
Panel B: Bitcoin benchmark							
0.007***	-0.118	0.606	-0.220**	0.015***	-0.0006	0.174***	0.16
(18.19)	(-0.769)	(0.725)	(-1.967)	(11.45)	(-0.519)	(10.21)	

Notes: *p<0.1, **p<0.05, ***p<0.01 and t-statistics are in parentheses.

Table 3.7 Regression results for WIKI

	c	$DR_{m,t}^2$	$R_{m,t}^2$	D	$\lvert R_{m,t}\rvert$	R^2
1% extreme sentiment conditions						
Panel A: cap-weighted market portfolio						
Euphoria	0.005***	0.747***	-0.314***	0.028***	0.195***	0.26
	(18.32)	(3.377)	(-3.800)	(13.05)	(15.93)	
Dysphoria	0.005***	-2.764	-0.265***	-0.002	0.204***	0.18
	(17.41)	(-0.252)	(-3.072)	(-1.239)	(15.77)	
Panel B: Bitcoin benchmark						
Euphoria	0.007***	-0.124	-0.320***	0.031***	0.202***	0.15
	(18.32)	(-0.622)	(-2.856)	(10.56)	(11.91)	
Dysphoria	0.007***	-7.470	-0.275**	-0.004	0.208***	0.11
	(18.09)	(-0.402)	(-2.491)	(-1.438)	(12.04)	
5% extreme sentiment conditions						
Panel A: cap-weighted market portfolio						
Euphoria	0.005***	0.418***	-0.352***	0.017***	0.174***	0.31
	(18.75)	(3.676)	(-4.319)	(18.23)	(14.68)	
Dysphoria	0.005***	-0.535	-0.250***	-0.003***	0.200***	0.18
	(17.67)	(-0.535)	(-2.893)	(-3.297)	(15.35)	
Panel B: Bitcoin benchmark						
Euphoria	0.007***	-0.057	-0.270***	0.028***	0.159***	0.28
	(19.51)	(-0.421)	(-2.586)	(22.46)	(10.16)	
Dysphoria	0.007***	-0.933	-0.251**	-0.005***	0.201***	0.11
	(18.52)	(-0.580)	(-2.274)	(-4.046)	(11.58)	

Notes: *p<0.1, **p<0.05, ***p<0.01 and t-statistics are in parentheses.

Table 3.8 Regression results for WIKI within both emotions

c	$D_{euphoria}R^2_{m,t}$	$D_{dysphoria}R^2_{m,t}$	$R^2_{m,t}$	$D_{euphoria}$	$D_{dysphoria}$	$\lvert R_{m,t}\rvert$	R^2
1% extreme sentiment conditions							
Panel A: cap-weighted market portfolio							
0.005***	0.749***	-2.377	-0.308***	0.028***	-0.002	0.194***	0.26
(18.36)	(3.385)	(-0.228)	(-3.735)	(13.05)	(-1.287)	(15.78)	
Panel B: Bitcoin benchmark							
0.007***	-0.124	-7.136	-0.313***	0.031***	-0.004	0.200***	0.15
(18.39)	(-0.620)	(-0.393)	(-2.784)	(10.55)	(-1.445)	(11.76)	
5% extreme sentiment conditions							
Panel A: cap-weighted market portfolio							
0.005***	0.428***	-0.093	-0.334***	0.017***	-0.002***	0.169***	0.32
(18.98)	(3.767)	(-0.102)	(-4.103)	(18.13)	(-3.241)	(14.13)	
Panel B: Bitcoin benchmark							
0.007***	-0.044	-0.291	-0.244**	0.028***	-0.004***	0.151***	0.28
(19.94)	(-0.330)	(-0.201)	(-2.333)	(22.37)	(-4.002)	(9.580)	

Notes: *p<0.1, **p<0.05, ***p<0.01 and t-statistics are in parentheses.

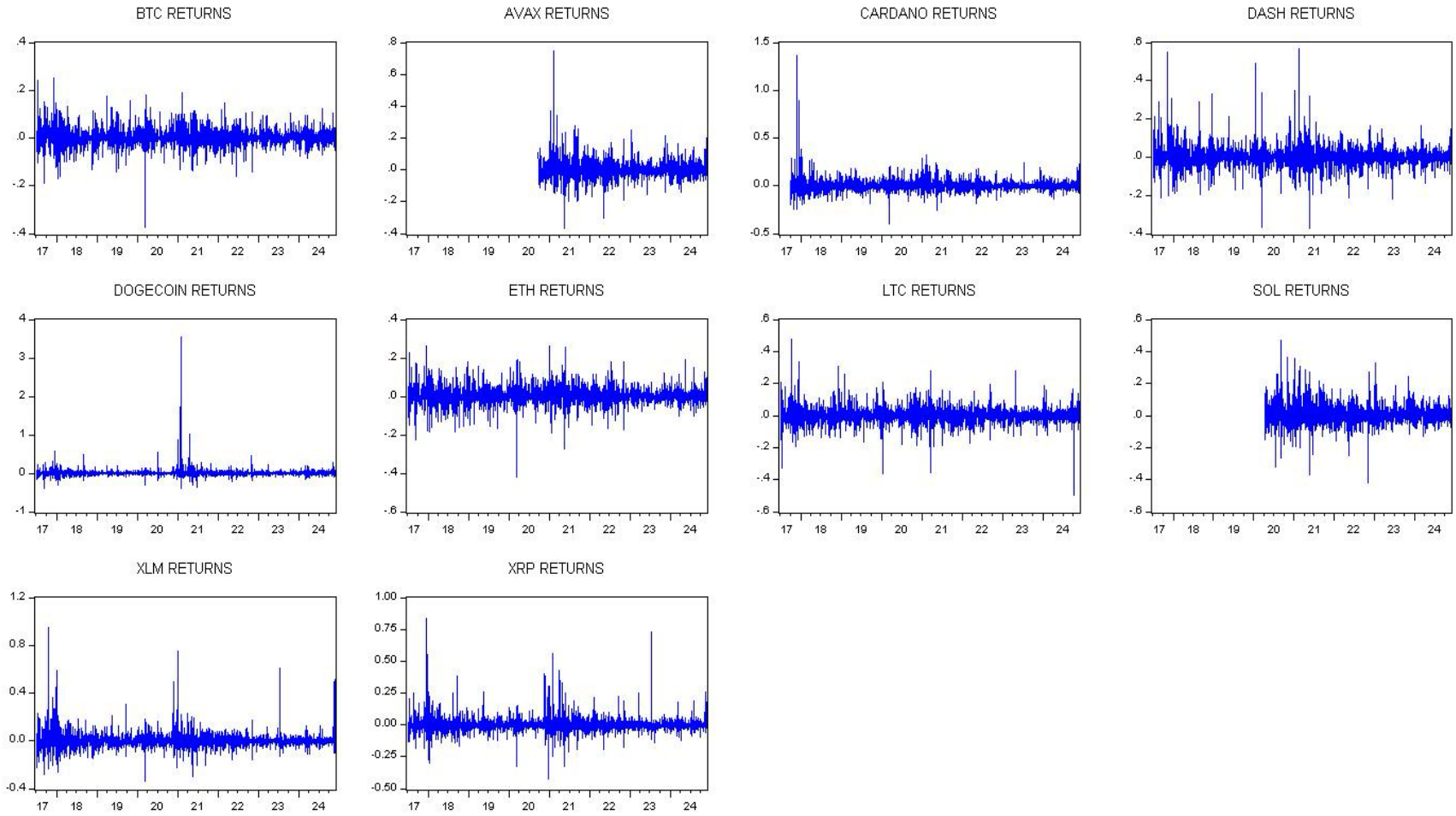


Figure 3.1 Cryptocurrency returns

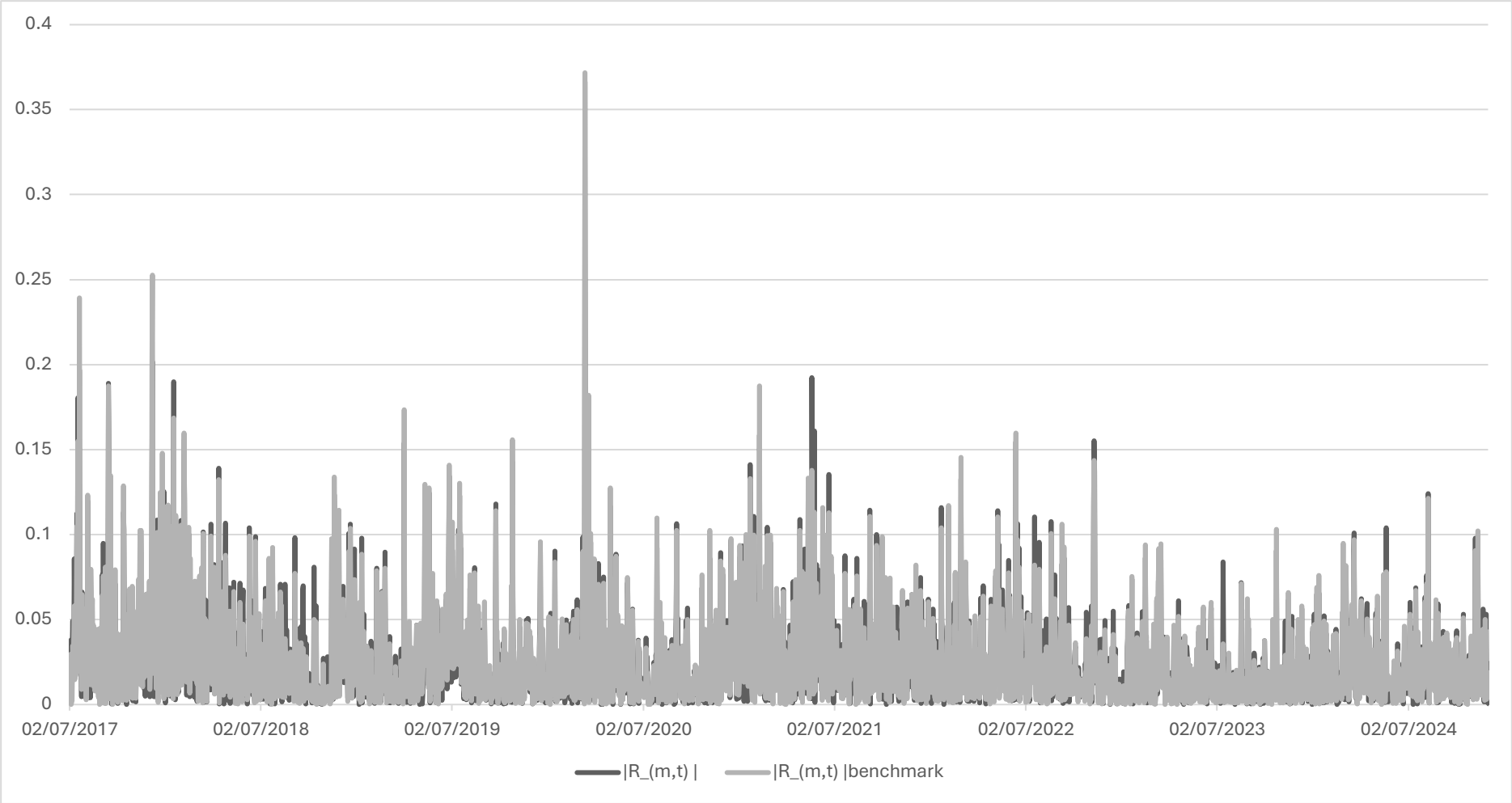


Figure 3.2 Cap-weighted portfolios of the top 10 cryptocurrency and Bitcoin benchmark

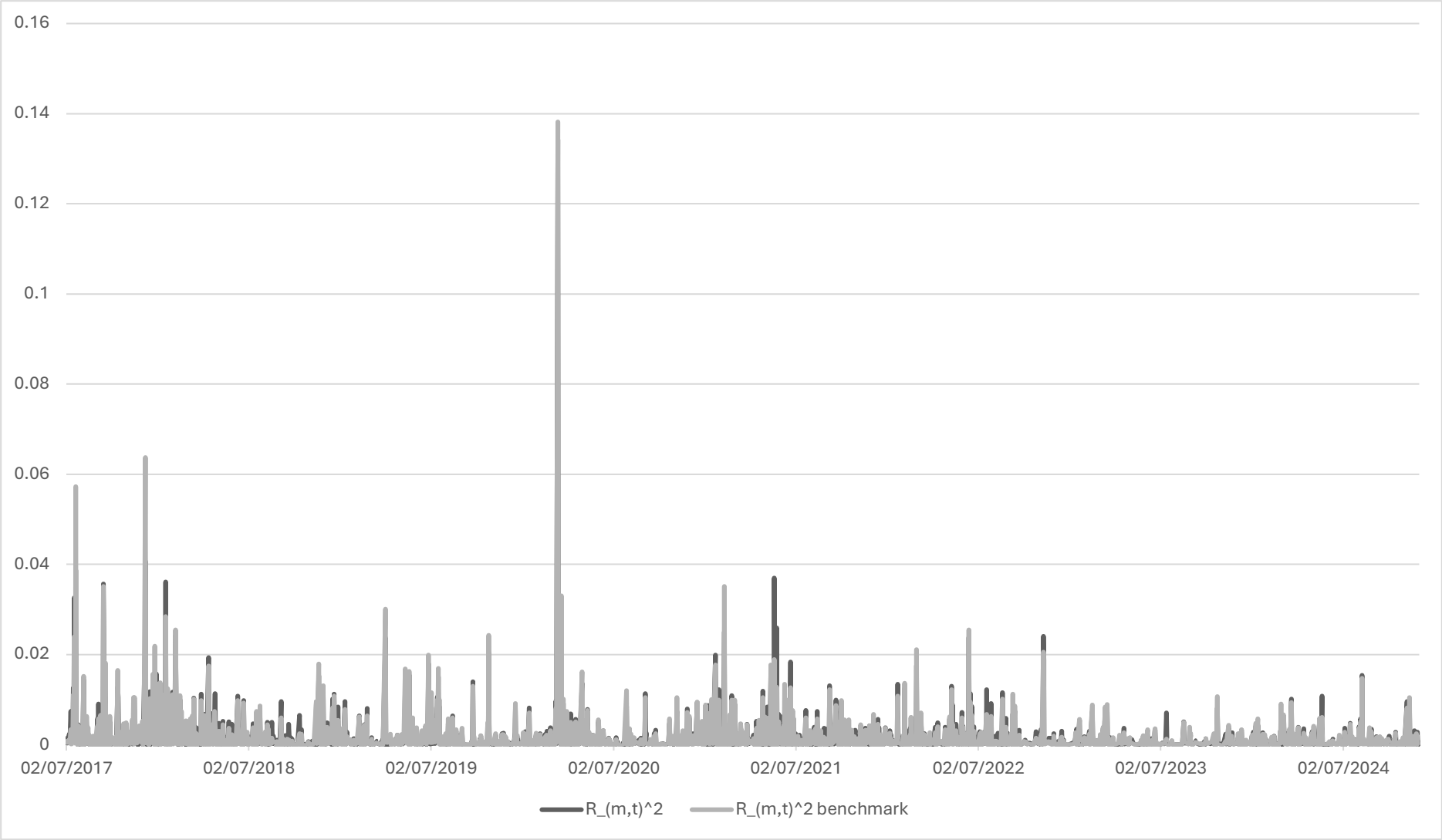


Figure 3.3 $R^2_{m,t}$ graphs

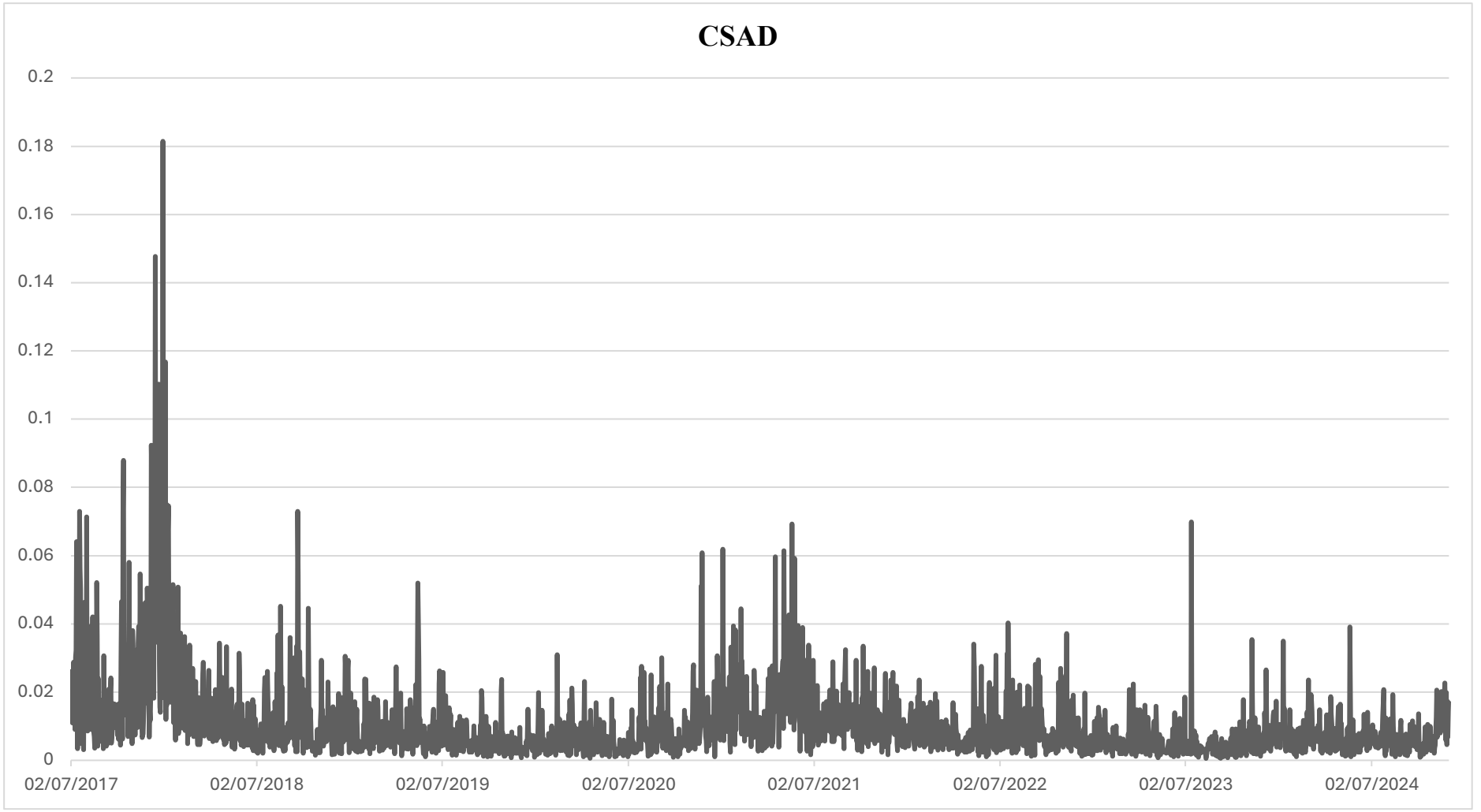


Figure 3.4 CSAD

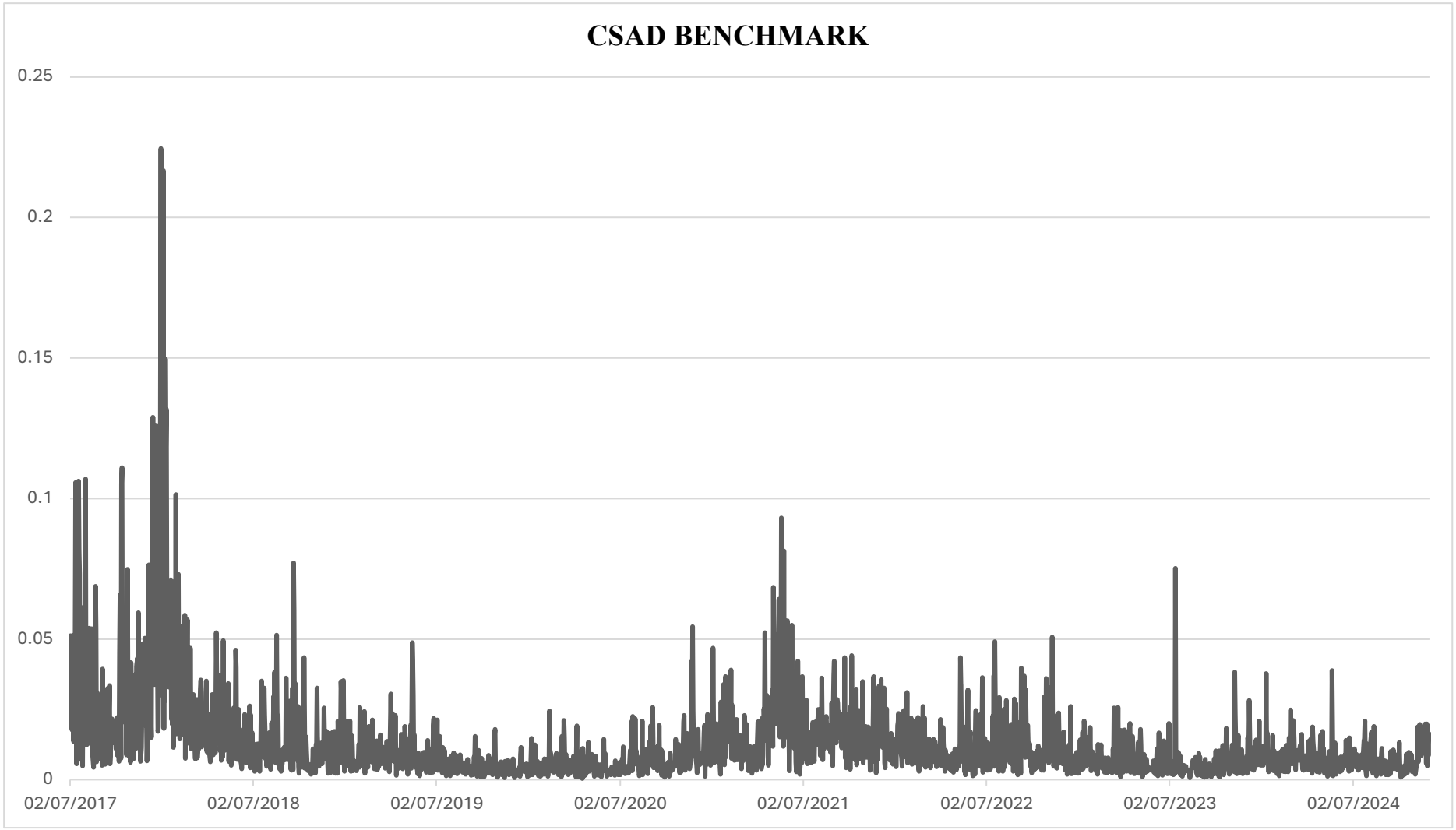


Figure 3.5 CSAD benchmark

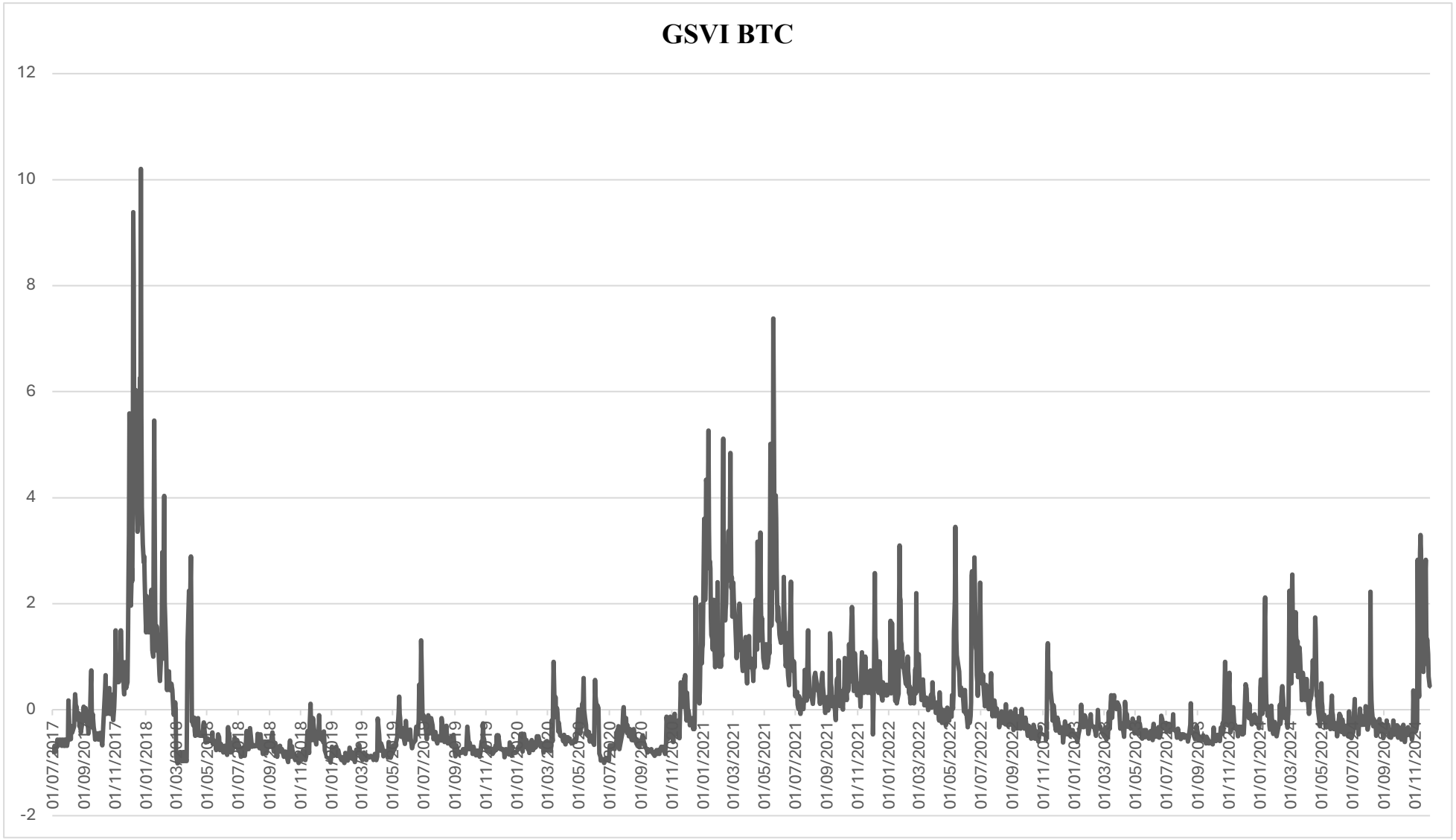


Figure 3.6 Google search volume index – search term: bitcoin

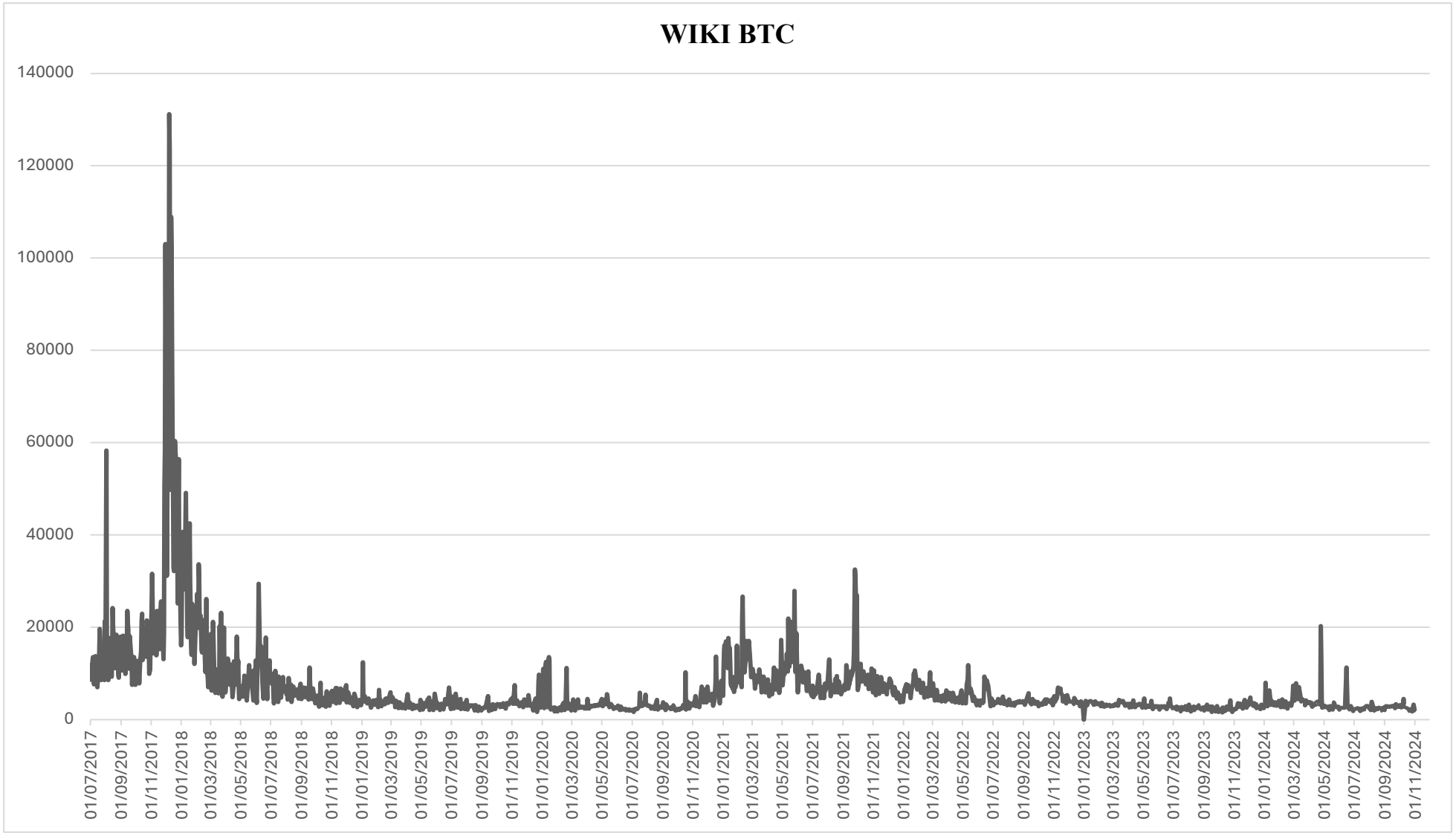


Figure 3.7 Wikipedia search term: bitcoin

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