NFT Market Reaction to Twitter Sentiment: An Event Study

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Abstract

Social media is increasingly popular for financial services, e.g., stock price prediction, but little attention has been drawn to its impact on the emerging NFT. Due to a lack of systematic knowledge of the nature of cryptocurrencies' returns and volatility in relation to other key financial assets, whether the pattern of the influence of social media on the stock markets applies to the NFT markets is still questionable. In this paper, we study the NFT market reaction to the celebrities' tweets over a one-year time using the event study methodology. This research can potentially contribute to the literature by formulating a solid framework to explain the essential differences between NFT and stock markets.

1 Introduction

Many people's lives have become increasingly reliant on social media. According to a recent survey (Martínez-de Morentin et al. [2021]), half of the youngsters aged eight to seventeen have social networking profiles such as Facebook, Instagram, Twitter, etc. Not just young people, people of all ages and professions use social networking sites to communicate. Among all, Twitter, which has revolutionized the way people purchase, vote, and launch revolutions, is now revolutionizing the industry of celebrity endorsements.

Celebrities, e.g., the president, entrepreneurs, and pop singers, can pose tweets available to everyone. Therefore, Twitter provides a channel through which celebrities affect ordinary people and public markets directly and effectively. For example, in August 2018, Tesla saw its stock rise by 7% after Tesla's CEO Elon Musk tweeted about going private at $420 per share.

This influential power of social media has also drawn people's attention to one emerging financial asset, the NFT. A NFT, e.g., Bitcoin, Ether, Tether, is a digital asset that can circulate without a central monetary authority such as a government or bank. In January 2021, Tesla stated that it purchased around $1.5 billion in Bitcoin and planned to accept it as payment in the future. The announcement drove Bitcoin's price to rise 17 percent to $44,220, a new high. This event suggests that the NFT marketplace is vulnerable to unexpected events and social media orientation.

Despite extensive research, how NFT markets react to Twitter sentiment remains an open question. On the one hand, many works have studied the social media impact on traditional financial markets and found evidence that there is a link between tweets and the financial markets (De Long et al. [1990], Schumaker et al. [2012], Bollen et al. [2011], Bollen et al. [2011], Arias et al. [2014], Makrehchi et al. [2013], Nofer and Hinz [2015], Zhao et al. [2016]). Still, none of them is done on the emerging NFT markets. On the other hand, while Bouri et al. [2019b] revealed that Bitcoin returns are closely tied to most other assets, especially commodities, demonstrating that the Bitcoin market is not entirely isolated, Gil-Alana et al. [2020] found inconsistent evidence that cryptocurrencies are isolated from traditional financial asset classes. Therefore, it is significant to systematically examine whether the pattern of the effect of social media on the stock markets applies to the NFT markets.

To provide empirical evidence on NFT market reaction to Twitter sentiment, we collect data sets from two sources for our study: 1) tweets data from Twitter; 2) NFT price data from CoinMarketCap. Our data set includes the celebrities' (defined as users with more than 30,000 followers by Campos-Pardillos and Balteiro [2020]) tweets mentioning the top 5 cryptocurrencies, namely "Bitcoin," "Either," "Tether," "BNB," and "USD Coin," as well as those users' basic information, and the top 5 cryptocurrencies' daily prices, from January 1, 2021, to December 31, 2021. We also gathered a data set capturing all NFT events in our observation window to filter out occurrences directly connected to cryptocurrencies that were afterward tweeted by celebrities.

In this work, we investigate the following research questions: 1) Does celebrities' sentiment about NFT on Twitter affect the NFT market? 2) How does this impact vary across different types of celebrities? We use the event study methodology to estimate the impact of celebrities' tweet sentiment towards different types of cryptocurrencies on their price. Based on the Efficient Market Hypothesis (Fama [1991]), the event study examines how the market reacts to unanticipated events while accounting for market-wide swings in NFT returns.

The rest of the paper is organized as follows: Section 2 gives a comprehensive literature review. Section 3 discusses the theory and develops the hypotheses. Section 4 describes the research context and the data collection procedure. Section 5 presents the research Methodology and models. Section 6 summarizes the paper and discusses future work.

2 Literature Review

Our study is related to two streams of research. First, we review the social media impact on financial markets. Second, our research is related to a stream of literature that studies the distinctions between stock and NFT markets.

2.1 Social media impact on financial markets

Great interest can be found in the literature using social media sentiment analysis to predict the financial market. For a long time, investors have embraced the Efficient Market Hypothesis (Fama [1970]), which states that good returns in the financial market cannot be acquired by researching the previous value of stock prices. However, some economists believe that stock values in the financial sector may be predicted to some extent (Malkiel [2003]). Indeed, according to Atsalakis and Valavanis [2009], which analyzed over 100 publications published in the subject, there is numerous research in the scientific literature that provide algorithms to anticipate the financial market.

Studies on financial behavior show that emotions can influence investment decisions (De Long et al. [1990]). Schumaker et al. [2012] show that market attitudes are influenced by news or financial disclosures. As a result, especially with the rise of social media, there is a growing interest in using Sentiment Analysis (SA) to forecast stock market moves. (Bollen et al. [2011]). Bollen et al. [2011]'s research aims to determine the sentiment of Twitter postings and link them with financial market activity. According to the findings, the correlation with the daily fluctuations closing values of the Dow Jones Industrial Average (DJIA) had an accuracy of 86.7Arias et al. [2014] studied if a public mood indicator collected from Twitter's daily posts may enhance the forecasting of social, economic, or commercial factors. The findings revealed that nonlinear models can forecast financial trends using Twitter data, but linear models consistently fail to predict any sort of financial time series. Makrehchi et al. [2013] created a study that considers the sentiment of daily Tweets and forecasts the upcoming financial market movement. Consequently, the authors discovered that the day's aggregated emotion is linked to market performance. The generated plan was tested as an investing strategy in the stock market, yielding a 20% return in four months. Nofer and Hinz [2015] measured the sentiment in Twitter. The study found that when the amount of Twitter followers in each magazine is considered, there is a link between tweets and the financial market. In the German financial market, the stock portfolio achieved a return of up to 36% during a six-month period. Through SA of the social network Sina Weibo, Zhao et al. [2016] demonstrated a financial market forecast approach. On average, the SA presented a precision of 62% to 68%, while the market forecast showed 53% to 60% accuracy, on average.

However, all these works discussed above investigated the influence of social media on the stock markets, but none is done on the NFT markets. Next, we dig into the literature on the differences between NFT and stocks.

2.2 NFT VS. Other Financial Assets

Cryptocurrencies have become a worldwide phenomenon regularly and prominently addressed by the media, venture capitalists, banking, and governmental entities. (Glaser et al. [2014]). The recent sharp increase in Bitcoin trading volume has been linked to the rise in cryptocurrencies and the rapid growth of NFT markets, resulting in comprehensive literature on NFT markets (Hileman and Rauchs [2017]). Since Bitcoin was first proposed by Nakamoto [2008], several studies have been conducted on Bitcoin, focusing on market efficiency (Urquhart [2016]; Nadarajah and Chu [2017]; Bariviera [2017]; Vidal-Tomás and Ibañez [2018]), price volatility (Dyhrberg [2016]; Katsiampa [2017]), price clustering (Urquhart [2017]), speculation (Cheah and Fry [2015]) and transaction costs (Kim [2017]). As a result of the introduction of various types of cryptocurrencies in recent years, the market size of NFT markets has rapidly increased. Some key studies have examined some cryptocurrencies properties such as market returns and volatility (Omane-Adjepong et al. [2019b]; Omane-Adjepong et al. [2019a]), herding behaviour in NFT markets (Bouri et al. [2019b]; Bouri et al. [2019c]), portfolio diversification across cryptocurrencies (Liu [2019]), regime shifting models (Mensi et al. [2019]; Bouri et al. [2019a]; Omane-Adjepong et al. [2019b]; Omane-Adjepong et al. [2019a]), return-volume relationship (Bouri et al. [2019b]), or speculation (Yermack [2015]; Blau [2018]).

Studies have explored many aspects of cryptocurrencies and their connections to other financial assets. For example, Corbet et al. [2018] investigated the dynamic interactions between cryptocurrencies and other financial assets, demonstrating that cryptocurrencies may provide diversification benefits to investors with short investment horizons. Liu and Tsyvinski [2021] discovered that cryptocurrencies (Bitcoin, Ripple, and Ethereum) have a risk-reward trade-off that differs from stocks, currencies, and precious metals. Bouri et al. [2019b] investigated the connections between Bitcoin and traditional financial asset classes. Based on a smooth transition VAR-GARCH-in-mean model, the results reveal that Bitcoin returns are closely tied to most other assets, especially commodities, demonstrating that the Bitcoin market is not entirely isolated. Baumöhl [2019] discovered a negative correlation between forex and cryptos and proposed that investing in these assets could provide diversification benefits to investors. Yi et al. [2018] used LASSO–VAR analysis to investigate the volatility connectedness in the NFT market and discovered that volatility connectedness swings cyclically and that volatility shocks transmit from mega-caps to others. Ji et al. [2019] came to the same conclusion: Bitcoin and Litecoin (mega-caps) are at the heart of the connection, with Bitcoin causing the most spillover effect. Using the regime-switching skew-normal model, Matkovskyy and Jalan [2019] investigated the contagion impact between five equities indices and Bitcoin markets and discovered strong contagion effects from finance to Bitcoin markets. Yang [2020] also discovered a sizeable nonlinear association between Taiwan's stock market and Bitcoins.

Meanwhile, Corbet et al. [2018] demonstrated that cryptocurrencies are somewhat apart from financial assets. In a similar study, Trabelsi [2018] did not find a substantial spillover impact between cryptos and stocks. The spillover index technique was used in these investigations, along with a spectral representation of variance decomposition networks. According to Kostika and Laopodis [2019], cryptocurrencies do not have any short- or long-term stochastic tendencies similar to equity markets or currency rates. Kurka [2019] discovered shock transmission between traditional assets and Bitcoin under conditional analysis. Aysan et al. [2019] used connectivity measurements to show that global geopolitical risk significantly impacts Bitcoin returns and volatility. Zeng et al. [2020] discovered a weak link between Bitcoin and traditional assets. More recently, Gil-Alana et al. [2020] used fractional integration techniques to investigate the bidirectional relationships between six prominent cryptocurrencies and six stock markets. Their findings show no co-integration between the six cryptocurrencies, particularly between cryptocurrencies and stock market indices, implying that cryptocurrencies are isolated from traditional financial asset classes.

Due to the lack of a systematic understanding of the behaviors of the returns and volatility of cryptocurrencies in connection with other significant financial assets, whether the pattern of the influence of social media on the stock markets applies to the NFT markets is still questionable.

2.3 Our Contribution

Our research connects the above two streams of literature by studying the effect of social media sentiment on NFT markets. We focus on a particular type of effect (i.e., celebrity effect) in a typical platform (i.e., Twitter) on the top 5 NFT markets (i.e., "Bitcoin", "Either", "Tether", "BNB", and "USD Coin"). This setting allows us to perform an event study on whether a celebrity's tweets directly affect NFT markets.

3 Theory and Hypothesis

3.1 Celebrity Endorsement and Twitter Sentiment

3.1.1 Celebrity Endorsement in financial markets

Indeed, there is well-developed theoretical literature concentrating on the possible positive effects of celebrity endorsements. Celebrity endorsements are used for a variety of reasons, including the fact that they make advertisements more credible and increase customer recognition. (Kamins et al. [1989]; Friedman and Friedman [1979]). Celebrities are thought to aid in brand identification and develop a good attitude as well as a distinct personality for the endorsed brand (Petty et al. [1983]; Kamins et al. [1989]; McCracken [1989]). When celebrities appear in advertising campaigns, it is widely assumed that businesses have a better chance of expressing their message to consumers (Choi and Rifon [2007]).

Celebrity breaches are predicted to have a detrimental impact on corporate valuation. However, according to Louie et al. [2001], negative occurrences have a negative impact on firm value only when the celebrity is responsible for the event. The effect on firm valuation was positive if the celebrity was not considered deserving of blame for the tragedy. Two more recent studies, both of which focused solely on celebrity infractions, showed only little evidence for a negative impact on firm valuation due to celebrity misbehavior (Bartz et al. [2013]) or, the Tiger Woods scandal had a significant negative impact on the market value of the major sponsors. (Knittel and Stango [2014]). As a result, while it appears that celebrity endorsements and celebrity behavior can have both positive and negative effects on business valuation, the specific nature of this link remains unknown, and additional study is needed.

3.1.2 Twitter Sentiment Analysis (TSA) in financial markets

Public mood states or sentiments influence the stock returns (Das and Chen [2007]; Zimbra et al. [2015]). Emotions, in addition to information, have a substantial influence on human decision-making, according to psychological studies (Damasio [1994]; Bollen et al. [2011]; Kahneman and Tversky [2013]). Behavioral finance has produced more evidence that emotion and mood play a substantial role in financial decisions (Nofsinger [2005]). As a result, it's logical to believe that public mood and attitude can influence stock market values.

In the last five years, sentiment tracking systems that extract measures of public mood straight from Twitter have made substantial development. Even though each "tweet," or individual user contribution, is limited to only 140 characters, the sum of millions of tweets published to Twitter at any given moment may provide an accurate picture of public mood and emotion. Sentiment analysis tasks include identifying sentiment target/subject, opinion holder identification, and identifying sentiment for various characteristics of a topic, product, or organization, as well as classifying sentiment polarity conveyed in the text (e.g., positive, negative, neutral). (Abbasi et al. [2008]). Positive tweets express a preference for a candidate in a political TSA (Mejova et al. [2013]) and optimism about a firm's future financial performance in a stock Twitter sentiment analysis (Smailović et al.

[2013]). Based on these theories and the cryptocurrency and stock markets literature, we formulate the following four hypotheses.

Hypothesis 1a *A positive tweet from a celebrity exerts a positive effect on the cryptocurrency market.*

Hypothesis 1b *A negative tweet from a celebrity exerts a negative effect on the cryptocurrency market.*

Hypothesis 1c *A neutral tweet from a celebrity exerts no effect on the cryptocurrency market.*

Hypothesis 1d *On average, the effect size of a negative tweet from a celebrity is more significant than a positive tweet.*

3.2 Heterogeneous Celebrity Effects

3.2.1 Experts vs. Non-experts in Cryptocurrency

Studies of both celebrities in general (Agrawal and Kamakura [1995]) and athletes (Elberse and Verleun [2012]; Farrell et al. [2000]) have discovered a substantial influence, or anomalous return, on stock prices on the day a celebrity endorsement is disclosed, with typical excess returns ranging from a quarter to half percent. Hence, it motivates us to consider how various sorts of celebrities may have varied effects depending on their areas of expertise. As a result, the following three hypotheses emerge.

Hypothesis 2a *Both positive tweets and negative tweets of cryptocurrency experts have a direct effect on the cryptocurrency market.*

Hypothesis 2b *Both positive tweets and negative tweets of non-experts have a direct effect on the cryptocurrency market.*

Hypothesis 2c *The effect size of experts is larger than non-experts.*

3.2.2 Male Celebrity vs. Female Celebrity

Persuasion research shows that men and women respond differently to male and female communicators (e.g., Reid et al. [2009]), and there might be fascinating interactions between the celebrity's gender and the gender of the intended audience. Based on this, we postulate the following hypothesis.

Hypothesis 3 *The effect size of a male celebrity is more significant than that of a female celebrity.*

3.3 Heterogeneous market effects

Bhosale and Mavale [2018] observed that in terms of stability of the performance, Bitcoin is much more consistent than Ethereum. Al-Yahyaee et al. [2020] studied the multifractality, long-memory process, and efficiency hypothesis of six major cryptocurrencies (Bitcoin, Ethereum, Monero, Dash, Litecoin, and Ripple) using the time-rolling MF-DFA approach. The results show that among all the cryptocurrencies, Ethereum (Bitcoin) has the highest (lowest) market volatility. More interestingly, Zhang et al. [2019] found that the Ethereum-Bitcoin pair, among Ripple-Bitcoin, Ethereum-Ripple, and Litecoin-Ripple, exhibited the highest correlation. These results make us reasonable to draw the following hypotheses.

Hypothesis 4a *Ethereum market is more affected than the Bitcoin market.*

Hypothesis 4b *There is a spillover effect from one market to another.*

4 Research Context and Data

4.1 Research Context

Our study necessitates data sets that characterize both NFT-related tweets and NFT markets. We combine data sets from two sources for our empirical study: 1) tweets data from Twitter; 2) NFT price data from CoinMarketCap. We conduct an event study on whether celebrity tweets about NFT affect the NFT markets with all these data sets.

4.1.1 Twitter Data

Twitter is an American microblogging and social networking service on which users post and interact with messages known as "tweets." Registered users can post, like, and retweet tweets, but unregistered users can only read publicly available ones. Users interact with Twitter through browser or mobile frontend software or programmatically via its APIs. Tweets were initially restricted to 140 characters, but the limit was doubled to 280 for non-CJK languages in November 2017. Audio and video tweets remain limited to 140 seconds for most accounts.

Twitter was created by Jack Dorsey, Noah Glass, Biz Stone, and Evan Williams in March 2006 and launched in July of that year. By 2012, more than 100 million users posted 340 million tweets a day, and the service handled an average of 1.6 billion search queries per day. In 2013, it was one of the ten most-visited websites and described as "the SMS of the Internet." By the start of 2019, Twitter had more than 330 million monthly active users. In practice, most tweets are written by a minority of users.

While Ashton Kutcher was the first Twitter user to get one million followers, many other celebrities have joined the Twitter bandwagon and now have several million followers. By April 2022, Barack Obama (131.7 million), Justin Bieber (114.3 million), and Katy Perry (108.9 million) reign as the top three most-followed Twitter users. There is undoubtedly no single traditional marketing vehicle that can reach such a broad audience, and celebrities have been able to capitalize on the attention they gain from Twitter by using social media sites to build their brands. Twitter allows followers to show their loyalty towards celebrities, as following a celebrity shows commitment. So while it is true that Lady Gaga has more Twitter followers than Elon Musk, celebrities have been able to successfully use Twitter to maintain their brands and draw fans in.

The Advertising Standards Authority (ASA), which makes the guidelines that social media influences must follow, has announced that anyone with more than 30,000 social media followers is now considered a celebrity (Campos-Pardillos and Balteiro [2020]). Followed by this criterion, we collect twitter users with followers of more than 30,000 as celebrities in our context. In this paper, we investigate how these celebrities' tweet sentiment toward different types of cryptocurrencies influence their price markets.

The Twitter company provides APIs for academic research to obtain tweet data. Academic research access was built to serve the needs of the academic research community via specialized, greater levels of access to public Twitter data for free. New and existing Twitter developers will need to complete an Academic Research application to gain access to this track. We collect the celebrities' tweets mentioning the top 5 cryptocurrencies, namely "Bitcoin," "Either," "Tether," "BNB," and "USD Coin," in the past year, as well as those users' basic information. We generate two dummy variables, indicating the tweet's sentiment (by text mining technology) and whether the user is an expert in finance or technology (with a preset list). The variables of each record are summarized in table 1.

Table 1: Description of Tweet Data Variables used in this Study

Variable	Description
tweet_id	The unique id of the tweet.
time	The day-level time of the tweet.
cry_type	The related NFT, 0-"Bitcoin", 1-"Either", 2-"Tether", 3-"BNB", and 4-"USD Coin".
seg	A generated dummy variable indicating the sentiment of the tweet, 0-positive, 1-negative, 2-neutral.
user_id	The unique id of the Twitter user.
user_exp	A generated dummy variable indicating whether the user is an expert in finance or technology, 0-non-expert, 1-expert.
gender	0-male, 1-female.
num_fol	The number of the user's followers.
num_pos	The number of tweets the user post per month in the past one year.
num_like	The number of likes of this tweet.
num_com	The number of comments of this tweet.
num_for	The number of forwards of this tweet.

4.1.2 NFT market Data

Next, we obtain the panel data of the top 5 cryptocurrencies' daily prices for the past year from CoinMarketCap. CoinMarketCap is a NFT industry utility that aggregates and reports recently-traded prices for hundreds of cryptocurrencies traded on hundreds of platforms worldwide. For each currency, it reports the total value of the outstanding currency (the "market capitalization"), its total trading volume, and its rank by trading volume over the past month and the past 24 hours. The web page also ranks NFT trading platforms according to their reported trading volumes across all coins or tokens that they list. CoinMarketCap also provides APIs for academic research access. We obtain the variables of each record as shown in table 2.

To filter out the events directly related to cryptocurrencies and later tweeted by celebrities, we collected a data set recording all the NFT events in the past year. The variables are summarized in table 3.

Table 2: Description of NFT Data Variables used in this Study

Variable	Description
cc_id	The unique id of the NFT.
cry_type	The related NFT, 0-"Bitcoin", 1-"Either", 2-"Tether", 3-"BNB", and 4-"USD Coin".
date	The date of this record.
Price	The price of the NFT in that day.
Volume	The volume of the NFT in the past 24 hours.
var_24	The price variation in the past 24 hours.
var_7d	The price variation in the past 7 days.

Table 3: Description of Event Data Variables used in this Study

Variable	Description
event_id	The unique id of the event.
cc_id	The id of the corresponding NFT.
date	The date of this event.

5 Research Methodology

5.1 Twitter Sentiment Analysis

Sentiment analysis is a technique that automatically tracks sentiments on social media platforms. In this study, sentiment analysis entails categorizing remarks as Positive, Negative, or Neutral. Sentiment analysis uses Natural Language Processing (NLP) to make sense of human language, and machine learning to automatically deliver accurate results.

Performing sentiment analysis on Twitter data involves two steps: 1) create a sentiment analysis model; 2) analyze our Twitter data using the sentiment analysis model.

MonkeyLearn is a machine learning platform provided by the Twitter company that makes it easy to build and implement sentiment analysis. This tool has been widely used in research to conduct text sentiment analysis (Rakshitha and Gowrishankar [2018], Basmmi et al. [2020], Sadriu et al. [2022], Kusnaedi and Hisyam [2021], Wang et al. [2017], Byrne et al. [2021], Contreras et al. [2021], Shibly et al. [2021]). As depicted in Fig 1, MonkeyLearn shows the sentiment prediction results with a confidence rate, and it allows to upload of a CSV file for predicting multiple results in one run. We will use other different text mining models for the robustness check.

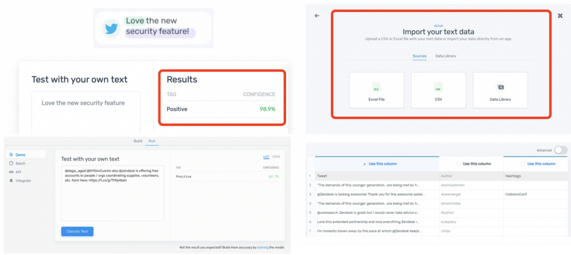

Figure 1: Demo of MonkeyLearn

5.2 Event Study

We use the event study methodology to estimate the impact of celebrities' tweet sentiment towards different types of cryptocurrencies on their price. Based on the Efficient Market Hypothesis (Fama [1991]), the event study examines how the market reacts to unanticipated specific events while accounting for market-wide swings in NFT returns.

The adjusted returns (often referred to as abnormal returns) reflect the effect of an economic event on the value of a NFT in the marketplace (MacKinlay [1997]). Therefore, we are able to measure the celebrity effects on NFT prices by observing the price behavior over relatively short periods when the tweets are made.

We first define the timeline for the event study, as depicted in Fig. 2. The initial tweet post date is defined as the event date $t = 0$. The estimation window consists of 250 trading days, from Day $T_3 = -259$ to Day $T_2 = -1$. The abnormal return, that is, the measure of the NFT market's reaction to the tweet event, is calculated over an event window of three trading days (Day $T_2 = -1$ to Day $T_1 = +1$).

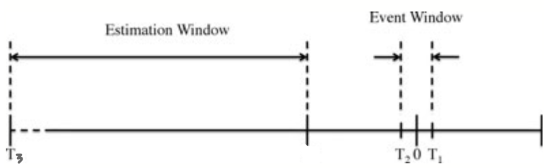

Figure 2: Timeline of the event

We used the Market Model (Brown and Warner [1985]) to calculate abnormal returns. For any NFT i, we have

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it}$$

with $E[\epsilon_{it}] = 0$ and $Var[\epsilon_{it}] = \sigma_\epsilon^2$, where R_{it} is the return of NFT i on day t; R_{mt} is the return of market portfolio on day t; ϵ_{it} is the disturbance term; and α_i, β_i, and σ_ϵ^2 are the parameters of the model. In this study, the proxy for NFT i's corresponding market portfolio is a value-weighted market index of all cryptocurrencies traded.

We ran an ordinary least square (OLS) regression over the estimation period (i.e., from Day T_3 to Day T_2) to estimate the parameters of the market model, α_i, β_i, and σ_ϵ^2. Then, we calculated the abnormal return of NFT i on trading day t in the event window using the following formula:

$$AR_{it} = R_{it} - \bar{\alpha_i} - \hat{\beta_i} R_{mt}$$

for $t \in T2, ..., T1$, where AR_{it} is the abnormal return of NFT i at day t. The abnormal return is the ex-post return of the NFT over the event window minus the expected return had the event not taken place. Under the null hypothesis that the event (the tweet) has no impact on returns, $AR_{it} \sim N(0, \sigma_\epsilon^2)$. Following MacKinlay [1997], we aggregated the abnormal returns across time for each event observation as the Cumulative Abnormal Return (CAR) during our event window:

$$CAR_i(T2, T1) = \sum_{t=T_2}^{T_1} AR_{it}$$

Finally, we developed a cross-sectional OLS regression model for the determinants of CAR.

$$
\begin{aligned}
CAR_i = &\beta_1 \times TweetSentiment_i + \\
&\beta_2 \times TweetSentiment_i \times Gender + \\
&\beta_3 \times TweetSentiment_i \times Expert + \\
&\beta_4 \times TweetSentiment_i \times follower + \\
&\beta_5 \times TweetSentiment_i \times Poster + \\
&\beta_6 \times TweetSentiment_i \times Like + \\
&\beta_7 \times TweetSentiment_i \times Comment + \\
&\beta_8 \times TweetSentiment_i \times forward + \\
&\beta_9 \times TweetSentiment_i \times Type + \\
&\sum_{i=1}^{5} \alpha_i NFT_i + \sum_{i=1}^{5} \gamma_i Event_i + \epsilon_i
\end{aligned}
$$

We included NFT fixed effects in the model as dummy variables NFT_i. We also controlled the event $Event_i$, which is directly related to cryptocurrencies, during the period of the observation window of each tweet (i.e., from T2 to T1) and later tweeted by celebrities.

6 Summary and Follow-up Work

This paper followed an event study framework to investigate how NFT markets react to Twitter sentiment. We have done intensive literature reviews and formulated our research questions, data collection procedure, and research path. Next, we will collect the actual data and fit our empirical models. Then, we will modify our hypotheses accordingly to the results and continue to explore various heterogeneous celebrity effects. Hopefully, we could contribute to the literature by formulating a solid framework to explain the essential differences between NFT and stock markets.

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