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The Return and Volatility Connectedness of NFT Segments and Media Coverage: Fresh Evidence Based on News About the COVID-19 Pandemic

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ARTICLE INFO
JEL Classification:
C5
F3
G10
G12
Keywords:
connectedness
COVID-19
non-fungible tokens (NFT)
spillover
media coverage

ABSTRACT
We study the relationship between return and volatility of non-fungible tokens (NFT) segments and media coverage during the outbreak of the COVID-19 pandemic in a connectedness framework. We document media coverage as a net transmitter of spillover for both the return and volatility of NFT segments. We find that NFTs representing the Utilities segment is a major transmitter of spillover. Our findings have important implications for portfolio managers, regulators, and policymakers.

1. Introduction

NFTs (non-fungible tokens) are digital asset rights that are stored on the blockchain with a distinct identifier and metadata that distinguishes them from others. They may take the form of an image, song, movie, a coded piece of virtual land, or a virtual trade card. NFTs are widely traded on the internet; furthermore, the blockchain cryptographically validates each NFT, thus ensuring that the owner is always known due to its ownership record on a digital ledger (Dowling, 2020). The term “NFT” has garnered a lot of attention over the past couple of years (as per Google Trends1). Subsequently, there has been a significant increase in interest for NFTs in the

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1 https://trends.google.com/trends/explore?date=today%205-y&geo=US&q=nft.
This spectacular rise of NFTs as an asset class is attracting attention from practitioners and academics, and is exacerbated by the peculiar situation that the global financial markets are experiencing due to the ongoing pandemic. Since the start of the COVID-19 pandemic, the literature on the implications of the pandemic on financial contagion and asset allocation has been rapidly expanding (Umar and Gubareva, 2021) (Umar et al., 2021). The COVID-19 pandemic has been in the news constantly throughout the world on both traditional and social media. According to Huynh and Frijns (2018), the frequent news flow improves investors’ asset allocation. Furthermore, during periods of market stress, investors intensify their quest for assets that can preserve their wealth (Spierdijk & Umar, 2015). Thus, the rise of NFTs during this unprecedented economic climate presents an interesting opportunity to investigate the impact of media coverage on asset prices.

Despite the growing popularity and increased media attention, no previous study has examined the return and volatility connectedness of NFTs and media coverage. In this study, we provide the first exploration of both the return and volatility connectedness of NFTs and media coverage—specifically during the COVID-19 pandemic. Therefore, we add to this nascent strand of literature by investigating the impact of media coverage on the NFT market segments. Earlier papers have analyzed the overall NFT

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Fig. 1. Return Graphs. This figure shows the time series of NFT returns and MCI series.

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1 https://www.bloomberg.com/news/articles/2022-01-06/nft-market-surpassed-40-billion-in-2021-new-estimate-shows.
market and its relationship with other asset classes. However, to the best of our knowledge, this is the first study to analyze the impact of media coverage on the various segments of NFT markets.

We employ five major NFT segments: Art, Collectibles, Games, Metaverse, and Utilities and the Media Coverage Index (MCI), which is a widely used proxy for pandemic-related news and concerns.

Our findings show an increase in return and volatility connectedness, thus indicating that NFT segments are particularly susceptible to the increasing flow of news related to the COVID-19 pandemic. Our time-varying analyses show that Metaverse and Collectibles are the net receivers of return spillover; meanwhile, Art is a net receiver of volatility spillover across the network. MCI, on the other hand, appears to be a network-wide net return and volatility transmitter.

The remainder of the paper is presented as follows. The data and methodology are explained in Section 2. The results are presented in Section 3. Finally, Section 4 concludes the paper.

2. Data and Methodology

2.1. Data

We study the return and volatility connectedness between five main segments of NFTs (Art, Collectibles, Games, Metaverse, and Utilities), as well as the RavenPack Media Coverage Index (MCI). Our sample ranges from January 1, 2020, to December 31, 2021, and is motivated by the availability of the MCI data. Fig. 1 displays the graphs of the series employed; meanwhile, Table 1 depicts the main statistical characteristics of our study sample. Among the NFT segments, Collectibles (1.56%) have the highest average return, followed by Art (1.24%), Metaverse (1.11%), Utilities (1.01%), and Games (0.46%). Table 2 indicates that the overall correlation is low among sample variables and that the highest correlation is between Art and Collectibles (0.18), followed by Collectibles and Utilities (0.17). Table 2 also indicates that MCI has a very low correlation with all the NFTs.

2.2. Methodology

We use the TVP-VAR-based connected approach of Antonakakis et al. (2018). This approach extends the seminal Diebold and Yilmaz’s (2014) dynamic connectedness framework by employing the TVP-VAR framework of Koop and Korobilis (2014). This approach is particularly suitable for relatively short periods and is widely used in similar contexts (Aharon & Demir, 2021; Umar et al., 2021a).

Table 1

| Art   | Collectibles | Games  | Metaverse | Utilities | MCI |
|-------|--------------|--------|-----------|-----------|-----|
| Mean  | 1.24%        | 1.56%  | 0.46%     | 1.11%     | 1.01%| 6648.12% |
| Median| 0.66%        | 0.43%  | 0.16%     | 0.50%     | -0.38%| 7080.00% |
| Maximum| 80.40%      | 178.38%| 224.54%   | 150.94%   | 234.48%| 8295.00% |
| Minimum| -107.05%    | -95.14%| -148.94%  | -129.55%  | -171.96%| 20.00% |
| Std. Dev.| 15.16%      | 20.44% | 21.28%    | 23.00%    | 29.02%| 1405.69% |
| Skewness| 0.07        | 1.84   | 1.36      | 0.94      | 1.04 | -2.79 |
| Kurtosis| 12.68       | 19.62  | 38.16     | 13.26     | 18.99| 12.08 |
| Observations| 522        | 522    | 522       | 522       | 522 | 522 |

This table reports the sample statistics of the NFT returns and MCI.

Table 2

| Art | Collectibles | Games | Metaverse | Utilities | MCI |
|-----|--------------|-------|-----------|-----------|-----|
| Art | 1.00         |       |           |           |     |
| Collectibles | 0.18 | 1.00 |           |           |     |
| Games | 0.07 | 0.12 | 1.00      |           |     |
| Metaverse | 0.14 | 0.14 | 0.02      | 1.00      |     |
| Utilities | 0.06 | 0.17 | 0.00      | -0.03     | 1.00 |
| MCI | 0.02         | 0.04  | 0.02      | -0.03     | 0.00| 1.00 |

This table reports the correlation matrix of NFT returns and MCI.

3 Please see Cepoi, 2020; Umar et al., 2021; Akhtaruzzaman et al., 2022.
4 The RavenPack MCI is based on the ratio of news sources via social media to all news sources covering the COVID-19 pandemic. In this way, the MCI encapsulates the dynamic of coronavirus knowledge among investment agents, and so depicts COVID-19 advances and ramifications on societal morality and mental health. The Media Coverage Index (MCI) ranges from zero to one hundred, with one hundred representing the most complete COVID-19 media coverage.
5 We source the media coverage data from RavenPack (https://www.ravenpack.com/blog/coronavirus-new-monitor/) and for NFTs data from https://nonfungible.com/.
Table 3 shows the static analysis of the return series of NFTs segments and MCI. The term “From” in the last column denotes spillover from the network of all other variables to the variable. Spillover from each variable to the network of all other variables is shown in the third last row by the term “TO others.” The term “NET” in the last row denotes the net directional spillover of each variable. The total connectedness index of the network of all variables is indicated by the bold term “TCI” in the bottom right corner.

We use a TVP-VAR(p) model:

\[ Z_t = a_t Z_{t-1} + \varepsilon_t; \quad F_{t-1} \sim N(0, A_t), \]  \( a_t = a_{t-1} + \mu_i; \quad \mu_{t-1} \sim N(0, B_t), \]

where \( Z_t \) represents \( N \times 1 \)-dimensional vector, \( F_{t-1} \) is the array of data accessible at time \( t-1 \). \( Z_{t-1} \) represents the \( N_p \times 1 \)-lagged array of dependent parameters. \( a_t \) represents \( N \times Np \)-matrix of time-varying coefficients. \( \varepsilon_t \) and \( \mu_t \) stand for \( N \times 1 \)-dimensional arrays of error terms. \( A_t \) and \( B_t \) stand for \( N \times N \) and \( N_p \times N_p \) variance-covariance matrices for \( \varepsilon_t \) and \( \mu_t \), respectively. After estimating the TVP vector-autoregressive model, the time-varying-parameter vector-autoregressive model needs to be transformed to its vector moving averages. According to Diebold and Yilmaz (2014), the main foundations of the connectedness indices are the time-varying parameters of vector moving averages (VMA). Both the generalized impulse response function (GIRF) and the generalized forecast-error variance decomposition (GFEVD) concepts were proposed by Koop et al. (1996) and Pesaran and Shin (1998), respectively; furthermore, the Diebold and Yilmaz’s (2014) connectedness approach is based on them. As a result, Eq. (1) is transformed as follows:

\[ Z_t = a_t Z_{t-1} + \varepsilon_t = Y_t, \]

where \( Y_t = (Y_{1,t}, Y_{2,t}, \ldots, Y_{p,t})^T \) is an \( N \times N \)-dimensional matrix such as \( Y_{i,t} = \sum_{k=1}^{p} a_{i,j} Y_{j,t-k} \) if \( i \neq 0 \), and is \( I_N \) otherwise. Therefore, the GIRF explains how all parameters react to a change in parameter \( i \). The GFEVD, \( \theta^{j}_{i,t}(J) \), represents the \( j \)-to-\( i \) directional connectedness. It represents the influence of parameter \( j \) on parameter \( i \). The forecast-error variance can be expressed as follows:

\[ \psi^{j}_{i,t}(J) = \frac{\sum_{k=1}^{t-1} \theta^{j}_{i,t}}{\sum_{k=1}^{t} \theta^{j}_{i,t}} , \]

In Eq. (3), \( \psi^{j}_{i,t}(J) \) represents the part, which is the variance in one parameter exercised across other parameters, \( \theta^{j}_{i,t}(J) = A_{j,t}^{-\frac{1}{2}} Y_{j,t} A_{i,t}^{\frac{1}{2}} \psi_{ij,t}(J) \) and \( \sum_{j=1}^{N} \theta^{j}_{i,t}(J) = 1 \) and \( \sum_{j=1}^{N} \psi_{ij,t}(J) = N \).

The total connectedness index (TCI) is given by:

\[ H^{i}_{i}(J) = \frac{\sum_{i=1}^{N} \psi_{ij,t}(J)}{N} \times 100. \]

The spillover that a parameter \( i(j) \) receives from a parameter \( j(i) \) can be given as:

\[ H^{i}_{i,j}(J) = \frac{\sum_{i=1}^{N} \psi_{ij,t}(J)}{\sum_{j=1}^{N} \psi_{ij,t}(J)} \times 100. \]

\[ H^{i}_{i,j}(J) = \frac{\sum_{i=1}^{N} \psi_{ij,t}(J)}{\sum_{j=1}^{N} \psi_{ij,t}(J)} \times 100. \]

Finally, we can calculate a net connectedness, which is just an effect of parameter \( i \) on all the variables as:

\[ H^{i}_{i}(J) = H^{i}_{i,j}(J) H^{i}_{i,j}(J). \]

If \( H^{i}_{i}(J) > 0 \), the parameter \( i \) is a transmitter; whereas if \( H^{i}_{i}(J) < 0 \), the parameter \( i \) is a receiver of spillover. Fig. 2.
3. Results

3.1. Average Connectedness Analysis

Tables 2 and 3 report the average connectedness of the MCI and return and volatility of NFT segments, respectively. We notice that Table 4 shows the static analysis of the volatility series of NFTs segments and MCI. The term “From” in the last column denotes spillover from the network of all other variables to the variable. Spillover from each variable to the network of all other variables is shown in the third last row by the term “TO others.” The term “NET” in the last row denotes the net directional spillover of each variable. The total connectedness index of the network of all variables is indicated by the bold term “TCI” in the bottom right corner.

![Graph showing pairwise connectedness of NFT Returns and MCI]

**Fig. 2.** Pairwise Connectedness of NFT Returns and MCI. This figure shows the pairwise connectedness of the returns of NFT segments and MCI. The red color signifies the highest net transmitter (base of the arrow) in Table 3, whereas blue lines signify the highest net recipient (edge of the arrow) in Table 3. The grey color is for other variables.
the overall connectedness of volatility (11.20%) is slightly higher than the returns (8.23%), thus implying a higher volatility dependence. We notice that MCI, Utilities, and Art are net remitters of return spillover; on the other hand, MCI and Utilities are the net transmitters of volatility spillover. In particular, the magnitude of the net transmission value for MCI is sizably high for the volatility spillover.

Fig. 2 and Fig. 3 display the pairwise spillover for MCI and return and volatility of NFT segments, respectively. We notice that MCI is a transmitter of spillover to all NFT segments for both return and volatility. Among the NFT segments, Utilities is a prominent transmitter to all other segments; meanwhile, Collectibles and Metaverse are the main recipients of spillover from other NFT segments for both return and volatility.

3.2. Time-Varying Connectedness

The total return and volatility spillover plots for total connectedness for NFT segments and MCI are shown in Fig.s 4 and 5, respectively. The return and volatility spillovers were higher (around 16%) during the first quarter of 2020, coinciding with the outbreak of the COVID-19 pandemic. The overall return and volatility spillovers dropped around 10% after the first quarter and remained at the same level until the end of 2020. However, in the first half of 2021, the return and volatility connectedness of NFT segments and MCI increased by 17% and 25%, respectively. This period coincides with a $2.5 billion record trade of NFTs and the $69 million sales of an NFT titled “Everydays: The First 5,000 Days” by digital artist Beeple in March 2021, as well as the start of the third wave of COVID-19 in the early months of that year. According to a UNICEF report\(^6\), not only has media coverage increased during the third wave, but people’s trust in the media has risen as well (compared to the first and second waves). Following this finding, the

\(^6\) [https://www.unicef.org/georgia/media/4736/file/COVID-19-Study-Analytical-Report-1-st-2nd-and-3rd-waves-Eng.pdf](https://www.unicef.org/georgia/media/4736/file/COVID-19-Study-Analytical-Report-1-st-2nd-and-3rd-waves-Eng.pdf).
The overall return and volatility spillovers both fell by around 10% and remained at the same level until the end of 2021.

The overall return and volatility patterns are in line, as seen in Fig. 4 and 5. The increased return and volatility connectedness are recorded during the first and third waves of the COVID-19 outbreak-related concerns, which led to lockdowns in multiple countries. These findings also suggest that all NFTs are extremely interconnected and respond to news about the pandemic’s spread.

Next, we discuss the transmitters and recipients of spillover in a time-varying setting reported in Fig. 6 (return) and Fig. 7.
(volatility). Positive (negative) values in Figs 6 and 7 represent periods when a variable serves as a transmitter (recipient) of spillover to (from) all other variables. The net directional connectedness of the returns series is shown in Fig. 6. Both MCI and Utilities are consistently the largest net transmitters across the network, emphasizing MCI’s role in promoting the spread of financial contagion. Metaverse and Collectibles, on the other hand, appear to be the largest net receivers across the network for most of the sample span; this confirms that these two NFTs were the most impacted by the pandemic.

Similarly, the net total directional connectedness of the volatility series in Fig. 7 shows that MCI is the largest net transmitter across the network. Meanwhile, Art appears to be the largest net receiver across the network for the majority of the sample time, particularly during the first wave of the pandemic. The other NFT segments appear to be both net transmitter and receiver during the overall span.

Fig. 6. Net Directional Connectedness of NFT Returns and MCI. This figure shows the time-varying net directional spillover from each of the returns of NFT segments and MCI to all other variables.
of the analysis. Lastly, Fig. 8 shows the time-varying spillover from MCI to NFT segments. We notice a sizable spillover from MCI to both return and volatility of NFT segments, thus underscoring the importance of media coverage.\footnote{We conducted a robustness analysis of our results by employing the Daily Infectious Disease Equity Market Volatility Tracker (available at http://www.policyuncertainty.com/infectious_EMV.html) as an alternative proxy for media coverage. Our results are qualitatively similar to the results reported with MCI as a proxy for media coverage. However, to conserve space, we do not report these results here. We acknowledge an anonymous referee for this useful comment.}

Overall, we gain important insights from the total net directional return and volatility connectedness analyses in Figs. 6 and 7, respectively. The net directional return and volatility transmission and reception are higher during the first and third waves of the COVID-19 outbreak. However, the net directional return (-8% to +8%) and volatility (-35% to +40%) connectedness is more pronounced during the first wave of the pandemic and is in line with the study of Aharon and Demir (2021). The first wave has a higher net return and volatility connectedness, indicating that this is when the global systemic crisis first struck. Still, due to widespread vaccination and herd immunity, the effects of COVID-19 are less severe in the subsequent waves; it is no longer a new phenomenon in the world.
4. Conclusion

We investigated the returns and volatility of NFT segments and media coverage since the beginning of the COVID-19 outbreak. A TVP-VAR model is used to demonstrate how media attention contributes to the spread of infectious disease, as this method solves the
problem regarding the small size of the rolling window. Our findings on the returns and volatility spillover from each parameter to the system throughout the sample period, with a sizable increase during the first and third waves of COVID-19 outbreaks, correspond to the first quarters of 2020 and 2021, respectively. This increase in connectedness during the pandemic underscores the susceptibility of NFT segments to media-induced sentiment. Furthermore, our dynamic analyses show that among the NFT segments, Metaverse and Collectibles appear to be recipients of spillover for returns, whereas Art appears to be a net recipient of spillover for volatility. On the other hand, MCI appears to be a net transmitter for both return and volatility.

Our findings have far-reaching implications. Our findings show differences in the return and risk characteristics of various NFT segments with the identification of net transmitter and net recipient of spillover. Moreover, during times of crisis, both the hedging and diversification benefits of the NFTs segments drop; this information may be useful for portfolio managers in making better portfolio choices and hedging strategies that are linked to this digital asset class. Additionally—to successfully implement risk-mitigation tactics during the crisis—global investors, portfolio managers, and policymakers must grasp the role of the media in promoting the propagation of shocks during the crisis. In particular, for regulators and policymakers seeking market stability during periods of extreme uncertainty, the reported characteristics of NFTs can help them design policies for digital assets. Our investigation is limited to the return and volatility connectedness of NFT segments, as well as media coverage, during the COVID-19 period. Other digital asset classes, such as cryptocurrencies and decentralized financial assets, could be included in future research to widen this line of inquiry and conduct a comparative analysis. Similarly, future extensions of our work may include a bifurcation of pre/post-COVID-19 analysis, as well as the inclusion of global drivers of connectedness.\footnote{We thank two anonymous referees for their useful comments.}

CRediT authorship contribution statement

**Zaghum Umar:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Afsheen Abrar:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Adam Zaremba:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Tamara Teplova:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Xuan Vinh Vo:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The article was prepared within the framework of the Basic Research Program at HSE University. This research is partly funded by the Institute of Business Research, University of Economics Ho Chi Minh City, Ho Chi Minh City, Vietnam. Adam Zaremba acknowledges the support of the National Science Center of Poland [grant no. 2021/41/B/HS4/02443].

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2022.103031.

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