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CRYPTOCURRENCIES: THE ROLE OF INVESTOR ATTENTION*

ABSTRACT

This study examines the relationship between investor attention, and the six major cryptocurrency returns by market capitalization from 2017 to 2022. Employing two measures for investor attention based on Google search volume index and raw Wikipedia searches, we test the predictive power of investor attention in different time periods, focusing on the periods before and after 2020. 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. Our results show that Google search volume index typically presents more predictability than Wikipedia searches. Moreover, results also reveal that given increased volatility, the relation between cryptocurrency returns and Google search volume index has weakened over time.

Keywords: Cryptocurrency Returns; Investor Attention; Google Search Volume Index; Predictability
JEL Classification: G12; G41

RIASSUNTO

Criptovalute: il ruolo del sentimento dell'investitore

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the predictive power of investor attention in different time periods, focusing on the periods before and after 2020. 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. Our results show that Google search volume index typically presents more predictability than Wikipedia searches. Moreover, results also reveal that given increased volatility, the relation between cryptocurrency returns and Google search volume index has weakened over time.

1. Introduction

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, Fernando and Fernando, 2022). For example, studies of investor behavior in the cryptocurrency market have shown that investor attitudes taken from social networks such as Twitter and Wikipedia (Kraaijeveld and De Smedt, 2020; Kristoufek, 2013; Dias, Fernando and Fernando, 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 and Gonçalves, 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 e.g. 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 Google search volume index (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 have also moderated the effect

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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.

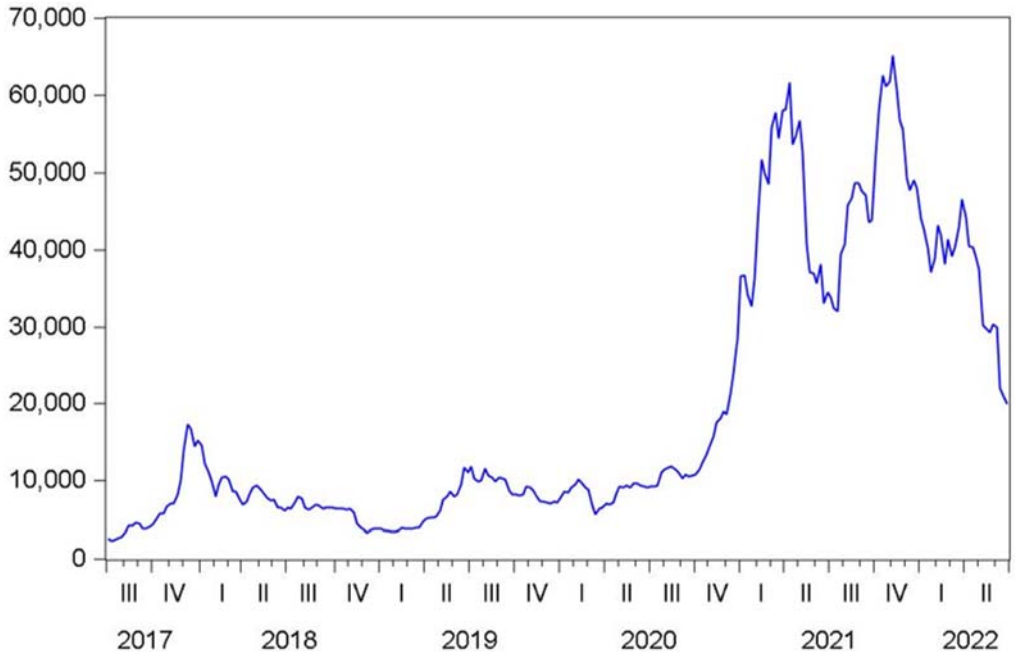
The market for cryptocurrencies was first described by Nakamoto (2008). Cryptocurrencies are digital currencies, using blockchain technology which is both decentralized and trustable (Almeida and Gonçalves, 2023; López-Cabarcos *et al.*, 2021; Kraaijeveld and De Smedt, 2020). Since 2020, there has been growing interest in decentralized finance (DeFi) protocols and platforms (Metelski and Sobieraj, 2022). Since cryptocurrencies have decentralized infrastructure, they potentially move financial control from centralized financial organizations to individual investors and give users more influence over their investments. This can be particularly so in countries where trust in traditional financial organizations is low, given historical uncertainty, corruption and inefficiencies. Blockchain is a transparent and immutable technology and thus can encourage confidence among consumers while fostering financial integration by promoting digital trade (El Hajj and Farran, 2024). Growing customer demand for easy access and management of both traditional fiat money and digital assets has posed important challenges to traditional banks, such as liquidity, credit, and operational risks to the international banking system. Sudden crashes in the crypto market can increase the risk of bank defaults when financial institutions hold crypto assets directly on their balance sheets (direct exposure) or extend credit to companies within the crypto ecosystem (indirect exposure). Furthermore, the shift of bank deposits into private digital assets (such as stablecoins) constrains banks' credit-creation capacity, giving rise to the risk of bank disintermediation (Basel Committee, 2019; Consultative Group of Directors of Financial Stability, 2023; Aldasoro, Frost and Ito, 2026).

However, the introduction of cryptocurrencies into the framework of traditional banking systems has resulted in an innovation disruption and encouraged emerging partnerships between financial organizations and fintech firms. For example, Barclays has entered in partnership with fintech startups to supply Bitcoin services to access the fast-growing world of cryptocurrencies, while Citigroup has built its own cryptocurrency trading platform to provide direct Bitcoin services to clients (Kayani and Hasan, 2024).

Bitcoin is the pioneer and the largest cryptocurrency in terms of market capitalization, with a market share that exceeded 85% of the total cryptocurrency market value from 2010 to 2016.

Following the crash in mid-December 2017, more than 200 billion US dollars of Bitcoin's total market capitalization vanished within six weeks, resulting in cumulative losses of 41% from the peak. It was during this period that the term 'crypto winter' was first coined[1]. 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 a crypto winter. This large crash followed an equally startling 43-fold price increase (Gerlach, Demos and Sornette, 2019) – see Figure 1. Another episode of "crypto winter" took place at the end of the 2021 and throughout 2022, partly due to the US Federal Reserve tightening monetary policy after a lax stance in response to the Covid-19 pandemic[2]. 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[3].

FIGURE 1 – *Bitcoin Price*



Note: This figure shows the Bitcoin price (US$) from 2017 to 2022.

[1] "*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

[2] weforum.org/stories/2022/06/cryptocurrency-crash-crypto-winter

[3] https://www.chicagofed.org/publications/chicago-fed-letter/2023/479

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In this paper, we consider the six largest cryptocurrencies by market capitalization for the period 2017 to 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 to Liu and Tsyvinski (2021) who find a positive association for the period 2011 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 to 2020 and 2020 to 2022, we shed some light on our findings. We show that Bitcoin and Ethereum returns *are associated* with GSVI for the period 2017 to 2020, in line with previous work such as Liu and Tsyvinski (2021), Dias, Fernando and Fernando (2022), and Raza *et al.* (2023); however, we do not find any significant effect from 2020 to 2022. These results suggest that the association between investor attention and cryptocurrency returns has 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 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 detailed 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 the GSVI and Bitcoin returns (e.g., Liu and Tsyvinski, 2021; Kristoufek, 2013; Dias, Fernando and Fernando,

2022; and Raza *et al.*, 2023). 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 remaining part of the paper is organised as follows. The next section provides a review of the literature on investor attention measures. Section 3 presents the data and the methodology employed for analysing the relationship between returns of the selected cryptocurrencies and GSVI and WIKI. The results are discussed in Section 4, while Section 5 concludes.

2. Literature review and hypothesis development

2.1. 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, Engelberg and Gao, 2011). Studies in the literature have used different alternatives to measure investor attention. For example, Da, Engelberg and Gao (2011) used GSVI as a direct measurement to gauge investor sentiment. Barber and Odean (2008), on the other hand, used stock news, abnormal trading volume, and extreme daily returns as indicators of investor sentiment in their study.

Several studies use Google search volume index (GSVI) as a measure of investor attention, starting with Da, Engelberg and Gao (2011). In their study, they present 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 examine the relationship between investor interest and the Russell 3000 index stock returns, using weekly data from January 2004 to June 2008, and finding that an increase in GSVI predicts higher stock returns in the next two weeks and returns reversal within a year. This pioneering study argues that GSVI is an appropriate measure of investor interest, measuring the attention of individual investors, particularly retail investors.

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

Another study by Swamy, Dharani and Takeda (2019) investigates whether GSVI can forecast stock returns. They use 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 find that a higher GSVI predicts positive and significant returns in the first and second weeks. Moreover, higher GSVI quantiles predict higher excess returns.

Halousková, Stašek and Horváth (2022) investigate 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 use daily data from the MSCI stock market indices and GSVI for a total of 51 countries from 22/06/2021 to 08/03/2022, finding that GSVI is useful in forecasting stock returns during Russia's invasion of Ukraine in February 2022. Lastly, Birindelli, Chiappini and Jalal (2023) study whether investors' interest in the Sustainable Finance Disclosure Regulation (SFDR) drives European stock markets. They use 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 analyse them using the non-parametric causality method of Balcilar, Bekiros and Gupta (2017). According to the study's findings, investor attention has a considerable predictive power for stock markets, particularly in bearish and normal market conditions.

2.2. 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 note that most of the studies have been published in the last five years. This quote from the Financial Times may be an example of 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" (Oliver, 2024).

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 study the relationship between attention measures and Bitcoin prices, finding a positive correlation. Another study by Urquhart (2018) investigates the role of GSVI on the volume and volatility of Bitcoin. They estimate a VAR model and run Granger causality tests for weekly data between 01/08/2010 – 31/07/2017, showing 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 VAR model, however, attention does not have 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, dividing the data into two subsamples, they find 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, this paper shows that while 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) use a VAR model and conclude that GSVI can forecast cryptocurrency volatility, but cannot forecast returns. Another study by Eom *et al.* (2019) examines the relationship between Bitcoin returns, volatility and GSVI for the period 03/10/2011 to 31/05/2017, finding that volatility can be explained by past changes in investor attention; however, again, returns cannot be predicted.

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The findings of these papers contrast to Urquhart (2018) who finds that investor attention has little ability to predict actual volatility, volume or returns.

Only a few studies focus on the relationship between GSVI and cryptocurrencies other than Bitcoin. Liu and Tsyvinski (2021) assess the relationship between Bitcoin, Ethereum and Ripple weekly returns and the GSVI for the period 01/01/2011 to 31/12/2018. They find 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 twenty negative phrases including 'Bitcoin down', 'Bitcoin bearish' and 'Bitcoin dump'. Other work includes Lin (2021) investigating the relationship between the weekly returns of Bitcoin, Ethereum, Ripple, Litecoin and Tether cryptocurrencies, and the GSVI. They conclude that though 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.* (2021) test the relation between these same cryptocurrencies' weekly returns (except for Tether), and the GSVI. They find 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 is more influential on cryptocurrency returns than for bullish ones.

More contemporary studies include new cryptocurrencies such as DASH and NEM. For example, Aslanidis, Bariviera and López (2022) use the daily returns and volatility of Bitcoin, Ethereum, Litecoin, Ripple and Dash over the period 07/08/2015 to 22/04/2021. Using the Shannon Transfer Entropy method, they find that for up to six days, there is a bidirectional transfer between GSVI and cryptocurrency returns. Additionally, there is an important tail dependency between Google searches and cryptocurrency returns. Shannon Transfer Entropy is a flexible, non-parametric approach 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, Bariviera and López, 2022). Furthermore, Raza *et al.* (2023) add NEM returns using nonlinear causality-in-quantile methodology and conclude 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 as to 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, Fernando and Fernando, 2022; and Raza *et al.*, 2023). However, it also needs to be noted that, while realised volatility and volume have a large influence on the next 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, consider first the following hypothesis:

H1: There is a positive association between the GSVI and WIKI attention measures, and selected cryptocurrency weekly returns from 2017 to 2022.

In particular, given recent empirical research has found a positive association between investor attention and cryptocurrency returns (e.g., Liu and Tsyvinski, 2021), *H1* 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:

H2: The positive association between the GSVI and Wikipedia searches, and selected cryptocurrency weekly returns, has weakened in the period from 2020 to 2022.

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3. DATA AND METHODOLOGY

3.1. Data

Our dependent variable is the returns of the six largest cryptocurrencies by market capitalization. The US dollar exchange rate 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 7-day average. Following Liu and Tsyvinski (2021), cumulative future log-returns for one-week to eight-week horizons are calculated.

We employ GSVI to build our first investor attention measure, by using the word "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 percent of 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, Engelberg and Gao (2011) was the first paper to apply GSVI as a measure of investor attention, testing the reliability of Google searches through using terms such as "recession" and "bankruptcy". For example, they examine the term "recession" and the related GSVI shows a dramatic increase from mid-2007 to early 2008. This is just before the global economic crisis occurred in December 2008. They also examine the term "bankruptcy", the related GSVI revealing peaks (once) in 2005 and (once) in 2009. According to the American Bankruptcy Institute, real bankruptcies in the United States 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 normalizing 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 computationally too demanding and therefore Google Trend 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 5 years is only available at monthly frequency, as opposed to weekly. For this reason, we employ 5 years as the study's time

span. Hence, we use weekly data from 26/06/2017 to 26/06/2022. We then apply the normalization formula used by Liu and Tsyvinski (2021), essentially normalizing the GSVI data by using the average of the previous four weeks, so that the series have a mean of zero and a standard deviation of one.

The second investor sentiment 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 word "Bitcoin", "Ethereum", "Ripple", "Dash", "Litecoin" and "Stellar" for worldwide searches. The same normalization steps followed for GSVI are also carried out for WIKI.

3.2. Methodology

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-stationarity is rejected for all series, we confirm that the series are stationary and include them in the model in levels[4].

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

$$R_{t,t+i} = \alpha + \beta_1 GSVI_t + \beta_2 Gold_t + \beta_3 USDindex_t + \beta_4 S\&P500index_t + u_t \quad (1)$$

$$R_{t,t+i} = \alpha + \beta_1 WIKI_t + \beta_2 Gold_t + \beta_3 USDindex_t + \beta_4 S\&P500index_t + u_t \quad (2)$$

where R are the returns of the cryptocurrency between t and $t+i$, where i is 1 to 8 weeks. Investor attention is measured with the $GSVI$ in equation (1) and with $WIKI$ in equation (2). The models include typical control variables, such as the returns of gold, the US dollar index, and the S&P 500 index (Dyhberg, 2016; Kjærland *et al.*, 2018; López-Cabarcos *et al.*, 2021). 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 2.2.

[4] These results are available on request from the authors.

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3.3. Descriptive Statistics

Table 1 presents descriptive statistics of the cryptocurrency returns, GSVI and WIKI, and the control variables. When the data is separated into two sub-periods, 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 the greater potential for larger gains on the buy side. However, returns are typically negatively skewed in the second sub-period between 2020 and 2022, suggestive of a greater risk of larger negative outcomes.

Tables 2, 3 and 4 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 negative correlation between Bitcoin returns and GSVI in each sample period. Similarly, Bitcoin returns and WIKI have negative correlation, except for the sub-period 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.

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TABLE 1 - *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%

Note: Table 1 reports the weekly summary statistics of returns for each cryptocurrency, the GSVI and Wikipedia for each cryptocurrency searches, gold, US dollar index and S&P500 index.

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TABLE 2 - *Correlation Table 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	US DOLLAR 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											

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TABLE 2 - *continued*

Panel A. 2017-2022	BTC	ETH	LTC	DASH	XRP	XLM	GSVI-BTC	GSVI-ETH	GSVI-LTC	GSVI-DASH	GSVI-XRP	GSVI-XLM	GOLD	US DOLLAR INDEX	S&P 500	WIKI-BTC	WIKI-ETH	WIKI-LTC	WIKI-DASH	WIKI-XRP	WIKI-XLM
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 2 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. t-statistics are in parentheses.

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TABLE 3 - *Correlation Table 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							

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TABLE 3 - *continued*

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
S&P 500	0.07	0.09	0.18	0.09	-0.00	-0.06	-0.10	0.03	-0.02	-0.03	0.03	0.16	0.37	0.77	1						
	(0.70)	(0.86)	(1.75)	(0.89)	(-0.01)	(-0.64)	(-0.97)	(0.35)	(-0.25)	(-0.34)	(0.30)	(1.55)	(3.81)	(11.88)							
WIKI-BTC	-0.14	-0.11	-0.10	0.05	-0.10	-0.13	0.10	0.06	0.05	0.20	0.04	-0.02	0.14	-0.00	-0.01	1					
	(-1.39)	(-1.09)	(-1.04)	(0.55)	(-1.02)	(-1.29)	(1.00)	(0.63)	(0.56)	(1.99)	(0.40)	(-0.26)	(1.36)	(-0.04)	(-0.16)						
WIKI-ETH	0.06	-0.05	0.04	0.25	0.00	0.01	-0.00	-0.04	-0.04	0.41	0.01	0.05	0.19	0.07	-0.02	0.50	1				
	(0.61)	(-0.55)	(0.39)	(2.53)	(0.05)	(0.11)	(-0.04)	(-0.40)	(-0.46)	(4.34)	(0.15)	(0.49)	(1.89)	(0.72)	(-0.19)	(5.62)					
WIKI-LTC	0.05	0.09	0.07	0.05	0.13	0.04	0.16	0.21	0.26	0.04	0.53	0.21	-0.03	0.01	0.02	0.44	0.05	1			
	(0.50)	(0.92)	(0.72)	(0.52)	(1.32)	(0.42)	(1.61)	(2.10)	(2.58)	(0.43)	(6.02)	(2.10)	(-0.30)	(0.13)	(0.20)	(4.74)	(0.50)				
WIKI-DASH	-0.11	0.00	-0.04	-0.01	0.03	-0.02	0.06	-0.07	0.01	-0.02	0.01	0.10	-0.15	-0.12	-0.11	-0.04	-0.37	0.05	1		
	(-1.07)	(0.04)	(-0.42)	(-0.12)	(0.31)	(-0.23)	(0.60)	(-0.75)	(0.13)	(-0.22)	(0.10)	(1.01)	(-1.47)	(-1.21)	(-1.14)	(-0.46)	(-3.89)	(0.54)			
WIKI-XRP	-0.01	0.04	-0.00	-0.15	-0.07	-0.08	0.02	-0.05	0.05	0.01	-0.03	-0.12	0.01	-0.03	-0.06	0.04	0.02	-0.06	0.09	1	
	(-0.10)	(0.38)	(-0.02)	(-1.53)	(-0.72)	(-0.79)	(0.26)	(-0.54)	(0.51)	(0.13)	(-0.31)	(-1.23)	(0.15)	(-0.31)	(-0.60)	(0.43)	(0.27)	(-0.58)	(0.88)		
WIKI-XLM	-0.29	-0.31	-0.24	-0.16	0.03	-0.04	0.08	-0.01	0.00	0.04	0.16	-0.00	-0.07	-0.03	-0.05	-0.01	-0.05	0.02	0.17	0.03	1
	(-2.94)	(-3.14)	(-2.41)	(-1.56)	(0.33)	(-0.46)	(0.84)	(-0.18)	(0.08)	(0.38)	(1.61)	(-0.07)	(-0.67)	(-0.32)	(-0.48)	(-0.11)	(-0.55)	(0.23)	(1.69)	(0.35)	

Notes: Table 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 – 2020. t-statistics are in parentheses.

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TABLE 4 - *Correlation Table 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										

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TABLE 4 - *continued*

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
GSVI-XLM	-0.04	0.01	-0.03	0.36	0.41	0.61	0.45	0.67	0.80	0.36	0.52	1									
	(-0.48)	(0.15)	(-0.38)	(4.29)	(4.92)	(8.48)	(5.62)	(9.87)	(14.89)	(4.24)	(6.78)										
GOLD	-0.13	-0.17	-0.14	-0.04	0.13	0.19	0.21	0.21	0.23	0.04	-0.01	0.34	1								
	(-1.53)	(-1.97)	(-1.58)	(-0.49)	(1.46)	(2.20)	(2.39)	(2.34)	(2.59)	(0.48)	(-0.19)	(3.94)									
USDOLLAR INDEX	-0.07	-0.02	-0.06	-0.12	-0.04	-0.07	0.04	0.03	0.01	-0.04	-0.05	0.02	0.26	1							
	(-0.77)	(-0.30)	(-0.66)	(-1.37)	(-0.43)	(-0.79)	(0.47)	(0.36)	(0.11)	(-0.51)	(-0.63)	(0.26)	(2.99)								
S&P 500	-0.04	-0.01	-0.02	-0.01	0.12	0.10	-0.02	0.01	0.03	-0.05	0.04	0.09	0.23	0.72	1						
	(-0.54)	(-0.16)	(-0.23)	(-0.20)	(1.39)	(1.10)	(-0.30)	(0.20)	(0.43)	(-0.57)	(0.51)	(1.08)	(2.63)	(11.63)							
WIKI-BTC	0.02	0.05	-0.05	0.06	-0.04	0.05	0.37	0.28	0.25	0.15	0.00	0.11	-0.00	-0.13	-0.11	1					
	(0.29)	(0.59)	(-0.58)	(0.72)	(-0.53)	(0.61)	(4.41)	(3.21)	(2.91)	(1.67)	(0.07)	(1.28)	(-0.05)	(-1.53)	(-1.28)						
WIKI-ETH	-0.03	0.02	-0.06	0.09	0.02	0.16	0.51	0.63	0.47	0.20	0.05	0.39	0.10	-0.07	-0.04	0.57	1				
	(-0.32)	(0.25)	(-0.71)	(1.06)	(0.28)	(1.83)	(6.63)	(8.95)	(5.83)	(2.33)	(0.55)	(4.67)	(1.17)	(-0.78)	(-0.49)	(7.66)					
WIKI-LTC	0.12	0.11	0.07	0.06	0.00	0.11	0.32	0.22	0.23	0.09	0.11	0.21	0.05	-0.06	-0.01	0.46	0.63	1			
	(1.41)	(1.20)	(0.77)	(0.74)	(0.10)	(1.21)	(3.81)	(2.53)	(2.61)	(1.06)	(1.27)	(2.34)	(0.58)	(-0.67)	(-0.12)	(5.68)	(8.89)				
WIKI-DASH	0.09	0.00	0.04	-0.00	0.11	-0.08	-0.14	-0.15	-0.20	0.03	-0.13	-0.15	0.02	-0.10	-0.09	0.17	0.14	0.13	1		
	(1.08)	(0.07)	(0.44)	(-0.00)	(1.21)	(-0.94)	(-1.63)	(-1.70)	(-2.31)	(0.40)	(-1.53)	(1.67)	(0.21)	(-1.14)	(-1.06)	(1.89)	(1.63)	(1.43)			
WIKI-XRP	0.19	0.11	0.13	0.00	0.03	0.06	0.05	-0.01	-0.05	-0.04	0.03	0.00	-0.00	-0.01	0.01	0.22	0.32	0.88	0.08	1	
	(2.18)	(1.26)	(1.52)	(0.09)	(0.42)	(0.65)	(0.61)	(-0.13)	(-0.57)	(-0.48)	(0.40)	(0.06)	(-0.03)	(-0.20)	(0.13)	(2.48)	(3.74)	(20.51)	(0.88)		
WIKI-XLM	0.04	0.03	-0.02	0.04	-0.08	-0.09	0.17	0.10	0.06	0.04	-0.09	-0.03	-0.02	0.02	-0.07	0.15	0.19	0.04	-0.01	-0.03	1
	(0.53)	(0.38)	(-0.22)	(0.51)	(-0.91)	(-1.06)	(1.98)	(1.19)	(0.72)	(0.45)	(-1.01)	(-0.33)	(-0.26)	(0.27)	(-0.76)	(1.71)	(2.19)	(0.46)	(-0.14)	(-0.36)	

Notes: Table 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 2020 – 2022. t-statistics are in parentheses.

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4. EMPIRICAL RESULTS

Table 5 reports the results of the estimation of the regression equation (1) without controls, whereas Table 6 reports the results with the controls. Applying a level of significance of 5 percent or less, we find no significant association between Bitcoin returns and the GSVI for the full sample period 2017-2022. This rejection of *H1* 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 *H1* 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 from 2017 to 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 *H2*, 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 *H2* 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 for 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 to 2020 period, relative to the 2020-2022, we still find several positive and significant coefficients in the later period (aside from Litecoin). Therefore, although *H2* appears to hold for

the newer cryptocurrencies, the positive association between the GSVI and returns, weakens much less than for Bitcoin and Ethereum.

The regression results for WIKI are reported in Table 7 without controls, and in Table 8 with controls. Examining the full sample clearly indicates different results from GSVI, with *H1* being rejected for more cryptocurrencies (i.e., there are less 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 *H2*, 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 Table 7 and Table 8 show that WIKI has less predictability for cryptocurrency returns than the GSVI and that notably, WIKI does not affect Bitcoin returns across any period.

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TABLE 5 - *Results of Regression (1) of 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 (1.57)	0.02* (1.74)	0.02* (1.82)	0.03* (1.90)	0.03 (1.16)	0.02 (0.55)	0.02*** (2.90)	0.04*** (3.08)	0.04*** (2.79)	0.05*** (2.79)	0.05** (2.16)	0.02 (0.69)	-0.00 (-0.08)	0.00 (0.03)	0.00 (0.35)	0.00 (0.58)	0.00 (0.07)	0.02 (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 (1.43)	0.01 (0.93)	0.02 (1.19)	0.03 (1.18)	0.02 (0.68)	0.01 (0.23)	0.02 (1.16)	0.04 (1.45)	0.09** (2.31)	0.13*** (2.72)	0.22*** (3.91)	0.19*** (2.91)	0.00 (1.11)	0.00 (0.51)	0.01 (0.63)	0.01 (0.58)	-0.01 (-0.26)	-0.02 (-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*** (2.91)	0.29*** (2.80)	0.30*** (2.97)	0.26** (1.98)	0.13 (0.73)	0.15 (0.88)	0.44*** (3.81)	0.52*** (3.06)	0.44** (2.48)	0.35** (2.07)	0.65*** (4.48)	0.89*** (6.62)	0.20** (2.27)	0.25** (2.27)	0.28** (2.49)	0.24 (1.64)	0.04 (0.23)	0.04 (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*** (5.79)	0.09*** (5.55)	0.10*** (4.60)	0.11*** (4.21)	0.12*** (3.52)	0.10*** (2.68)	0.06*** (5.79)	0.10*** (5.92)	0.13*** (6.47)	0.16*** (6.80)	0.18*** (4.64)	0.15*** (3.03)	0.06*** (2.88)	0.07*** (2.62)	0.05** (2.09)	0.04* (1.77)	0.03 (1.15)	0.01 (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*** (2.99)	0.02* (1.74)	0.03* (1.69)	0.03* (1.74)	0.00 (0.35)	-0.00 (-0.35)	0.02*** (2.90)	0.03* (1.73)	0.03 (1.64)	0.03* (1.67)	0.01 (0.49)	-0.00 (-0.19)	-0.01 (-0.47)	-0.05 (-0.83)	-0.02 (-0.25)	-0.01 (-0.22)	-0.05 (-0.40)	-0.05 (-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*** (5.59)	0.10*** (4.68)	0.10*** (3.69)	0.12*** (3.50)	0.12** (2.24)	0.12** (2.29)	0.08*** (5.30)	0.09*** (4.24)	0.10*** (3.05)	0.12*** (2.82)	0.12* (1.82)	0.13* (1.88)	0.13*** (5.61)	0.13*** (4.39)	0.11*** (3.08)	0.11*** (3.06)	0.13** (1.99)	0.11* (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 5 reports the results of the regression equation (1) for Google searches for all three periods. *p<0.1, **p<0.05, ***p<0.01 and t-statistics are in parentheses.

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TABLE 6 - *Results of Regression (1) the GSVI and 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 $index_t$	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
	(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 $index_t$	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
	(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 $index_t$	-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
	(-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

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TABLE 6 - *continued*

	Panel A. 2017 – 2022 term						Panel B. 2017 – 2020 term						Panel C. 2020 – 2022 term					
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 index$_t$	-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
	(-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 index$_t$	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
	(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 index$_t$	-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
	(-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 6 reports the results of the regression equation (1) for Google searches and control variables for all three periods. *p<0.1, **p<0.05, ***p<0.01 and t-statistics are in parentheses.

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TABLE 7 - *Results of Regression (2) WIKI*

	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)
$WIKI_t$	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 7 reports the results of the regression equation (2) for Wikipedia searches for all three periods. *p<0.1, **p<0.05, ***p<0.01 and t-statistics are in parentheses.

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TABLE 8 - *Results of Regression (2) WIKI and 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)
$WIKI_t$	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)

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TABLE 8 - *continued*

	Panel A. 2017 – 2022 term						Panel B. 2017 – 2020 term						Panel C. 2020 – 2022 term					
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

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TABLE 8 - *continued*

	Panel A. 2017 – 2022 term						Panel B. 2017 – 2020 term						Panel C. 2020 – 2022 term					
	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

Note: Table 8 reports the results of the regression equation (2) for Wikipedia searches and control variables for all three periods. *p<0.1, **p<0.05, ***p<0.01 and t-statistics are in parentheses.

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The above results are robust to other approaches and further analysis. In a first step, the CBOE Volatility Index (VIX) was added to the right-hand side of (1) and (2) and all regressions re-estimated – all results remain qualitatively unchanged. In a second step, and to examine whether a bidirectional relationship exists between cryptocurrency returns and our measures of investor sentiment, we employ a bivariate VAR (with up to eight lags) and Granger Causality tests. 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[5].

5. Conclusion

The purpose of this study is to examine the relation between investor attention measured by Google Search Volume Index (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 consideration of 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), document a positive and significant relation between investor attention and returns, particularly for Bitcoin. This indicates that investor sentiment 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

[5] To save space, the results of the "added VIX" regressions and the Granger Causality test for each cryptocurrency over the full sample period and the two subsample periods, are available from the authors on request.

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Wikipedia searches and one could argue 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 for Bitcoin and Ethereum returns are positively and significantly associated with this measure of investor attention over the period 2017 to 2020 but not over 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 detailed information sources. It should be noted this weakening of the predictability relation, although still present, happens less for cryptocurrencies such as Ripple, Stellar, and Dash.

Furthermore, following 2020, institutional investors, such as hedge funds, family offices, and asset managers, began showing keen interest in crypto markets, driven by the search for yield in a low-return environment and portfolio diversification strategies. The entry of institutional investors into this space accelerated, particularly with the approval of crypto-focused investment funds and Exchange Traded Funds (ETFs). These instruments served as a "gateway" for institutional capital. Crypto exchanges also increasingly shifted their business models to cater to these institutional clients (Hermans *et al.*, 2022; Auer *et al.*, 2023). These changes in the crypto world may also play a role in explaining the impact of the post-2020 weakening.

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 not considered in the paper. For future research, more cryptocurrencies, particularly those much less traded and where investors may have different information requirements, should be examined.

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