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Investor Sentiment and Cryptocurrency Price Volatility: An Empirical Study Based on FinBERT Sentiment Recognition and VAR Model

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Abstract. In recent years, cryptocurrency markets have experienced severe price fluctuations and exhibited obvious bubble characteristics, with investor sentiment playing an important role. This paper takes Bitcoin as the research object, uses the Generalized Supremum Augmented Dickey-Fuller (GSADF) method to identify price bubble intervals, and constructs investor sentiment indicators, including net sentiment, fear, and market attention through the Financial Bidirectional Encoder Representations from Transformers (FinBERT) model. Subsequently, combining Ordinary Least Squares (OLS) and Vector Autoregression(VAR) models, this paper analyze the relationship between sentiment variables and Bitcoin returns during bubble periods, and examine the dynamic impact of sentiment shocks through impulse response functions. The research results show that in the static framework, sentiment direction has certain explanatory power for returns, but the overall impact is limited; in the dynamic framework, market attention shows significant persistence and self-reinforcing characteristics, and has an important impact on price volatility through intertemporal feedback mechanisms, while fear is more reflected in risk amplification effects. Overall, the VAR model is significantly better than static regression models in depicting the dynamic interaction between sentiment and prices.

Keywords: Cryptocurrency, investor sentiment, FinBERT, GSADF, VAR

1. Introduction

In recent years, the cryptocurrency market has developed rapidly, but its prices exhibit high volatility and periodic bubble characteristics. This phenomenon indicates that the cryptocurrency asset market is driven to some extent by investor behavioral factors, not merely by fundamental information. Existing research points out that cryptocurrency assets such as Bitcoin show obvious explosive growth and structural changes at different stages, with market prices often deviating from their potential value in the short term and forming bubble dynamics [1]. Further research finds that cryptocurrency bubbles have recurring and periodically concentrated characteristics, but their formation mechanisms remain highly controversial [2]. Therefore, based on identifying bubble stages, exploring the behavioral factors affecting price volatility is of great significance for understanding the operating mechanisms of the cryptocurrency market.

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At the same time, the popularity of social media has profoundly changed the way information spreads in financial markets. In the cryptocurrency market, investors rely more on social media platforms to obtain information and express opinions. Since cryptocurrencies lack a unified fundamental valuation anchor, their prices are largely influenced by changes in investor expectations and market sentiment. In terms of sentiment identification methods, traditional dictionary methods struggle to fully capture the complex semantics in financial contexts, while transformer-based financial language models and large language models can extract more structured sentiment signals, providing more reliable tools for investor sentiment measurement [3, 4]. Research shows that social media discussions and investor sentiment have significant information content in the cryptocurrency market and can influence price volatility and even promote bubble formation [5]. Based on this, this paper proposes the hypothesis: during cryptocurrency bubble periods, investor sentiment on social media has a positive impact on asset returns.

From a theoretical perspective, behavioral finance theory provides an important explanatory framework for the relationship between sentiment and asset prices. Investor overconfidence, limited rationality, and incomplete information diffusion may lead to overreaction in asset prices [6]. At the same time, limited attention and herd behavior may prompt investors to imitate others' investment decisions under incomplete information conditions, thereby amplifying market volatility [7]. In the social media environment, narrative dissemination and market attention diffusion may also form self-reinforcing positive feedback mechanisms during bubble stages [8]. Based on this, this paper proposes the hypothesis: different types of sentiment affect prices through different channels: Attention mainly drives price trends, while Fear mainly works by amplifying volatility or adjusting sentiment structure.

In terms of empirical methods, existing research mainly uses machine learning models or static regression analysis to examine the predictive ability of sentiment variables for cryptocurrency asset returns [9]. However,static models mainly depict the contemporaneous correlation between variables, making it difficult to reveal the dynamic feedback mechanism between sentiment and prices. The vector autoregression (VAR) model can simultaneously depict the endogenous interaction between variables in a multivariate system and reveal shock transmission paths through lag structures. Existing research shows that there is a significant dynamic causal relationship between investor sentiment and cryptocurrency asset returns, with their impact often gradually transmitted through intertemporal adjustments [10]. At the same time, market attention has obvious persistence and path dependence characteristics in dynamic systems, able to continuously influence price changes through information diffusion and investor participation behavior [11]. Based on this, this paper proposes the hypothesis: the VAR model is superior to static regression models in depicting the relationship between investor sentiment, market attention, and cryptocurrency prices during bubble periods.

2. Research design

2.1. Price data acquisition and preprocessing

This paper first obtains daily trading data of Bitcoin (BTC) from the Binance exchange for the period 2017.08.17-2026.01.01 through the official Binance Application Programming Interface (API), including opening price, closing price, highest price, lowest price, and trading volume. Binance is chosen as the data source mainly because of its large trading volume, high liquidity, and strong representativeness in the cryptocurrency market.

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In the data preprocessing stage, this paper standardizes the price series to ensure a continuous time series without duplicate records. Given that the closing price reflects the final price level after full digestion of market trading information within a day, which can more accurately depict medium- and long-term price trends, and this practice is consistent with existing bubble identification literature, this paper uses the closing price to construct a daily logarithmic return series to depict the daily price changes of Ethereum.

2.2. GSADF method for identifying price bubble intervals

After obtaining the complete price series, this paper adopts the Generalized Sup Augmented Dickey-Fuller (GSADF) method to identify price bubbles in the Ethereum price series.

Based on critical values obtained from Monte Carlo simulations, this paper defines continuous time periods where GSADF statistics significantly exceed critical values as bubble intervals for Ethereum prices. Subsequently, all empirical analyses are conducted around these bubble intervals to avoid interference from non-bubble periods on sentiment effects.

2.3. Social media data acquisition and sentiment indicator construction in bubble intervals

Following the identification of price bubble periods, this paper also develops an interest on investor sentiment performance during bubbles periods. Targeted, in particular, this paper takes out text information of the posts relevant to Bitcoin "BTC" in the X platform during the bubble intervals via web crawling technology. The concept of keyword filtering is primarily centered on the basic vocabulary that includes "BTC" and "Bitcoin" as the keywords that guarantee maximum relevance of text message to the object of the research. In order to ensure that the timestamps of various sources of data can be compared across a time dimension, this paper transforms all timestamps into daily dates using a UTC benchmark and uses this as the basis to construct and perform regression on variables.

There were 109, 357 original posts, which were received in bubble times. Following the text processing which entails deduplication, invalid and text removal of text, 93 and 989 valid posts were acquired respectively. Following the completion of text processing, this paper can classify the emotions of a post by applying the Financial Bidirectional Encoder Representations from Transformers (FinBERT) sentiment analysis model. FinBERT is a pre-trained language model that is trained and finetuned on financial corpora, and which is better at detecting positive, negative and neutral emotions in financial data and does not suffer the risk of bias due to general sentiment engines in finance language.

2.4. VAR regression setting for sentiment-price relationship

Having constructed a sentiment indicator, the paper, in its turn, applies the vector autoregression (VAR) model to empirically estimate the dynamism model between investor sentiment and Ethereum prices at the times of a bubble. The VAR model is able to illustrate the relationship between two or more endogenous variables without rigidly assuming that any of them are dependent or cause another; this is essential when examining the possibility of a two-way relationship between sentiment and prices.

The model setting of the current paper confirms the dynamism of the sentiment shock on price changes by adding Ethereum daily returns and sentiment indicators to the VAR system to assess the impulse response functions (IRF) of mentioning the dynamic trajectories of sentiment shocks. This

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approach contributes to uncovering: in the bubble phase, will the investor sentiment impact prices in short-run shocks or long-term effects, thus establishing empirical evidence of the operation of the mechanisms of sentiment in the cryptocurrency markets.

3. Variable definitions and empirical strategy

3.1. Key outcome variables

This paper uses Bitcoin daily logarithmic return Return as the core outcome variable to depict price changes:

$$Return_t = ln(P_t) - ln(P_{t-1}) \tag{1}$$

Simultaneously, price volatility indicators are introduced to analyze the impact of sentiment on market uncertainty:

$$Volatility_t = |Return_t| \tag{2}$$

3.2. Mechanism measurement: sentiment indicator construction

For each post i (belonging to date t), FinBERT outputs three emotion labels: positive (pos), negative (neg), neutral (neu).

The total daily discussion volume (number of valid posts) is:

$$\mathrm{Total_t}=\mathrm{Pos_t}+\mathrm{Neg_t}+\mathrm{Neu_t} \tag{3}$$

Based on social media texts, this paper constructs three types of sentiment indicators:

(1) Net Sentiment Index:

$$NetSent_t = \frac{Pos_t - Neg_t}{Total_t} \tag{4}$$

Defined as the proportion of the difference between positive and negative posts to total discussion volume, reflecting the degree of market sentiment bias toward optimism or pessimism, used to measure market sentiment direction

(2) Fear Index:

$$Fear_t = \frac{Neg_t}{Total_t} \tag{5}$$

Defined as the proportion of negative posts to total daily posts, depicting negative and uncertain emotions, used to measure risk perception

(3) Attention Index:

$$\mathrm{Attention_t} = \mathrm{Total_t} \tag{6}$$

Defined as the total number of valid posts about Bitcoin on that day, used to reflect market attention intensity.

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3.3. Model specification

This paper first uses OLS to examine the contemporaneous impact of investor sentiment on Bitcoin daily returns during bubble periods, with the model specified as:

$$\mathrm{Return}_t = \alpha + \beta_1 \mathrm{NetSent}_t + \beta_2 \mathrm{Attention}_t + \beta_3 \mathrm{Fear}_t + \varepsilon_t \tag{7}$$

Additionally, this paper adopts VAR model, incorporating sentiment indicators and returns into the same system to capture dynamic relationships among variables, with the model specified as:

$$Y_t = \begin{bmatrix} \mathrm{Return}_t \\ \mathrm{NetSent}_t \\ \mathrm{Attention}_t \\ \mathrm{Fear}_t \end{bmatrix} \tag{8}$$

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + \varepsilon_t \tag{9}$$

IRF analyzes the short-term and medium-term impact paths of sentiment shocks on prices.

4. Results

4.1. Bubble interval identification and sentiment indicator establishment

According to GSADF results, bubble intervals are obtained as shown in Table 1, and VAR parameter settings are determined based on bubble interval lengths.

Table 1. Bitcoin bubble interval sample size and VAR lag order setting

bubble_start	bubble_end	N_merged	chosen_VAR_p
2020/12/16	2021/5/11	142	4
2024/2/26	2024/4/12	46	2
2019/6/14	2019/7/13	29	1

Figure 1 shows the daily net sentiment and fear index changes within bubble period subsamples. Generally, rising net sentiment means increasing proportion of positive discussions; rising fear means increasing proportion of negative discussions. The attention indicator is used to measure the scale effect of daily discussion volume.

To avoid redundancy in the main text, the regression results section only reports empirical results for the bubble period 2020.12.16-2021.05.11. This stage has the longest duration, sufficient sample size, and corresponds to the most typical round of bubble rise in Bitcoin history, with strong representativeness.

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Figure 1. Bitcoin daily sentiment index (X) - bubble period (picture credit : original)

4.2. OLS static regression results

Figure 1: Bitcoin daily sentiment index (X) - bubble period (picture credit : original)

variable	coef	std_err	t	p_value
const	-0.0274	0.0205	-1.3356	0.1839
NetSent	0.6283	0.1769	3.5526	0.0005
Attention	0.0001	0.0001	1.1020	0.2724
Fear	0.1380	0.2404	0.5743	0.5667

Table 2 reports static regression results of investor sentiment indicators on Bitcoin daily returns during bubble intervals.

Results show that NetSent has a significant positive impact on returns, established at the 1% significance level, indicating that during this bubble stage, there is a relatively clear positive correlation between overall market sentiment optimism and Bitcoin returns. This result suggests that during periods of rapid price increase in bubbles, sentiment direction still reflects changes in investor risk preference to some extent.

In contrast, although regression coefficients for Attention and Fear are positive, they are not statistically significant, indicating that single market attention expansion or panic sentiment is insufficient to directly explain return changes in the current period. This means that in the static framework, sentiment direction variables have more immediate explanatory power for prices compared to sentiment intensity or participation degree.

From the perspective of overall explanatory power, the model's R^2 is 0.141, and adjusted R^2 is 0.123. Considering that cryptocurrency returns have high volatility and significant noise characteristics, this explanatory power falls within a reasonable range in financial time series

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research. However, the model's explanatory power still has obvious upper limits, suggesting that sentiment's impact on prices is not completely achieved through contemporaneous relationships, but may be gradually transmitted through intertemporal feedback and dynamic adjustment mechanisms.

Based on the above results, this paper further introduces the VAR model in subsequent analysis to systematically depict dynamic interactive relationships among sentiment, attention, and Bitcoin prices during bubble periods.

4.3. VAR dynamic model and mechanism supplement

The results of the estimation of the VAR of the relationship between the returns on Bitcoin, the level of investor sentiment, and the focus of the market in the bubble period are presented in Table 3. However, compared to the case of a static regression, the VAR model enables the variables in the system to influence each other, and, due to its ability to capture the dynamic transmission process of sentiment shocks in multiple lags, it is more appropriate to study the multifaceted behavioral feedback process of a bubble phase.

The findings have shown that in the equation of return, NetSent has no statistically significant contemporaneous effect on the returns of Bitcoin, but lagged effects are significant in some periods implying a direction effect of the sentiment on prices is delayed to some extent. This discovery suggests that the investor mood does not have an immediate reflection in the movement of prices in the bubble stage but is distributed gradually to the prices of markets due to the readjustment of intertemporal expectations.

Table 3. Results of investor attention and bitcoin returns within the bubble interval

equation	term	coef	std_err	p_value
Return	const	-0.0030	0.0377	0.9363
Return	L1.Return	-0.1168	0.0971	0.2292
Return	L1.NetSent	0.2747	0.2071	0.1847
Return	L1.Attention	0.0000	0.0001	0.9918
Return	L1.Fear	0.0683	0.2719	0.8017
Return	L2.Return	-0.0250	0.0990	0.8004
Return	L2.NetSent	0.3360	0.2099	0.1094
Return	L2.Attention	-0.0001	0.0001	0.4414
Return	L2.Fear	0.5632	0.2716	0.0381
Return	L3.Return	-0.0058	0.0966	0.9521
Return	L3.NetSent	0.1070	0.2125	0.6146
Return	L3.Attention	0.0000	0.0001	0.7606
Return	L3.Fear	-0.0462	0.2780	0.8681
Return	L4.Return	-0.0618	0.0939	0.5103
Return	L4.NetSent	-0.2433	0.2085	0.2433
Return	L4.Attention	0.0000	0.0001	0.8375
Return	L4.Fear	-0.4047	0.2808	0.1496
NetSent	const	0.0182	0.0246	0.4580
NetSent	L1.Return	0.0884	0.0632	0.1620

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Table 3. (continued)

NetSent	L1.NetSent	0.1099	0.1349	0.4152
NetSent	L1.Attention	0.0000	0.0000	0.2966
NetSent	L1.Fear	0.0057	0.1770	0.9743
NetSent	L2.Return	0.0225	0.0645	0.7268
NetSent	L2.NetSent	0.0691	0.1366	0.6132
NetSent	L2.Attention	-0.0001	0.0000	0.2158
NetSent	L2.Fear	0.1203	0.1769	0.4964
NetSent	L3.Return	0.0141	0.0629	0.8231
NetSent	L3.NetSent	0.0076	0.1384	0.9563
NetSent	L3.Attention	0.0000	0.0000	0.9955
NetSent	L3.Fear	-0.2201	0.1810	0.2239
NetSent	L4.Return	-0.0117	0.0611	0.8484
NetSent	L4.NetSent	0.0397	0.1358	0.7698
NetSent	L4.Attention	0.0000	0.0000	0.7789
NetSent	L4.Fear	-0.0926	0.1828	0.6126
Attention	const	162.9341	54.8531	0.0030
Attention	L1.Return	0.3709	141.1792	0.9979
Attention	L1.NetSent	426.6726	301.0783	0.1564
Attention	L1.Attention	0.2348	0.0952	0.0137
Attention	L1.Fear	-244.1375	395.2927	0.5368
Attention	L2.Return	34.3550	143.9250	0.8113
Attention	L2.NetSent	-51.0433	305.0918	0.8671
Attention	L2.Attention	0.0905	0.0979	0.3552
Attention	L2.Fear	404.0201	394.8564	0.3062
Attention	L3.Return	53.3400	140.3538	0.7039
Attention	L3.NetSent	-84.2188	308.9262	0.7851
Attention	L3.Attention	0.0404	0.0981	0.6806
Attention	L3.Fear	18.7630	404.0867	0.9630
Attention	L4.Return	-117.6402	136.5227	0.3889
Attention	L4.NetSent	324.2384	303.0988	0.2847
Attention	L4.Attention	0.1173	0.0932	0.2080
Attention	L4.Fear	-207.3418	408.2068	0.6115
Fear	const	0.0134	0.0182	0.4621
Fear	L1.Return	-0.0480	0.0468	0.3049
Fear	L1.NetSent	-0.0150	0.0997	0.8802
Fear	L1.Attention	-0.0000	0.0000	0.6612
Fear	L1.Fear	0.0458	0.1309	0.7267
Fear	L2.Return	-0.0263	0.0477	0.5816
Fear	L2.NetSent	0.0277	0.1011	0.7841

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Table 3. (continued)

Fear	L2.Attention	0.0000	0.0000	0.1359
Fear	L2.Fear	0.1010	0.1308	0.4402
Fear	L3.Return	-0.0276	0.0465	0.5524
Fear	L3.NetSent	0.0389	0.1023	0.7039
Fear	L3.Attention	-0.0000	0.0000	0.6870
Fear	L3.Fear	0.2118	0.1339	0.1136
Fear	L4.Return	0.0154	0.0452	0.7328
Fear	L4.NetSent	0.0276	0.1004	0.7836
Fear	L4.Attention	0.0000	0.0000	0.6419
Fear	L4.Fear	0.1229	0.1352	0.3632

According to Table 4, fear lagged term reveals that there is a substantial impact on the yield equation, showing that the negative sentiment shock involves a stronger effect on the price movement in the future with some time lag. This result is counter to the conclusion of using the previously obtained regressions which states that the ability of fear is constrained, indicating that the analysis of the role of fear in the price determinations may be underestimated by simple models.

The lagged term of the variable is also positive in the Attention equation with a very strong positive value showing market attention possesses specific features of inertia and self-reinforcement in the situation of market bubbles. It means that when the market is already in the state of high-level attention, the level of investor participation and information distribution will further increase and will provide a long-term basis of price volatility in relation to future behavior. This outcome also explains the non-significant level in the contemporary coefficient of the variable consideration of attention in the static regression but identified more pronounced structural characteristics when analyzed in dynamic context.

Table 4. R^2 for variables in the BTC-VAR model

Return	NetSent	Attention	Fear
0.0827	0.1048	0.2041	0.1063

In totality, the coefficient of determination of the attention equation in the VAR model is much higher as compared to that of the return equation. This implies that, when market bubbles are taking place, attention is the behavioral variable with the strongest endogenous structure but that returns are strongly driven by unobservables and stochastic shocks. This feature is congruent with the more empirical finding in financial markets of higher levels of noise in prices, but behavioral variables usually have a more structural structure.

To conclude, the VAR model has a clear upper hand compared to the static OLS regression. Although the contemporaneous relationship between sentiment variables and returns can be described as the outcome of a statical regression, the VAR model can demonstrate the dynamic feedback documents and lag effect interactions between sentiment, attention, and prices. It, therefore, provides a deeper reflection on the role of investor behavior in the price formation process in the times of market bubbles. Thus, the rest of the paper will be based on impulse response analysis to develop the dynamic impact of sentiment shocks further.

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4.4. Impulse response functions

Figure 2 shows the outcome of the impulse response in the case of Bitcoin returns, investor sentiment and attention focus on the bubble phase. To begin with, there exist significant short-run responses to returns on that returns have large short-run inertia, but short-run self-reinforcing mechanisms are not evinced in the survival of Bitcoin returns.

Second, in the initial phases, net sentiment just shows a restricted positive reaction to a market shock in returns (Rodley-Salvigundi, 2020). This implies that the influence of sentiment on prices is directional, and extremely short-term and volatile. This finding also reinforces the result obtained in the case of static regressions that sentiment direction has a low explanatory power.

Conversely, market attention has different self-reinforcing traits in times of speculative bubbles. The response of attention to its shocks is massive, and its response is slow to discount, this shows that the investor attention in the bubble phase has a high degree of path dependence and persistence. Whilst the current contribution of attention on returns is non-statistically significant, it has an indirect contribution on the price-making process by dynamic feedback.

In addition, the effects of Fear on returns can be seen mostly at the volatility level, the effect is not directionally consistent, and it is rather moderate, and therefore, fear can be more a risk enhancer than a market driver. Altogether, the findings of the impulse response result indicate that investor attention is the structurally most important behavioral variable during the bubble periods, and the effect of market sentiment on the prices is due to dynamic adjustments and no longer depends on immediate, contemporaneous relations.

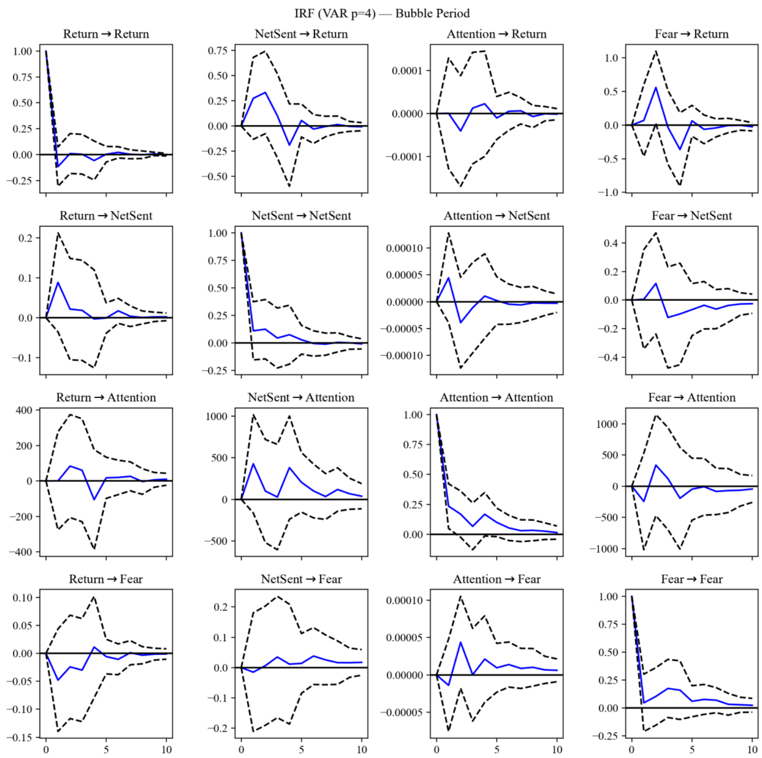

Figure 2. Impulse response of sentiment-price dynamics during the bitcoin bubble period based on the VAR model (picture credit : original)

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5. Robustness tests

To test the robustness of this paper's conclusions, this paper further replaces the research object from Bitcoin to Ethereum, using its daily trading data from Binance exchange 2017.08.17-2026.01.01, redoing static regression and dynamic analysis under the same research framework. The results show that the main conclusions are generally consistent: investor sentiment and market attention both affect cryptocurrency price volatility during bubble stages, with attention variables still showing stronger persistence and structural characteristics, while sentiment effects are transmitted more through dynamic mechanisms. Compared to Bitcoin, sentiment effects in Ethereum samples are more significant overall, but do not change this paper's core judgment that "market attention is a more critical behavioral variable during bubble periods." This indicates that this paper's conclusions are not dependent on single asset samples and have good cross-asset robustness.

6. Conclusion

This paper analyzes the behavioral finance impact mechanism of social media investor sentiment on cryptocurrency price volatility. First, using Bitcoin daily price data from the Binance exchange 2017.08.17-2026.01.01, and identifying price bubble intervals through the GSADF method; subsequently, collecting relevant text data from the X platform during bubble periods, and constructing three types of sentiment indicators: NetSent, Fear, and Attention with the help of the FinBERT model. In terms of empirical models, this paper first uses OLS static regression to test the immediate impact of sentiment variables on returns, then depicts the dynamic feedback relationship between sentiment and prices through the VAR model, and analyzes the transmission paths of sentiment shocks using impulse response functions. The research results show that in the static framework, sentiment direction has certain explanatory power for returns, but the overall impact is limited; while in the dynamic framework, market attention shows significant persistence and self-reinforcing characteristics, and has a more important impact on price volatility through intertemporal feedback mechanisms. In contrast, fear sentiment has a weaker direct impact on price trends, but is reflected more in risk amplification and volatility transmission mechanisms within the system. Overall, the VAR model is significantly superior to static regression models in depicting the dynamic interaction between sentiment and prices. The research results indicate that during cryptocurrency bubble stages, price changes are not only affected by sentiment direction but more importantly by the diffusion of investor attention and information transmission mechanisms.

Although this paper expands existing research from two aspects: sentiment identification methods and dynamic models, there are still certain limitations. First, sentiment indicators mainly come from English text data on the X platform, failing to cover other social media platforms and investor sentiment in different language environments; therefore, they may underestimate the overall characteristics of global investor behavior. Second, social media data collection is still limited by platform interface restrictions, unable to fully capture all relevant discussion information. Third, this paper mainly conducts analysis based on daily data, which may be hard to capture higher-frequency market sentiment shock processes. Future research can further introduce multi-platform, multi-language sentiment data and combine higher frequency trading data to more comprehensively depict the relationship between sentiment transmission and price volatility. Meantime, in terms of methods, it is worth considering introducing TVP-VAR, structural VAR, or machine learning models to analyze the dynamic changes of sentiment effects in different market stages.

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