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Emotional Reactions, Sentiment Disagreement, and Bitcoin Trading*

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Abstract

Purpose - This study aims to explore the influence of emotional discrepancies among investors on the cryptocurrency market. It focuses on how varying emotions affect market dynamics such as volatility and trading volume in the context of Bitcoin trading.
Design/methodology/approach - This study involves analyzing data from Bitcointalk.org, consisting of 57,963 posts and 2,215,776 responses from November 22, 2009, to December 31, 2022. Tools used include the Linguistic Inquiry and Word Count (LIWC) software for classifying emotional content and the Python Pattern library for sentiment analysis.
Findings - The results show that heterogeneous emotional feedback, whether positive or negative, significantly influences Bitcoin's intraday volatility, skewness, and trading volume. These findings are more pronounced when the underlying emotion in the feedback is amplified.
Research implications or Originality - This study underscores the significance of emotional factors in financial decision-making, especially within the realm of social media. It suggests that investors and market strategists should consider the emotional landscape of online forums when making investment choices or formulating market strategies. The research also paves the way for future studies regarding the behavioral impact of emotions on the cryptocurrency market.

Keywords: Bitcoin, Emotional Reactions, Return, Trading Volume, Volatility
JEL Classifications: G12, G14, G41

Ⅰ. Introduction

When we describe our trading outcome on social media platforms, we often associate a certain emotional value, for example, happy or angry, to it (Ahn and Kim, 2021). The attributions of a specific emotional value are naturally subjective at the individual level. It should be noted that other investors may disagree with such emotional values. Motivated by the existence of emotional discrepancies in the cryptocurrency profession, we aim to explore what happens in the cryptocurrency market when differences of emotion exist among investors. We further investigate whether our emotion-based explanation holds the promise of conveying a joint account of volatility and trading volume in the financial market (Andersen, 1996; Aalborg et al., 2019).

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Social media is an important venue for financial market participants to freely express and share their opinions and feelings on various topics (Chen et al., 2014). Several peer investors add comments and feedback to their original posts, thereby making aggregate feelings, moods, and emotions formed online play an important role in personal decision-making (Nandwani and Verma, 2021). We crawl investor opinions on Bitcoin at Bitcointalk.org. This online community has approximately 3.5 million registered users; thus, it is the largest community that engages in various discussions about cryptocurrency. As with most online community bulletin boards, users can post on specific topics. Subsequently, other users who are interested in this topic or have different opinions can post their feedback in the form of replies. We collect all posts and feedback on the bulletin board from November 22, 2009, to December 31, 2022, and the dataset consists of 57,963 posts and 2,215,776 responses (feedback).

We utilize the Linguistic Inquiry and Word Count (LIWC) software to classify textural information into positive and negative emotions and the Python Pattern library to derive the overall tone (i.e., sentiment) of each text. The results show that heterogeneous emotional feedback has a significant impact on Bitcoin's intraday volatility, skewness, and trading volume. These statistical associations are more pronounced when the underlying emotion is amplified through emotional feedback, regardless of whether it is positive or negative.

The remainder of this paper is organized as follows. Section 2 briefly summarizes the relevant literature. In Section 3, we elaborate on how to quantify the differences in emotion in the cryptocurrency market. Section 4 presents the data and results. Section 5 discusses potential research avenues in the future and concludes the paper.

II. Literature Review

1. Relationship Between Sentiments and Cryptocurrency Values

Financial theory argues that the impact of new information will change investor expectations and eventually affect the value of assets such as stock price (Fama, 1970). In other words, theory would infer the value of cryptocurrencies such as Bitcoin also follows new information and investor expectations (Toufaily et al., 2021). In modern society, investor exchanges of opinions through online bulletin boards and social media have fundamentally changed the way information is disseminated, and such changes play an important role in creating and disseminating new information (Mai et al., 2018). For example, online bulletin boards can quickly disclose new information, not only positive information such as information on new cryptocurrency listing and accepting Bitcoin transactions in new stores. But negative information can also be disclosed such as cryptocurrency exchange bankruptcy and policy restrictions. Therefore, there is a possibility that the active exchanges of information and sentiments by investors online can build expectations and affect the fluctuations in the value of cryptocurrencies.

There is a rapidly growing body of empirical research examining the relationship between online sentiments and asset values. Chen et al. (2014) conduct text analysis of articles published on social media and find that investor opinions expressed in commentaries as well as views expressed in articles can predict long-term stock returns and earnings surprises. Another research examining the dynamic relationship between online sentiments and asset values finds that both online behavioral metrics (e.g., web traffic) and social media-based metrics (e.g., sentiments in the web blogs) are important leading indicators of firm equity value (Luo et al., 2013). Similarly, Yu et al. (2013) find that sentiments expressed in social media such as blogs, forums, and Twitter have a stronger relationship with firm stock returns than in conventional media. In the context of cryptocurrency market, Mai et al. (2018) investigates the relationship between social media and Bitcoin value using text analysis and vector error correction models and find that positive (negative) sentiments of forum posts are significantly associated with higher (lower) future Bitcoin prices. Xie et al. (2020) focus on the cohesiveness of investor opinions that can be observed in online bulletin boards. They find that in the relationship between bulletin board sentiment and Bitcoin price changes, less cohesive networks are more powerful at predicting the next day returns than more cohesive ones. Similarly, Shi et al. (2022) find that sentiment homophily in online bulletin board leads to undesirable consequences for investor decisions on future returns as well as for the market as a whole. Ahn and Kim (2020) also investigate the impact of investor opinions disagreement expressed in online bulletin board on predicting Bitcoin price fluctuations and argue that sentiment disagreement affects volatility and price jumps rather than price returns.

Current literature suggests that online opinions can be useful in predicting the value (including fluctuations) of financial markets. According to research by Tumarkin and Whitelaw (2001), information posted online bulletin boards can affect investors in a variety of ways. Bulletin boards can provide a trading signpost if posts and feedback contain new information, or at least provide market sentiments. Thus, investors can be aware of trading momentum and follow trading recommendations. That may promote convergence in market prices, but if the financial power is lacking, it should stimulate other investors to move prices in the desired direction. Ultimately, this can lead to sentiment disagreement on online bulletin boards.

2. Relationship Between Emotions and Cryptocurrency Values

Although many previous financial studies have used sentiment and emotion as the same meaning and used them for empirical analysis to predict the value of assets, sentiment and emotion do not share the same concepts. They work separately, but emotion is regarded as an antecedent of sentiments. Emotion refers to complex psychological states, such as happiness and sadness, whereas sentiment is defined as a mental attitude created through the existence of emotion (Gordon, 2017). Broad (1954) also argues that emotion is formed based on subjective experience and physiological response, and sentiment is dispositional ideas about a certain object formed under the influence of emotion. Emotions can be measured in various aspects through neurological changes, physical activities (e.g., facial movements, hand tremors, heart rate), and self-reports of feelings (Kratzwald et al., 2018; Mauss and Robinson, 2009). Although these measured factors may overlap with different emotions, Ekman (1992) nonetheless argues that there are universally recognized and basic or fundamental emotions: anger, fear, sadness, enjoyment, disgust, and surprise. To support that these emotions are fundamental, he investigates that there are six general characteristics in common (e.g., short duration), while three types of characteristics (e.g., patterns of autonomic nervous system activity) that differ between emotions exist.

Emotion analysis is the extraction of individuals' emotions or feelings such as happiness, joy, sadness, and anger. Because people can convey emotions through various aspects, judging and extracting emotions from text alone is not easy. In addition, it has become more difficult to judge emotions in texts because new terminologies (e.g., emojis, slang) that can describe emotional states are constantly appearing. To overcome these limitations, when performing emotion analysis, most previous studies employ Ekman's model that divides various human emotions into basic emotions (Ekman, 1992). For example, Broadstock and Zhang (2019) analyze Twitter hashtags to extract various emotions (e.g., anger, fear, and joy) and find that these emotions are significantly related to a firm's intraday trading returns. Ahn and Kim (2023) argue that visceral emotions are related to Bitcoin's return volatility. However, despite the existence of basic emotion classification model, most of the past studies simply extract positive or negative emotions, such as sentiment analysis. In such a case, as mentioned above, emotion precedes sentiment, so articles with positive emotion do not mean that the overall sentiment of articles is positive. For example, Ahn and Kim (2021) argue that each positive or negative emotions and basic emotions have different effects on Bitcoin price fluctuations.

3. Emotional Discrepancies

We want to highlight that there is little research examining emotional discrepancies between online posts and their related feedback. Although several studies have verified the effect of sentiment disagreement in online message boards on financial assets (e.g., Ahn and Kim, 2020; Cen et al., 2013), it is difficult to find studies measuring emotional discrepancies between posts and feedback and examining their effects on sentiment disagreement and asset values in the cryptocurrency market. When investors post their opinions online, depending on whether their opinions are emotionally supported or disapproved, overall sentiment may appear in various ways (Stets, 2006). Therefore, rather than simply deriving emotions and sentiments by counting the number of relevant words, it is necessary to investigate how emotional feedback amplifies or reduces the overall emotional level inherited in posts.

We separately carry out emotion analysis and sentiment analysis to detect whether the author's emotion or viewpoint is generally positive or negative. For sentiment analysis example, if there are five-star ratings, such as online reviews, we can treat the posts with 1-star and 2-star ratings to be associated with negative sentiment and 4-star and 5-star ratings as positive sentiments (Ye et al., 2009). However, when ratings do not exist, sentiment analysis is performed by building a domain-specific dictionary based on words with polarity. Representatively, Loughran and McDonald (2011) build a sentiment dictionary that can be used in the financial market, consisting of 354 positive and 2,355 negative words. Similarly, for emotion analysis, based on the Ekman's model, it is possible to perform emotion analysis on each post and feedback based on predefined positive and negative emotion words. Therefore, we explore the influence of emotion and sentiment, focusing on emotional discrepancies in the context of cryptocurrency.

Ⅲ. Quantifying Emotional Discrepancies in the Cryptocurrency Market

Emotion or sentiment analysis refers to the extraction of individuals' emotions, feelings, or sentiments. Most studies hinge on Ekman's (1992) model that categorizes a variety of human emotions into the following six elements: anger, fear, sadness, enjoyment, disgust, and surprise. Emotion analysis under the Ekman framework simply involves counting the number of emotional words using a predefined emotion dictionary. For example, Broadstock and Zhang (2019) utilize a counting measure of emotions in Twitter hashtags and find that the emotional contents are significantly related to a firm's intraday trading returns. Ahn and Kim (2023) show that a simple counting measure of visceral emotions is related to Bitcoin's intraday return volatility and trading volume.

We delve deeper into the emotional contents of online posts in the cryptocurrency community. When investors post their opinions online, depending on whether their opinions are emotionally supported or disapproved, the overall sentiment may appear in various ways (Stets, 2006). Therefore, rather than simply deriving emotions and sentiments by counting the number of relevant words, it is necessary to investigate how emotional feedback amplifies or reduces the overall emotional level inherited in posts.

We want to point out that, although most studies use emotion and sentiment analytics interchangeably, the two terms differ in several ways. Emotion analysis is a methodology for identifying human emotions, such as happiness, anger, or sadness, whereas sentiment analysis aims to simply evaluate whether a specific write-up is positive, negative, or neutral in tone (Bollen et al., 2011; Ahn and Kim, 2020). Thus, we carry out sentiment analysis separately to detect whether the author's viewpoint is generally positive or negative. For example, if there are 5-star ratings, such as online reviews, we can treat the posts with 1-star and 2-star ratings to be associated with negative sentiments and 4-star and 5-star ratings as positive sentiments (Ye et al., 2009). However, when ratings do not exist, sentiment analysis is performed by building a domain-specific dictionary based on words with polarity, as in the case of emotion analysis. Representatively, Loughran and McDonald (2011) build a sentiment dictionary that can be used in the financial market, consisting of 354 positive and 2,355 negative words.

In summary, emotion and sentiment do not share the same concepts. They work separately, but emotion is an antecedent of sentiment. Emotion comprises complex psychological states, such as happiness and sadness, whereas sentiment is defined as a mental attitude created through the existence of emotion (Gordon, 2017). Broad (1954) also argues that emotion is formed based on subjective experience and physiological response, while sentiment is a dispositional idea about a certain object formed under the influence of emotion. Therefore, we explore the influence of emotion by controlling for the impact of sentiment, which enables us to focus on emotional discrepancies in the context of cryptocurrency.

Ⅳ. Empirical Design and Results

We analyze 57,963 posts and 2,215,776 responses published in Bitcointalk.org from November 22, 2009, to December 31, 2022. First, we conduct an emotion analysis at the post and feedback levels to measure the emotional discrepancies between daily posts and feedback.

We utilize the LIWC software, which provides analysis results for 93 emotion categories, such as positive emotion, negative emotion, anger, and anxiety. Words corresponding to 93 emotion categories are defined in the dictionary; therefore, the software counts emotional words by comparing them with words in the text. In addition, it provides a stemming function, which is a technique that uses morphological analysis of words to remove the derivational affixes, to make a more accurate comparison with emotional words by inferring their original form. For example, the words "welcome" and "welcoming" represent positive emotions. However, because it is impossible to define all the derivatives of these words, the morphological form of the word "welcom" is inferred and compared with the emotion dictionary. Although Ekman's model presents six basic human emotions, we categorize them into positive and negative emotions. The positive (negative) emotion category consists of enjoyment and surprise (anger, fear, sadness, and disgust).

For every post, we calculate the Euclidean similarity measure to quantify emotional discrepancies as follows:

$$Emotional\,Discrepancy = Avg\sqrt{\sum_{i=1}^{k}(P - F_i)^2} \tag{1}$$

where P is the emotion value derived from the post and F is the emotion value derived from the responses. Because one post can hold multiple responses, k represents the number of responses. To compute the daily emotion discrepancies for positive (negative) emotions, we first compute the Euclidean similarity for positive (negative) emotions on each post on a given day and then average the similarity values across posts on that specific day.

We go one step further by rearranging all the feedback in each post into two groups: amplifying and reducing. Feedback with a value higher than the positive (negative) emotion value of the post is defined as feedback that amplifies positive (negative) emotion; conversely, feedback with a value lower than the positive (negative) emotion value of the post is defined as feedback that reduces positive (negative) emotions. When the emotional discrepancies are calculated without grouping, if the positive emotion value of one post is 0.5 and the positive emotion values of two feedback are 1 and 0, respectively, both emotional discrepancies are derived as 0.5. That is, it is difficult to determine the direction of the emotion discrepancies. For each group, emotional discrepancies are calculated using Euclidean similarity. Consequently, one post has three positive-related (negative-related) variables: positive (negative) emotions of posts, positive (negative) emotions with amplifying feedback, and positive (negative) emotions with reducing feedback. For a given day, we take the average of each of these three values across posts.

Second, we reiterate that emotion is often intertwined with sentiment. To control for the effect of sentiment in the empirical analysis, we separately quantify sentiment using the Python Pattern library provided by the Computational Linguistics and Psycholinguistics (CLiPS) Research Center, which contains 917 positive and 1,018 negative sentiment words. Each of the positive and negative sentiment words has a specific polarity value. A polarity value closer to -1 indicates an extremely negative sentiment word, and a value closer to 1 indicates a very positive sentiment word. To perform sentiment analysis, polar words are found in the text, and the sum of the corresponding polarity values represents the sentiment of the text. One concern is that words in the Python Pattern library dictionary may not be specific to the financial market context. Therefore, we combine the Python Pattern library with Loughran and McDonald's (2011) dictionary (i.e., 354 positive and 2,355 negative words) that defines positive and negative words frequently used in the finance and economics contexts. This library also provides the functions of lemmatization, which is a technique that uses the morphological analysis of words to remove inflectional endings and return the base form of a word, and proper handling of indefinite adverbs, enabling more accurate sentiment analysis. Following Ahn and Kim (2020), who show that sentiment disagreement is associated with trading activities in the cryptocurrency market, we define our sentiment disagreement metric as the standard deviation of the sentiment values of posts and feedback written each day. 〈Table 1〉 summarizes the descriptive statistics of the key variables.

Table 1. Summary Statistics

Variable	N	Mean	Std. Dev.	Min	P25	Median	P75	Max
Positive Emotions	4575	0.5110	0.5583	0.0000	0.1942	0.3957	0.6642	9.6283
Positive Emotions - Amplifying Feedback	4575	3.2328	2.7796	0.0000	1.6093	2.3975	4.0331	54.5450
Positive Emotions - Reducing Feedback	4575	1.3010	1.2797	0.0000	0.5927	1.0884	1.6891	22.7307
Negative Emotions	4575	1.3310	1.0659	0.0000	0.6300	1.1081	1.7950	20.0000
Negative Emotions - Amplifying Feedback	4575	2.5516	1.6626	0.0000	1.4602	2.1861	3.3006	25.0000
Negative Emotions - Reducing Feedback	4575	2.1184	1.6260	0.0000	1.0705	1.7695	2.8216	20.0000
Sentiment	4575	0.1155	0.0330	-0.4062	0.1025	0.1195	0.1347	0.3547
Sentiment Disagreement	4575	0.2041	0.0358	0.0000	0.1808	0.2080	0.2291	0.5113

Notes: Data are daily. N is the number of observations. Std. Dev. refers to the standard deviation.

We collect Bitcoin's closing prices and trading volume data from Coinmarketcap.com. The price and trading volume data span from September 13, 2011, to December 31, 2022. The Chicago Mercantile Exchange (CME)'s cryptocurrency benchmarks are based on several leading crypto exchanges, and Bitstamp is one of the CME benchmark pricing sources. Thus, we utilize Bitstamp's tick data to compute Bitcoin's intraday volatility and skewness. The intraday volatility and skewness metrics are calculated over a 10-minute interval to minimize microstructural noise in the cryptocurrency market. For each Bitcoin's daily return, log trading volume, realized intraday volatility, and intraday skewness, we explore whether emotional disagreement is associated with Bitcoin's price dynamics. We consider the following set of regressions:

$$Y_{t+1} = X_t\beta_1 + C_t\gamma_1 + \epsilon_{1,t} \quad (2)$$

where time (t) is daily; Y is a column vector whose elements are either return, log trading volume, intraday volatility, or intraday skewness; X is an explanatory variable matrix that denotes emotional discrepancies; C is a control variable matrix; ε is a white noise vector. The control variables in the regression above include the logarithm of Bitcoin's market capitalization (Li et al., 2020), momentum, seasonality, idiosyncratic volatility, economic policy index, sentiment, and sentiment disagreement. Momentum is the average daily return from *t*-140 to *t*-2 (Grobys and Sapkota, 2019). The seasonality variable is the average weekday returns for the last 20 weeks of seasonality (Long et al., 2020). Idiosyncratic volatility is the standard deviation of idiosyncratic returns in the cryptocurrency market over the last 20 trading days. We employ a market model, using 3,300 cryptocurrencies to form a market portfolio (Zhang and Li, 2020). Daily economic policy index data are obtained from Policyuncertainty.com (Davis, 2016). We quantify sentiment-related metrics following Ahn and Kim (2020) and control for the impact of sentiment and sentiment disagreement in the regression. Because emotions and sentiments may be carried over for a prolonged period (Jiang et al., 2018), we compute the five-day moving average of the independent variables and run a predictive regression.

Table 2. Positive Emotions

	Daily Returns	ln(Trading Volume)	Intraday Volatility	Intraday Skewness
Amplifying Feedback	0.0010 [0.27]	-0.3612*** [-21.50]	0.0001*** [4.39]	0.0434 [1.63]
Reducing Feedback	-0.0006 [0.67]	0.0250 [0.28]	0.0001*** [4.34]	-0.0142 [-0.39]
N	3508	3276	3505	3505
F statistics	2.09**	6888.63***	45.76***	5.07***

Notes: Time is daily. N denotes the number of observations. Heteroscedasticity-consistent test statistics are reported in square brackets. ***, **, and * represent the statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Negative Emotions

	Daily Returns	ln(Trading Volume)	Intraday Volatility	Intraday Skewness
Amplifying Feedback	0.0032 [1.63]	-0.4521*** [-17.14]	0.0002*** [3.51]	0.0780 [1.62]
Reducing Feedback	0.0002 [0.79]	-0.0169 [-0.96]	0.0001 [1.30]	-0.0557* [-1.78]
N	3508	3276	3505	3505
F statistics	2.33**	6480.17***	47.75***	5.20***

Notes: Time is daily. N denotes the number of observations. Heteroscedasticity-consistent test statistics are reported in square brackets. ***, **, and * represent the statistical significance at the 1%, 5%, and 10% levels, respectively.

〈Table 2〉 and 〈Table 3〉 present the results, where we provide evidence that emotional feedback is mainly associated with Bitcoin's higher moment trading metrics. In 〈Table 2〉, the degree of investment feedback that amplifies emotional disagreement in the cryptocurrency profession is associated with lower future trading volume (p-value=0.0000), higher intraday volatility (p-value=0.0000), and higher intraday skewness (p-value=0.1037). The emotional replies that mitigate the emotional contents in the original post are significantly positively associated with intra-day volatility, implying that emotional heterogeneity begets a higher level of intra-day volatility. In 〈Table 3〉, we further find that this phenomenon is more salient for negative reactions. For negative emotions, amplifying feedback is correlated with lower future trading volumes (p-value=0.0000), higher intraday volatility (p-value=0.0000), and higher intraday skewness (p-value=0.1047). It appears that the replies that reduce the emotional elements in the original post are correlated with a lower level of intraday skewness in the near future. In general, the results suggest that when investors amplify their emotions, the cryptocurrency market becomes relatively more volatile and skewed and investors trade less.

We now move on to explore whether sentiment disagreement mediates the link between emotional reactions and Bitcoin's price dynamics. We consider the following set of regressions:

$$Y_{t+1} = X_t\beta_1 + C_t\gamma_1 + \epsilon_{1,t} \tag{3}$$

$$D_{t+1} = X_t\beta_2 + \epsilon_{2,t} \tag{4}$$

$$Y_{t+1} = D_t\beta_3 + C_t\gamma_2 + \epsilon_{3,t} \tag{5}$$

where time (t) is daily; Y is a column vector whose elements are either return, log trading volume, or intraday volatility; X is an explanatory variable matrix that denotes emotional discrepancies; C is a control variable matrix; D is a column vector that represents sentiment disagreement; ε is a white noise vector. The control variables in the regression above are the same as those in Eq. (2).

Table 4. Positive Emotions

Regression 1	Daily Returns	Intraday Volatility	ln(Trading Volume)
Positive Emotions	-0.0013 [-0.31]	0.0003 [0.98]	0.0689*** [4.15]
Amplifying Feedback	-0.0025 [-1.47]	-0.0001 [-1.28]	-0.0776*** [-12.39]
Reducing Feedback	0.0028 [1.46]	-0.0001 [-0.86]	-0.0672*** [-9.00]
N	2643	2643	2643
F statistics	2.14**	8.81**	44358.10***

Regression 2	Sentiment Disagreement
Positive Emotions	-0.0055*** [-4.15]
Amplifying Feedback	0.0147*** [20.15]
Reducing Feedback	0.0045*** [7.40]
N	2643
F statistics	1102.32***

Regression 3	Daily Returns	Intraday Volatility	ln(Trading Volume)
Sentiment Disagreement	-0.0043 [-0.14]	0.0083*** [13.25]	-54.4762*** [-82.36]
N	2643	2643	2643
F statistics	0.02	58.81***	4941.12***

Notes: Time is daily. N denotes the number of observations. Heteroscedasticity-consistent test statistics are reported in square brackets. ***, **, and * represent the statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Negative Emotions

Regression 1	Daily Returns	Intraday Volatility	ln(Trading Volume)
Negative Emotions	-0.0015	0.0001	0.0793
	[-0.63]	[0.47]	[10.11]
Amplifying Feedback	-0.0002	0.0001	-0.0744***
	[-0.05]	[0.97]	[-10.13]
Reducing Feedback	0.0001	-0.0002	-0.0369***
	[0.09]	[-0.86]	[-7.29]
N	2643	2643	2643
F statistics	1.66	9.40***	42264.50***

Regression 2	Sentiment Disagreement
Negative Emotions	-0.0023***
	[-3.44]
Amplifying Feedback	0.0142***
	[18.44]
Reducing Feedback	0.0021***
	[4.84]
N	2643
F statistics	876.97***

Regression 3	Daily Returns	Intraday Volatility	ln(Trading Volume)
Sentiment Disagreement	-0.0043	0.0083***	-54.4762***
	[-0.14]	[13.25]	[-82.36]
N	2643	2643	2643
F statistics	0.02	58.81***	4941.12***

Notes: Time is daily. N denotes the number of observations. Heteroscedasticity-consistent test statistics are reported in square brackets. ***, **, and * represent the statistical significance at the 1%, 5%, and 10% levels, respectively.

〈Table 4〉 and 〈Table 5〉 present the results. Regression 1 in 〈Table 4〉 and 〈Table 5〉 shows that emotional feedback is not directly associated with Bitcoin's trading metrics. However, Regressions 2 and 3 imply that emotional reactions are indirectly linked to intraday volatility and trading volumes in the cryptocurrency market, where sentiment disagreement is a mediating variable. When emotional reactions at the micro level are more diverse, sentiments at the macro level become more dispersed. Sentiment disagreement is empirically associated with more volatile markets and less trading. We also find that this phenomenon is more salient in amplifying reactions. When investors amplify their emotions, the cryptocurrency market becomes relatively more volatile, and investors trade less. For example, the coefficients and test statistics in Regression 2 are 0.0147 for amplifying feedback and 0.0045 for reducing feedback, as shown in 〈Table 4〉. The same asymmetry tilted towards amplifying feedback is observed for negative emotions.

V. Concluding Remarks

The cryptocurrency community bulletin board has become a popular venue for individual investors to share their emotions on cryptocurrencies. We investigate the extent to which emotional misalignment transmitted through emotional feedback in the cryptocurrency profession predicts Bitcoin's trading dynamics. We conduct emotion and sentiment analytics for all posts published on one of the most popular cryptocurrency platforms for investors in the cryptocurrency market. We find that the emotional discrepancies expressed in both posts and commentaries have statistical power in predicting intraday volatility, trading volume, and intraday skewness. Our results suggest that asset pricing theories incorporate behavioral issues, such as emotional dispersion, induced by heterogeneous emotional reactions (Loewenstein, 2000). These insights highlight a few key points, as summarized by Hong and Stein (2007). First, the opinions expressed in the community are likely to have a large impact on market outcomes. Second, asset pricing models of disagreement might be promising for a better understanding of the origins of the unique price dynamics in cryptocurrencies.

Various trading-related metrics in the cryptocurrency market with no apparent link to each other have been shown to be associated with emotional disagreement, which highlights the importance of limited attention (Hirshleifer, Lim, and Teoh, 2011) and heterogeneous priors exhibited though emotions, sentiments, and opinions (Morris, 1994) in the financial market. Disagreement models that can deliver a comprehensive joint account of a catalog of Bitcoin's trading dynamics could be an interesting extension of this study.

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