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COIN SPECIFIC SENTIMENTS MATTER FOR THE NON-FUNGIBLE TOKENS SPILLOVERS: HOW AND WHEN?

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ABSTRACT

This paper explores the impact of sentiment on return spillovers among seven major Non-Fungible Tokens (NFTs). Using daily sentiment data from Thomson Reuters MarketPysch Indices and controlling for uncertainty factors and NFT sales, we examine the relationship between media sentiment and NFTs return spillovers using a TVP-VAR model. Our findings show that individual NFTs sentiment is important for spillover dynamics and the effect of sentiment changes based on market uncertainty. The study highlights the need for NFTs investors to focus on market sentiment themes rather than overall sentiment.

Keywords: Spillovers; Cryptocurrency; TVP-VAR; Sentiment; COVID-19.
JEL Classifications: C21; C22; G11; G14; G17.

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I. INTRODUCTION

As the cryptocurrencies improve their traits in the blockchain setup, the store of value features of the coins gains popularity. Indeed, digital copyright concepts are even gaining more prevalence in the digital era, where the value is produced in the digital world and has to be valued and stored with digital means. Hence, a new token standard (ERC1155) was founded in the Ethereum blockchain to produce Non-Fungible Tokens (NFTs) in 2018 and has gained popularity at an incredible rate (Urquhart, 2021).[1] NFTs stand out as a remedy to define the sole ownership of almost everything, mainly digital, intangible products and services such as images, sound, and videos.

The Non-Fungible Token market, in particular, has gained significant attention due to its unique features and potential applications. Some of the emerging NFTs focus on creating digital assets for the general public, while others focus on specific sectors like Gaming, Metaverse or Sports. These new cryptocurrencies have accelerated the enhancement of the technology and further the adoption of NFTs. For instance, Chilliz solely focuses on sports and hosts more than 80 global Sports Teams' fan tokens in its network.[2] People are even more interested in a digital world and live more in the "metaverse" after being distanced from the real world during COVID-19 lockdowns. Furthermore, the NFTs market has started to attract more attention in social media and traditional news due to the NFTs sales of celebrities for exorbitant prices. For instance, Jack Dorsey, CEO of Twitter, sold his genesis tweet as an NFTs for over 2.9 million dollars.[3] Singer Eminem, actress Paris Hilton, famous NFL player Rob Gronkowski, or Edward Snowden earn millions of dollars from NFTs sales.[4]

However, the cryptocurrency market is known for its high level of volatility, and news and events can have a significant impact on the sentiments and prices of different coins and assets (Akyildirim *et al*., 2021). The NFTs market is no exception, and news and events related to NFTs can spillover to other markets, leading to positive or negative sentiments and price movements. For example, a positive news event related to an NFTs project or platform may lead to positive sentiments and price movements in its underlying coin, as well as other coins in the market. On the other hand, a negative news event may lead to negative sentiments and price movements across the market.

This paper studies the role of sentiment on return spillovers among the seven major NFTs by controlling uncertainty related factors and NFTs sales both in terms of number and US Dollar amounts in different categories such as art, sport, game, and metaverse. We use daily NFTs specific sentiment data from Thomson Reuters MarketPysch Indices (TRMIs), which uses advanced text mining techniques to extract sentiment from various news and social media sources. In particular, TRMIs provide 42 different sentiment indicators that capture different dimensions

1 https://eips.ethereum.org/EIPS/eip-1155
2 www.chiliz.com/en/our-story/
3 https://www.cnbc.com/2021/03/22/jack-dorsey-sells-his-first-tweet-ever-as-an-nft-for-over-2poin.html
4 https://cointelegraph.com/news/nft-auction-celebrating-nfl-star-rob-gronkowski-drives-1-8m-in-s
https://finance.yahoo.com/news/nsa-whistleblower-edward-snowden-sells-205146376.html
https://finance.yahoo.com/news/paris-hilton-launches-own-nfts-132000108.html

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such as emotions (i.e., gloom, joy, trust) and market fundamentals, risks, and innovation concepts (market risk, volatility, scam, adoption, fork, hodl etc.) within the news. We first compute return spillovers using the TVP-VAR model and examine whether media sentiment drives the return spillovers in the NFTs market. Next, we investigate how the effect of sentiment changes across different uncertainty regimes. Finally, we identify sentiment themes that significantly influence the spillovers among NFTs.

Our motivation for examining the link between NFT market spillovers and coin specific sentiments stems from the growing popularity of non-fungible tokens has garnered significant attention in recent times. However, there is still some uncertainty around how the sentiment towards individual NFT coins affects the overall NFT market. This uncertainty highlights the importance of understanding return spillovers, which refers to the relationship between the returns of different NFT coins.

Return spillovers in the NFT market occur when changes in the return of one NFT coin impact the return of another NFT coin. For instance, a sudden increase in the value of a specific NFT coin can lead to a spillover effect in the rest of the NFT market, causing other NFT coins to also experience a rise in their returns due to increased investor interest and demand. The news media sentiment can play a significant role in affecting NFT coin return spillovers. News and media coverage of NFT coins can influence public perception and investor sentiment, which in turn can have a significant impact on the returns of NFT coins. Therefore, the examination of the relationship between NFT market spillovers and coin-specific sentiments is crucial for several reasons. Firstly, it sheds light on how news media sentiment shapes the opinions and attitudes of market participants, which in turn affects spillovers among NFT coins. This information is valuable for investors and traders who are seeking to maximize their returns and minimize their risk in the digital asset market. Secondly, understanding the connection between NFT market spillovers and coin-specific sentiments is crucial for policymakers and regulators. By gaining a deeper understanding of the interconnectedness of markets, regulatory and policy decisions can be made to create a more stable and efficient market.

Recently, several papers have focused on the NFTs' price dynamics and their relation within the cryptocurrency market. For instance, Dowling (2022) analyzes whether NFT pricing is driven by other cryptocurrencies using a wavelet coherence analysis and demonstrates the co-movement between NFT prices and Bitcoin and Ethereum. Aharon and Demir (2021) examine the return connectedness of NFTs and other financial assets such as bonds, currencies, gold, etc., and find that while NFTs are often seen as shock transmitters, their function alters during stressful periods, and they become shock receivers. Demir *et al*. (2022) investigate the relationship between football match outcomes and the token values of the teams and find that both defeats and victories in the UEFA Champions League have an impact on the fan token abnormal returns. Some studies focus on the practical and legal aspects of NFTs. For instance, Wang *et al*. (2021) explain what NFT is in general and discuss opportunities and challenges for NFTs. Since NFTs are digital intellectual properties, Okonkwo (2021) focuses on NFTs from a copyright, intellectual property and patent perspective and examine issues like the relationship between copyright commissions and NFT platforms. Giesselman *et al*. (2021) explain taxation of digital assets and discuss legal issues like the ambiguity of location of NFT sales since they occur online.

Our main findings are summarized below. Return spillover calculation shows that after COVID-19 outbreak and during elevated tensions in the cryptocurrency market, FROM and TO spillovers start reflecting increasing standing of individual stories for each NFT coin. Our results also show that the sentiments negatively and significantly affect the FROM and TO spillovers. This effect remains significant, even after controlling the NFT market and uncertainties related to economic policy and COVID-19. We find a statistically significant relation between sentiment and return spillover measures only in low uncertainty periods, implying that the heightened uncertainty due to EPU or COVID limits the effect of sentiment on return spillovers in the NFT market. We also cover a variety of sentiment subjects to determine which individual sentiment themes influence the market by looking at the sentiment breakdown based on the underlying indices. These sentiments are also grouped into four categories as 1) emotional themes; 2) market fundamentals; 3) innovative aspects and 4) risks. The regression results reveal that investor sentiment on topics related to the category of the market fundamentals impacts the return spillovers among NFTs in most cases. Hence, we conclude that it is critical for NFT investors to concentrate on the market fundamentals themes driving the markets rather than the overall sentiment.

Our study contributes to the NFTs literature in multiple ways. Firstly, previous studies have attempted to investigate spillovers in the cryptocurrency market using aggregated measures of spillovers, which can lead to a loss of detail in the analysis of the relationships between NFT coins (see, for instance, Yi *et al*., 2018; Ji *et al*., 2019; Elsayed *et al*., 2022; Balcilar *et al*., 2022; among others). Yousaf and Yarovaya (2022) investigate the relationship between NFTs, Defi assets, and other assets including oil, gold, Bitcoin, and the S&P 500 using a TVP-VAR framework. It is found that NFTs and Defi assets have limited impact on the returns and volatility of traditional asset classes, but some assets such as Bitcoin, oil, and some NFTs and Defi assets do have some level of influence. They also show total spillover increased during the COVID-19 pandemic and the cryptocurrency boom of 2021. Using the same model, Umar *et al*., (2022) examine the interplay between returns and volatility in the NFT market and its coverage in the media during the COVID-19 pandemic. The results suggest that media coverage acts as a catalyst for transmitting return and volatility spillovers to NFTs, with a particular emphasis on the Utilities segment.

However, our study uses a more granular and detailed measure of spillovers, which we refer to as the “FROM and TO” measure of spillovers. This measure allows for a more nuanced analysis of the relationships between NFT coins, providing a clearer understanding of the return dynamics in the NFTs market. The “FROM” measure refers to the impact that one NFT coin has on another, while the “TO” measure refers to the impact that another NFT coin has on the first. By considering both the “FROM” and “TO” measures, we are able to gain a deeper insight into the relationships between NFT coins. This is particularly important given the relatively high degree of interdependence between NFT coins in the NFTs market.

Secondly, we also examine the role of sentiment on return spillovers among the seven major NFTs by controlling for uncertainty-related factors and NFT sales in terms of both number and US Dollar amounts in different categories such as art, sport, game, and metaverse. This provides a deeper understanding of the drivers of spillovers in the NFTs market. Thirdly, our results show that NFT coin-specific individual sentiments matter for the spillovers dynamics, and the effects of sentiment on spillovers also vary with respect to the uncertainty levels in the market. We find that the effect of sentiment on spillover measures decreases in magnitude during high uncertainty periods. This highlights the importance of considering the market fundamentals themes of sentiments driving the markets, rather than the overall sentiment, when making investment decisions in the NFTs market. Finally, instead of focusing on the overall sentiment index, as was done in previous media-based sentiment studies (Akyildirim *et al*., 2021), we cover a variety of sentiment subjects and identify market-moving themes that need to be followed by the investors to hedge against the potential spillovers in the NFTs market.

The rest of the paper is organised as follows: Section II presents the data and methodology used in the paper. Subsequent to that, Section III delves into a discussion of the results and Section IV provides the concluding remarks.

II. DATA AND METHODOLOGY

A. Dataset

We collect NFT cryptocurrency prices, sentiment, NFT sales in USD, wallet count, US economic policy uncertainty (EPU), and Covid related uncertainty (EMVID) data spanning 1 November 2019 to 30 June 2021. The NFT cryptocurrencies, Theta (THETA), Tezos (XTZ), Chilliz (CHZ), Digibyte (DGB), Enjin (ENJ), Decentraland (MANA), and Wax (WAXP), are selected according to higher market capitalization and more extended data availability in the Coinmarketcap NFT Cryptocurrencies Category to obtain the sample that covers long period with more liquid cryptocurrencies. The daily price data is collected from Coinmarketcap, while NFT sales and wallet data are obtained from Nonfungible database since it provides sub-category data like Sports, Art, Game, Metaverse, unlike the Coinmerketcap.

The NFTs level daily sentiment data is collected from Thomson Reuters Reuters MarketPsych Indices (TRMIs) database, which provides sentiment indices for each NFT using a proprietary system developed by MarketPsych Analytics. The TRMIs database covers 42 NFTs-specific sentiment indices and processes news content from hundreds of media sources to derive these sentiment values. We group these sentiment indices into four types (1) emotional, (2) market fundamentals, (3) risk aspect, and (4) innovation aspect. The individual member of the grouped categories is shown in Table A.1 in Appendix. The emotional sentiment indices provide insight into how people are feeling about NFTs, while market fundamentals sentiment indices give us a better understanding of how NFTs are performing in the market. The risk aspect sentiment indices help us to understand the perceived risks associated with investing in NFTs, and the innovation aspect sentiment indices provide insight into how NFTs are perceived as innovative or disruptive technologies.

The process of calculating sentiment indices starts with the collection of news content related to NFTs from various media sources. MarketPsych Analytics uses Natural Language Processing (NLP) techniques to analyze the text data to determine the tone of the each media content. Once the sentiment of each article has been identified, the system aggregates the sentiment values for all articles related to each NFT to generate a daily sentiment index for that NFT. This index provides a summary of the overall sentiment expressed in the news media about the NFT in question, allowing us to see how public perception of the NFT is changing over time. The analysis of the text data is based on the sentiment lexicon developed by MarketPsych Analytics. This sentiment lexicon is a comprehensive dictionary of words and phrases that are associated with positive, negative, or neutral emotions. The sentiment indices are calculated on a daily basis and are updated continuously as new news content becomes available. This allows the TRMIs database to provide a real-time view of the sentiment towards NFTs, making it a valuable resource for researchers and investors interested in understanding the NFT market.

B. Methodology: Calculation of Spillover Measures

To construct spillover measures, we follow the time-varying parameter vector auto-regressions (TVP-VAR) approach of Antonakakis *et al*. (2020). In particular, the TVP-VAR can be formulated as:

$$z_t = B_t z_{t-1} + u_t, \qquad u_t \sim N(0, S_t) \tag{1}$$

$$\text{vec}(B_t) = \text{vec}(B_{t-1}) + v_t, \qquad v_t \sim N(0, R_t) \tag{2}$$

where z_t, z_{t-1} and u_t are $k\times1$ dimensional vectors and B_t and S_t are $k\times k$ dimensional matrices. $vec(B_t)$ and v_t are $k^2\times1$ dimensional vectors whereas R_t is a $k^2\times k^2$ dimensional matrix. The optimal 1-lag length is selected by the Bayesian information criterion (BIC). Furthermore, we compute the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) and transform the TVP-VAR to its vector moving average (VMA) representation based on the Wold theorem using the following equation: $z_t = \sum_{i=1}^{p} B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j}$. The (scaled) GFEVD normalizes the (unscaled) GFEVD, $\phi_{ij,t}^{g}(H)$, in order that each row adds up to unity. Hence, $\Phi_{ij,t}^{g}(H)$ represents the influence variable j has on variable i in terms of its forecast error variance share which can be defined as:

$$\phi_{ij,t}^{g}(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} \left(\iota_i' A_t S_t \iota_j\right)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} \left(\iota_i A_t S_t A_t' \iota_i\right)} \; \bar{\phi}_{ij,t}^{g}(H) = \frac{\phi_{ij,t}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij,t}^{g}(H)} \tag{3}$$

where $\sum_{j=1}^{k} \tilde{\phi}_{ij,t}^{g}(H) = 1, \sum_{i,j=1}^{k} \tilde{\phi}_{ij,t}^{g}(H) = k$, and ι_i corresponds to a selection vector with unity on the ith position and zero otherwise. Then, we compute the spillover measures using the GFEVD as follows:

$$TO_{j\mathrm{t}} = \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H), \tag{4}$$

$$FROM_{jt} = \sum_{i=1, i \neq j}^{k} \bar{\phi}_{ji,t}^{g}(H), \tag{5}$$

where $\bar{\phi}_{ij,t}^{g}(H)$ represents the impact a shock in variable *j* has on variable *i*. Equation (4) illustrates the aggregated impact of a shock in variable *j* has on all other variables which is defined as total directional connectedness to others, whereas equation (5) indicates the aggregated influence all *other* variables have on variable *j* (*total directional connectedness from others*).

III. MAIN FINDINGS

A. Spillovers in the NFT Market

Table 1 presents the time-averaged values of the spillovers measures "TO" and "FROM" computed from Eqs. (4)-(5). While the shocks from one component of the network to itself are represented by the entries on the diagonal, the numbers on the upper and lower part of the diagonal show the spillovers among the NFT coins. The column *i* in the table displays the impact that a shock in the coin *i* has on the rest of the other coins (rows), described as the directional connectedness to others. The row *j* in the table shows the impact the rest of the variables have on the coin *j*, which is described as the total directional connectedness from others. Table 1 shows that the own-variance shares of shocks do not show significant variation from one coin to another. For instance, looking at the spillovers from Tezos to others, we observe that the highest values are for Digibyte (13.68%) and Decentraland (13.26%). On the other hand, in terms of the spillovers from others to Tezos again, Decentraland (12.96%) and Enjincoin (11.74%) constitute the most significant two. In terms of the aggregated average "TO" measures, which are given as a separate row at the bottom of the table, Tezos, Decentraland, and Enjincoin are ranked top three with values 10.10%, 9.73%, and 9.41%, respectively. On the other hand, Decentraland, Tezos, and Enjincoin are ranked top based on "FROM" measures.

Table 1.
NFTs Market Spillover Measures

This table presents the average values of the "TO" and "FROM" spillover measures calculated between different NFTs. The diagonal elements of the table indicate the spillover values from one NFT to itself, while the off-diagonal elements show the spillovers between different NFTs. The row starting with "TO" at the bottom of the table provides the average of all "TO" measures. The column starting with "FROM" in this table represents the average of the "FROM" measures. Each value in the column represents the average value of the "FROM" measure for a specific cryptocurrency in the network. The intersection of "FROM" and "TO" represents the overall spillover effect.

	Theta	Tezos	Chiliz	Decentraland	Enjincoin	Digibyte	Wax	FROM
Theta	42.83	10.49	11.02	8.45	10.01	8.89	8.31	8.17
Tezos	9.00	36.67	10.31	12.96	11.74	11.22	8.09	9.05
Chiliz	10.10	11.25	38.60	11.75	11.80	7.42	9.08	8.77
Decentraland	7.53	13.26	11.41	36.53	13.39	7.86	10.03	9.07
Enjincoin	9.20	12.30	11.25	13.69	36.76	7.72	9.08	9.03
Digibyte	9.05	13.68	8.43	9.43	8.66	44.69	6.05	7.90
Wax	9.32	9.72	10.73	11.86	10.29	5.99	42.09	8.27
TO	7.74	10.10	9.02	9.73	9.41	7.01	7.23	60.26

Figure 1.
TO and FROM Measures from TVP-VAR Model

This figure presents the results of the TVP-VAR model with a lag length of one, as determined by the Bayesian Information Criterion (BIC). The model was used to examine the total directional connectedness between NFT coins, as measured by the "FROM" and "TO" measures. The figure displays the changes in these measures over time, using a 10-step-ahead generalized forecast error variance decomposition. The aim of the figure is to show how the level of connectedness between NFT coins varies over time, and to provide a visual representation of the results obtained from the TVP-VAR model.

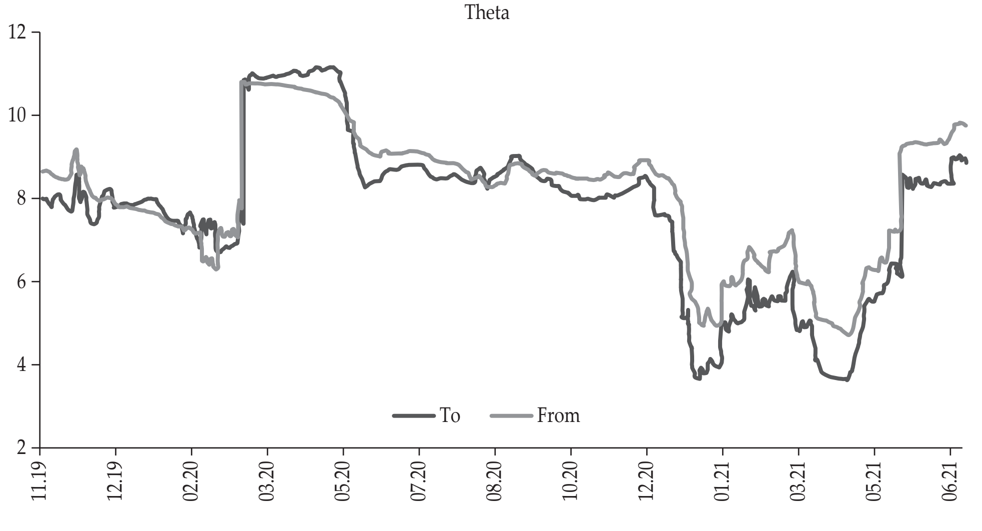

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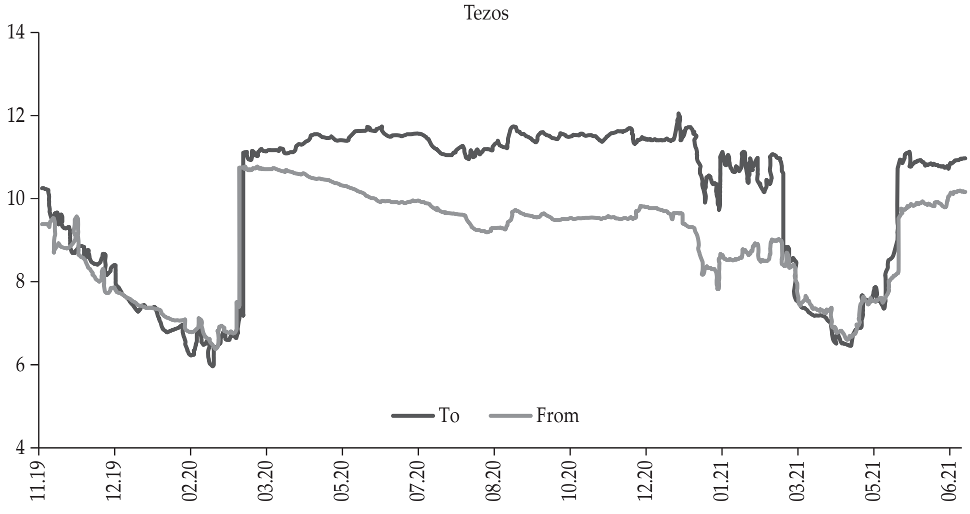
Figure 1.
TO and FROM Measures from TVP-VAR Model (Continued)



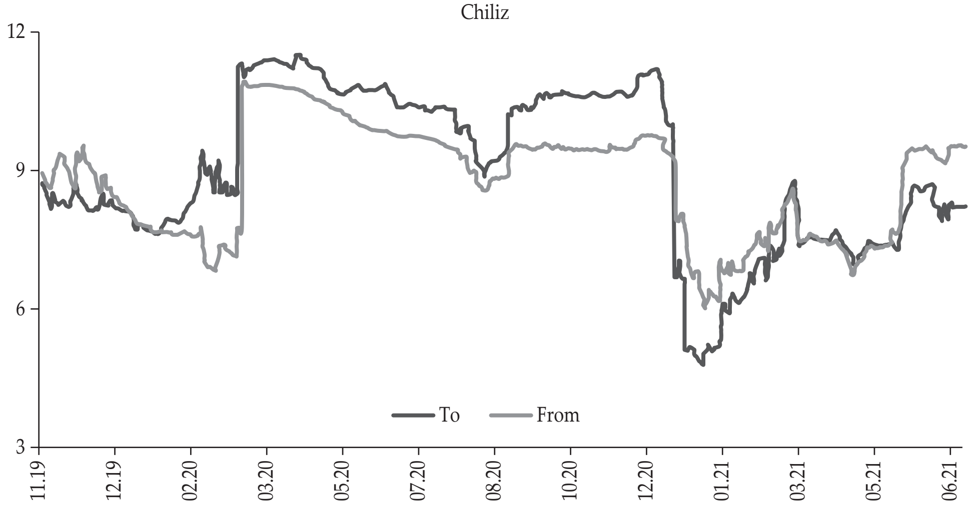
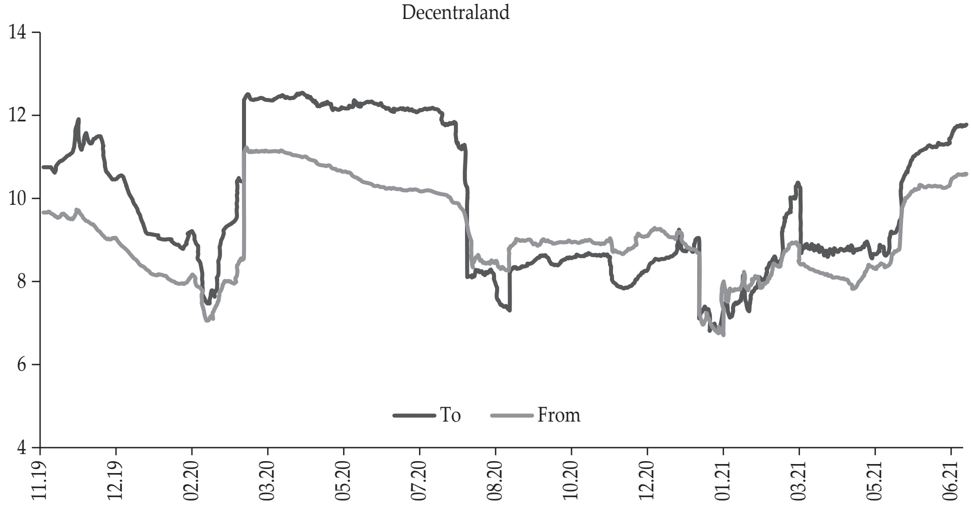


Figure 1.
TO and FROM Measures from TVP-VAR Model (Continued)



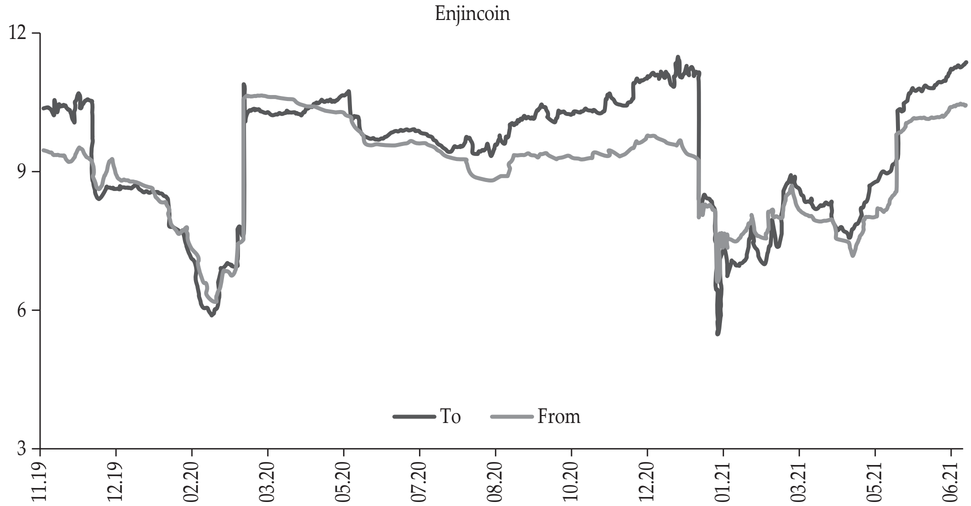
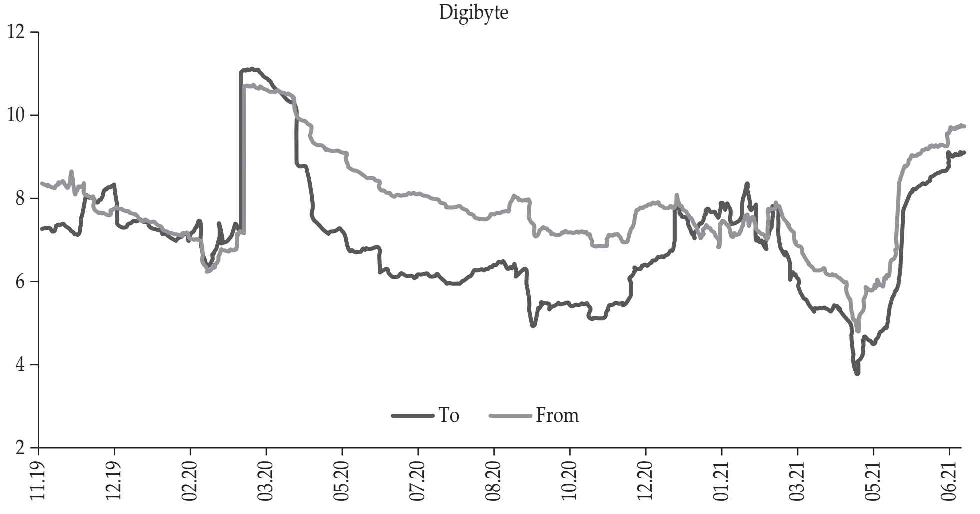


Figure 1.
TO and FROM Measures from TVP-VAR Model (Continued)



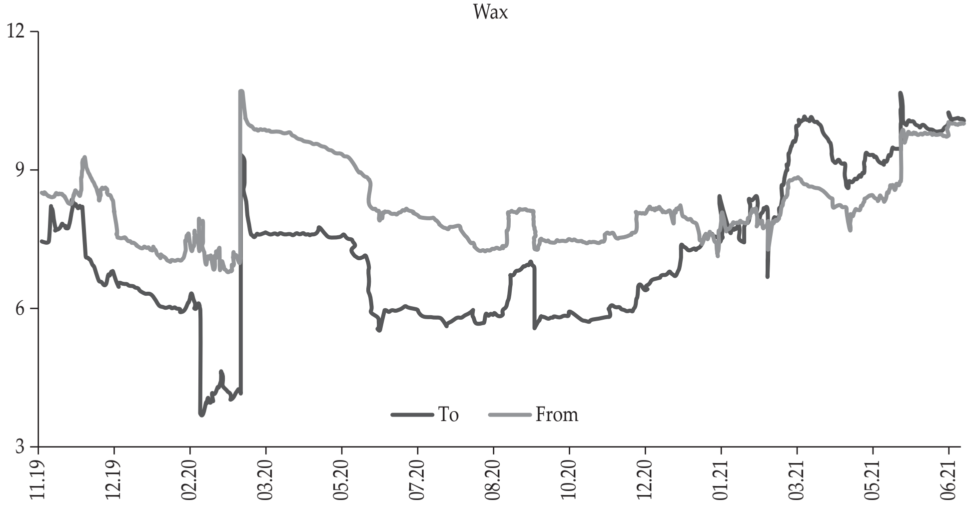


Figure 1 shows the time evolution of spillover measures in the sample period. First, we observe a significant jump both in “TO” and “FROM” measures for all the coins around March 2020, which coincides with the pandemic outbreak around the world. The fast and feverish reaction to the increasing uncertainty at the individual and country levels caused “TO” and “FROM” measures to quickly attain their historical records. It is clear from these figures that up to this black swan event, while both “TO” and “FROM” measures move very close to each other, the difference between “TO” and “FROM” measures spreads out after the pandemic. For instance, although Tezos starts to give more shocks to the system than what it receives, the situation is the opposite for Digibyte. Furthermore, for all the coins except for Wax, “TO” and “FROM” measures reach their lowest points either in January or May of 2021. These periods, in general, coincide with increasing price trends in the cryptocurrency ecosystem. On the other hand, rising values of “TO” and “FROM” measures corresponds to the 30% plunge of Bitcoin prices with a major sell-off in the cryptocurrency markets. This period also coincides with China’s ban on cryptocurrencies. Hence, the individual stories of the different NFT coins gained importance at the heightened tension episodes in the cryptocurrency market. This result is rather expected considering that an NFT coin is acclaimed to be valued based on the changes in the valuation of another activity in either art, games or sports. This result, in a sense, confirms this presumption on the valuing of the NFT coin and linking the value to the real market activities where this NFT coin is prescribed.

Then, the next question comes if the NFT coins are valued not on overall speculative trends in the cryptocurrency market but on the individual stories of each NFT coin matter. How do we approach understanding the stories of each coin? The following section attempts to uncover each of these individual stories from a sentiment analysis perspective.

Indeed, this approach is more meaningful considering that what matters is not the stories attempted to be generated by the issuers of each coin but how these stories are perceived in the market. In a sense, each NFT coin-specific sentiment data serve for this purpose. It captures the reflections of each coin‘s stories in the market. Furthermore, sentiments in each coin reflect the narratives attempted to be generated by the owners of each coin and all the other discursive and emotional activities taking place in the market through the interactions of all players in the market. Hence, the sentiments measured through social media and other media channels are like the final outcome of all these relatively invisible transactions in the market. In other words, the sentiments data is making the invisible hand of the market visible for the analysis. Therefore, our coin-specific TRMI sentiment data set makes a big difference due to portraying a more complete picture for each NFT coin, where individual coin-specific sentiments should matter even more due to the nature of NFT coins.

B. Does the Sentiment Drive the Returns Spillovers of NFT Market?

We now focus on how sentiment indices derived from media content relate to the degree to which the NFT market is interconnected. Considering that investors can trade in a range of different cryptocurrencies at once, even on various cryptocurrency exchanges, this provides the rationale for exploring the relationship between sentiment and return spillovers in the NFT market. To evaluate this hypothesis, we use the following panel regression model:

$$\text{Spillover}_{\text{it}} = \alpha_i + \beta \text{ Sentiment}_{it} + \gamma X_t + \epsilon_{it} \qquad (6)$$

where Spillover_{it} alternatively represents spillover measures of *TO* or *FROM* computed by using the Eq.(4) and Eq.(5), respectively. X_t consists of control variables introduced in Section II.

Table 2 presents the results from estimation of Equation (6). The findings show that the estimated coefficient β is negative and statistically significant at the 5%, 10% level for *FROM* and *TO*. Moreover, its effect remains significant, even after control ling the NFT market and uncertainties related to economic policy and COVID-19. Hence, the estimation results show that an increase in NFT sentiment has a negative effect on the return spillovers of NFT coins and suggest that individual stories about the NFT market may lead to decreased connections between different NFT coins. In this context, return spillovers refer to the impact that changes in the return of one NFT coin have on the returns of another NFT coin.

Table 2.
Sentiment and Return Spillovers in the NFT Market

This table shows the results for the panel regression that is represented in equation (6) with directional spillover measures (either FROM or TO) as dependent variable. ∗∗∗, ∗∗ and ∗ indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are shown in parentheses.

Variables	**FROM (1)**	**FROM (2)**	**TO (3)**	**TO (4)**
Sentiment	-0.336***	-0.348***	-0.563***	-0.575***
	(0.0933)	(0.0851)	(0.133)	(0.128)
Total NFT USD	0.417***		0.417***	
	(0.0387)		(0.0545)	
Art USD		-0.246***		-0.245***
		(0.0167)		(0.0257)
Game USD		-0.377***		-0.377***
		(0.0210)		(0.0311)
Metaverse USD		-0.0901***		-0.0913***
		(0.0165)		(0.0265)
Sport USD		0.0690***		0.0683***
		(0.0118)		(0.0178)
Wallet	-0.726***	0.847***	-0.733***	0.841***
	(0.0527)	(0.0561)	(0.0768)	(0.0859)
USEPU	0.593***	0.513***	0.597***	0.515***
	(0.0433)	(0.0418)	(0.0591)	(0.0584)
EMVID	0.128***	0.146***	0.126***	0.146***
	(0.0257)	(0.0265)	(0.0360)	(0.0375)
Constant	7.159***	6.324***	7.229***	6.394***
	(0.365)	(0.336)	(0.554)	(0.536)
Observations	4,256	4,256	4,256	4,256
Adj. R^2	0.338	0.436	0.418	0.456

There could be several explanations for the negative reaction of return spillovers to sentiment. One possible explanation is that increased sentiment in the NFT market can lead to increased media attention and public interest, resulting in an influx of new investors and increased demand for certain NFT coins. This increased demand can drive up the value of those NFT coins, leading to decreased connections and decreased spillovers with other NFT coins in the market.

A second possible explanation is that increased sentiment in the NFT market can lead to increased speculation and hype. When speculation and hype drive up the value of certain NFT coins, they may become over-valued and disconnected from their underlying assets and value. This can lead to decreased connections and spillovers with other NFT coins in the market.

As NFTs are like collectible items such as art, sports memorabilia, and Pokémon cards, their value might fluctuate based on demand for each specific digital collectible, which is dependent on the individual story behind it. The value of an NFT is based on the value that the collector places on that item, leading to heterogeneous price movements. Given the many different types of NFTs available, with varying utility to different individuals, changes in the sentiment of a specific NFT can rapidly affect its pricing and lead to extraordinary price movements in the corresponding NFT.

The results of the study further confirm that the USD values of NFT coins play a significant role in affecting return spillovers. The total value of NFT coins, as measured by the Total NFT USD variable, has a negative impact on both FROM and TO spillovers. This robustness of the results is checked by estimating the equation (6) using the number of NFT sales instead of the dollar amount of NFT sales, as reported in Table A.2. The results show that the findings are robust to different measures of NFT market activity.

Moreover, when the USD values of NFT coins in different categories such as art, sport, game, and metaverse are controlled separately, it is found that the coefficient of sports coins has a highly significant impact on increasing spillovers. On the other hand, the values of other NFT types (art, sport, and metaverse) reduce spillovers. This highlights the unique impact that various categories of NFT coins have on return spillovers.

C. Effect of Sentiment During High Uncertainty Periods

Considering that uncertainties related to economic policy and COVID-19 can vary substantially over time, we now examine how the effect of sentiment changes across the different regimes of uncertainty. Hence, we first create two dummy variables based on the median values of the uncertainty indices. In particular, l^{High} is the dummy variable equal to 1 for the periods when uncertainty level above the median, whereas l^{Low} takes the value of 1 for periods when uncertainty level below the median. Subsequently, we run the following panel regression:

$$\text{Spillover}_{\text{it}} = \alpha_i + B_H \text{ Sentiment}_{it} \times l^{\text{High}} + B_l \text{ Sentiment}_{it} \times l^{\text{Low}} + \gamma X_t + \epsilon_{it} \quad (7)$$

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where I^{High} and I^{Low} dummy variables alternatively represent the periods of high and low uncertainties for EPU and COVID-19.

Table 3 presents the findings of our analysis of the relationship between sentiment and return spillovers in the NFT market during low and high uncertainty periods. We discovered that there is only a statistically significant correlation between sentiment and return spillovers during low uncertainty periods. The heightened uncertainty in the market due to factors such as Economic Policy Uncertainty (EPU) or the COVID-19 pandemic appear to limit the impact of sentiment on return spillovers in the NFT market. This might be because NFT investors tend to move towards safe haven cryptocurrencies such as Bitcoin or Ethereum during periods of high uncertainty, which weakens the correlation between sentiment and return spillover measures (Corbet *et al*., 2020). Hence, the relation of sentiment and return spillover measures weaken among NFTs, indicating that the degree of connectedness in the NFT markets depends on the level of uncertainty.

Table 3.
The Relation of Sentiment and NFT Market in High Uncertain Periods

This table shows the results for the panel regression that is represented in equation (7) with directional spillover measures (either FROM or TO) as dependent variable. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are shown in parentheses.

Variables	**FROM (1)**	**FROM (2)**	**TO (3)**	**TO (4)**
Sentiment * High EPU	0.311	0.159		
	(0.217)	(0.518)		
Sentiment * Low EPU	-0.743***	-1.026***		
	(0.0886)	(0.151)		
Sentiment * High EMVID			-0.164	-0.342
			(0.184)	(0.419)
Sentiment * Low EMVID			-0.488***	-0.752**
			(0.109)	(0.215)
Total NFT USD	0.568***	0.567	0.326*	0.328
	(0.140)	(0.405)	(0.135)	(0.382)
Wallet	-1.053***	-1.054	-0.594**	-0.604
	(0.261)	(0.643)	(0.222)	(0.533)
EMVID	0.366***	0.361**		
	(0.0445)	(0.115)		
USEPU			0.722***	0.719**
			(0.0825)	(0.213)
Constant	10.83***	10.88***	6.567***	6.678***
	(1.218)	(2.803)	(0.721)	(1.656)
Observations	4,256	4,256	4,256	4,256
Adj. R^2	0.307	0.407	0.335	0.417

D. Which Topics of News-Media Sentiment do Influence the NFT Return Spillovers?

Instead of focusing just on the overall sentiment index, as was done in previous media-based sentiment studies, we now cover a variety of sentiment subjects. It is possible to determine which individual sentiment themes influence the market by looking at the sentiment breakdown based on the underlying indices. We modify our panel regression as the following:

$$\text{Spillover}_{\text{it}} = \alpha_i + \beta \text{ SentimentTopics}_{it} + \gamma X_t + \epsilon_{it} \tag{8}$$

where $\text{SentimentTopics}_{it}$ alternatively represents 42 different sentiment topics covering a wide variety of thematic indices, including 1) emotional themes such as optimism, pessimism, joy, anger ; 2) market fundamentals such as market risk, price forecast, volatility, price momentum; 3) innovative aspects such as code upgrade, in- novation, developer sentiment ; and 4) risks such as attack, scam, criminal activity, regulatory crackdown. X_t consists of control variables introduced in Section II.

Table 4 provides the results of estimating equation (8) in our study, which explores the relationship between investor sentiment and the return spillovers of NFTs. Our findings reveal important insights into the impact of investor sentiment on NFT returns. Firstly, we observe that in most cases, investor sentiment related to the fundamentals of the NFT market has a significant impact on return spillovers among NFTs. This aligns with previous studies that have shown that the prices of cryptocurrencies are influenced by their underlying fundamentals, such as network size and the adoption of the blockchain (Liu and Tsyvinski, 2021). Additionally, our use of TRMIs (Topic-specific Return Spillover Indices) is valuable in capturing sentiment related to market fundamentals, which is likely to precede trading decisions.

Table 4.
The Importance of Sentiment Topics

This table shows the results for the panel regression that is represented in equation (8) with directional spillover measures (either FROM or TO) as dependent variable. Our independent variables are sentiment topics and control variables. For simplicity, we do not show the estimation results of control variables in the table. ∗∗∗, ∗∗ and ∗ indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are shown in parentheses.

Variables	**FROM**		**TO**	
Emotional	**Coefficient**	**Adj. R2**	**Coefficient**	**Adj. R2**
optimism	-0.304	0.336	-0.388	0.416
joy	-0.879*	0.337	-0.832	0.416
loveHate	-1.088*	0.337	-1.247	0.416
trust	-0.230	0.336	-0.784	0.416
anger	-0.353	0.336	0.266	0.416
conflict	0.457*	0.336	0.234	0.416
fear	0.272	0.336	0.415	0.416
gloom	1.684***	0.337	2.204***	0.416
stress	0.250	0.336	-0.478	0.416
surprise	-0.320	0.336	-0.893*	0.416
emotionVsFact	-0.0827	0.336	-0.142*	0.416

Table 4.
The Importance of Sentiment Topics (Continued)

Variables	FROM		TO	
Emotional	**Coefficient**	**Adj. R2**	**Coefficient**	**Adj. R2**
Market Fundamentals				
priceDirection	-0.517***	0.338	-1.214***	0.421
priceForecast	-0.0297	0.336	-0.115	0.416
volatility	0.700*	0.337	1.437***	0.417
priceMomentum	-1.336**	0.337	-2.912***	0.417
marketRisk	-1.029***	0.339	-2.112***	0.421
longShort	-0.392*	0.337	-0.836***	0.417
longShortForecast	-0.776	0.336	-1.435	0.416
adoption	-0.665***	0.336	-1.484***	0.416
adoptionForecast	-6.162**	0.337	-6.693*	0.416
fOMO	-13.59**	0.337	-20.36**	0.417
hodl	-0.876	0.336	-2.303**	0.416
Innovative Aspect				
innovation	-1.433*	0.336	-2.025	0.416
codeSentiment	-0.722	0.336	-1.992	0.416
codeUpgrade	-1.211	0.336	-1.726	0.416
developerSentiment	1.006	0.336	0.237	0.416
transactionSpeed	-0.625	0.336	-0.169	0.416
anonymity	0.603	0.336	1.284	0.416
fork	7.568	0.336	12.92	0.416
forkForecast	22.37**	0.336	41.19***	0.416
timeUrgency	-0.326	0.336	-0.849**	0.417
Risk Aspect				
regulatoryCrackdown	1.943	0.336	6.059	0.416
regulatoryIssues	-2.469	0.336	-0.422	0.416
litigation	2.179*	0.336	3.458*	0.416
scam	-0.917	0.336	2.680	0.416
majorityAttack	4.786**	0.336	10.81***	0.416
criminalActivity	-1.580	0.336	-0.117	0.416
attack	17.33**	0.336	18.90	0.416
noobs	-2.443***	0.337	-3.220***	0.416
vulnerability	7.593	0.336	6.917	0.416
violence	-0.731	0.336	-0.513	0.416
uncertainty	-0.697	0.337	-1.566**	0.417

It is crucial for NFT investors to focus on the market fundamental themes driving the NFT market instead of relying solely on overall sentiment. This is because market responses to sentiment topics significantly affect price movements and can have a meaningful impact on the returns of NFT investments. Therefore, our findings highlight the importance of considering market fundamentals when investing in NFTs.

IV. CONCLUSION

Our results show that NFT coin-specific individual sentiments matter for spillovers in the NFT market. The effects of sentiments on spillovers also vary with respect to the uncertainty levels in the market. Most importantly, our paper empirically concludes that NFT investors need to concentrate on the market fundamentals themes of sentiments driving the markets rather than the overall sentiment measure. Return spillover calculation shows that after the COVID-19 outbreak and during elevated tensions in the cryptocurrency market, FROM and TO spillovers start reflecting the increasing standing of individual stories for each NFT coin. Our results also show that the sentiments negatively and significantly affect the FROM and TO spillovers. This effect remains significant, even after controlling the NFT market and uncertainties related to economic policy and COVID-19. We find a statistically significant relation between sentiments and return spillover measures only in low uncertainty periods, implying that the heightened uncertainty due to EPU or COVID limits the effect of sentiment on return spillovers in the NFT market. We also cover a variety of sentiment subjects to determine which particular sentiment themes influence the market by looking at the sentiment breakdown based on the underlying indices.

Additionally, our findings could be valuable for policymakers and regulators who are looking to manage financial stability risks posed by cryptocurrency markets. Our study provides insights into the spillover effects of cryptocurrency markets, which could help regulators and policymakers in making informed decisions to ensure financial stability. Moreover, the results of our study may also serve as a starting point for policymakers and regulators to develop regulations and policies that can better mitigate the potential spillover risks posed by cryptocurrency markets.

In future research, we aim to further investigate the impact of various sentiments on the cryptocurrency markets. Our goal is to better understand the underlying drivers of sentiment in the cryptocurrency markets and how these drivers influence market outcomes. This can be achieved by conducting a more in-depth sentiment analysis, which could provide valuable insights into the market's underlying dynamics and help to make the "invisible hand" of the market more visible. Through this, we aim to contribute to the ongoing research on cryptocurrency markets and provide policymakers and regulators with valuable insights that can help them address financial stability issues.

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Appendix

Table A.1.
Classification of the TRMIs

This table shows the multi-dimensional sentiment data that is grouped in four different categories: (1) emotional, (2) market fundamentals, (3) risk aspect, and (4) innovation aspect. The individual member of the grouped categories is shown in the Table. The emotional sentiment indices provide insight into how people are feeling about NFTs, while market fundamentals sentiment indices give us a better understanding of how NFTs are performing in the market. The risk aspect sentiment indices help us to understand the perceived risks associated with investing in NFTs, and the innovation aspect sentiment indices provide insight into how NFTs are perceived as innovative or disruptive technologies.

Emotional	Market Fundamentals	Innovative Aspect	Risks Aspect
optimism	price direction	innovation	regulatory crackdown
joy	price forecast	code sentiment	regulatory issues
loveHate	volatility	code upgrade	litigation
trust	price momentum	developer sentiment	scam
anger	market risk	transaction speed	majority attack
conflict	long-short	anonymity	criminal activity
fear	long-short forecast	fork	attack
gloom	adoption	fork forecast	noobs
stress	adoption forecast	time urgency	vulnerability
surprise	FOMO		violence
emotion vs. fact	hodl		uncertainty

Table A.2.
Sentiment and Return Spillovers in the NFT Market - Number of NFT Sales

This table shows the results for the panel regression that is represented in equation (6) with directional spillover measures (either FROM or TO) as dependent variable. We also replace the US amount of NFT sales with number of NFT sales. ∗∗∗, ∗∗ and ∗ indicate significance at the 1%, 5% and 10% levels, respectively. Robust standard errors are shown in parentheses.

Variables	**FROM (1)**	**FROM (2)**	**TO (3)**	**TO (4)**
Sentiment	-0.336***	-0.318***	-0.563***	-0.546***
	(0.0933)	(0.0924)	(0.133)	(0.132)
Total NFT Number	0.417***		0.417***	
	(0.0387)		(0.0545)	
Art NFT Number		-0.256***		-0.254***
		(0.0283)		(0.0416)
Game NFT Number		-0.114***		-0.114***
		(0.0227)		(0.0312)
Metaverse NFT Number		-0.0604***		-0.0602**
		(0.0163)		(0.0241)
Sports NFT Number		-0.175***		-0.175***
		(0.0170)		(0.0256)
Wallet	-0.726***	0.314***	-0.733***	0.303***
	(0.0527)	(0.0669)	(0.0768)	(0.0973)
USEPU	0.593***	0.675***	0.597***	0.677***
	(0.0433)	(0.0443)	(0.0591)	(0.0605)
EMVID	0.128***	0.177***	0.126***	0.176***
	(0.0257)	(0.0270)	(0.0360)	(0.0394)
Constant	7.159***	5.702***	7.229***	5.783***
	(0.365)	(0.418)	(0.554)	(0.611)
Observations	4,256	4,256	4,256	4,256
Adj. R^2	0.338	0.349	0.418	0.422

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