SEVGİ SÖYLEMEZGİL IS ONLINE INVESTOR ATTENTION PRICED IN CRYPTOCURRENCY MARKETS? Bilkent University 2023

IS ONLINE INVESTOR ATTENTION PRICED IN CRYPTOCURRENCY MARKETS?

A Master's Thesis

by
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Ankara
August 2023

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IN CRYPTOCURRENCY MARKETS?

The Graduate School of Economics and Social Sciences of
İhsan Doğramacı Bilkent University

By

SEVGİ SÖYLEMEZGİL

In Partial Fulfillment of the Requirements for the Degree of
MASTER OF SCIENCE

THE DEPARTMENT OF
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ANKARA

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By Sevgi Söylemezgil

I certify that I have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science in Business Administration.

Ahmet Şensoy
Advisor

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ABSTRACT

IS ONLINE INVESTOR ATTENTION PRICED IN CRYPTOCURRENCY MARKETS?

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MSc, Department of Management

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August 2023

This study examines the relationship between investor attention on online platforms and cryptocurrency returns. Using a dataset from Twitter, Reddit, and Google Trends for the ten largest cryptocurrencies, I constructed an Investor Attention Index by employing Principal Component Analysis. Using linear regression, vector autoregression and a long-short portfolio methods, I explore the link between investor attention and returns. The results suggest that the attention index is not able to explain crypto returns, however, the inverse relationship is found to be highly significant. This finding may be interpreted as cryptocurrencies being already priced by the time they become popular on online platforms, hence the retail investor attention represented by the data is not a factor that affects the prices of crypto assets.

Keywords: Investor Attention, Cryptocurrency Returns, Online Engagement, Vector Autoregressive (VAR) Model, Principal Component Analysis (PCA)

ÖZET

KRİPTO PARA PİYASALARINDA ÇEVRİMİÇİ YATIRIMCI İLGİSİ FİYATLANDIRILIYOR MU?

Söylemezgil, Sevgi

Yüksek Lisans, İşletme Bölümü

Tez Yöneticisi: Doç. Dr. Ahmet Şensoy

Ağustos 2023

Bu çalışma, yatırımcıların çevrimiçi platformlardaki duyarlılığı ile kripto para getirileri arasındaki ilişkiyi incelemektedir. En büyük on kripto para birimi için Twitter, Reddit ve Google Trends'ten bir veri seti ile Temel Bileşen Analizi kullanarak bir Yatırımcı Duyarlılık Endeksi oluşturdum. Doğrusal regresyon, vektör otoregresyon ve uzun-kısa portföy yöntemlerini kullanarak, yatırımcıların dikkati ile getiriler arasındaki bağlantıyı açıklamaya çalışıyorum. Sonuçlar, Yatırımcı Duyarlılık Endeksi'nin kripto getirilerini açıklayamadığını, ancak ters ilişkinin oldukça anlamlı olduğunu gösteriyor. Bu bulgu, kripto para birimlerinin çevrimiçi platformlarda popüler hale geldiklerinde zaten fiyatlandırıldığı şeklinde yorumlanabilir, dolayısıyla verilerin temsil ettiği bireysel yatırımcı ilgisi, kripto varlıkların fiyatlarında etken bir faktor degildir.

Keywords: Yatırımcı Duyarlılığı, Kripto Para Getirileri, Çevrimiçi Etkileşim, Vektör Otoregresyon Modeli, Temel Bileşen Analizi

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CHAPTER I

INTRODUCTION

Over the past years, cryptocurrencies have been a popular discussion topic among investors. Along with its drawbacks, it comes with opportunities that no other available assets can provide. For instance, low transaction costs, liquidity, and the pseudonym nature of cryptocurrencies could be the most compelling features that attract investors. However, on the other hand, cryptocurrencies are vulnerable to speculations, market manipulations, and hack attacks. Nonetheless, despite these disadvantages, it is still used by many investors as an investment vehicle. According to Cointelegraph's 2022 Institutional Demand for Cryptocurrencies Report, institutional investors account for 79% of Coinbase's daily trading volume, and the top ten investors include companies like Microstrategy, Tesla, and even a country, the Republic of El Salvador. The interest in digital assets has also grown among prominent banks. For example, JP Morgan launched its own "JPM Coin" and created an entire blockchain division named "Onyx". (Isidore, 2019) Morgan Stanley is the leading investor among the banks with $1 billion who is followed by Goldman Sachs with $698 million investment in cryptocurrency according to the Blockdata

Research (2022).

This heightened use of cryptocurrencies as an investment tool comes with the question of "how to price these assets?". Scholars tried to answer this question by searching for several factors which may have an impact on cryptocurrencies. A strand of literature focused on empirical testing of the traditional stock market factors and fundamental factors and find that returns are well explained by the stock market factors (Sovbetov, 2018; Shen et al., 2020, Liu et al., 2020), and fundamental factors such as network size and computing power (Pagnotta and Buraschi, 2018; Biais et al., 2023; Bhambwani et al., 2019).

Another strand of literature focuses on investor sentiment and attention. Investors play a crucial role in the cryptocurrency market due to limited information availability and the absence of central authority. Kahneman (1973) says that attention is a scarce cognitive resource, and individuals are only able to evaluate a limited number of options. Similarly, Barber and Odean (2008) find that an average retail investor does not have the time and resources to go through all the options in their purchase decision, hence they tend to buy attention-grabbing assets. Given these, in a cryptocurrency market where information is limited and asymmetric, retail investors with limited sources and attention would invest in attention-grabbing, speculative assets. This is also linked to a form of Efficient Market Hypothesis (EMH), the semi-strong form of market efficiency, which assumes all the publicly available information will be reflected in the security prices. In this sense, the investor component of cryptocurrency markets has been studied by several researchers, however, it suggests mixed results. Some studies find that investor attention explains cryptocurrency returns, prices, volatility, and trading volume (Nasir et al., 2019; Aalborg et al., 2019, Katsiampa et al. 2019; Bleher and Dimpfl, 2019); while others find that the direction of the relationship is the exact opposite, meaning returns, prices, and volatility explains investor attention (Urquhart, 2018; Lin, 2021; Smales, 2022). These studies mainly used the following two proxies for investor attention: Google Search Volume Index (or Google Trends) and Twitter. However, to my knowledge, there is not a single study where both proxies are combined and tested. Hence, in this study, I combine the investor attention coming from not only Google and Twitter but also Reddit, as I think it serves as an information source for retail investors. Along with the implications of the semi-strong form of market efficiency, I hypothesize that all the available information on popular social media platforms and Google will be priced. Hence, in this study, I built an "Investor Attention Index" that will work as a more comprehensive proxy for investor attention on cryptocurrencies. The index is constructed by employing Principal Component Analysis (PCA) on the following data: the weekly number of tweets containing the name of the selected coin on Twitter, the weekly number of posts on the subreddit of the selected coin, and the weekly search volume of the selected coin on Google between the years 2018 and 2022 for the ten largest cryptocurrencies by market capitalization. Then, I examine the relationship between the Investor Attention Index and returns by using linear regression and vector autoregression methods. My results suggest that attention does not predict returns, but past returns predict attention. This result complies with the findings of previous studies in the literature.

The rest of this thesis is structured as follows: Chapter 2 reviews the literature, Chapter 3 details the data and methods used in the analysis, Chapter 4 presents and comments on the findings and Chapter 5 concludes the discussion.

CHAPTER II

LITERATURE REVIEW

2.1. Literature Review on Cryptocurrency Pricing

The literature on cryptocurrency pricing focuses on the predictive power of several factors on cryptocurrency returns. Some articles study the effect of uncertainty on cryptocurrency returns. Bouri et al. (2017) show that uncertainty negatively affects Bitcoin returns by using the first principal component of the Volatility Indexes (VIXs) of 14 developed and developing stock markets as the measure of uncertainty. Similarly, Demir et al. (2018) find that economic policy uncertainty has predictive power on Bitcoin returns. Their results suggest that the economic policy uncertainty (EPU) index is negatively associated with cryptocurrency returns and Bitcoin can be used as a hedging tool against uncertainty.

Another strand of literature focuses on the empirical testing of traditional stock market factors on cryptocurrency markets. Sovbetov (2018) investigates the factors affecting the prices of the most common five cryptocurrencies and finds that market beta, trading volume and volatility are significant factors for all five cryptocurrencies both in the short and long run. In addition, these findings suggest that in the long run, the attractiveness of cryptocurrencies also plays a pivotal role in their price determination. Further, Shen et al. (2020) propose a three-factor pricing model for cryptocurrencies by considering 1786 cryptocurrencies. They find that size and reversal factors have explanatory power on cryptocurrency returns and perform better than the traditional Cryptocurrency Capital Asset Pricing Model (C-CAPM) which only takes excess market return into account. Moreover, their results suggest that small cryptocurrencies tend to have higher average returns, and the loser portfolios perform better than the winners. In the same vein, Liu et al. (2020) construct three common risk factors for cryptocurrency markets, namely market return, size, and momentum. By employing cross-sectional and time-series regressions with a dataset of 78 cryptocurrencies, they find that size and momentum are significant factors in cryptocurrency markets. Similarly, Liu, Tsyvinski, and Wu (2022) show that size and momentum factors strongly capture the cross-section of cryptocurrency returns, and a three-factor model with an excess market return also works well in pricing cryptocurrencies.

Another group of studies examines the fundamental factors' effect on cryptocurrency prices. Pagnotta and Buraschi (2018), Biais et al. (2018) and Bhambhwani et al. (2019) show that the hash rate (computing power) and network size (number of users) of blockchain drive cryptocurrency prices. They point out that these factors are important because they measure the trustworthiness and transaction benefits of a blockchain. On the other hand, some papers focus on the effect of production costs on cryptocurrencies and show that the mining cost is a determinant in cryptocurrency price formation. (Cong et al., 2020; Sockin and Xiong, 2020). Liu and Tsyvinski (2020) studies both the effects of network and production factors on cryptocurrency returns. Their results indicate that returns are well explained by the network factors but not by the production factors. They also emphasize the importance of investor attention in their research. More precisely, they report that investor attention as proxied by the Google Search Volume Index (GSVI) positively predicts cryptocurrency returns and note that investor attention is one of the determinants of cryptocurrency prices. Investor attention is the main focus of this study and the literature on this topic will be presented in the second part of this chapter.

2.2. Literature Review on Investor Attention

The growing literature on cryptocurrency pricing points out an important factor that should be taken into consideration in understanding cryptocurrency price dynamics: investor attention. Burggraff et al. (2020) argue that the valuation of cryptocurrencies is not driven by the fundamentals of traditional assets but rather by investor sentiment and spillover effects. Hence, many papers up-to-date has focused on determining to what extent investor attention affects cryptocurrency prices and volatility. However, these studies differ in terms of their analysis techniques and proxies for investor attention.

Several papers use the Google search volume data, a.k.a. Google Trends, as proxy for investor attention. Urquhart (2018) is one of the first papers to investigate the relationship between investor attention and realized volatility and volume by employing Google Trends data as proxy for investor attention. Utilizing the search volume data for the keyword "Bitcoin" within USA for the period between 2010 to 2017, he finds that realized volume and volatility significantly affect the next day attention of Bitcoin, but attention fells short to explain realized volatility, volume and returns significantly.

Nasir et al. (2019) examine the nexus between investor sentiment and cryptocurrency returns using Google search volumes. Their results suggest that Google search values significantly influence Bitcoin returns, however, its effect on trading volumes is non-significant. In contrast to the findings of Nasir et al. (2019), Aalborg et al. (2019) report that Google searches for Bitcoin can predict the trading volume of Bitcoin, however, it does not have predictive power on Bitcoin returns. Similarly, Dastgir et al. (2019) investigate the causal relationship between Bitcoin attention measured by Google Trends searches and Bitcoin returns by using a Copula-based Granger causality test. They conclude that there is a bi-directional causal relationship between Bitcoin attention and returns, however, this relationship mainly exists in right and left tails.

Extending the focus from Bitcoin to major altcoins, Katsiampa et al. (2019) uses Google Trends data to show that past investor attention – or information demand as mentioned in the paper – explains the returns of the five largest cryptocurrencies except Ethereum. However, Bleher and Dimpfl (2019) find that Google Trends can predict volatility but as opposed to Katsiampa et al. (2019) it does not predict returns. Lin (2021) uses Google search probability which is derived from Google Trends data to get rid of unrelated noises that may exist. According to his results, past returns explain future attention but not vice versa. The results are robust when controlled for macroeconomic effects. Smales (2022) shows that investor attention as proxied by Google Trends is positively associated with cryptocurrency returns, volatility, and liquidity. Consistent with Urquhart (2018) and Lin (2021); he finds that returns predict future investor attention but attention does not predict future returns.

Some articles use popular social media websites as sources for investor attention. Shen et al. (2019) employ a number of tweets on Twitter as a proxy for investor attention. They argue that the number of tweets is a better measure than Google Trends for the attention of well-informed investors. Using the linear and non-linear Granger causality tests, they find that volume of tweets significantly affects the realized volatility and trading volume; but it does not influence the future returns of Bitcoin. Building up on that, Philippas et al. (2019) combine the informative signals coming from Twitter and Google Trends by employing a jump-diffusion model to examine the relationship between Bitcoin information demand and prices. They find that Bitcoin prices are partially affected by media attention, i.e., Twitter and Google Trends, and media acts as a source of information, especially during high uncertainty periods. Furthermore, Aharon et al. (2022) employ a different technique to explore the nexus between Twitter-based uncertainty and cryptocurrency performance by using two novel Twitter uncertainty indices, namely Twitter Market Uncertainty (TMU) and Twitter Economic Uncertainty (TEU). Their empirical analysis shows that there is a causal link between Twitter uncertainty and cryptocurrency returns which is particularly stronger in the tails of Bitcoin returns. In the same vein, Suardi et al. (2022) examine the effect of social media tweets on Bitcoin by employing the Valence Aware Dictionary for

Sentiment Reasoning (VADER). Their findings indicate that investor attention has predictive power on trading volume but not on returns and volatility.

CHAPTER III

DATA AND METHODOLOGY

The data set for cryptocurrencies consists of the ten largest cryptocurrencies by market size on CoinMarketCap in January 2022. The weekly cryptocurrency price data is collected from Yahoo Finance, covering the period from January 2018 to January 2022 which varies by cryptocurrency due to data availability. As a proxy for investor attention, I used three different data sources. First, I collected the weekly number of comments in the selected cryptocurrency's subreddit from Reddit using Pushshift API. Second, I collected the weekly tweets that included the selected cryptocurrency's name from Twitter API. I filtered for the double entries, bots, deleted tweets and posts on subreddits to reduce the noise in the data. Lastly, I employ the weekly Google Search Volume (GSV) data from Google Trends. Then, combining all these three datasets and using the Principal Component Analysis (PCA) method, I constructed the Investor Attention Index. PCA helps to reduce the dimensionality in the data while still keeping the variance maximum. The first two components of the index accounts for, on average, 90% of the variance in data. Hence, with the help of PCA, I gathered three different data sources together while keeping 90% of the information at the same time. Next, I centralized the index values with a mean of 100 and a standard deviation of 10. Please find the indices below.

Figure 1: Bitcoin Attention Index

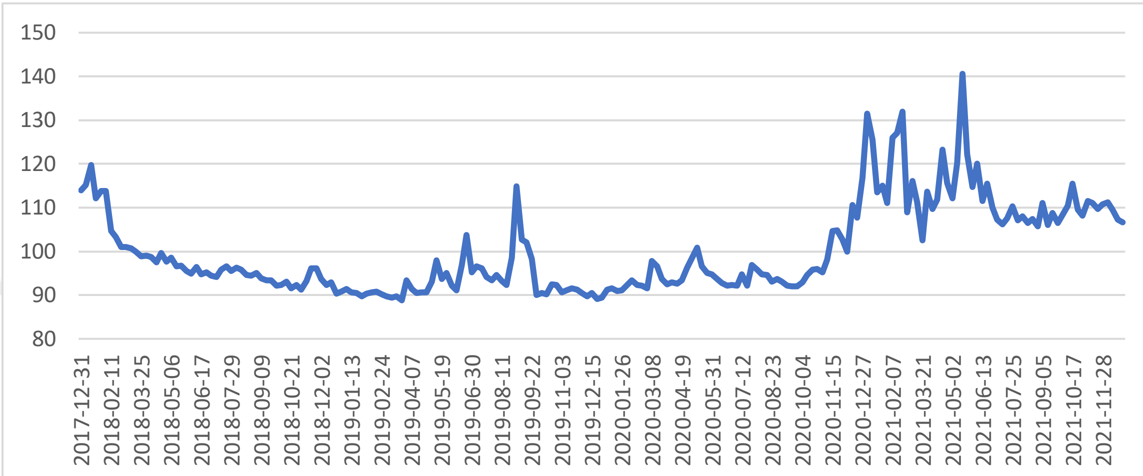


Figure 2: Ethereum Attention Index

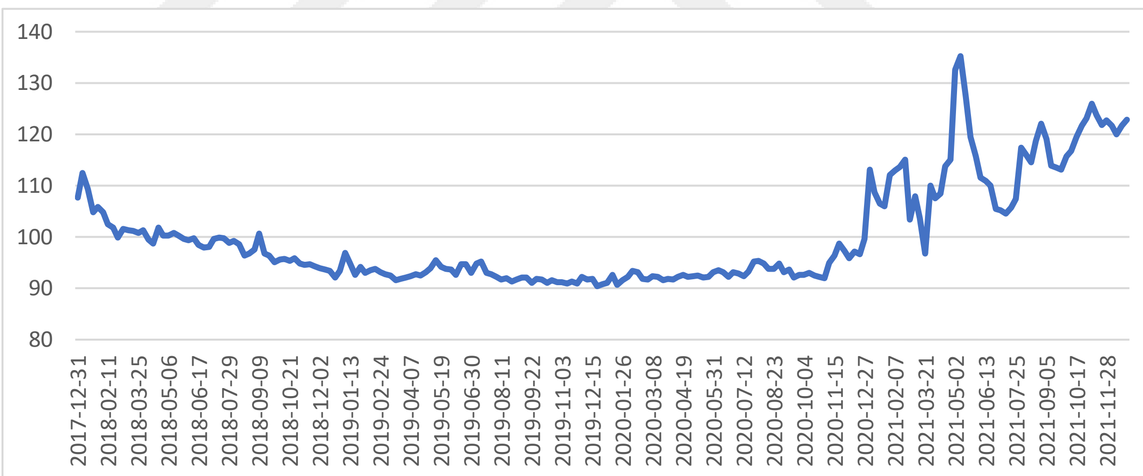


Figure 3: Solana Attention Index

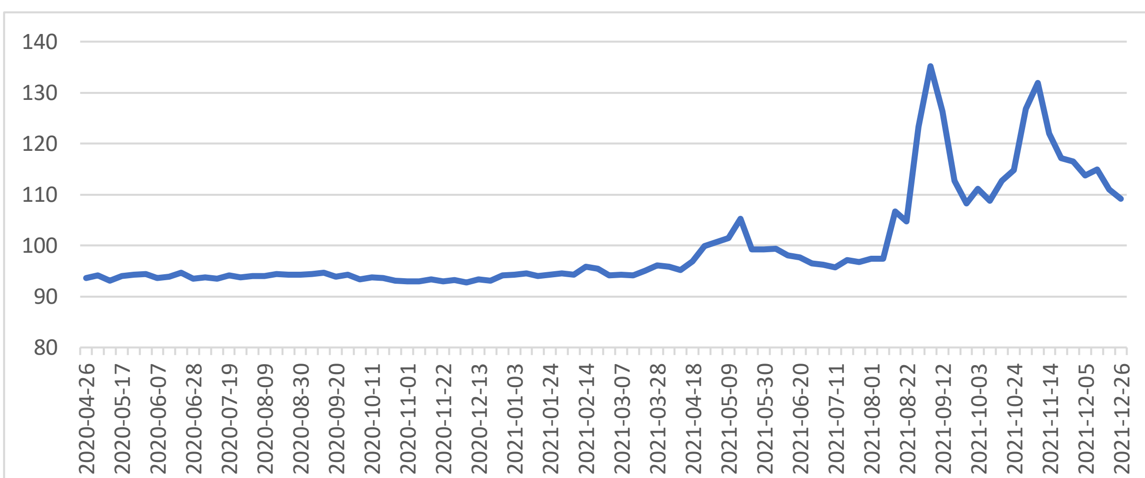


Figure 4: Cardano Attention Index

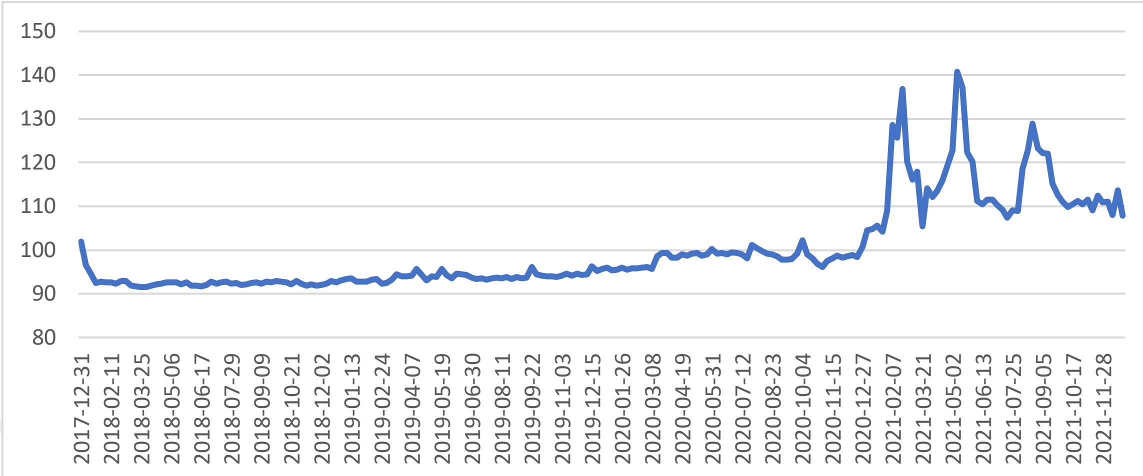


Figure 5: Ripple Attention Index

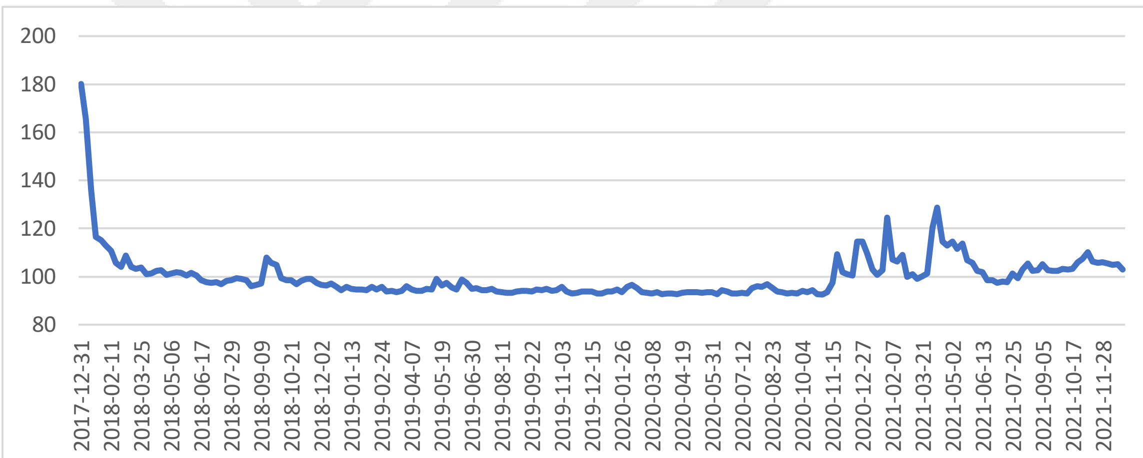


Figure 6: Terra Attention Index

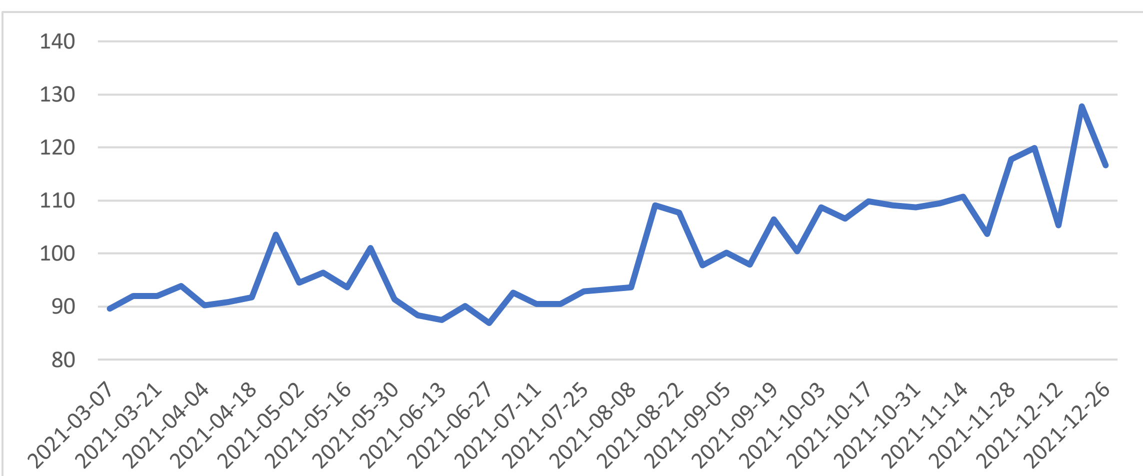


Figure 7: Polkadot Attention Index

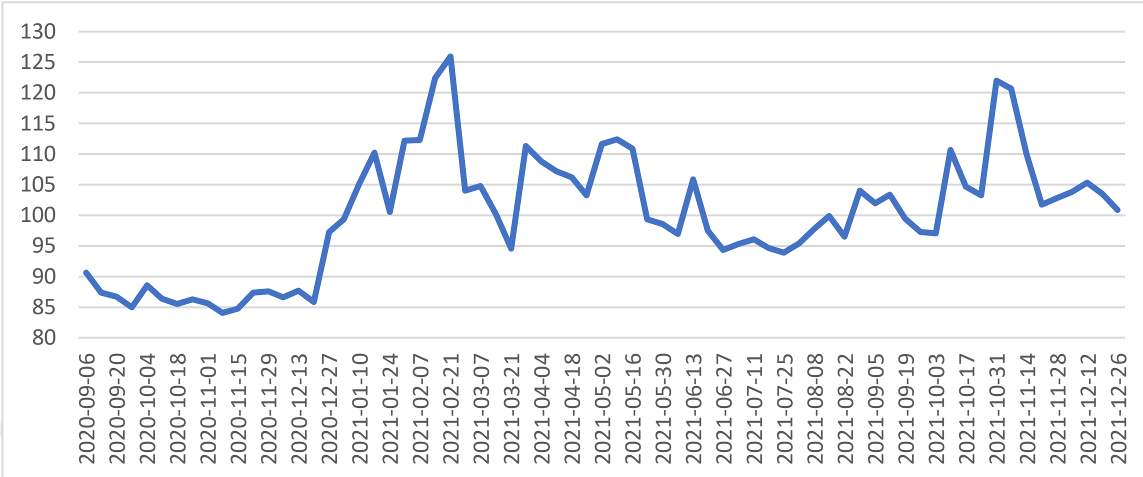


Figure 8: Avalanche Attention Index

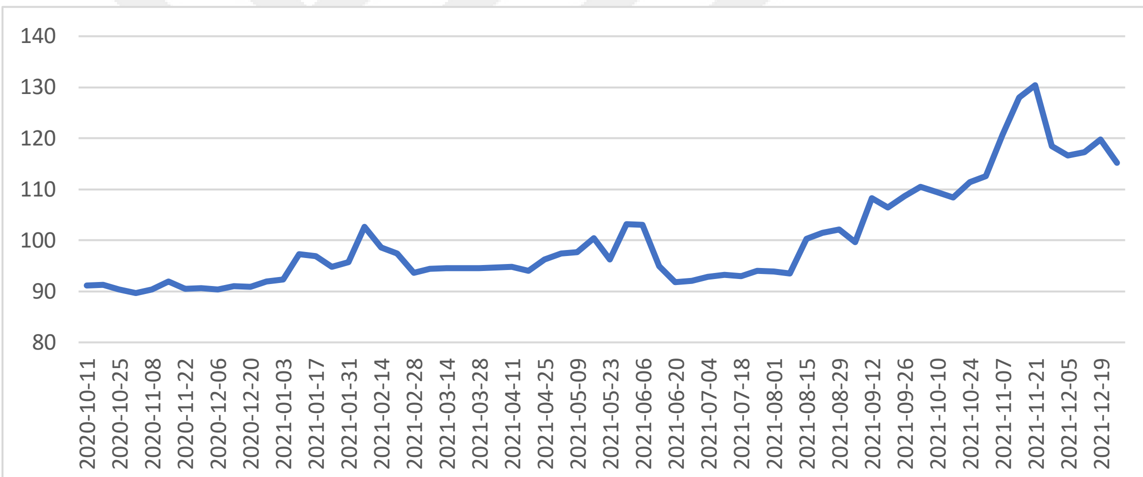


Figure 9: Dogecoin Attention Index

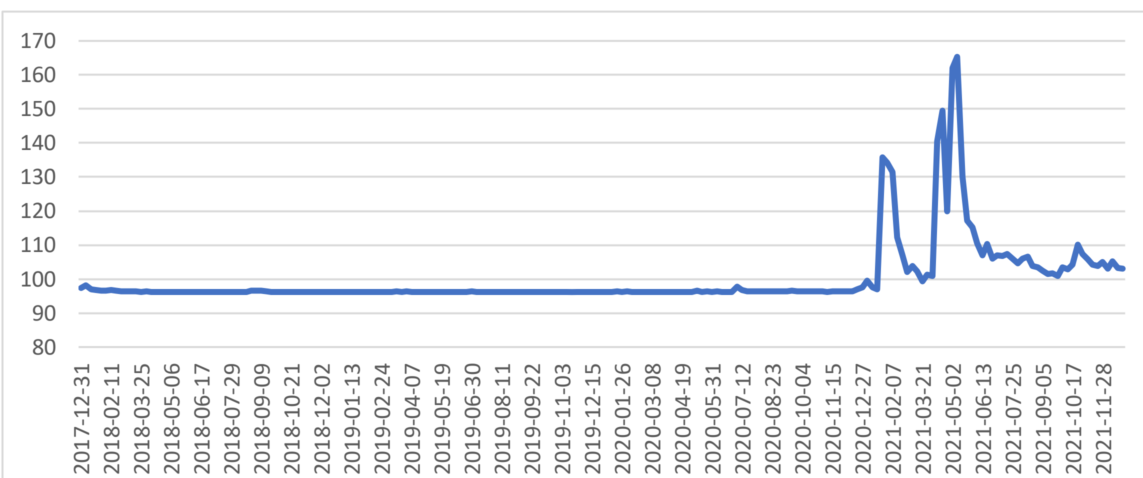
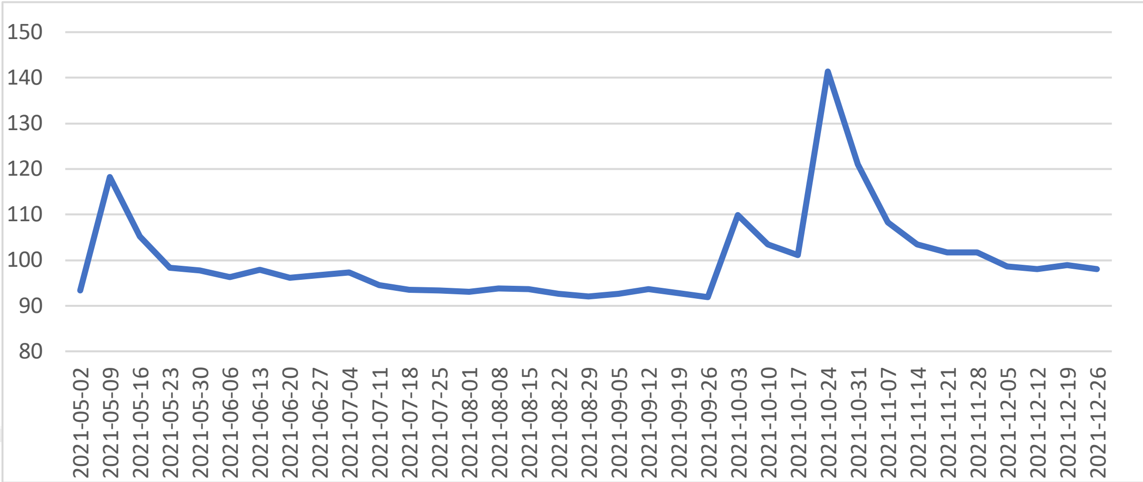


Figure 10: Shiba Inu Attention Index



I collected several weekly control variables such as novel cryptocurrency indices: the Cryptocurrency Uncertainty Index (UCRY), the Central Bank Digital Currency Attention Index (CBDC), and the Index of Cryptocurrency Environmental Attention (ICEA); an investor expectation indicator Chicago Board Options Exchange's CBOE Volatility Index VIX; commodity market variables gold spot prices from the Commodity Exchange Group's COMEX, and weekly crude oil prices for West Texas Intermediate (WTI) from Federal Reserve Bank of St. Louis' website and foreign exchange market variable US Dollar Index (USD) from ICE futures and a global equity index MSCI All Worlds Index. I also included 4-week momentum effects to account for the effect of momentum on returns. Table 1 below demonstrates the descriptive statistics for the Bitcoin price, Cryptocurrency Attention Index for Bitcoin, and the above-mentioned control variables.

Table 1: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Price	209	18, 628.0	17, 987.4	3, 252.8	65, 466.8
Attention Index	209	100.0	10.0	88.8	140.6
UCRY	209	101.0	1.8	99.3	108.3
CBDC	209	100.7	1.7	99.6	106.0
ICEA	209	101.5	2.6	99.7	112.0
VIX	209	20.2	8.7	9.3	74.6
US Dollar Index	209	114.6	3.4	106.9	124.3
Oil	209	57.3	13.7	3.3	83.8
Gold	209	1, 558.2	249.3	1, 176.5	2, 010.1
4-week Momentum	209	571.3	89.7	397.1	757.1

The minimum and maximum values that Investor Attention Index takes are 88.8 and 140.6 respectively whereas the values for other cryptocurrency indices vary between 99 and 112. Table 2 provides the correlations between variables. Investor Attention Index and UCRY, CBDC, and ICEA are relatively highly correlated with 0.78, 0.67, and 0.72.

Table 2: Correlation Table

	Attention Index	UCRY	CBDC	ICEA	VIX	USD	Oil	Gold	Momentum
Attention Index	1								
UCRY	0.78	1							
CBDC	0.67	0.84	1						
ICEA	0.72	0.87	0.95	1					
VIX	-0.02	0.01	-0.1	-0.11	1				
USD	-0.65	-0.51	-0.38	-0.46	0.18	1			
Oil	0.3	0.36	0.5	0.52	-0.62	-0.32	1		
Gold	0.46	0.51	0.46	0.46	0.37	-0.29	-0.29	1	
Momentum	0.71	0.81	0.85	0.85	-0.12	-0.49	0.45	0.67	1

Hence, I will first regress returns on past attention to see the relationship between returns and my index:

$$\Delta Ret_{t+1} = \beta_0 + \beta_1 \Delta Att_t \qquad (1)$$

Secondly, I will regress future attention on past returns to examine if attention has predictive power over returns:

$$\Delta Att_{t+1} = \beta_0 + \beta_1 Ret_t \qquad (2)$$

Thirdly, I will regress returns on past returns to check if returns predict itself:

$$Ret_{t+1} = \beta_0 + \beta_1 \Delta Ret_t \qquad (3)$$

Finally, I will conduct a multiple linear regression analysis that includes all the control variables to explore the relationship between returns and independent variables in my sample.

$$\begin{aligned} \mathrm{Ret}_{t+1} &= \beta_0 + \beta_1 \Delta \mathrm{Att}_t + \beta_2 \Delta \mathrm{UCRY}_t + \beta_3 \Delta \mathrm{CBDC}_t \\ &+ \beta_4 \Delta \mathrm{ICEA}_t + \beta_5 \Delta \mathrm{VIX}_t + \beta_6 \Delta \mathrm{MSCI} + \beta_7 \Delta \mathrm{Oil}_t \\ &+ \beta_8 \Delta \mathrm{Gold}_t + \beta_9 \Delta \mathrm{Mom}_t + \beta_{10} \Delta \mathrm{USD}_\mathrm{t} \qquad (4) \end{aligned}$$

In order to understand the joint behavior of variables over time, I employed a vector autoregression (VAR) analysis in this research. The key assumption of VAR involves the stationarity of the variables in the analysis. To test for stationarity, I used the Augmented-Dickey Fuller (ADF) Test. The variables are verified to be stationary and the number of observations in my dataset is feasible for VAR modeling except for the cryptocurrencies Terra and Shiba Inu because of limited data availability.

Finally, I conducted a long-short portfolio analysis. First, I generated two equally-weighted portfolios: high-attention and low-attention cryptocurrency portfolios which are ranked on the basis of their index values at a point in time. Then, I calculated their returns. If the mean of the difference of their returns is significantly higher than zero, this means that taking long positions in high-attention and taking short positions in low-attention portfolios will generate positive returns.

CHAPTER IV

EMPIRICAL RESULTS

In this chapter, we first show the results obtained from linear regressions and vector autoregression (VAR) to see if there is a causal link between past and future returns. Next, we will move on to the cross-sectional regression results.

4.1. Time-Series Approach

In this subsection, I present the linear regression results obtained from the models (1), (2), (3) and (4), and vector autoregression model.

4.1.1. Time-Series Results for Bitcoin

Table 3 presents the linear regression results for Bitcoin. The first column of the table demonstrates the regression results for past attention and future returns. The model is insignificant, and the beta coefficient is small. The second column shows the result for regression (2). The effect of last week's returns on next week's attention is insignificant. The third column shows the effect of last week's returns on next week's returns; the model and the coefficient are again insignificant. The fourth column represents the multiple linear regression results. The coefficients of the Cryptocurrency Uncertainty Index (UCRY) and gold prices (Gold) are significant at 0.1. However, again, the model overall is insignificant.

Table 3: Linear Regression Results for Bitcoin

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att_t	0.001 (0.002)			0.001 (0.002)
Ret_t		−0.787 (3.003)	0.089 (0.069)	
$UCRY_t$				0.018* (0.011)
$CBDC_t$				−0.022 (0.018)
$ICEA_t$				−0.017 (0.013)
VIX_t				−0.002 (0.003)
$MSCI_t$				0.0001 (0.001)
USD_t				0.005 (0.013)
Oil_t				−0.060 (0.044)
$Gold_t$				−0.720* (0.396)
Mom_t				0.00000 (0.00000)
Constant	0.005 (0.007)	−0.032 (0.320)	0.005 (0.007)	0.006 (0.007)
Observations	208	208	208	208
R^2	0.004	0.0003	0.008	0.061
Adjusted R^2	-0.001	-0.005	0.003	0.013
Residual Std. Error	0.106 (df = 206)	4.605 (df = 206)	0.106 (df = 206)	0.105 (df = 197)
F Statistic	0.730 (df = 1; 206)	0.069 (df = 1; 206)	1.663 (df = 1; 206)	1.283 (df = 10; 197)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The regression results suggest that the Investor Attention Index falls short to explain the variations in the future returns of Bitcoin and cannot be used as a predictor for Bitcoin returns.

Next, I present the vector autoregression results for Bitcoin in Table 4. The optimal lag length for the data is found as one by AIC. Our main model of interest is model 1 which takes place in the first column of the table. The overall model is insignificant and the Adjusted R^2 value is very low. Hence, we can conclude that our lagged independent variables cannot explain the variations in return.

Table 4: VAR Results for Bitcoin

	Dependent variable:									
	Ret	Att	UCRY	CBDC	ICEA	VIX	MSCI	USD	Oil	Gold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ret.l1	0.123*	6.778**	0.002	0.003	0.004	−0.276***	0.067***	−0.009**	0.188	0.019
	(0.073)	(2.818)	(0.005)	(0.003)	(0.004)	(0.099)	(0.018)	(0.004)	(0.120)	(0.014)
Att.l1	0.001	−0.205***	0.00003	−0.0002*	0.0001	−0.002	−0.0002	−0.00002	−0.0004	−0.001
	(0.002)	(0.073)	(0.0001)	(0.0001)	(0.0001)	(0.003)	(0.0005)	(0.0001)	(0.003)	(0.0004)
UCRY.l1	1.873*	−163.170***	−0.523***	−0.002	−0.172**	−1.142	0.130	0.037	1.894	0.141
	(1.118)	(43.347)	(0.079)	(0.049)	(0.067)	(1.518)	(0.274)	(0.056)	(1.843)	(0.210)
CBDC.l1	−1.977	201.534***	0.266**	−0.177**	−0.010	2.161	0.065	−0.115	−1.747	−0.371
	(1.827)	(70.864)	(0.130)	(0.079)	(0.110)	(2.481)	(0.449)	(0.091)	(3.013)	(0.344)
ICEA.l1	−1.873	232.653***	0.477***	0.160***	0.044	−0.089	−0.001	0.010	−0.008	0.227
	(1.399)	(54.243)	(0.099)	(0.061)	(0.084)	(1.899)	(0.343)	(0.070)	(2.307)	(0.263)
VIX.l1	0.015	3.901	0.003	−0.001	0.007*	−0.058	−0.016	−0.012***	−0.098	0.002
	(0.072)	(2.800)	(0.005)	(0.003)	(0.004)	(0.098)	(0.018)	(0.004)	(0.119)	(0.014)
MSCI.l1	0.342	28.815*	0.026	0.020	0.031	−1.268**	−0.176	−0.100***	−0.155	−0.130
	(0.434)	(16.849)	(0.031)	(0.019)	(0.026)	(0.590)	(0.107)	(0.022)	(0.716)	(0.082)
USD.l1	0.401	2.618	−0.128	0.024	−0.013	−2.615	0.056	0.100	−0.777	0.365
	(1.509)	(58.517)	(0.107)	(0.066)	(0.090)	(2.049)	(0.371)	(0.075)	(2.488)	(0.284)
Oil.l1	−0.058	−0.930	−0.005*	−0.001	−0.0004	0.066	0.007	0.001	−0.261***	0.008
	(0.044)	(1.687)	(0.003)	(0.002)	(0.003)	(0.059)	(0.011)	(0.002)	(0.072)	(0.008)
Gold.l1	−0.819**	−8.830	−0.039	−0.003	−0.019	0.598	0.006	−0.023	0.736	−0.107
	(0.396)	(15.349)	(0.028)	(0.017)	(0.024)	(0.537)	(0.097)	(0.020)	(0.653)	(0.075)
const	0.006	−0.205	−0.0001	0.0001	0.0001	0.006	0.002	0.001	−0.0001	0.002
	(0.007)	(0.287)	(0.001)	(0.0003)	(0.0004)	(0.010)	(0.002)	(0.0004)	(0.012)	(0.001)
Observations	207	207	207	207	207	207	207	207	207	207
R^2	0.070	0.258	0.268	0.087	0.057	0.089	0.082	0.218	0.094	0.105
Adjusted R^2	0.023	0.220	0.231	0.040	0.009	0.043	0.035	0.178	0.047	0.059
Residual Std. Error (df = 196)	0.105	4.067	0.007	0.005	0.006	0.142	0.026	0.005	0.173	0.020
F Statistic (df = 10; 196)	1.477	6.812***	7.176***	1.860*	1.183	1.914**	1.749*	5.471***	2.024**	2.296**

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Moving on to the second column, our attention index seems to predict itself and the overall model is significant. The increase in change in attention in the last week is negatively associated with next week's attention. On the other hand, lagged return is positively associated with attention at the significance level of 0.05. This result may imply that past returns create an increase in attention on online platforms. This result is economically meaningful and aligns with previous research.

4.1.2. Time-Series Results for Ethereum

The linear regression estimation results for Ethereum are presented in Table 5. The beta coefficient of Model (1) is estimated as 0.001 and it is insignificant. The Investor Attention Index is not a good predictor of future returns. On the other hand, the second model produced a highly significant estimator and the model's F-statistic is also statistically significant. This tells us that past returns are suitable predictors for changes in next week's attention. In the third column, we see that past returns do not predict future returns. In the fourth column, where multiple linear estimation results are displayed, our attention index is not a predictor of returns when control variables are added. UCRY and ICEA have significant coefficients, however, the model is insignificant.

Table 5: Linear Regression Results for Ethereum

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att_t	0.001			0.001
	(0.003)			(0.004)
Ret_t		4.588***	0.056	
		(1.350)	(0.069)	
$UCRY_t$				3.036**
				(1.338)
$CBDC_t$				-0.859
				(2.468)
$ICEA_t$				-3.901**
				(1.932)
VIX_t				0.002
				(0.097)
$MSCI_t$				0.455
				(0.589)
USD_t				0.253
				(2.024)
Oil_t				-0.047
				(0.059)
$Gold_t$				-0.376
				(0.532)
Mom_t				0.00000
				(0.00003)
Constant	0.005	0.047	0.005	0.005
	(0.010)	(0.191)	(0.010)	(0.010)
Observations	208	208	208	208
R^2	0.001	0.053	0.003	0.045
Adjusted R^2	-0.004	0.049	-0.002	-0.003
Residual Std. Error	0.141 (df = 206)	2.750 (df = 206)	0.141 (df = 206)	0.141 (df = 197)
F Statistic	0.109 (df = 1; 206)	11.558*** (df = 1; 206)	0.644 (df = 1; 206)	0.932 (df = 10; 197)
Note:				*p<0.1; **p<0.05; ***p<0.01

The second half of our analysis for Ethereum is presented in Table 6. The optimal lag length is determined as one. Even though there are significant slope estimators, the models in columns 1, 6, and 7 are not significant hence we cannot use these models to interpret any relations between our variables. However, in the second column, we observe that past

Table 6: VAR Results for Ethereum

	Dependent variable:									
	Ret	Att	UCRY	CBDC	ICEA	VIX	MSCI	USD	Oil	Gold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ret.l1	0.082	5.257***	0.004	0.001	0.001	−0.122	0.043***	−0.007**	0.068	0.015
	(0.077)	(1.479)	(0.004)	(0.002)	(0.003)	(0.079)	(0.014)	(0.003)	(0.095)	(0.011)
Att.l1	0.0003	−0.068	0.0005**	0.0002	0.001***	0.001	−0.0003	−0.0001	−0.001	0.00002
	(0.004)	(0.071)	(0.0002)	(0.0001)	(0.0001)	(0.004)	(0.001)	(0.0001)	(0.005)	(0.001)
UCRY.l1	3.297**	−36.764	−0.509***	−0.043	−0.164***	−1.794	0.125	0.022	1.746	0.012
	(1.361)	(26.188)	(0.070)	(0.044)	(0.053)	(1.394)	(0.251)	(0.050)	(1.674)	(0.191)
CBDC.l1	−1.024	83.463*	0.219*	−0.201**	−0.096	1.978	0.014	−0.097	−1.704	−0.442
	(2.480)	(47.714)	(0.128)	(0.080)	(0.096)	(2.540)	(0.457)	(0.092)	(3.050)	(0.348)
ICEA.l1	−3.881**	−38.338	0.470***	0.153**	0.025	−0.020	−0.028	0.014	−0.102	0.208
	(1.884)	(36.256)	(0.097)	(0.061)	(0.073)	(1.930)	(0.347)	(0.070)	(2.317)	(0.265)
VIX.l1	0.009	−0.248	0.002	−0.002	0.004	−0.046	−0.020	−0.011***	−0.113	−0.0002
	(0.097)	(1.871)	(0.005)	(0.003)	(0.004)	(0.100)	(0.018)	(0.004)	(0.120)	(0.014)
MSCI.l1	0.375	−4.593	0.011	0.014	0.005	−1.319**	−0.187*	−0.095***	−0.125	−0.145*
	(0.593)	(11.415)	(0.031)	(0.019)	(0.023)	(0.608)	(0.109)	(0.022)	(0.730)	(0.083)
USD.l1	0.174	2.286	−0.122	0.035	0.005	−2.900	0.144	0.088	−0.506	0.407
	(2.026)	(38.985)	(0.104)	(0.066)	(0.079)	(2.076)	(0.373)	(0.075)	(2.492)	(0.285)
Oil.l1	−0.046	0.017	−0.005*	−0.001	0.0002	0.054	0.009	0.0002	−0.254***	0.009
	(0.059)	(1.126)	(0.003)	(0.002)	(0.002)	(0.060)	(0.011)	(0.002)	(0.072)	(0.008)
Gold.l1	−0.431	3.097	−0.035	−0.0002	−0.006	0.505	0.021	−0.026	0.811	−0.103
	(0.534)	(10.267)	(0.027)	(0.017)	(0.021)	(0.547)	(0.098)	(0.020)	(0.656)	(0.075)
const	0.005	0.024	−0.0001	0.0001	0.00004	0.006	0.002	0.001	0.0004	0.002
	(0.010)	(0.192)	(0.001)	(0.0003)	(0.0004)	(0.010)	(0.002)	(0.0004)	(0.012)	(0.001)
Observations	207	207	207	207	207	207	207	207	207	207
R^2	0.051	0.107	0.297	0.078	0.284	0.058	0.061	0.222	0.085	0.096
Adjusted R^2	0.002	0.061	0.262	0.031	0.247	0.010	0.013	0.182	0.038	0.049
Residual Std. Error (df = 196)	0.141	2.719	0.007	0.005	0.005	0.145	0.026	0.005	0.174	0.020
F Statistic (df = 10; 196)	1.049	2.344**	8.298***	1.668*	7.775***	1.215	1.264	5.580***	1.812*	2.072**
Note:								*p<0.1; **p<0.05; ***p<0.01		

returns are positive predictors of changes in attention, which is the same result as we obtained from the linear regression of Model (2). We can conclude that the Investor Attention Index is not a predictor of future returns, however, the relationship is significant in the reverse direction.

4.1.3. Time-Series Results for Solana

The linear regression results for Solana are presented in Table 7. The only significant model among the four models is the second model. Hence, we can only incorporate the second model's results into our conclusion. It shows that, as in the case of Ethereum, past returns predict future attention, and the relationship is not significant in the reverse direction.

Table 7: Linear Regression Results for Solana

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att_t	0.001			0.001
	(0.006)			(0.007)
Ret_t		4.349**	0.114	
		(1.966)	(0.108)	
$UCRY_t$				2.914
				(2.289)
$CBDC_t$				4.086
				(4.087)
$ICEA_t$				-4.659
				(2.934)
VIX_t				-0.318
				(0.309)
$MSCI_t$				0.238
				(1.552)
USD_t			4.659	
				(5.233)
Oil_t				-0.205
				(0.414)
$Gold_t$				0.900
				(1.199)
Mom_t				-0.0001
				(0.001)
Constant	0.064***	-0.099	0.057**	0.068***
	(0.022)	(0.426)	(0.023)	(0.025)
Observations	87	87	87	87
R^2	0.0004	0.054	0.013	0.081
Adjusted R^2	-0.011	0.043	0.001	-0.039
Residual Std. Error	0.209 (df = 85)	3.798 (df = 85)	0.208 (df = 85)	0.212 (df = 76)
F Statistic	0.036 (df = 1; 85)	4.893** (df = 1; 85)	1.125 (df = 1; 85)	0.674 (df = 10; 76)
Note:				*p<0.1; **p<0.05; ***p<0.01

However, this result is not supported by the VAR estimation. In column 2 of Table 8, we see that the model is not significant even though one period lagged returns has a positive

Table 8: VAR Results for Solana

	Dependent variable:								
	Ret	Att	UCRY	CBDC	ICEA	VIX	MSCI	USD	Oil
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ret.l1	0.060	3.791*	0.004	0.0002	−0.018	0.005	−0.001	0.052**	−0.018
	(0.120)	(2.149)	(0.006)	(0.004)	(0.064)	(0.012)	(0.003)	(0.024)	(0.012)
Att.l1	0.0001	0.153	−0.0002	0.00004	−0.001	0.0003	−0.0001	0.0001	0.0004
	(0.006)	(0.111)	(0.0003)	(0.0002)	(0.003)	(0.001)	(0.0001)	(0.001)	(0.001)
UCRY.l1	1.903	−37.288	−0.477***	−0.036	−1.737	−0.104	0.046	0.796*	−0.173
	(2.220)	(39.631)	(0.118)	(0.071)	(1.188)	(0.218)	(0.052)	(0.439)	(0.216)
CBDC.l1	1.439	91.093	0.551***	−0.046	1.424	−0.047	−0.056	−2.328***	−0.316
	(3.870)	(69.098)	(0.206)	(0.123)	(2.071)	(0.380)	(0.091)	(0.765)	(0.377)
ICEA.l1	−0.455	−3.658	0.027	0.003	0.107	−0.024	−0.005	0.006	0.023
	(0.307)	(5.478)	(0.016)	(0.010)	(0.164)	(0.030)	(0.007)	(0.061)	(0.030)
VIX.l1	−0.277	5.920	0.087	0.093*	0.028	−0.299*	−0.106***	0.048	0.045
	(1.571)	(28.042)	(0.083)	(0.050)	(0.841)	(0.154)	(0.037)	(0.310)	(0.153)
MSCI.l1	4.447	−9.123	−0.453	0.075	−3.265	−0.077	0.052	0.854	0.349
	(5.169)	(92.290)	(0.275)	(0.165)	(2.767)	(0.508)	(0.122)	(1.021)	(0.504)
USD.l1	−0.196	−1.032	−0.016	−0.018	0.068	−0.034	0.006	0.279***	0.010
	(0.417)	(7.450)	(0.022)	(0.013)	(0.223)	(0.041)	(0.010)	(0.082)	(0.041)
Oil.l1	0.852	11.008	−0.058	0.026	−0.146	0.042	−0.018	0.281	0.019
	(1.197)	(21.372)	(0.064)	(0.038)	(0.641)	(0.118)	(0.028)	(0.237)	(0.117)
Gold.l1	0.067**	−0.181	−0.0004	0.0003	−0.009	0.007**	−0.0002	0.006	0.002
	(0.026)	(0.459)	(0.001)	(0.001)	(0.014)	(0.003)	(0.001)	(0.005)	(0.003)
Observations	86	86	86	86	86	86	86	86	86
R^2	0.064	0.162	0.229	0.086	0.046	0.083	0.172	0.237	0.082
Adjusted R^2	−0.047	0.062	0.138	−0.022	−0.067	−0.025	0.074	0.147	−0.026
Residual Std. Error (df = 76)	0.212	3.782	0.011	0.007	0.113	0.021	0.005	0.042	0.021
F Statistic (df = 9; 76)	0.574	1.627	2.512**	0.795	0.403	0.769	1.755*	2.624**	0.757

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

and significant estimator. Hence, we cannot conclude that past returns are a suitable explanatory variable for future changes in Investor Attention Index for Solana.

4.1.4. Time-Series Results for Cardano

The linear regression results are displayed in Table 9. The models in the second and third columns are the only significant models by their F-statistics. The attention index is not a good predictor for future returns however past returns are highly significant predictors for future attention changes in Cardano. One unit of change in returns leads to a 5.301 increase in attention scores. Moving on to the next column, we see that past returns are significant predictors of future returns for Cardano in our sample.

Table 9: Linear Regression Results for Cardano

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att_t	0.002			0.004
	(0.004)			(0.004)
Ret_t		5.301***	0.137**	
		(1.311)	(0.069)	
$UCRY_t$				2.318
				(1.583)
$CBDC_t$				−2.793
				(2.894)
$ICEA_t$				−5.442**
				(2.330)
VIX_t				−0.027
				(0.114)
$MSCI_t$				0.294
				(0.687)
USD_t				−1.704
				(2.391)
Oil_t				−0.037
				(0.069)
$Gold_t$				−0.792
				(0.625)
Mom_t				0.032
				(0.044)
Constant	0.002	0.021	0.002	0.004
	(0.012)	(0.220)	(0.012)	(0.012)
Observations	208	208	208	208
Adjusted R^2	-0.003	0.069	0.014	0.011
Residual Std. Error	0.168 (df = 206)	3.177 (df = 206)	0.167 (df = 206)	0.167 (df = 197)
F Statistic	0.317 (df = 1; 206)	16.351*** (df = 1; 206)	3.951** (df = 1; 206)	1.227 (df = 10; 197)
Note:				*p<0.1; **p<0.05; ***p<0.01

VAR estimation results are similar to the linear regression estimation results. We are mainly interested in the first and second columns of the \ref{tab: var-ada}. The model in the first column is not significant, hence, once again we see that the attention index is unable to predict future returns.

Table 10: VAR Estimation Results for Cardano

	Dependent variable:									
	Ret	Att	UCRY	CBDC	ICEA	VIX	MSCI	USD	Oil	Gold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ret.l1	0.148**	5.416***	0.004	0.003*	0.006**	−0.140**	0.036***	−0.005**	0.132*	0.002
	(0.075)	(1.415)	(0.003)	(0.002)	(0.003)	(0.065)	(0.012)	(0.002)	(0.078)	(0.009)
Att.l1	0.003	−0.103	0.0003*	−0.0002**	0.0003*	0.002	−0.0004	−0.00000	−0.003	0.0004
	(0.004)	(0.075)	(0.0002)	(0.0001)	(0.0001)	(0.003)	(0.001)	(0.0001)	(0.004)	(0.0005)
UCRY.l1	2.514	−64.178**	−0.521***	−0.035	−0.161***	−1.676	0.054	0.035	1.837	−0.050
	(1.578)	(29.915)	(0.070)	(0.043)	(0.058)	(1.370)	(0.248)	(0.050)	(1.644)	(0.189)
CBDC.l1	−2.745	60.212	0.276**	−0.192**	0.002	1.792	0.100	−0.124	−1.708	−0.375
	(2.881)	(54.626)	(0.127)	(0.079)	(0.107)	(2.502)	(0.453)	(0.091)	(3.002)	(0.346)
ICEA.l1	−5.453**	−11.260	0.408***	0.186***	−0.026	0.167	−0.085	0.034	0.015	0.115
	(2.318)	(43.946)	(0.102)	(0.063)	(0.086)	(2.013)	(0.364)	(0.073)	(2.415)	(0.278)
VIX.l1	−0.018	2.175	0.004	−0.002	0.008*	−0.047	−0.021	−0.012***	−0.108	−0.001
	(0.113)	(2.149)	(0.005)	(0.003)	(0.004)	(0.098)	(0.018)	(0.004)	(0.118)	(0.014)
MSCI.l1	0.066	11.804	0.023	0.013	0.027	−1.218**	−0.200*	−0.097***	−0.277	−0.126
	(0.694)	(13.154)	(0.031)	(0.019)	(0.026)	(0.602)	(0.109)	(0.022)	(0.723)	(0.083)
USD.l1	−2.089	69.152	−0.119	0.019	−0.006	−2.688	0.098	0.094	−0.794	0.430
	(2.386)	(45.234)	(0.105)	(0.065)	(0.088)	(2.072)	(0.375)	(0.075)	(2.486)	(0.286)
Oil.l1	−0.031	0.399	−0.005	−0.001	0.0002	0.049	0.010	0.00002	−0.250***	0.009
	(0.069)	(1.302)	(0.003)	(0.002)	(0.003)	(0.060)	(0.011)	(0.002)	(0.072)	(0.008)
Gold.l1	−0.785	−7.374	−0.037	−0.001	−0.016	0.420	0.050	−0.029	0.860	−0.094
	(0.621)	(11.774)	(0.027)	(0.017)	(0.023)	(0.539)	(0.098)	(0.020)	(0.647)	(0.075)
const	0.005	0.012	−0.0001	0.0001	0.0001	0.005	0.002	0.0005	0.001	0.002
	(0.012)	(0.222)	(0.001)	(0.0003)	(0.0004)	(0.010)	(0.002)	(0.0004)	(0.012)	(0.001)
Observations	207	207	207	207	207	207	207	207	207	207
R^2	0.075	0.127	0.289	0.093	0.100	0.069	0.061	0.216	0.096	0.091
Adjusted R^2	0.028	0.082	0.253	0.047	0.054	0.022	0.013	0.176	0.050	0.044
Residual Std. Error (df = 196)	0.166	3.143	0.007	0.005	0.006	0.144	0.026	0.005	0.173	0.020
F Statistic (df = 10; 196)	1.584	2.839***	7.967***	2.020**	2.175**	1.454	1.271	5.411***	2.081**	1.952**
Note:										*p<0.1; **p<0.05; ***p<0.01

On the other hand, the model in the second column is significant and we verify the result that past returns predict future changes in attention.

4.1.5. Time-Series Results for Ripple

The linear regression and VAR estimation results for Ripple are displayed in Table 11 and Table 12, respectively. In the second column of Table 11, we see that past returns are again powerful predictors of future attention.

Table 11: Linear Regression Results for Ripple

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att_t	0.004			0.004
	(0.003)			(0.003)
Ret_t		5.517***	0.022	
		(1.704)	(0.068)	
$UCRY_t$				0.811
				(1.604)
$CBDC_t$				1.348
				(2.935)
$ICEA_t$				−5.735**
				(2.250)
VIX_t				−0.100
				(0.117)
$MSCI_t$				0.238
				(0.699)
USD_t				−0.689
				(2.454)
Oil_t				−0.096
				(0.070)
$Gold_t$				−0.800
				(0.636)
Mom_t				−0.041
				(0.040)
Constant	−0.002	−0.334	−0.004	−0.001
	(0.012)	(0.301)	(0.012)	(0.012)
Observations	208	208	208	208
Adjusted R^2	0.008	0.044	-0.004	0.028
Residual Std. Error	0.171 (df = 206)	4.331 (df = 206)	0.172 (df = 206)	0.169 (df = 197)
F Statistic	2.703 (df = 1; 206)	10.485*** (df = 1; 206)	0.101 (df = 1; 206)	1.591 (df = 10; 197)
Note:				*p<0.1; **p<0.05; ***p<0.01

In the VAR estimation for Ripple where the optimal lag is found as three, we again see the same relationship between these variables. Differing from the previous results, in Ripple's case, we see that one and three-period lagged attention predicts future returns and the model is significant at 1%. We can also see that one-period-lagged ICEA and two-period-lagged CBDC have significant coefficients for the returns of Ripple.

Table 12: VAR Results for Ripple

	Dependent variable:									
	Ret	Att	UCRY	CBDC	ICEA	VIX	MSCI	USD	Oil	Gold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ret.l1	0.027	8.010***	−0.001	0.003	−0.001	−0.222***	0.031***	−0.002	0.038	0.009
	(0.076)	(1.519)	(0.003)	(0.002)	(0.003)	(0.065)	(0.012)	(0.002)	(0.080)	(0.009)
Att.l1	0.008**	−0.085	0.0003*	0.0002**	0.0003**	−0.002	0.001	−0.0002*	−0.0004	0.001
	(0.003)	(0.070)	(0.0002)	(0.0001)	(0.0001)	(0.003)	(0.001)	(0.0001)	(0.004)	(0.0004)
UCRY.l1	0.822	−39.004	−0.668***	−0.098**	−0.155**	−0.390	−0.132	0.095	0.783	−0.126
	(1.832)	(36.789)	(0.082)	(0.050)	(0.061)	(1.582)	(0.285)	(0.058)	(1.928)	(0.228)
CBDC.l1	3.678	47.243	0.233*	−0.230***	0.052	3.722	−0.364	−0.050	−2.669	−0.617
	(3.027)	(60.794)	(0.135)	(0.082)	(0.101)	(2.614)	(0.471)	(0.095)	(3.186)	(0.377)
ICEA.l1	−7.005***	−15.533	0.451***	0.147**	−0.029	0.302	0.017	−0.027	0.549	0.441
	(2.418)	(48.553)	(0.108)	(0.066)	(0.081)	(2.087)	(0.376)	(0.076)	(2.544)	(0.301)
VIX.l1	−0.142	−0.468	0.010	0.0002	0.010**	−0.059	−0.019	−0.013***	−0.167	0.004
	(0.132)	(2.656)	(0.006)	(0.004)	(0.004)	(0.114)	(0.021)	(0.004)	(0.139)	(0.016)
MSCI.l1	0.110	−12.415	0.033	0.015	0.030	−1.289*	−0.161	−0.110***	−0.756	−0.140
	(0.784)	(15.746)	(0.035)	(0.021)	(0.026)	(0.677)	(0.122)	(0.025)	(0.825)	(0.098)
USD.l1	−0.796	50.421	−0.212	0.032	−0.047	−2.216	−0.085	0.128	−4.123	0.451
	(2.988)	(60.004)	(0.133)	(0.081)	(0.100)	(2.580)	(0.465)	(0.094)	(3.144)	(0.372)
Oil.l1	−0.075	−0.008	−0.006*	−0.001	−0.0001	0.064	0.010	−0.0002	−0.318***	0.002
	(0.074)	(1.488)	(0.003)	(0.002)	(0.002)	(0.064)	(0.012)	(0.002)	(0.078)	(0.009)
Gold.l1	−0.806	21.189	−0.036	0.003	−0.007	0.976*	−0.037	−0.012	0.394	−0.073
	(0.680)	(13.659)	(0.030)	(0.018)	(0.023)	(0.587)	(0.106)	(0.021)	(0.716)	(0.085)
Ret.l2	−0.093	−3.729**	0.004	0.003	0.009***	−0.027	−0.004	−0.0001	0.016	0.002
	(0.078)	(1.565)	(0.003)	(0.002)	(0.003)	(0.067)	(0.012)	(0.002)	(0.082)	(0.010)
Att.l2	0.003	−0.133**	−0.00002	0.00004	−0.0002	−0.006**	0.0004	0.0001	0.001	−0.0001
	(0.003)	(0.063)	(0.0001)	(0.0001)	(0.0001)	(0.003)	(0.0005)	(0.0001)	(0.003)	(0.0004)
UCRY.l2	2.073	−59.401	−0.314***	−0.139**	0.011	0.274	0.201	0.043	−0.097	−0.094
	(2.087)	(41.911)	(0.093)	(0.057)	(0.070)	(1.802)	(0.325)	(0.066)	(2.196)	(0.260)
CBDC.l2	12.066***	234.106***	−0.106	−0.113	−0.086	0.157	−0.141	0.129	−0.944	−0.636
	(3.187)	(64.005)	(0.142)	(0.086)	(0.107)	(2.752)	(0.496)	(0.100)	(3.354)	(0.397)
ICEA.l2	−2.400	−53.402	0.078	0.075	−0.180**	−2.592	0.399	−0.143*	0.541	0.543*
	(2.457)	(49.348)	(0.110)	(0.067)	(0.082)	(2.122)	(0.382)	(0.077)	(2.586)	(0.306)
VIX.l2	−0.008	−1.829	0.0001	0.001	0.004	−0.098	−0.031	0.002	−0.180	−0.008
	(0.134)	(2.683)	(0.006)	(0.004)	(0.004)	(0.115)	(0.021)	(0.004)	(0.141)	(0.017)
MSCI.l2	0.142	13.308	−0.007	0.005	0.019	0.129	−0.025	−0.008	−0.771	0.012
	(0.901)	(18.101)	(0.040)	(0.024)	(0.030)	(0.778)	(0.140)	(0.028)	(0.949)	(0.112)
USD.l2	4.553	22.898	−0.044	−0.019	−0.067	−1.261	0.535	−0.029	0.169	0.071
	(3.028)	(60.809)	(0.135)	(0.082)	(0.101)	(2.614)	(0.471)	(0.095)	(3.186)	(0.377)
Oil.l2	0.031	−0.324	−0.005	−0.001	−0.002	0.024	−0.010	0.002	−0.232***	−0.006
	(0.076)	(1.536)	(0.003)	(0.002)	(0.003)	(0.066)	(0.012)	(0.002)	(0.080)	(0.010)
Gold.l2	0.181	10.242	−0.007	0.018	−0.021	−0.262	−0.063	0.043*	−1.095	0.059
	(0.701)	(14.078)	(0.031)	(0.019)	(0.023)	(0.605)	(0.109)	(0.022)	(0.738)	(0.087)
Ret.l3	0.105	1.648	0.003	−0.001	0.002	0.049	−0.00004	−0.002	−0.043	0.005
	(0.081)	(1.623)	(0.004)	(0.002)	(0.003)	(0.070)	(0.013)	(0.003)	(0.085)	(0.010)
Att.l3	−0.006**	−0.055	0.0003**	−0.0001	−0.0001	−0.001	−0.0002	−0.0001	0.0001	0.0004
	(0.003)	(0.058)	(0.0001)	(0.0001)	(0.0001)	(0.002)	(0.0004)	(0.0001)	(0.003)	(0.0004)
UCRY.l3	3.137*	−1.003	−0.071	−0.010	0.276***	1.220	−0.112	0.005	−1.236	0.133
	(1.864)	(37.424)	(0.083)	(0.051)	(0.062)	(1.609)	(0.290)	(0.059)	(1.961)	(0.232)
CBDC.l3	−4.975	7.895	0.085	0.062	0.005	8.926***	−1.071**	0.220**	−0.920	−0.050
	(3.255)	(65.359)	(0.145)	(0.088)	(0.109)	(2.810)	(0.506)	(0.103)	(3.425)	(0.405)
ICEA.l3	0.166	−45.660	−0.057	−0.041	−0.351***	−4.120*	0.377	−0.195**	1.331	0.394
	(2.449)	(49.181)	(0.109)	(0.066)	(0.082)	(2.114)	(0.381)	(0.077)	(2.577)	(0.305)
VIX.l3	0.192	−1.716	0.007	0.001	0.002	0.158	−0.053***	0.010**	0.127	−0.018
	(0.129)	(2.587)	(0.006)	(0.003)	(0.004)	(0.111)	(0.020)	(0.004)	(0.136)	(0.016)
MSCI.l3	0.502	−8.170	0.012	0.013	0.001	0.921	−0.242*	0.045*	2.360***	−0.115
	(0.848)	(17.029)	(0.038)	(0.023)	(0.028)	(0.732)	(0.132)	(0.027)	(0.892)	(0.106)
USD.l3	−2.203	−29.153	−0.066	0.088	0.058	−0.865	0.215	0.0001	3.744	−0.144
	(2.444)	(49.070)	(0.109)	(0.066)	(0.082)	(2.110)	(0.380)	(0.077)	(2.571)	(0.304)
Oil.l3	0.0003	−1.123	−0.002	−0.0001	−0.0005	−0.010	0.014	−0.004*	−0.091	−0.018**
	(0.073)	(1.476)	(0.003)	(0.002)	(0.002)	(0.063)	(0.011)	(0.002)	(0.077)	(0.009)
Gold.l3	−0.042	5.292	0.015	0.020	0.021	−0.650	0.362***	−0.050**	−0.617	−0.009
	(0.664)	(13.342)	(0.030)	(0.018)	(0.022)	(0.574)	(0.103)	(0.021)	(0.699)	(0.083)
const	−0.004	−0.182	0.0002	0.00004	0.0002	0.00004	0.002	0.0004	0.003	0.002
	(0.012)	(0.250)	(0.001)	(0.0003)	(0.0004)	(0.011)	(0.002)	(0.0004)	(0.013)	(0.002)
Observations	205	205	205	205	205	205	205	205	205	205
R^2	0.256	0.308	0.397	0.259	0.389	0.228	0.232	0.329	0.232	0.183
Adjusted R^2	0.127	0.189	0.293	0.131	0.283	0.095	0.099	0.213	0.100	0.042
Residual Std. Error (df = 174)	0.161	3.224	0.007	0.004	0.005	0.139	0.025	0.005	0.169	0.020
F Statistic (df = 30; 174)	1.991***	2.587***	3.818***	2.028***	3.690***	1.716**	1.747**	2.838***	1.753**	1.302

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Ripple is the first currency in that we have found a significant relationship between past attention and future returns so far. This could be due to the increased vulnerability of the coin's value stemming from the SEC's lawsuit against Ripple towards the end of 2020. The case remains still open and the final decision is yet to be made by the court as of July 2023.

4.1.6. Time-Series Results for Terra

Our linear regression estimation results in Table 13 show that only the fourth model is significant. When we examine the coefficients of the model, we see that only UCRY, ICEA, and USD have explanatory power on future returns with significance levels of 1%, 1%, and 5% respectively. Unfortunately, the attention index is unable to explain future returns and the opposite direction of the relation is also insignificant. The linear regression estimation falls short to find a connection between the attention index and returns.

Unfortunately, the limited data availability of Terra does not allow us to conduct a VAR analysis. The results from the linear regression estimations conclude the analysis for Terra.

Table 13: Linear Regression Results for Terra

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att_t	−0.005			−0.007
	(0.006)			(0.006)
Ret_t		6.247	−0.108	
		(3.796)	(0.156)	
$UCRY_t$				8.380***
				(2.958)
$CBDC_t$				0.767
				(4.684)
$ICEA_t$				−12.000***
				(3.412)
VIX_t				−1.019*
				(0.561)
$MSCI_t$				2.134
				(3.989)
USD_t				20.664**
				(10.105)
Oil_t				−1.041
				(1.208)
$Gold_t$				−1.494
				(2.531)
Mom_t				−0.001
				(0.003)
Constant	0.032	0.389	0.034	0.025
	(0.044)	(1.089)	(0.045)	(0.043)
Observations	42	42	42	42
R^2	0.018	0.063	0.012	0.515
Adjusted R^2	-0.007	0.040	-0.013	0.358
Residual Std. Error	0.287 (df = 40)	6.987 (df = 40)	0.288 (df = 40)	0.229 (df = 31)
F Statistic	0.714 (df = 1; 40)	2.709 (df = 1; 40)	0.482 (df = 1; 40)	3.290*** (df = 10; 31)
Note:				*p<0.1; **p<0.05; ***p<0.01

4.1.7. Time-Series Results for Polkadot

Our dataset consists of 68 weeks (observations) for Polkadot because of limited data availability on Reddit. The regression estimation results for Polkadot is presented in Table

14. Only one out of four models are significant, which suggests that past returns predict future attention. A one standard deviation increase in returns leads attention to increase by 12.647 units.

Table 14: Linear Regression Results for Polkadot

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att	−0.004			−0.004
	(0.004)			(0.004)
Ret		12.647***	−0.069	
		(3.361)	(0.122)	
UCRY				6.141***
				(2.242)
CBDC				−3.171
				(3.967)
ICEA				−6.446**
				(2.819)
VIX				−0.355
				(0.362)
MSCI				1.220
				(1.937)
USD				3.654
				(6.290)
Oil				−0.096
				(0.861)
Gold				−0.797
				(1.472)
Mom				0.002
				(0.003)
Constant	0.027	−0.170	0.028	0.021
	(0.025)	(0.706)	(0.026)	(0.026)
Observations	68	68	68	68
R^2	0.013	0.177	0.005	0.218
Adjusted R^2	-0.002	0.164	-0.010	0.081
Residual Std. Error	0.210 (df = 66)	5.777 (df = 66)	0.210 (df = 66)	0.201 (df = 57)
F Statistic	0.855 (df = 1; 66)	14.159*** (df = 1; 66)	0.321 (df = 1; 66)	1.588 (df = 10; 57)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 15 displays the VAR estimation results for Polkadot where the optimal length is found as four. Our two main models of interest (first and second column) are not significant, so we are unable to make comments on the relationship between attention and return from these estimation results. This may be due to a small sample size problem which is one of the major drawbacks of VAR estimation.

Table 15: VAR Results for Polkadot

	Dependent variable:									
	Ret	Att	UCRY	CBDC	ICEA	VIX	MSCI	USD	Oil	Gold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ret.l1	0.205	10.278	−0.0001	0.015*	0.010	−0.019	0.007	−0.004	−0.001	0.011
	(0.230)	(7.268)	(0.013)	(0.008)	(0.009)	(0.113)	(0.024)	(0.004)	(0.033)	(0.018)
Att.l1	−0.013*	−0.641***	0.001*	−0.0004*	0.0001	−0.002	0.0002	−0.0001	0.001	0.001
	(0.007)	(0.220)	(0.0004)	(0.0002)	(0.0003)	(0.003)	(0.001)	(0.0001)	(0.001)	(0.001)
UCRY.l1	8.636*	12.572	−0.586**	0.020	0.001	−0.058	−0.420	0.092	0.272	−0.278
	(4.227)	(133.427)	(0.245)	(0.141)	(0.166)	(2.071)	(0.434)	(0.079)	(0.607)	(0.331)
CBDC.l1	−9.713	−52.776	−0.003	−0.483**	−0.515*	−1.380	0.524	0.110	−0.565	−0.863
	(6.836)	(215.798)	(0.396)	(0.227)	(0.268)	(3.349)	(0.701)	(0.128)	(0.981)	(0.535)
ICEA.l1	−8.216	4.904	0.728**	0.247	0.018	1.592	−0.185	−0.068	−1.071	0.920**
	(4.917)	(155.231)	(0.285)	(0.164)	(0.193)	(2.409)	(0.504)	(0.092)	(0.706)	(0.385)
VIX.l1	−0.046	25.692	0.007	−0.021	0.010	−0.312	−0.016	−0.004	0.011	0.034
	(0.666)	(21.019)	(0.039)	(0.022)	(0.026)	(0.326)	(0.068)	(0.012)	(0.096)	(0.052)
MSCI.l1	1.763	114.088	0.140	0.051	−0.037	−0.633	−0.398	−0.066	0.248	−0.018
	(3.641)	(114.944)	(0.211)	(0.121)	(0.143)	(1.784)	(0.373)	(0.068)	(0.523)	(0.285)
USD.l1	1.053	155.761	−0.762	0.096	−0.381	−1.018	−0.836	0.355	−3.259	2.132*
	(13.509)	(426.438)	(0.782)	(0.449)	(0.530)	(6.618)	(1.386)	(0.252)	(1.939)	(1.057)
Oil.l1	0.732	68.419	−0.074	−0.040	0.017	−0.473	−0.041	0.028	0.098	−0.017
	(1.603)	(50.592)	(0.093)	(0.053)	(0.063)	(0.785)	(0.164)	(0.030)	(0.230)	(0.125)
Gold.l1	3.674	164.451*	−0.225	0.125	0.053	1.290	−0.159	0.001	−0.247	0.071
	(2.705)	(85.394)	(0.157)	(0.090)	(0.106)	(1.325)	(0.277)	(0.050)	(0.388)	(0.212)
Ret.l2	0.450*	13.370*	−0.002	0.015*	0.024**	0.103	−0.017	−0.0001	−0.042	−0.005
	(0.227)	(7.163)	(0.013)	(0.008)	(0.009)	(0.111)	(0.023)	(0.004)	(0.033)	(0.018)
Att.l2	−0.011	−0.664**	−0.0002	−0.001**	−0.001**	−0.003	0.001	0.0001	0.002*	0.00001
	(0.008)	(0.264)	(0.0005)	(0.0003)	(0.0003)	(0.004)	(0.001)	(0.0002)	(0.001)	(0.001)
UCRY.l2	7.907*	147.191	−0.324	−0.048	0.127	1.765	−0.218	0.057	0.972	−0.597
	(4.497)	(141.960)	(0.260)	(0.150)	(0.176)	(2.203)	(0.461)	(0.084)	(0.645)	(0.352)
CBDC.l2	−0.864	80.388	−0.411	−0.535**	−0.522*	0.076	−0.324	0.154	−0.813	−0.378
	(6.507)	(205.418)	(0.377)	(0.216)	(0.255)	(3.188)	(0.667)	(0.121)	(0.934)	(0.509)
ICEA.l2	−5.976	−163.502	0.141	0.232	0.074	−3.223	0.373	−0.168	−0.258	0.980**
	(5.505)	(173.785)	(0.319)	(0.183)	(0.216)	(2.697)	(0.565)	(0.103)	(0.790)	(0.431)
VIX.l2	0.078	3.831	0.007	−0.002	0.019	0.076	−0.024	−0.011	−0.015	0.026
	(0.584)	(18.444)	(0.034)	(0.019)	(0.023)	(0.286)	(0.060)	(0.011)	(0.084)	(0.046)
MSCI.l2	−0.310	23.975	0.141	0.035	−0.003	3.145	−0.566	−0.045	−1.450**	0.133
	(3.815)	(120.441)	(0.221)	(0.127)	(0.150)	(1.869)	(0.391)	(0.071)	(0.548)	(0.299)
USD.l2	−4.303	−241.060	0.307	−0.084	−0.121	6.000	−1.084	0.246	−2.948*	−1.383
	(10.744)	(339.158)	(0.622)	(0.357)	(0.421)	(5.263)	(1.102)	(0.200)	(1.542)	(0.841)
Oil.l2	2.156	50.996	−0.050	0.002	0.042	0.241	−0.030	−0.007	0.451*	−0.015
	(1.529)	(48.277)	(0.089)	(0.051)	(0.060)	(0.749)	(0.157)	(0.029)	(0.219)	(0.120)
Gold.l2	2.022	49.322	0.052	0.138*	0.149	1.000	−0.174	0.037	−0.044	−0.025
	(2.271)	(71.692)	(0.132)	(0.076)	(0.089)	(1.113)	(0.233)	(0.042)	(0.326)	(0.178)
Ret.l3	0.271	12.436	0.003	0.013	0.013	−0.082	0.011	0.004	0.051	−0.034*
	(0.247)	(7.793)	(0.014)	(0.008)	(0.010)	(0.121)	(0.025)	(0.005)	(0.035)	(0.019)
Att.l3	−0.011	−0.598**	0.0004	−0.001*	−0.001	0.005	−0.001	0.0001	−0.002	−0.0002
	(0.009)	(0.288)	(0.001)	(0.0003)	(0.0004)	(0.004)	(0.001)	(0.0002)	(0.001)	(0.001)
UCRY.l3	3.291	30.521	−0.223	0.142	0.386*	1.011	−0.201	−0.016	0.828	−0.709*
	(5.219)	(164.745)	(0.302)	(0.174)	(0.205)	(2.557)	(0.535)	(0.097)	(0.749)	(0.408)
CBDC.l3	−3.716	195.670	0.320	0.076	0.043	4.911	−0.296	0.242*	−0.310	−0.235
	(7.286)	(229.990)	(0.422)	(0.242)	(0.286)	(3.569)	(0.747)	(0.136)	(1.046)	(0.570)
ICEA.l3	0.211	−118.735	−0.127	0.017	−0.154	−4.832	0.189	−0.224*	−0.975	1.409***
	(6.034)	(190.470)	(0.349)	(0.201)	(0.237)	(2.956)	(0.619)	(0.113)	(0.866)	(0.472)
VIX.l3	−0.130	−5.451	0.034	−0.030	−0.027	0.680**	−0.113*	0.030***	−0.217**	−0.071
	(0.559)	(17.661)	(0.032)	(0.019)	(0.022)	(0.274)	(0.057)	(0.010)	(0.080)	(0.044)
MSCI.l3	−3.493	6.751	0.407	0.113	−0.054	4.867**	−0.614	0.156*	−1.558**	−0.230
	(4.214)	(133.019)	(0.244)	(0.140)	(0.165)	(2.064)	(0.432)	(0.079)	(0.605)	(0.330)
USD.l3	9.987	478.381	−0.048	0.932**	0.449	1.555	0.044	0.004	2.324	−0.432
	(10.951)	(345.685)	(0.634)	(0.364)	(0.429)	(5.365)	(1.123)	(0.204)	(1.572)	(0.857)
Oil.l3	−0.794	−12.767	−0.057	−0.053	−0.018	1.106	−0.207	0.018	0.041	−0.198
	(1.486)	(46.919)	(0.086)	(0.049)	(0.058)	(0.728)	(0.152)	(0.028)	(0.213)	(0.116)
Gold.l3	4.561*	81.091	−0.031	0.152*	0.166	0.460	0.055	−0.053	0.502	−0.428**
	(2.474)	(78.106)	(0.143)	(0.082)	(0.097)	(1.212)	(0.254)	(0.046)	(0.355)	(0.194)
Ret.l4	0.515*	0.959	−0.003	0.009	0.006	−0.048	0.009	−0.008	0.057	0.016
	(0.255)	(8.059)	(0.015)	(0.008)	(0.010)	(0.125)	(0.026)	(0.005)	(0.037)	(0.020)
Att.l4	−0.018*	−0.425	0.001	−0.0004	−0.001	0.005	−0.0002	0.0003	−0.002	−0.001
	(0.009)	(0.295)	(0.001)	(0.0003)	(0.0004)	(0.005)	(0.001)	(0.0002)	(0.001)	(0.001)
UCRY.l4	2.536	−182.579	−0.141	−0.001	0.052	0.168	−0.322	0.011	−0.353	−0.254
	(4.328)	(136.622)	(0.251)	(0.144)	(0.170)	(2.120)	(0.444)	(0.081)	(0.621)	(0.339)
CBDC.l4	0.420	15.569	0.128	0.148	0.726**	2.114	−0.288	−0.227	2.103*	−0.512
	(7.125)	(224.931)	(0.413)	(0.237)	(0.279)	(3.491)	(0.731)	(0.133)	(1.023)	(0.558)
ICEA.l4	−5.223	−50.455	0.123	−0.155	−0.243	−1.505	0.210	0.141	−1.125	0.911*
	(5.898)	(186.189)	(0.342)	(0.196)	(0.231)	(2.889)	(0.605)	(0.110)	(0.847)	(0.462)
VIX.l4	0.435	27.367	0.024	−0.010	−0.036	0.056	0.033	0.002	0.137	−0.102*
	(0.702)	(22.170)	(0.041)	(0.023)	(0.028)	(0.344)	(0.072)	(0.013)	(0.101)	(0.055)
MSCI.l4	5.979	134.556	0.082	0.085	−0.026	2.339	−0.015	−0.049	−0.186	0.110
	(3.687)	(116.377)	(0.213)	(0.123)	(0.145)	(1.806)	(0.378)	(0.069)	(0.529)	(0.289)
USD.l4	13.504	26.451	0.020	0.029	0.732*	8.997*	−1.814*	0.004	−2.130	−0.251
	(9.502)	(299.950)	(0.550)	(0.316)	(0.373)	(4.655)	(0.975)	(0.177)	(1.364)	(0.744)
Oil.l4	0.360	8.491	0.069	0.037	0.027	0.399	0.029	0.041	−0.102	−0.188*
	(1.300)	(41.045)	(0.075)	(0.043)	(0.051)	(0.637)	(0.133)	(0.024)	(0.187)	(0.102)
Gold.l4	2.800	85.287	0.021	0.140*	0.163*	1.463	−0.222	0.014	−0.085	−0.192
	(2.386)	(75.305)	(0.138)	(0.079)	(0.094)	(1.169)	(0.245)	(0.045)	(0.342)	(0.187)
const	−0.008	−1.876	−0.002	−0.001	−0.0001	−0.052*	0.012**	−0.001	0.017**	0.001
	(0.056)	(1.764)	(0.003)	(0.002)	(0.002)	(0.027)	(0.006)	(0.001)	(0.008)	(0.004)
Observations	64	64	64	64	64	64	64	64	64	64
R^2	0.628	0.592	0.703	0.682	0.784	0.687	0.509	0.708	0.751	0.707
Adjusted R^2	−0.019	−0.118	0.186	0.129	0.408	0.142	−0.344	0.201	0.317	0.197
Residual Std. Error (df = 23)	0.217	6.856	0.013	0.007	0.009	0.106	0.022	0.004	0.031	0.017
F Statistic (df = 40; 23)	0.971	0.834	1.359	1.232	2.086**	1.260	0.597	1.397	1.733*	1.386
Note:										*p<0.1; **p<0.05; ***p<0.01

4.1.8. Time-Series Results for Avalanche

The linear regression estimation for Avalanche is presented in Table 16. The sample size consists of 63 weeks due to limited data availability. Two out of four models are significant in our estimation as can be seen in the second and third columns which imply that past attention and past returns have explanatory power on future returns.

A partially similar result is obtained from the VAR estimation that is presented in Table 17. The optimal lag length is determined as four by AIC. When we examine the table, we see that in the second column, one, two, and four-period lagged returns predict attention for Avalanche. Along with lagged returns, lagged UCR, ICEA, USD, and Gold affect future changes in attention for Polkadot. However, the reliability of the results of VAR estimation is questionable since the sample size is 59. Hence, it is better to rely more on linear regression estimates for this analysis.

Table 16: Linear Regression Results for Avalanche

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att	0.001			0.007
	(0.010)			(0.011)
Ret		5.008***	0.248*	
		(1.588)	(0.126)	
UCRY				5.106*
				(2.897)
CBDC				−2.858
				(5.035)
ICEA				−5.200
				(3.611)
VIX				−0.018
				(0.499)
MSCI				3.614
				(2.626)
USD				5.157
				(8.947)
Oil				−0.624
				(1.144)
Gold				−1.545
				(2.006)
Mom				−0.001
				(0.002)
Constant	0.047	0.120	0.035	0.047
	(0.033)	(0.409)	(0.032)	(0.037)
Observations	63	63	63	63
R^2	0.0003	0.140	0.060	0.156
Adjusted R^2	-0.016	0.126	0.044	-0.007
Residual Std. Error	0.260 (df = 61)	3.179 (df = 61)	0.252 (df = 61)	0.259 (df = 52)
F Statistic	0.019 (df = 1; 61)	9.942*** (df = 1; 61)	3.872* (df = 1; 61)	0.958 (df = 10; 52)

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

Table 17: VAR Results for Avalanche

	Dependent variable:									
	y									
	Ret	Att	UCRY	CBDC	ICEA	VIX	MSCI	USD	Oil	Gold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ret.l1	0.395	3.913*	−0.013	0.002	−0.004	−0.084	0.023	0.001	0.026	0.010
	(0.230)	(2.187)	(0.010)	(0.007)	(0.007)	(0.092)	(0.016)	(0.004)	(0.022)	(0.016)
Att.l1	−0.025	0.050	0.001	0.0001	−0.001	0.006	−0.002	0.0003	0.0002	−0.0001
	(0.024)	(0.225)	(0.001)	(0.001)	(0.001)	(0.009)	(0.002)	(0.0004)	(0.002)	(0.002)
UCRY.l1	10.121*	91.988*	−0.848***	−0.041	−0.117	−0.245	−0.419	0.123	0.124	−0.211
	(4.984)	(47.384)	(0.221)	(0.155)	(0.160)	(1.989)	(0.337)	(0.078)	(0.487)	(0.340)
CBDC.l1	−0.377	−14.100	0.134	−0.214	−0.149	−1.676	0.348	0.049	−0.615	−0.519
	(8.190)	(77.869)	(0.363)	(0.255)	(0.263)	(3.269)	(0.554)	(0.128)	(0.800)	(0.558)
ICEA.l1	−12.263**	114.752**	0.573**	0.241	−0.129	0.119	0.028	−0.061	−0.132	0.607
	(5.743)	(54.599)	(0.254)	(0.179)	(0.185)	(2.292)	(0.388)	(0.090)	(0.561)	(0.391)
VIX.l1	−0.323	1.582	0.059	−0.039	−0.029	0.047	−0.054	0.003	−0.102	0.026
	(0.932)	(8.864)	(0.041)	(0.029)	(0.030)	(0.372)	(0.063)	(0.015)	(0.091)	(0.064)
MSCI.l1	2.426	96.546*	0.514*	0.031	−0.138	1.818	−0.767*	−0.097	−0.697	0.172
	(5.698)	(54.171)	(0.252)	(0.177)	(0.183)	(2.274)	(0.385)	(0.089)	(0.557)	(0.388)
USD.l1	−6.685	368.851*	−1.398	−0.229	−1.261*	−1.275	−0.733	0.346	−3.507*	1.030
	(19.016)	(180.793)	(0.842)	(0.592)	(0.611)	(7.589)	(1.285)	(0.298)	(1.858)	(1.296)
Oil.l1	−1.430	−4.519	−0.072	−0.116	−0.084	−0.433	0.005	0.040	0.321	−0.159
	(2.281)	(21.687)	(0.101)	(0.071)	(0.073)	(0.910)	(0.154)	(0.036)	(0.223)	(0.155)
Gold.l1	−0.514	83.396**	−0.361**	0.011	−0.092	−0.421	0.119	−0.010	0.463	0.031
	(3.607)	(34.295)	(0.160)	(0.112)	(0.116)	(1.440)	(0.244)	(0.056)	(0.352)	(0.246)
Ret.l2	0.131	−4.574*	−0.003	0.009	0.023**	0.024	−0.002	−0.004	−0.051*	0.015
	(0.275)	(2.613)	(0.012)	(0.009)	(0.009)	(0.110)	(0.019)	(0.004)	(0.027)	(0.019)
Att.l2	−0.029	−0.013	0.0002	−0.00001	−0.001	0.014	−0.002	0.00004	−0.001	−0.001
	(0.021)	(0.199)	(0.001)	(0.001)	(0.001)	(0.008)	(0.001)	(0.0003)	(0.002)	(0.001)
UCRY.l2	6.523	58.624	−0.471	0.029	0.218	1.455	−0.245	−0.017	0.069	−0.317
	(6.558)	(62.351)	(0.290)	(0.204)	(0.211)	(2.617)	(0.443)	(0.103)	(0.641)	(0.447)
CBDC.l2	9.848	42.657	−0.310	−0.550*	−0.447	−1.580	0.052	0.188	0.566	−0.398
	(8.705)	(82.760)	(0.385)	(0.271)	(0.280)	(3.474)	(0.588)	(0.136)	(0.851)	(0.593)
ICEA.l2	−7.046	−119.592*	0.042	0.085	−0.152	−1.558	0.392	−0.175	−0.986	0.781
	(6.735)	(64.029)	(0.298)	(0.210)	(0.216)	(2.688)	(0.455)	(0.105)	(0.658)	(0.459)
VIX.l2	−0.599	7.514	0.068*	−0.015	0.019	0.183	−0.030	−0.004	−0.047	0.017
	(0.817)	(7.770)	(0.036)	(0.025)	(0.026)	(0.326)	(0.055)	(0.013)	(0.080)	(0.056)
MSCI.l2	−2.649	66.825	0.231	−0.128	−0.164	3.248	−0.224	−0.053	−1.573**	−0.163
	(6.137)	(58.348)	(0.272)	(0.191)	(0.197)	(2.449)	(0.415)	(0.096)	(0.600)	(0.418)
USD.l2	13.850	−81.928	−0.214	−0.407	−0.634	6.857	0.308	0.045	−4.533**	−1.392
	(17.558)	(166.934)	(0.777)	(0.547)	(0.564)	(7.007)	(1.187)	(0.275)	(1.716)	(1.196)
Oil.l2	−0.830	9.940	−0.006	0.015	0.044	0.226	−0.012	−0.008	0.179	0.045
	(2.128)	(20.229)	(0.094)	(0.066)	(0.068)	(0.849)	(0.144)	(0.033)	(0.208)	(0.145)
Gold.l2	4.023	62.516*	−0.125	0.070	0.088	0.881	−0.040	0.020	−0.671*	0.138
	(3.720)	(35.370)	(0.165)	(0.116)	(0.120)	(1.485)	(0.251)	(0.058)	(0.364)	(0.253)
Ret.l3	0.122	0.216	0.018	−0.003	−0.0004	0.040	−0.017	0.006	0.049*	−0.024
	(0.277)	(2.630)	(0.012)	(0.009)	(0.009)	(0.110)	(0.019)	(0.004)	(0.027)	(0.019)
Att.l3	−0.022	−0.023	−0.0004	0.0004	−0.0003	−0.0005	−0.001	−0.0001	−0.001	0.001
	(0.018)	(0.175)	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)	(0.0003)	(0.002)	(0.001)
UCRY.l3	4.897	27.557	−0.232	0.186	0.685***	−0.592	−0.053	−0.080	0.364	−0.163
	(6.875)	(65.359)	(0.304)	(0.214)	(0.221)	(2.743)	(0.465)	(0.108)	(0.672)	(0.468)
CBDC.l3	7.501	73.891	0.523	0.196	0.283	5.314	−0.579	0.212	−0.501	−0.071
	(9.325)	(88.655)	(0.413)	(0.290)	(0.300)	(3.721)	(0.630)	(0.146)	(0.911)	(0.635)
ICEA.l3	−9.689	−20.770	−0.121	−0.051	−0.562**	−3.566	0.188	−0.096	−1.243*	0.878*
	(6.535)	(62.130)	(0.289)	(0.204)	(0.210)	(2.608)	(0.442)	(0.102)	(0.639)	(0.445)
VIX.l3	0.873	−9.403	0.033	−0.041	−0.038	0.626*	−0.047	0.026*	−0.156*	−0.088
	(0.805)	(7.651)	(0.036)	(0.025)	(0.026)	(0.321)	(0.054)	(0.013)	(0.079)	(0.055)
MSCI.l3	−0.709	−0.293	0.246	−0.050	−0.191	2.611	0.145	0.094	−0.687	−0.477
	(6.224)	(59.174)	(0.275)	(0.194)	(0.200)	(2.484)	(0.421)	(0.097)	(0.608)	(0.424)
USD.l3	−9.557	−155.479	−0.479	0.925	0.722	−8.842	1.255	−0.010	4.465**	−0.756
	(17.979)	(170.933)	(0.796)	(0.560)	(0.578)	(7.175)	(1.215)	(0.281)	(1.757)	(1.225)
Oil.l3	2.748	−14.762	−0.056	−0.038	0.016	1.140	−0.130	0.021	−0.065	−0.153
	(1.990)	(18.924)	(0.088)	(0.062)	(0.064)	(0.794)	(0.135)	(0.031)	(0.195)	(0.136)
Gold.l3	5.647	−69.038	−0.084	0.095	0.262*	−0.350	0.314	−0.048	0.255	−0.486
	(4.229)	(40.204)	(0.187)	(0.132)	(0.136)	(1.688)	(0.286)	(0.066)	(0.413)	(0.288)
Ret.l4	0.176	4.344*	0.005	0.005	0.010	−0.041	0.016	−0.006	0.054**	−0.001
	(0.259)	(2.459)	(0.011)	(0.008)	(0.008)	(0.103)	(0.017)	(0.004)	(0.025)	(0.018)
Att.l4	0.004	0.038	−0.002**	−0.0005	−0.002**	0.007	−0.001	0.0002	−0.004**	−0.0004
	(0.019)	(0.180)	(0.001)	(0.001)	(0.001)	(0.008)	(0.001)	(0.0003)	(0.002)	(0.001)
UCRY.l4	8.594	−68.530	−0.292	0.064	0.335*	−2.123	0.117	−0.010	−0.746	−0.115
	(5.898)	(56.078)	(0.261)	(0.184)	(0.190)	(2.354)	(0.399)	(0.092)	(0.576)	(0.402)
CBDC.l4	−2.015	−73.895	0.594	0.032	0.848**	3.762	−0.435	−0.193	1.727*	−0.488
	(9.284)	(88.267)	(0.411)	(0.289)	(0.298)	(3.705)	(0.627)	(0.145)	(0.907)	(0.633)
ICEA.l4	−5.531	63.281	−0.047	−0.215	−0.605**	1.264	−0.047	0.140	−1.436*	0.475
	(7.741)	(73.592)	(0.343)	(0.241)	(0.249)	(3.089)	(0.523)	(0.121)	(0.756)	(0.527)
VIX.l4	0.320	12.556	0.041	−0.005	−0.026	0.038	0.014	−0.002	0.224**	−0.091
	(0.993)	(9.445)	(0.044)	(0.031)	(0.032)	(0.396)	(0.067)	(0.016)	(0.097)	(0.068)
MSCI.l4	2.587	−18.252	−0.087	−0.041	−0.179	1.212	0.396	−0.051	0.150	−0.058
	(5.412)	(51.453)	(0.240)	(0.169)	(0.174)	(2.160)	(0.366)	(0.085)	(0.529)	(0.369)
USD.l4	3.718	25.660	0.700	−0.154	0.738	10.489*	−1.683*	0.005	−4.585***	0.410
	(13.566)	(128.980)	(0.600)	(0.422)	(0.436)	(5.414)	(0.917)	(0.212)	(1.326)	(0.924)
Oil.l4	1.361	27.743	0.147*	0.090	0.176***	−0.023	−0.015	0.023	0.118	−0.095
	(1.822)	(17.324)	(0.081)	(0.057)	(0.059)	(0.727)	(0.123)	(0.029)	(0.178)	(0.124)
Gold.l4	−0.295	22.607	0.146	0.108	0.290**	−0.661	0.032	−0.016	0.695*	−0.089
	(3.626)	(34.471)	(0.160)	(0.113)	(0.117)	(1.447)	(0.245)	(0.057)	(0.354)	(0.247)
const	0.037	−0.579	−0.003	0.001	0.003	−0.057*	0.008	−0.0002	0.019**	0.004
	(0.076)	(0.718)	(0.003)	(0.002)	(0.002)	(0.030)	(0.005)	(0.001)	(0.007)	(0.005)
Observations	59	59	59	59	59	59	59	59	59	59
R^2	0.651	0.825	0.776	0.644	0.815	0.679	0.570	0.702	0.829	0.677
Adjusted R^2	−0.124	0.437	0.280	−0.149	0.403	−0.033	−0.387	0.038	0.449	−0.042
Residual Std. Error (df = 18)	0.277	2.634	0.012	0.009	0.009	0.111	0.019	0.004	0.027	0.019
F Statistic (df = 40; 18)	0.840	2.124**	1.563	0.812	1.980*	0.953	0.595	1.058	2.183**	0.942

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.1.9. Time-Series Results for Dogecoin

The linear regression results for Dogecoin is displayed in Table 18. In column 1, we see that the attention index for Dogecoin is unable to explain Dogecoin returns. However, in column 2, the coefficient for past return and the overall model are highly significant. This result may suggest that changes in returns lead to increased attention. Model 3 shows that past returns are a significant predictor of future returns. Model 4 suggests that Central Bank Digital Currency Attention is able to explain the future returns significantly.

Table 18: Linear Regression Results for Dogecoin

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att_t	0.001			0.002
	(0.003)			(0.003)
Ret_t		13.748^{***}	0.131^{*}	
		(1.669)	(0.069)	
$UCRY_t$				1.292
				(2.118)
$CBDC_t$				-7.028^{*}
				(3.956)
$ICEA_t$				−1.448
				(3.030)
VIX_t				−0.029
				(0.153)
$MSCI_t$				−0.246
				(0.923)
USD_t				−3.175
				(3.210)
Oil_t				−0.048
				(0.093)
$Gold_t$				−0.178
				(0.844)
Mom_t				0.068
				(0.282)
Constant	0.013	−0.126	0.011	0.016
	(0.015)	(0.371)	(0.015)	(0.016)
Observations	208	208	208	208
Adjusted R^2	-0.004	0.244	0.013	-0.022
Residual Std. Error	0.222 (df = 206)	5.351 (df = 206)	0.220 (df = 206)	0.224 (df = 197)
F Statistic	0.078 (df = 1; 206)	67.868^{***} (df = 1; 206)	3.641^{*} (df = 1; 206)	0.563 (df = 10; 197)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The vector autoregression estimation results tell a similar story in Table 19. The optimal length is determined as three by AIC. According to the first column where returns are regressed on lagged returns, attention, and control variables, The only significant estimators for returns are Central Bank Digital Currency Attention's 2-week and 3-week lagged estimators. However, the overall model is not significant. Moving on to the next column, where our attention index is the dependent variable, we see that one and two periods lagged past returns and one period lagged attention, two and three periods lagged CBDC and ICEA, and three periods lagged MSCI and Gold prices are powerful and significant estimators of future attention.

Table 19: Var Results for Dogecoin

	Dependent variable:									
	Ret	Att	UCRY	CBDC	ICEA	VIX	MSCI	USD	Oil	Gold
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ret.l1	0.127	7.538***	0.001	0.001	0.001	−0.172***	0.032***	−0.003	0.076	0.001
	(0.088)	(1.977)	(0.003)	(0.002)	(0.002)	(0.058)	(0.010)	(0.002)	(0.069)	(0.008)
Att.l1	−0.0001	−0.168**	0.0003**	0.0001	0.0003***	0.002	−0.0002	−0.00003	−0.001	−0.0001
	(0.004)	(0.081)	(0.0001)	(0.0001)	(0.0001)	(0.002)	(0.0004)	(0.0001)	(0.003)	(0.0003)
UCRY.l1	−0.958	−90.588	−0.594***	−0.095*	−0.193***	−1.175	−0.077	0.095	0.954	−0.158
	(2.590)	(58.291)	(0.085)	(0.053)	(0.063)	(1.705)	(0.300)	(0.061)	(2.026)	(0.240)
CBDC.l1	−2.007	−56.378	0.191	−0.225***	0.031	2.851	−0.380	−0.053	−2.863	−0.476
	(4.105)	(92.385)	(0.135)	(0.084)	(0.099)	(2.702)	(0.476)	(0.097)	(3.210)	(0.380)
ICEA.l1	2.271	5.304	0.287***	0.173**	−0.041	0.327	0.069	−0.003	0.279	0.288
	(3.324)	(74.820)	(0.109)	(0.068)	(0.080)	(2.189)	(0.386)	(0.078)	(2.600)	(0.308)
VIX.l1	−0.026	−3.119	0.002	−0.001	0.005	−0.059	−0.021	−0.010**	−0.154	−0.003
	(0.173)	(3.889)	(0.006)	(0.004)	(0.004)	(0.114)	(0.020)	(0.004)	(0.135)	(0.016)
MSCI.l1	−0.580	−19.281	0.019	0.016	0.016	−1.369**	−0.172	−0.101***	−0.835	−0.145
	(1.050)	(23.638)	(0.034)	(0.022)	(0.025)	(0.691)	(0.122)	(0.025)	(0.821)	(0.097)
USD.l1	−0.004	5.609	−0.202	0.025	−0.038	−1.332	−0.241	0.129	−4.416	0.485
	(3.983)	(89.653)	(0.131)	(0.082)	(0.096)	(2.622)	(0.462)	(0.094)	(3.115)	(0.369)
Oil.l1	−0.017	0.372	−0.006*	−0.001	−0.001	0.080	0.008	0.00005	−0.320***	0.001
	(0.099)	(2.232)	(0.003)	(0.002)	(0.002)	(0.065)	(0.012)	(0.002)	(0.078)	(0.009)
Gold.l1	0.654	10.385	−0.042	−0.004	−0.025	0.929	−0.063	−0.003	0.470	−0.076
	(0.923)	(20.766)	(0.030)	(0.019)	(0.022)	(0.607)	(0.107)	(0.022)	(0.722)	(0.085)
Ret.l2	0.012	−5.236**	−0.003	0.002	0.005**	−0.039	−0.001	0.001	0.065	−0.007
	(0.090)	(2.030)	(0.003)	(0.002)	(0.002)	(0.059)	(0.010)	(0.002)	(0.071)	(0.008)
Att.l2	−0.002	−0.070	0.0003***	−0.0001**	−0.0001	0.002	−0.00001	−0.0001	−0.001	0.001**
	(0.004)	(0.079)	(0.0001)	(0.0001)	(0.0001)	(0.002)	(0.0004)	(0.0001)	(0.003)	(0.0003)
UCRY.l2	−3.108	−33.537	−0.281***	−0.145**	−0.038	−0.282	0.245	0.043	0.022	−0.105
	(2.791)	(62.815)	(0.092)	(0.057)	(0.067)	(1.837)	(0.324)	(0.066)	(2.183)	(0.258)
CBDC.l2	18.465***	276.506***	−0.080	−0.071	−0.027	−0.820	−0.038	0.107	−1.055	−0.671*
	(4.245)	(95.541)	(0.139)	(0.087)	(0.103)	(2.795)	(0.492)	(0.100)	(3.320)	(0.393)
ICEA.l2	−2.207	−238.324***	0.109	0.077	−0.177**	−1.262	0.174	−0.118	0.646	0.374
	(3.354)	(75.495)	(0.110)	(0.069)	(0.081)	(2.208)	(0.389)	(0.079)	(2.623)	(0.311)
VIX.l2	−0.004	−2.012	−0.003	0.001	0.006	−0.048	−0.040*	0.004	−0.180	−0.018
	(0.178)	(3.997)	(0.006)	(0.004)	(0.004)	(0.117)	(0.021)	(0.004)	(0.139)	(0.016)
MSCI.l2	0.558	−1.512	−0.018	0.001	0.011	0.367	−0.066	−0.0002	−0.822	−0.011
	(1.202)	(27.047)	(0.039)	(0.025)	(0.029)	(0.791)	(0.139)	(0.028)	(0.940)	(0.111)
USD.l2	3.173	88.370	−0.009	−0.011	−0.080	−1.539	0.639	−0.046	−0.065	0.056
	(4.010)	(90.262)	(0.132)	(0.082)	(0.097)	(2.640)	(0.465)	(0.094)	(3.137)	(0.371)
Oil.l2	0.050	1.362	−0.004	−0.002	−0.002	0.046	−0.011	0.002	−0.237***	−0.007
	(0.102)	(2.285)	(0.003)	(0.002)	(0.002)	(0.067)	(0.012)	(0.002)	(0.079)	(0.009)
Gold.l2	0.754	10.311	0.004	0.023	−0.005	−0.029	−0.089	0.038*	−1.241*	0.060
	(0.916)	(20.625)	(0.030)	(0.019)	(0.022)	(0.603)	(0.106)	(0.022)	(0.717)	(0.085)
Ret.l3	−0.088	−3.620*	0.003	−0.0001	0.001	−0.086	0.003	0.001	0.010	−0.003
	(0.092)	(2.077)	(0.003)	(0.002)	(0.002)	(0.061)	(0.011)	(0.002)	(0.072)	(0.009)
Att.l3	0.003	0.278***	−0.0001	0.00001	0.0002**	0.002	−0.00001	−0.0001	−0.001	0.0003
	(0.004)	(0.081)	(0.0001)	(0.0001)	(0.0001)	(0.002)	(0.0004)	(0.0001)	(0.003)	(0.0003)
UCRY.l3	0.840	−0.282	−0.040	−0.026	0.227***	0.423	−0.029	−0.011	−1.079	0.204
	(2.479)	(55.783)	(0.081)	(0.051)	(0.060)	(1.632)	(0.287)	(0.058)	(1.938)	(0.229)
CBDC.l3	9.771**	598.762***	0.155	0.097	−0.032	8.249***	−1.036**	0.211**	−1.182	0.210
	(4.376)	(98.478)	(0.144)	(0.090)	(0.106)	(2.881)	(0.507)	(0.103)	(3.422)	(0.405)
ICEA.l3	0.127	−309.233***	−0.086	−0.085	−0.389***	−2.817	0.260	−0.169**	1.109	0.279
	(3.198)	(71.983)	(0.105)	(0.066)	(0.077)	(2.106)	(0.371)	(0.075)	(2.501)	(0.296)
VIX.l3	0.184	3.864	0.006	0.0003	−0.001	0.186	−0.057***	0.012***	0.125	−0.024
	(0.173)	(3.885)	(0.006)	(0.004)	(0.004)	(0.114)	(0.020)	(0.004)	(0.135)	(0.016)
MSCI.l3	1.106	52.313**	0.021	0.015	0.013	1.285*	−0.271**	0.042	2.248**	−0.120
	(1.122)	(25.250)	(0.037)	(0.023)	(0.027)	(0.739)	(0.130)	(0.026)	(0.877)	(0.104)
USD.l3	−1.641	12.822	−0.070	0.099	0.043	−1.694	0.276	−0.004	4.227*	−0.137
	(3.259)	(73.348)	(0.107)	(0.067)	(0.079)	(2.146)	(0.378)	(0.077)	(2.549)	(0.302)
Oil.l3	−0.040	−0.981	−0.002	−0.0005	−0.002	−0.015	0.015	−0.004	−0.089	−0.019**
	(0.098)	(2.204)	(0.003)	(0.002)	(0.002)	(0.064)	(0.011)	(0.002)	(0.077)	(0.009)
Gold.l3	−1.225	−42.213**	0.007	0.020	0.008	−0.648	0.365***	−0.044**	−0.638	−0.033
	(0.883)	(19.883)	(0.029)	(0.018)	(0.021)	(0.582)	(0.102)	(0.021)	(0.691)	(0.082)
const	0.006	−0.068	0.0001	−0.00002	0.0001	0.005	0.002	0.0004	0.001	0.002
	(0.017)	(0.375)	(0.001)	(0.0003)	(0.0004)	(0.011)	(0.002)	(0.0004)	(0.013)	(0.002)
Observations	205	205	205	205	205	205	205	205	205	205
R^2	0.185	0.481	0.413	0.241	0.430	0.196	0.234	0.327	0.240	0.191
Adjusted R^2	0.045	0.391	0.312	0.110	0.331	0.057	0.102	0.211	0.109	0.051
Residual Std. Error (df = 174)	0.215	4.837	0.007	0.004	0.005	0.142	0.025	0.005	0.168	0.020
F Statistic (df = 30; 174)	1.321	5.368***	4.085***	1.843***	4.371***	1.410*	1.769**	2.821***	1.828***	1.368

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.1.10. Time-Series Results for Shiba Inu

The sample has 34 weeks of observation for Shiba Inu Coin. Hence, in this subsection, I will only be presenting the linear regression estimation results since 34 observations are not sufficient to conduct a VAR analysis.

As can be seen in Table 20, the only significant model is model 2 in the second column. As we found earlier, it suggests that past returns predict attention and a one standard deviation change in returns leads to 22.181 units increase in attention. This coefficient has been the largest in magnitude compared to other cryptocurrencies in our data. This result supports the claims that Shiba Inu is a highly speculative coin in the crypto markets.

Table 20: Linear Regression Results for Shiba Inu

	Dependent variable:			
	Ret_{t+1}	Att_{t+1}	Ret_{t+1}	
	(1)	(2)	(3)	(4)
Att	−0.007			−0.005
	(0.005)			(0.007)
Ret		22.381^{***}	0.073	
		(4.760)	(0.177)	
UCRY				5.046
				(4.358)
CBDC				−1.870
				(9.795)
ICEA				−2.458
				(5.052)
VIX				-1.647^{*}
				(0.957)
MSCI				−10.143
				(6.101)
USD				14.136
				(18.039)
Oil				0.108
				(2.027)
Gold				−0.515
				(4.235)
Mom				2,256.589
				(4,167.351)
Constant	0.014	−0.357	0.011	0.008
	(0.050)	(1.376)	(0.051)	(0.057)
Observations	34	34	34	34
R^2	0.066	0.409	0.005	0.258
Adjusted R^2	0.037	0.390	-0.026	-0.020
Residual Std. Error	0.289 (df = 32)	8.000 (df = 32)	0.298 (df = 32)	0.297 (df = 24)
F Statistic	2.269 (df = 1; 32)	22.111^{***} (df = 1; 32)	0.170 (df = 1; 32)	0.930 (df = 9; 24)
Note:				*p<0.1; **p<0.05; ***p<0.01

4.2. Cross-Sectional Approach: Long-Short Portfolio Analysis

The cross-sectional regression concludes the second half of our analysis. In this approach, we ranked cryptocurrencies by their attention index values for every week. We used 35 weeks starting from May 2, 2021, to January 1, 2022, because of the limited data availability. We constructed a portfolio with the five cryptocurrencies that have the highest attention level and five cryptocurrencies that have the lowest attention level. Every week, we buy the high-attention portfolio and sell the low-attention portfolio. The hypothesis is the difference in the returns of these portfolios will be zero, meaning there are no arbitrage opportunities in these markets.

Table 21: Long Short Portfolio Results

Metric	Value
Mean Return	-0.0117
T-Statistic	-0.5562
P-Value	0.5818

However, in Table 21 above, we can see that the difference in returns is negative, meaning that if we were to buy high-attention cryptocurrencies and sell low-attention ones in this 35-week period, we would make a loss. This result is compliant with our previous findings: returns predict attention. The cryptocurrencies are already priced by the time they attract the attention of retail investors, hence buying them after they become popular results in losses.

CHAPTER V

SOCIETAL IMPACT

Cryptocurrencies have been a controversial discussion topic since their initiation. One of the most debated aspects is its opaqueness and the absence of a control mechanism that regulates the markets. Adding the limited information source availability on top of that, as we have witnessed multiple times in the past, these conditions may pave the way to market manipulations, hack attacks and bubbles.

In order to protect the investors in such situations, it is important to understand what drives the market and which information source is more reliable. This study shows that the number of tweets, subreddits or Google searches – the amount of talk going on about the cryptocurrencies on the Internet - is nothing but a noise for the prices. Hence, we are able to rule at least a few platforms out of the picture from the set of useful information resources.

We were also able to shed a little bit of light on investor behavior. Our results could help to raise investor awareness and potentially improve their decision-making process. This understanding could also be valuable for the financial institutions and policy makers who take part in developing policies that help stabilize the cryptocurrency markets. Ultimately, this study may help people to understand how to make better investment decisions and at least where not to look for information about cryptocurrencies.

CHAPTER VI

CONCLUSION

This thesis investigates the link between investor attention and cryptocurrency returns with the use of a more sophisticated proxy for investor attention that combines the attention derived from popular social media platforms and internet searches. We first construct an Investor Attention Index with the weekly data from Google Trends, Twitter, and Reddit by using Principal Component Analysis. Then, we explore the link between attention and returns by employing both linear regression and vector autoregression methods. We found that past returns are a significant predictor of future attention levels, however, the relationship is insignificant in the opposite direction.

As an additional test, we adopt a cross-sectional approach and make a long-short portfolio analysis. Our results show that buying high-attention cryptocurrencies and selling low-attention ones will end up in losses during our sample period.

The results of regression analyses suggest that Investor Attention Index is not a good predictor of future returns. This might be due to a few reasons: first, as I mentioned before, institutional investors dominate the cryptocurrency markets with 79% of the total trading volume. Since these investors have their own advanced analysis tools, they may not be affected by cryptocurrency-related attention increases on the internet. At the beginning of our paper, we assume that only retail investors would use social media and the Internet as information sources. Since their share in the market is around 20%, they may not be able to affect the returns as much as the institutional investors. Hence, this could be the reason why we could not capture a significant relationship between attention and return.

Secondly, the data used in our analysis may not be the correct measure of investor attention. There may be more relevant data that we fail to account for to measure investor attention. And lastly, even if the data we use in this paper is good for proxying the investor attention, the limited availability of our data may have affected the results. This analysis can be replicated in the future with larger datasets, enabling us to utilize novel techniques for big data analysis.

The cryptocurrency markets are volatile and ever-changing. Hence, the methods and variables proven to be working in the past for these markets may not be valid in today's atmosphere. Investor attention is one of the many factors that could have impacted the prices in the past but it seems that there exist more relevant factors affecting the market dynamics. Further research may focus on exploring new factors that impact the cryptocurrency market or using more advanced methods to understand how these markets really work.

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