The role of the media in speculative markets: Evidence from non-fungible tokens (NFTs)*

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September 3, 2022

Abstract

Extant literature debates the role of news media in speculative markets. Some show media hype leads to irrational behavior, while others argue news attenuates market imperfections. To disentangle these roles, we study news about non-fungible tokens (NFTs), which are a natural laboratory since the space is typified by extreme growth coupled with skewed returns. We examine properties of NFT news using a sample of 26,000 articles and 7.6 million trades. We link the intensity and tone of NFT news to subsequent increases in market activity. Yet, seller returns and return volatility decrease following news. Thus, the media plays an information gatekeeper role by increasing informed participation in unregulated tokenized assets. These findings are inconsistent with the media hyping speculative markets. Instead, journalists appear to educate readers on the risks of NFTs.

Keywords: News, Non-Fungible Tokens, Digital Assets, Cryptocurrency, Blockchain, Ethereum.

JEL codes: *G12, G14, G41*

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1. Introduction

There is a debate in the academic literature on the role the news media plays during periods of rapid growth in financial markets. Some argue that media coverage reduces information uncertainty and educates market participants on investment risks (e.g., Tetlock, 2010; Campbell et al., 2012; Engelberg et al., 2018). Others argue that journalists fixate on high growth or returns to make stories more interesting, which enhances the salience of information on market movements (e.g., Bhattacharya et al., 2009; Shiller, 2015, 2017). When news hypes large or quick profits, journalists can potentially exacerbate irrational investor behavior by creating the fear of missing out.

We revisit the debate over the role news media plays by studying the rapidly emerging non-fungible token (NFT) market. We present evidence that the NFT space is characterized by extreme growth and highly skewed and uncertain returns that typify speculative markets.[1] Prior work shows that asset prices do not fully incorporate market price information in speculative markets (Johnson et al., 2006). Thus, due to its speculative nature, the NFT setting is a natural laboratory for teasing out the educational versus hyping role of the media. Moreover, NFTs are a nascent asset class reflecting emerging technologies, which enhances the potential impact of media on participation outcomes.

NFTs are a blockchain technology that provide a representation of ownership of a digital or non-digital asset. NFTs can also represent access to digital content or physical access to an event. NFTs differ from fungible tokens, such as Bitcoin, in that they are unique, irreplaceable, and cannot be exchanged for an identical asset.[2] Most NFTs are currently based on the Ethereum blockchain, but they are not exclusive to this technology.

We begin by characterizing the exponential growth in the NFT marketplace and establishing stylized facts on participant outcomes. Using a sample of 7.6 million Ethereum-based

[1]We define *speculative markets* as those experiencing extreme growth in trading volume and asset prices, where prices could deviate from fundamental value (Johnson et al., 2006; Singleton, 2014; Hertzberg, 2018).

[2]For example, U.S. dollars are fungible assets. A $20 bill can be exchanged for two $10 bills as they have the same value. Similarly, a Bitcoin can be exchanged for another Bitcoin as it is a fungible token.

NFT trades over 2017 to 2021, we document extreme growth. Sample dollar volume of NFT transactions total $150,000 in 2017, $5.3 million in 2019, and $12 billion in 2021. The number of buyer and seller wallets also expand rapidly during this period, growing from approximately 4,000 of each in 2019 to over 774,000 buyer wallets and 376,000 seller wallets in 2021. Investor returns are highly volatile and exceed 70% in each sample year, although median returns are much lower. Overall, the NFT space has grown quickly and possesses characteristics of highly speculative assets that could attract media attention.

Next, we examine media coverage of NFTs using a database of almost 26,000 articles from 1,600 news sources, including national and local media outlets. Concurrent with the growth in the NFT marketplace, media coverage of NFTs grows substantially in recent periods, and especially in 2021. For example, the number of NFT news articles in our media database grows from approximately 200 in the fourth quarter of 2020 to 3,000 articles in the first quarter of 2021, and just under 12,000 articles in the fourth quarter of 2021.

A sentiment analysis reveals that 41% of NFT news articles contain positive content and 50% reflect a neutral tone. Only 9% of news reflects an overall negative sentiment. Moreover, a topical analysis of NFT news headlines reveals they frequently reference high investor returns, large trading volume, and the launch of new projects. These properties suggest that the media could be hyping the NFT space to attract reader interest.

We then examine the influence of news on the NFT marketplace. News coverage can lead to greater activity due to two roles of the media. In the first role, journalists can exacerbate investor enthusiasm by *hyping* rapid growth and creating a feedback loop that caters to participants. Media outlets have incentives to publish attention-grabbing stories to drive readership, web traffic, and revenue. Indeed, we find substantial anecdotal evidence of articles focusing on fast returns and extreme volume changes in the NFT space. Centering news on large price movements adds salience to the information and can lead to both greater and irrational participation by creating the fear of missing out that results in misestimating return probabilities (Hirshleifer, 2001; Barber and Odean, 2008; Shiller, 2015).

As further evidence of the potential hyping role, we find that the media often highlights celebrity ownership or participation in NFT projects, which can enhance the desirability or perceived exclusivity of ownership, similar to advertising via celebrity endorsement (Agrawal and Kamakura, 1995). Articles also describe novel and future uses of NFTs, lending credibility to the emerging technology. Finally, journalists sometimes explicitly hype NFTs by noting that non-participants could "miss out" on fast profits.

In the second role, the media can *educate* potential participants by providing balanced and factual information that leads to informed activity (Campbell et al., 2012; Engelberg et al., 2012b). NFTs are a novel and speculative asset class with unique risk properties that create challenges for investors trying to estimate their current and expected future intrinsic value. By discussing the pros and cons of investing in a speculative asset, the media can both facilitate participation and improve participant outcomes. In this role, the media reduces information frictions and serves as an information gatekeeper in an unregulated space.

Anecdotally, we note that many media articles follow a similar pattern of briefly defining an NFT, their potential use, and the steps required to participate in the marketplace. These articles can lower the learning curve for new participants. Some articles point cautiously to large price changes and highlight risks that are specific to NFTs. Others describe how participants might value NFTs based on factors such as smart-contract driven cash flows, tangibility, scarcity, and utility. Thus, we find robust anecdotal evidence that supports both the educational and hyping role of the media.

Based on these factors, we develop two testable hypotheses. First, we predict that NFT news—whether through hype or educating—will lead to greater marketplace activity, especially when the tone is not negative. To test this notion, we measure activity along several dimensions. Second, if the media is primarily hyping the NFT space, we hypothesize that returns and return volatility will be higher following news, especially when the tone is positive. Conversely, if the media primarily serves an educational role, we should observe declines in return volatility and returns following news as participants make informed decisions.

To shed light on these hypotheses, we merge our sample of 7.6 million NFT trades to approximately 26,000 NFT news articles on daily basis. For each day, we count the number of total, positive, neutral, and negative NFT articles. We then follow prior work (e.g., Tetlock, 2007) by employing a vector autoregression (VAR) framework to estimate the intertemporal link between measures of news to investor activity and returns. The VAR framework recognizes that news can be driven by and influence market activity. By incorporating lagged measures of both, we can uncover the Granger causality of news on near-term NFT outcomes.

We first validate our VAR approach through standard tests of stationarity and and identify one trading week as the optimal lag structure. We then use the VAR to explore which NFT characteristics lead to news coverage. We find that marketplace activity via trading, minting new NFTs, and new buyer and seller participants all result in greater news coverage. These findings are consistent with anecdotal evidence that the media is attracted to the NFT space due to its explosive growth. Surprisingly, the return properties of NFTs do not generate (i.e., Granger cause) additional news coverage. Thus, journalists do not appear to systematically respond to large price movements. Instead, the media reacts to marketplace data with lower information acquisition costs when deciding to cover the space.

We then test our hypothesis that NFT news leads to increased marketplace activity. We find that news robustly predicts and Granger causes near-term increases in trading, minting, and participation. Moreover, the effect of news on trading is long-lasting as it persists for at least one week. Thus, as news about NFTs grows, public awareness translates to activity in the marketplace. Consistent with our prediction, increases in activity are stronger when the tone of news is positive or neutral but not negative. Thus, regardless of the hyping or educational role of the media, we can empirically link news to greater NFT activity.

To disentangle these two roles, we examine the relation between news and subsequent NFT return properties. We find strong evidence that news is linked to reductions in return volatility. The effect is swift, significant, and not short lived. Moreover, our tests show that news Granger causes declines in volatility overall. For non-negative news, the decline in volatility is long-lasting. We interpret these findings as evidence that media coverage of speculative assets facilitates informed participation and reduces information frictions. These outcomes help stabilize markets as prices better reflect the true value of the asset.

As further evidence, we also examine the relation between news and returns. We find that seller returns are lower on the day after news, especially when the tone of the news is not positive. This result is further evidence that, on net, the media provides informative content rather than hype about NFTs. Although the relation between news and seller returns is not Granger causal overall, we do find that negative news has a long-lasting and negative impact on seller returns that is Granger causal. None of these results are consistent with the notion that media hype speculative markets. Instead, our findings imply that the media educates market participants in fast-growing and nascent space.

In our final set of tests, we examine whether the news source differentially influences market activity. We assign news sources to one of five media categories. *Financial* media provide the greatest coverage of NFTs and their stories are more positive in tone. *National* and *Tech* media tend to be more neutral in their coverage, which leads to more informed outcomes. Surprisingly, *Crypto*-related sources show no tendency to abnormally hype NFT markets. Their news helps drive trading and participation, but does not reflect hype as it is negatively related with return volatility and seller returns. *Local* media sources tend to provide more negative coverage of NFTs but do not influence activity or returns.

Overall, we find that media coverage of NFTs results in greater activity. Trading and minting increase and new participants enter the marketplace. Importantly, the media appear to play an educational role rather than simply hyping the large returns or volume in these speculative markets. Indeed, we find no evidence that news leads to irrational investor choices by amplifying the fear of missing out. Instead, the media primarily reduce information frictions and play an information gatekeeper role in an unregulated and nascent market.

Our findings come with some important caveats. Our analyses of participation and returns in a VAR framework do not predict the long-term impact of NFT news. Instead, they shed light on the intertemporal relation between news and speculative markets. It is possible that the media effects that we document do not extend beyond one week. Moreover, our return analysis only examines the gain or loss for an NFT that was sold following the news. Although these tests help us tease out whether the media is hyping or informing participants, they do not shed light on whether the *new* buyer earns an abnormal return. We are also careful to distinguish between "Granger causality" in a VAR framework and actual causal inferences. Our study identifies Granger causality, which indicates that news can predict future NFT outcomes. However, our research design does not allow us to claim causal relations and could still suffer from other limitations such as omitted variables bias.

Subject to the above, our paper contributes to the literature as follows. We first add to the debate on the media's role in financial markets. A large body of literature shows that news influences market outcomes (Tetlock, 2007; Tetlock et al., 2008; Fang and Peress, 2009; Tetlock, 2010, 2011; Dougal et al., 2012; Engelberg et al., 2012b). However, the literature is mixed on whether the media hypes (Bhattacharya et al., 2009; Shiller, 2015, 2017) or educates (Campbell et al., 2012; Engelberg et al., 2018) investors on speculative assets.

We study a speculative market in its infancy and show that news influences activity but plays a predominantly educational role. Returns and volatility decline following NFT news, indicating that journalists tend to provide important information on the risks of speculative markets rather than exploiting the fear of missing out to drive web traffic and generate revenue for their organization. Thus, our findings are contrary to the theory that the media's "narrative economics" exacerbates speculative activity (Shiller, 2015, 2017).

Second, we extend the literature on the role of information frictions in speculative markets. Prior work shows that, in speculative markets, prices do not fully reflect available information (Singleton, 2014; Johnson et al., 2006) and sellers have incentives to withhold information from future investors (Hertzberg, 2018). The combined effect leads to greater disagreement on prices and introduces a speculative premium. We show that the media serves an important information gatekeeper role in speculative markets, thereby reducing information frictions and helping to stabilize prices. In our setting, the information role of the media is enhanced given the decentralized and unregulated nature of the blockchain (Biais et al., 2019; Cheng et al., 2019; Gan et al., 2021).

We also contribute to the small but growing literature on NFTs by characterizing the extreme growth in NFT marketplaces and participants. Prior and contemporaneous work studies the relation between NFT market outcomes and returns on cryptocurrency and equity markets (Ante, 2021; Aharon and Demir, 2022; Dowling, 2022). Other work examines the value drivers of tokens (Cong et al., 2021; Valeonti et al., 2021; Schaar and Kampakis, 2022) or the market structure of NFTs (Nadini et al., 2021; van Haaften-Schick and Whitaker, 2022). A working paper by Kapoor et al. (2022) links social media activity to NFT valuations. However, these discussions likely originate by sellers and NFT marketplace participants rather than independent journalists. By contrast, we focus on the broad influence of news media outlets and examine their impact on new market participants.

Overall, we show that the news media plays an important investor protection role in the highly speculative and risky NFT space. By producing informative content to a fast growing number of participants, journalists help new entrants make informed decisions. Therefore, our findings should be of interest to academics, policymakers, and market participants.

We structure the rest of the paper as follows. Section 2 provides background information on NFTs. Section 3 describes the data and sample construction. We discuss our conceptual framework and formal hypotheses in Section 4. Section 5 presents the empirical design and results. We provide additional tests in Section 6. We conclude in Section 7.

2. Background on NFTs

2.1. NFTs Defined

A non-fungible token is a unit of data stored on a blockchain that is uniquely identifiable and therefore not interchangeable. NFTs can be thought of as digital certificates of ownership encoded as smart contracts (Evans, 2019). Due to the transparency of the blockchain, NFTs provide an indisputable confirmation of the current and historical ownership of the asset, potentially reducing information asymmetries and information acquisition costs for marketplace participants. Most NFTs are encoded on the Ethereum blockchain.[3] However, NFTs exist on other blockchains.[4]

2.2. Use of NFTs

Because NFTs are a means to verify ownership, they originated as a way for digital artists to monetize content such as images, video, or audio files (van Haaften-Schick and Whitaker, 2022). Over time, several novel uses of NFTs have emerged to generate potential utility or income for its owners (Valeonti et al., 2021). For example, NFTs might provide its owner access to exclusive content in the digital world (e.g., in a game or in the metaverse), or to physical locations in real life (e.g., access to an exclusive event). NFTs can also designate ownership of both digital and tangible assets, such as collectible sports videos, gaming add-ons, and real estate (Nadini et al., 2021).

[3] One example of an NFT on the Ethereum blockchain is Bored Ape Yacht Club, which are 10,000 unique digital characters. For example, Bored Ape #1294 sold for 119 Ether ($287,055) on January 22, 2022. See https://opensea.io/assets/0xbc4ca0eda7647a8ab7c2061c2e118a18a936f13d/1294.

[4] For example, NBA Top Shot built its own blockchain called Flow. For a media discussion of various NFT blockchains, see T.W. Lounge, "Choosing the right blockchain for your NFT," *Medium*, November 30, 2020, https://medium.com/phantasticphantasma/choosing-the-right-blockchain-for-your-nft-d1df2bebae91.

2.3. *Value of NFTs*

As with any asset, potential investors will estimate the intrinsic value of NFTs to estimate return probabilities. NFT participants might employ widely adopted finance valuation techniques such as a comparables method. Under this approach, participants look to recent transactions to estimate the relative value. Many NFTs, such as CryptoPunks, are based on digital art with similar overall properties (images of punks), but each NFT or related digital image might contain unique attributes (e.g., fedora or cowboy hat). Thus, estimating the value of NFTs could be based on recent selling prices of similar NFTs based on the popularity or scarcity of the project (Valeonti et al., 2021) or scarcity of specific attributes (Lee, 2022), all of which can enhance their collectible value.

Alternatively, participants might estimate NFT value by discounting expected cash flows (DCF). Under the DCF approach, the value of any asset is a function of the level, timing, and risk of its cash flows. NFT smart contracts may be designed such that the NFT generates a cash flow through rental or royalty payments (van Haaften-Schick and Whitaker, 2022).[5] NFTs might also be tethered to tangible assets that generate cash flows. Thus, NFT participants might estimate future cash flows and discount them to their present value based on the perceived riskiness of these cash flows and the opportunity cost of capital. However, not all NFTs contain these features and, thus, investors might simply estimate the cash flow based on the expected selling price at some future date.

Factors other than estimated cash flows could drive the value of NFTs.[6] In neoclassical models of economics, rational economic actors maximize their own utility and not simply their wealth (Akerlof and Yellen, 1985). NFTs might generate utility for its users based on application in digital or physical worlds. For example, NFTs can be used to unlock digital content in games or provide access to events in real life. Thus, the desirability and

[5]Similarly, NFTs might provide special perquisites or access to content that is valuable. In this case, the NFT would increase in value as the success or desirability of that project becomes more valuable.

[6]Prior work models the value of cryptocurrencies based on transaction demand on digital platforms rather than discounting cash flows (Cong et al., 2021; Biais et al., 2022).

exclusivity of this content could impact NFT value in a manner similar to other collectibles such as tangible art, stamps, and wine (Dimson and Spaenjers, 2011; Dimson et al., 2015; Lovo and Spaenjers, 2018; Penasse and Renneboog, 2021). NFTs might also generate utility for its owners by providing access to or signaling participation in a exclusive community (i.e., bragging rights of ownership).[7] NFTs can also potentially serve as store of wealth like physical art (Renneboog and Spaenjers, 2013; Schaar and Kampakis, 2022).

2.4. Risks of NFTs

NFTs are speculative assets that come with significant risks. In this subsection, we provide a non-exhaustive discussion of salient risk factors. The uncertainty of NFT cash flows elevates the role of price discovery. Potential buyers and sellers might rely on recent transactions to estimate the current or future value of an NFT. The transparency of the blockchain reduces the cost of acquiring this information. However, a concern in the NFT space is that transactions might reflect wash trades, where one party is both the buyer and the seller.[8] Although wash trades are not unique to NFTs (e.g., Grinblatt and Keloharju, 2004), they can impact returns by inflating the value of an asset with fictitious transaction prices and trading volume. Such manipulative actions give the appearance than an asset is more valuable and liquid than it actually is (White, 2016).

For NFTs based on digital images, video, or audio, another risk factor is that the content can endlessly duplicated at a low cost. Although a buyer might own the rights to an image through an NFT, others can "right click and save" (i.e., download) this image to their

[7]For example, Twitter allows its users to link their profile picture to an NFT and provides a hexagon-shape to signal its authenticity. See Richard Lawler, "Twitter brings NFTs to the timeline as hexagon-shaped profile pictures," *The Verge*, January 20, 2022, https://www.theverge.com/2022/1/20/22893502/nft-twitter-profile-picture-crypto-wallet-opensea-coinbase-right-click.

[8]Some media articles note the risks of wash trades. See Kevin Collier, "People are selling themselves their own NFTs to drive up prices," *NBC News*, February 3, 2022, https://www.nbcnews.com/tech/security/nft-sales-show-evidence-wash-trading-researchers-say-rcna14535.

computer.[9] Digital art thieves can also sell pirated versions of artwork as an NFT.[10]

2.5. Frictions in NFT Participation

New buyers and sellers will incur frictions that are unique to participating in the NFT space. During our sample period, participants must register for specialized NFT marketplaces (e.g., OpenSea or SuperRare) and create a separate digital wallet through a third party (e.g., MetaMask). The digital wallet holds purchased NFTs and stores cryptocurrency used in the transaction. Funding a wallet might involve converting fiat currency (e.g., U.S. dollars) to a cryptocurrency (e.g., Ether) on an exchange (e.g., Coinbase). The exchange will likely charge separate transaction fees for converting the fiat currency and for transferring the cryptocurrency to the digital wallet. Once the wallet is funded, the users can potentially bid on NFTs listed on OpenSea.

NFT participants also incur costs of recording the transaction on the blockchain. For NFTs recorded on the Ethereum blockchain, buyers or sellers must pay gas fees, which compensates miners for recording the transaction (Biais et al., 2019). The party responsible for paying gas fees depends on the transaction type and marketplace.[11] Sellers of original content may also incur costs to mint a new NFT, which is the process of recording an NFT for the first time on the blockchain. Over time, marketplaces have introduced the concept of lazy minting, which allows participants to delay payment of a gas fee until the NFT is sold or transferred.

[9] This problem is not exclusive to digital art. Pysical art can also be duplicated. One could acquire a duplicate of a famous painting, such as the *Mona Lisa* by Leonardo da Vinci. Even if the duplicate is a perfect replica, it does not hold the same value as the original *Mona Lisa* that is the property of the French Republic.

[10] See Kevin Collier, "NFT art sales are booming. Just without some artists' permission," *NBC News*, January 10, 2022, https://www.nbcnews.com/tech/security/nft-art-sales-are-booming-just-artists-permission-rcna10798.

[11] See "Who pays the gas fees when using Ethereum on OpenSea," https://support.opensea.io/hc/en-us/articles/360061699514-Who-pays-the-gas-fees-when-using-Ethereum-on-OpenSea.

3. Data and Descriptive Statistics

3.1. NFT Transaction Data

Our source of NFT data is Dune Analytics, which contains NFT transactions on the Ethereum, Polygon, Binance Smart Chain, Gnosis Chain, and Optimism blockchains. We focus on Ethereum-based NFT trades, which account for approximately 86% of NFT transactions in 2021.[12] Using Structured Query Language (SQL), we extract all recorded NFT transactions between June 23, 2017, and December 31, 2021. These data include NFT trades on five major NFT marketplaces: OpenSea, Rarible, SuperRare, Larva Labs, and Foundation. These marketplaces represent four of the top ten Ethereum-based marketplaces based on NFT trading volume in 2021.[13] OpenSea has the largest market share during our sample period, representing more than 60% of NFT sales in 2021.[14]

Our initial sample includes 8,989,371 observations. Like prior work (e.g., Schaar and Kampakis, 2022), we remove all transactions with missing NFT token identification, links to multiple items, transfers not matched to sales, and duplicate transactions based on identification, transaction amounts, and time stamps. We detail the number of observations removed for each step in the Internet Appendix. Our final sample includes 7,569,287 NFT trades over 2017 to 2021.

3.2. NFT Measures

Using data from Dune, we generate several daily measures of NFT properties. All transaction times and time periods are in Coordinated Universal Time (UTC). We create the variable, *minting*, which is the natural log of one plus the number of NFTs minted each day.

[12]See Elizabeth Howcroft, "NFT sales hit $25 billion in 2021, but growth shows signs of slowing," *Reuters*, January 11, 2022, https://www.reuters.com/markets/europe/nft-sales-hit-25-billion-2021-growth-shows-signs-slowing-2022-01-10/.

[13]See Jack Caporal, "The NFT Market: Average NFT Prices, Largest Marketplaces, and More," *Motley Fool*, February 3, 2022, https://www.fool.com/the-ascent/research/nft-market/.

[14]See Bernadette Doykos, "OpenSea Surges into 2022," *Boardroom*, January 3, 2022, https://boardroom.tv/opensea-nft-sale-surge/.

This measure represents the volume of new NFTs created over time.

To estimate NFT market participation, we count the number of buyer wallets and seller wallets generated on each day. We then create the variable *participants*, which is the log transformed number of buyer plus seller wallets each day plus one. We also count the number of *trades*, which is the natural log of one plus the number of NFT transactions each day.

To estimate investment returns, we first compute the percentage return on a single NFT trade in U.S. dollars. For this measure, we require the seller to have previously purchased the NFT, so our measure excludes the returns to content creators. We then estimate daily NFT *returns*, which is the value-weighted average returns for all NFTs traded each day.

Finally, we estimate NFT *volatility* as follows. We demean NFT *returns* to obtain a residual and then square this residual. We then subtract the past 15-day moving average of this squared residual (Tetlock, 2007).[15]

3.3. Growth in NFT Markets

Table 1 presents the time distribution of NFT trading. Panel A presents the yearly number of new and total NFT minting, trades, dollar volume, and market participants for each sample year. We find tremendous growth in each measure over time, with 2021 representing a breakout year. For example, year-over-year growth in NFT dollar volume is 255% in 2020 and 62,912% in 2021. Although the number of NFT trades grows steadily over 2017 to 2020, it significantly increases in 2021 to 7.4 million versus 0.1 million in the prior year. Panel A also shows that the number of buyer and seller wallets increases swiftly over time and especially in 2021.

[Insert Table 1 here]

Panel B presents the return distribution over time. Average NFT returns are high but somewhat consistent during our sample period, averaging between 70.4% and 158.2%.

[15] Our results below are robust to using alternative measures of participation (e.g., dollar volume) and to detrended measures of past volatility in which we subtract the past 30-day moving average of squared residuals from current squared residuals.

Volatility in returns are also relatively consistent each year. Median returns are lower than average returns, suggesting that some outliers drive the overall return averages. Thus, we winsorize returns at the 1% level in each tail for our regression analyses to reduce the influence of outliers. Median returns also trend downward over time, declining from 11% in 2018 to 3% in 2020 to 1% in 2021.

Panel C presents statistics on each NFT marketplace in our sample. Total dollar volume of trades during our sample period is $11.97 billion. Approximately 96% of NFT dollar volume is concentrated in the OpenSea marketplace. OpenSea also has the highest number of total NFTs and buyer and seller wallets.

Overall, Table 1 depicts rapid growth in NFT markets in terms of minting, transactions, dollar volume, and participants. The distribution of NFT returns are highly skewed and volatile, which leads to a high average returns. These statistical trends appear to depict the emergence of a new and fast-growing but speculative asset class.

3.4. News

To measure news, we use the RavenPack RPA 1.0 Global Macro database. RavenPack aggregates information on news articles from thousands of global sources and structures these data around entities, such as companies, organizations, or currencies. Since NFTs do not represent a specific entity in RavenPack, we extract all news on the Ethereum cryptocurrency, which has the RavenPack Entity ID equal to 0A2CF4.

We then identify NFT news based on the headline of each article. Those articles with the word *fungib** or *NFT** in the title are designated as NFT news. The others are labeled non-NFT news and excluded from our analysis. Our sample includes 25,932 NFT news articles. News articles about NFTs stem from 1,600 sources, including large media outlets such as *CNBC*, the *Wall Street Journal*, *CNN*, and *Bloomberg News*; regional newspapers and television stations; blogs; newswires; technology-focused media such as *The Verge*, *WIRED*, and *Gizmodo*; and digital asset news sources such as *Bitcoin Insider*, *CoinDesk*, and *Coin-*

telegraph. To gauge the intensity of NFT news discussions, we create the variable, *news*, which is the natural log of one plus the count of NFT news articles on a given day.

To measure the tone, we follow prior work (e.g., Kolasinski et al., 2013; Ho et al., 2013; Gao et al., 2018) by using a sentiment score from RavenPack. We use the composite sentiment score (CSS), which is a value between -1.00 and $+1.00$ based on the tone of each article.[16] RavenPack develops this score based on a proprietary analysis of emotionally charged words and phrases that experts expect to have a short-term price impact. Values of CSS less than zero tend to have a negative price impact, while those above zero have a positive impact. When CSS equals zero, the article is expected to have a neutral price signal. Using the CSS for each article, we create three variables that log transform the value of one plus the daily number of *positive news*, *negative news*, and *neutral news* articles.[17]

Table 2 reports the time trends in NFT news by calendar quarter during our sample period. There were 50 or fewer articles in each quarter through Q3 of 2020. The number of NFT articles grows to 207 in Q4 of 2020 and accelerates rapidly throughout 2021, totaling over 11,000 in Q4 of 2021 alone.

The sentiment of NFT news is mostly positive or neutral during our sample period. Approximately 40.5% (10,507/25,932) of media articles contain *positive news*, while 50.2% (13,013/25,932) are categorized as *neutral news*. The remaining 9.3% (2,412/25,932) are categorized as *negative news*.

[Insert Table 2 here]

We provide a summary of the most frequent 25 phrases and words in NFT news headlines in Table 3. News articles often reference NFT marketplaces and platforms. Headlines frequently reference art and specific NFT projects, such as Bored Ape Yacht Club. Media headlines also tend to use phrases that could depict hype, such as "NFT Craze" and "Ex-

[16] In addition to CSS, RavenPack provides an event sentiment score (ESS) value, but ESS is not well populated for Ethereum news. Ho et al. (2013) show that both ESS and CSS correlate with asset returns.

[17] We verify that CSS values tend to reflect sentiment. For example, the negative article by Cointelegraph, "CryptoPunks floor price slips below 80 ETH as NFT trading volume deflates by 50%," has a CSS of -0.38. The positive article by CNBC, "Mark Cuban is bullish on NFTs, and they're about to go more mainstream with an auction at Christie's," has a CSS of 0.3. An article by MSN, "What is NFT," has a CSS equal to 0.

clusive NFT" or provide references to sales, auctions, and the launch of new NFT projects.

[Insert Table 3 here]

3.5. Summary Statistics

Table 4 presents descriptive statistics of the daily measures used in our analysis. All variables expect returns and volatility are in natural log transformed. We present the mean, standard deviation, and distribution of each variable. Our sample has 1,081 calendar days as NFT markets do not close. While mean values of positive and neutral news are close to each other, the mean value of negative news is the lowest. In terms of NFT properties, mean values of minting, participants and trades are close to each other.

[Insert Table 4 here]

The average daily NFT return is 225% and the median return is 177% during our sample period. In comparison, the daily mean (median) return of Bitcoin, Ether, and the stock market are 0.30% (0.20%), 0.40% (0.30%) and 0.10% (0.00%) during our sample period.

4. Conceptual Framework and Hypotheses

In this section, we present a conceptual framework for the role of media in covering NFTs. We develop this framework based on related literature and extensive anecdotal evidence from NFT news articles. We then present formal hypotheses for these tests.

4.1. Conceptual Framework

Extant literature studies the impact of news media on financial markets and trading activities. Under multiple settings, prior work finds that news media influence stock returns (e.g., Tetlock, 2007; Tetlock et al., 2008; Fang and Peress, 2009; Tetlock, 2010, 2011; Dougal et al., 2012), short selling (e.g., Engelberg et al., 2012b) and stock return anomalies (Engelberg et al., 2018). Yet, little is known about the impact of news and journalists on *novel* speculative markets such as NFTs.

The media can play two roles in publishing articles on speculative markets such as NFTs: hyping or education. In one role, the media exacerbates investor enthusiasm for speculative assets by *hyping* the growth and returns. Such hype can create a contagion of investment behavior that results in a positive feedback loop. By catering to investor demand, hype can amplify asset prices and lead to speculative bubbles (e.g., Hirshleifer, 2001; Bhattacharya et al., 2009; Engelberg et al., 2012a; Shiller, 2015).

For example, Shiller (2015) argues that, *"[T]he news media are fundamental propagators of speculative price movements through their efforts to make news interesting to their audience. They sometimes strive to enhance such interest by attaching news stories to stock price movements that the public has already observed, thereby enhancing the salience of these movements and focusing greater attention on them."* (p. 95). Such discussions in news articles can lead to irrational behavior by investors such as herding or misestimating return probabilities due to the fear of missing out (Hirshleifer, 2001; Barber and Odean, 2008).

Consistent with the hyping role, we find anecdotal evidence of NFT news articles highlighting abnormal and fast returns and extreme growth in trading volume.[18] Media articles also frequently promote celebrity ownership of NFTs, which could enhance the desirability or perceived exclusivity and impact its value.[19] Indeed, prior work in the non-NFT space shows that celebrity endorsements can be an effective advertising tool to differentiate products (Agrawal and Kamakura, 1995). Articles also comment on the growing number of novel and potential future use of NFTs, which could lend credibility to their legitimacy as an investable asset.[20] Some articles explicitly note that participants do not want to miss out on

[18]See Mahnoor Khan, "People are buying and flipping NFTs at huge profits. Here's how they do it," *Fortune*, February 18, 2022, https://fortune.com/2022/02/18/how-to-make-money-flipping-nfts-on-open-sea/.

[19]For example, see Sophie Haigney, "What Makes Bored Ape NFTs So Desirable?," *The Wall Street Journal*, February 24, 2022, https://www.wsj.com/articles/bored-ape-nfts-so-expensive-11645709606.

[20]For example, media articles highlight the novel use of NFTs by politicians for fundraising and digital real estate. See Laura Romero and Soo Rin Kim, "Not just for artwork, NFTs are being used by political candidates to raise money, attract young supporters," *ABC News*, January 26, 2022, https://abcnews.go.com/Politics/artwork-nfts-political-candidates-raise-money-attract-young/story?id=82445596; and Lianne Kolirin, "World's first digital NFT house sells for $500,000," *CNN*, March 24, 2021, https://www.cnn.com/style/article/digital-nft-mars-house-scli-intl/index.html.

the growth in NFTs, which could lead to irrational behavior by creating a sense of urgency.[21]

In the other role, the media can *educate* readers by providing factual information that enable participants to make informed decisions (e.g., Campbell et al., 2012; Engelberg et al., 2012b). Anecdotally, we note that many media articles include at least a brief definition of an NFT.[22] Media articles often describe how and where to buy and sell NFTs.[23] These articles could facilitate transactions by shortening the learning curve and lowering the startup costs for new participants. Some articles point cautiously to large profits in NFT transactions and can inform investors on the risks of NFTs and expected payoffs.[24] Articles also describe how investors might value NFTs based on factors such as cash flows, tangibility, scarcity, and utility.[25] Many media articles highlight these risks and value implications.[26] Thus, there is

[21]See Sterling Campbell, "NFTs: What You're Missing And Where They're Going," *Forbes*, September 13, 2021, https://www.forbes.com/sites/columbiabusinessschool/2021/09/13/nfts-what-youre-missing-and-where-theyre-going/; Finurah Contributor, "Fear of Missing Out? Here's How Black Artists Can Capitalize On the NFT Craze Before It's Too Late," *Yahoo! News*, November 20, 2021, https://news.yahoo.com/fear-missing-black-artists-capitalize-193000099.html; and Accesswire, "APENFT The NFT Token You Can't Afford To Miss Out On," *Yahoo! News*, May 20, 2021, https://www.yahoo.com/now/apenft-nft-token-t-afford-080000331.html.

[22]For example, CNBC defines an NFT in an article as, "a unique digital asset designed to represent ownership of a virtual item.". See Ryan Browne, "Visa jumps into the NFT craze, buying a 'CryptoPunk' for $150,000," *CNBC*, August 23, 2021, https://www.cnbc.com/2021/08/23/visa-buys-cryptopunk-nft-for-150000.html. Similarly, Bloomberg News notes that NFTs, "allow holders of digital art, collectibles and all manner of other items to track ownership. See Joanna Ossinger and Emily Change, "Billionaire Steve Cohen Helps NFT Firm Recur Reach $333 Million Valuation," *Bloomberg News*, September 13, 2021, https://www.bloomberg.com/news/articles/2021-09-13/billionaire-cohen-helps-nft-firm-reach-333-million-valuation.

[23]See Kevin Roose, "What are NFTs?," *The New York Times*, March 18, 2022, https://www.nytimes.com/interactive/2022/03/18/technology/nft-guide.html; Richard Lehman, "Where To Buy NFTs: Top 10 NFT Marketplaces," *Seeking Alpha*, March 11, 2022, https://seekingalpha.com/article/4482960-where-to-buy-nfts.

[24]See Alyson Krueger, "How Much Real Money Can You Make From Virtual Art?," *The New York Times*, March 12, 2022, https://www.nytimes.com/2022/03/12/style/nft-art-profit.html.

[25]For example, see Hugo Chang, "Understanding the value of Non-Fungible Tokens (NFT)," *Medium*, March 25, 2020, https://medium.com/@changhugo/understanding-the-value-of-non-fungible-tokens-nft-49d2713bdfc4; "How to Assesss the Value of an NFT," *Binance Blog*, July 15, 2021, https://www.binance.com/en/blog/nft/how-to-assess-the-value-of-an-nft-421499824684902357; and Matthew Erskine, "Uncertainty in the Valuation of Non-Fungible Tokens," *Forbes*, February 2, 2022, https://www.forbes.com/sites/matthewerskine/2022/02/02/uncertainty-in-the-valuation-of-non-fungible-tokens/?sh=4ba5b17f6ddd.

[26]See Mitchell Clark, "NFTs, explained: I have questions about this emerging... um... art form? Platform?", *The Verge*, March 3, 2021 (Updated August 18, 2021), noting the "flex" of owning an original and popular NFT. See https://www.theverge.com/22310188/nft-explainer-what-is-blockchain-crypto-art-faq; and Luke Savage, "NFTs Are, Quite Simply, Bullshit," *Jacobin*, January 26, 2022, https://jacobinmag.com/2022/01/nfts-fallon-paris-hilton-bored-ape-digital-imagery-commodification.

substantial anecdotal evidence that the media is educating readers on the potential risks of an emerging but speculative asset class.

4.2. Formal Hypotheses

4.2.1. Determinants of News

We explore how the characteristics of NFTs influence media coverage. Journalists might be attracted to novel NFT markets due to its rapid growth and novelty. The properties of NFT returns might also attract media attention. For example, an increase in the price of popular projects could capture media interest and drive greater coverage of the marketplace. Similarly, large price swings could attract news coverage. Like other financial markets (e.g., Tetlock, 2007; Bhattacharya et al., 2009), we also expect the tone of news coverage to be positive during periods of high participation or returns and negative during periods of low participation or returns. Thus, we state our first hypothesis:

Hypothesis 1. *The level and tone of NFT news is influenced by NFT marketplace activity and returns.*

We might observe support for H1 in terms of market activity, but fail to find support using returns. Among these variables, the number of trades and NFTs minted are the easiest to observe on the blockchain as cost of information acquisition is low for journalists. For example, OpenSea reports market statistics including the number of NFTs, owners, and trading volume each day.[27] The properties of returns could be more costly to ascertain for the media. To compute overall market returns or return volatility, the journalist would need to process large amounts of blockchain information. Thus, we might not observe a relation between news and overall returns or return volatility.

[27]See "Top NFTs" at https://opensea.io/rankings.

4.2.2. News and Marketplace Activity

Next, we examine the impact of NFT news on marketplace activity, which we measure through *trades*, *minting*, and *participants*. We expect a positive association between *news* and *trades*. The media can provide information about NFTs and how to to transact, thereby educating potential participants or generating additional hype around NFT markets. Regardless of the channel through which media affects activity, we expect that when more people learn more about NFTs through news, trading activity will increase. We expect a stronger relation between news and trading when the news is non-negative in tone. Neutral or positive news can encourage participants to transact, while negative news, such as information on fraud or losses, might discourage trading.

We also expect to find greater *minting* after *news* for two possible reasons. First, existing sellers may increase their minting of NFTs in anticipation of new buyers entering the market. Second, new sellers might learn how to mint an NFT and enter the market to mint new NFTs to sell. Thus, we expect a positive relation between *news* and *minting*, especially when the news reflects positive sentiment.[28]

Next, we examine the relation of news with the number of participants in the NFT marketplace. Unlike traditional financial markets, each NFT transaction has a unique buyer and seller wallet that is visible on the blockchain. This feature allows us to track all transactions made by a particular buyer or seller wallet and enables to examine whether news increases market participation. Whether hype or education, NFT news could attract new participants to the market. As noted in Subsection 4.1, journalists often describe precisely how to transact in NFT markets, such as providing information on how to create a wallet and buy or sell in marketplaces. Thus, we expect news to attract new participants.

Taken together, we expect a positive relation between *news* and marketplace activity, especially when the news is non-negative. Formally, we state the following hypothesis:

[28]Our measure of *minting* is likely a lower bound on the effect of news about NFTs. As discussed in Section 2, sellers can "lazy mint" a new NFT, which is not captured on the blockchain until it is sold.

Hypothesis 2. *NFT news is positively associated with marketplace activity, especially when the news does not reflect negative sentiment.*

4.2.3. News and NFT Return Properties

Next, we attempt to tease out the hyping and education role of the media by examining the relation of news with the properties of NFT returns. If the main role of the media in the NFT market is educational, we expect a decline in return volatility after news. As Tauchen and Pitts (1983) note, initial trading in speculative markets is thin and prices are volatile. To the extent that the media informs participants on the possibilities and risk of the market, news should facilitate informed participation. Thus, prices should stabilize as they better reflect true value. Under this educational role, we expect news to reduce return volatility, especially when it is non-negative in tone.

Alternatively, if news is hyping NFT markets, we expect a positive relation between news and subsequent return volatility, as investors make decisions based on expectations of exorbitant returns. By paying higher prices, the market fails to stabilize and should experience increases in return volatility. It is also possible that NFT news serves both roles and that the net effect on return volatility is zero.

Finally, we examine the relation between news and seller returns. If the media educates participants on NFT risks and return probabilities, then participants will become more informed and prices will be closer to true value. Thus, if media acts as an information gatekeeper in speculative markets, news should negatively relate to future seller returns (Fang and Peress, 2009).

Conversely, if NFT news creates hype, we should observe a positive relation between news and seller returns. Such findings would be consistent with literature linking media to mispricing in the stock market (Barber and Odean, 2008; Tetlock, 2011; Engelberg et al., 2012a). In our case, we expect less informed buyers to overpay for NFTs and sellers to opportunistically transact around media coverage, thereby experiencing larger returns. It is also possible that news has no net effect on returns as either both forces are at play or news does not impact returns. Formally, we test the following hypothesis stated in the null form:

Hypothesis 3. *NFT news is not associated with NFT return properties.*

5. Empirical Design and Results

5.1. Vector Autoregression (VAR)

To test our hypotheses, we closely follow the methodology in Tetlock (2007), which analyzes the impact of news on stock markets. Specifically, we employ a multivariable VAR model that measures the interconnection of endogenous news and the properties of the NFT marketplace, while controlling for other exogenous factors such as financial market returns.

The VAR approach is ideal for our setting since news could be both dynamically driven by and impact NFT markets. Importantly, the VAR framework allows us to uncover the Granger causality of endogenous variables on outcomes, such as the impact of news on transactions (Granger, 1969). In our study, news "Granger causes" NFT marketplace outcomes if the lagged values of news provide significant information about future NFT outcomes after accounting for lagged variables of other time-series variables.

Our main variables of interest are: *news*, *trades*, *minting*, *participants*, *volatility*, and *returns*. We define these variables in the Appendix. In the VAR model, these variables are treated as endogenous (*Endog*) and are estimated with the number of lags described below.

We also include several exogenous control variables (*Exog*), which are daily returns on Bitcoin, Ether, and common stocks listed in the U.S. Some work links NFT returns to those of other financial assets such as equities and Ether (e.g., Aharon and Demir, 2022). However, Dowling (2022) finds a low correlation between cryptocurrency and NFT returns.

To estimate daily *Bitcoin return* and *Ether return*, we follow Dowling (2022) and Ante (2021) by estimating the percent change from the earliest and latest price on each day using data from CoinMarketCap.[29] The variable, *stock return*, is based on the daily return of the value-weighted stock index from the Center for Research in Security Prices (CRSP). For days when the U.S. stock market is closed, we set *stock return* equal to zero.

Before designing our VAR analysis, we test the stationarity of our time series data on NFTs. If our data exhibit non-stationary behavior, they must be transformed or de-trended prior to the VAR analysis. In the Internet Appendix, we pretest for unit roots in each of our endogenous and exogenous variables. Specifically, we conduct the Augmented Dickey–Fuller and Phillips–Perron test of each variable that tests the null hypothesis of a unit root. To the contrary, we find the levels of all variables are stationary. Thus, no de-trending is necessary.

Next, we select the appropriate lag length for our endogenous variables using selection statistics such as the modified Likelihood Ratio test, Akaike's information criterion, and the Hannan and Quinn information criterion (HQIC) test (Kumar et al., 2012). In the Internet Appendix, we find that a seven day lag structure (i.e., one week of trading activity) is optimal for our setting. The choice of one trading week is also consistent with the lag structure that Tetlock (2007) uses to examine news and stock returns (i.e., five trading days).

We then estimate the following equation using ordinary least squares (OLS):

$$
\begin{aligned}
y_t = \alpha_1 + & \beta_1 \cdot L7(News_t) + \gamma_1 \cdot L7(Trading_t) + \delta_1 \cdot L7(Minting_t) \\
& + \zeta_1 \cdot L7(Participants_t) + \eta_1 \cdot L7(Volatility_t) + \theta_1 \cdot L7(Returns_t) \\
& + \omega_1 \cdot Exog_{t-1} + \epsilon_t,
\end{aligned} \tag{1}
$$

where y_t are the *Endog* variables described above, and L7 is a lag operator that transforms any variable x_t into a row vector consisting of seven lags of x_t; that is, $L7(x_t) = [x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, x_{t-5}, x_{t-6}, x_{t-7}]$. All models include day-of-week fixed effects. We use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. We log transform *news*, *trades*, *minting*, and *participants* to attenuate the influence of heteroskedasticity. We also winsorize NFT variables at the 1% level in each

[29] See https://coinmarketcap.com/currencies/bitcoin/historical-data/ and https://coinmarketcap.com/currencies/ethereum/historical-data/.

tail in our regressions to reduce the influence of outliers.

In this model, we estimate a large number of coefficients. As is common with a VAR, we expect that many coefficients will lack statistical significance (Kumar et al., 2012). Thus, to examine whether the lags of one endogenous NFT variable, $L7(x_t)$, explain the current value of another y_t, we use a chi-squared test to establish Granger causality.

Specifically, we follow Tetlock (2007) in estimating the regressions using OLS and then conduct chi-squared tests that examine whether past values of endogenous variables Granger cause other NFT outcomes after conditioning on past values of each.

We conduct formal chi-squared tests around two hypotheses. First, we test the null hypothesis that the coefficients on all of the seven lags of an endogenous variable are jointly equal to zero, which we label $\chi^2(7)[Joint]$. If the null hypothesis is rejected, then the inclusion of the lags of variable x_t improve the forecast of (i.e., Granger cause) an NFT outcome y_t.

Second, we examine whether the NFT variables have a long-lasting impact on market outcomes. For this test, we also follow Tetlock (2007) in summing the coefficients of each of the seven lags on x_t and then conducting a chi-squared test where the null hypothesis is that the sum of of the lags for each variable equals zero. We label this test, $\chi^2(1)[Sum]$.

5.2. NFT News

We first test H1 by estimating Equation (1) with NFT *news* at time t as the dependent variable. For these tests, we are interested in what factors drive news coverage of NFTs. To determine if a variable Granger causes news, we conduct the two chi-squared tests for each variable and report the associated p-values in Table 5. For brevity, we present coefficients from this regression in the Internet Appendix.

[Insert Table 5 here]

Table 5 shows there is momentum in NFT news as prior articles relate to future news. The relation is long-lasting as the sum of lagged news over the prior week is positively related to future news. Moreover, Table 5 shows that NFT marketplace activity Granger causes *all news*. For example, in the tests on the joint lagged values of *trades*, *minting*, and *participants*, the chi-squared tests are significant at the 5% level or better. These effects are long-lasting as the chi-squared tests on the sum of the lags are also significant at the 5% level or better. The return properties of NFTs, however, do not predict *all news*. For example, the chi-squared tests for the joint tests of the lagged values of *volatility* and *returns* are not statistically significant. Thus, journalists might primarily rely on NFT marketplace information that is easier to observe, such as trading, when reporting on NFTs.

5.3. News and Trades

H2 predicts a positive relation between NFT news and trading activity. We test this hypothesis by estimating Equation (1), where the dependent variable is the number of *trades* in day t. Table 6 summarizes our findings. For this test and those of H3, we focus on the coefficients and chi-squared tests for the lagged values of *news*. We tabulate the coefficients for other *Endog* and *Exog* variables in the Internet Appendix for brevity.

[Insert Table 6 here]

Consistent with our prediction, Columns (1), (2), and (3) document a positive relation between *all news*, *positive news*, and *neutral news* with the number of *trades*. Specifically, NFT news increases the number of trades with a two-day delay. Moreover, there is strong evidence that non-negative news Granger causes trading as the chi-squared tests on the joint coefficients are all significant at the 1% level. We also find a long-lasting effect of news on trading as the chi-squared test on the sum of the coefficients on *all news* is positive and significant with a p-value of 0.051.

These findings provide supportive evidence for H2 and indicate that NFT news exerts a positive impact on trading. Consistent with our prediction, this relation is not present when the news contains negative sentiment.

5.4. News and Minting

H2 also predicts that NFT news will impact the creation of new NFTs. To test this notion, we estimate Equation (1) using *minting* as the dependent variable.

[Insert Table 7 here]

The results in Table 7 show that news positively relates to the number of NFTs minted with a slight delay. Specifically, Columns (1) and (3) show that *all news* and *neutral news* are positively associated with *minting* with a three to five day delay. Moreover, we find evidence of Granger causality for these types of news as the chi-squared tests on the joint coefficients are significant at the 5% level or better. However, the chi-squared tests on the coefficient sums are not significant, indicating that the impact of news on minting is not long-lasting. We find no relation between minting and positive or negative news.

5.5. News and New Participants

As a third test of H2, we examine the relation between news and the number participants as the dependent variable in Equation (1). The results are reported in in Table 8.

[Insert Table 8 here]

Columns (1) to (3) show that news increases participation with a two-day delay, especially when the news is positive in tone. The chi-squared tests on the joint lags show that all types of news except negative news Granger causes NFT marketplace participation. Thus, the tone of news articles impact the extent to which a story attracts new participants. We find no evidence that the relation between non-negative news and greater participation lasts beyond a few days, as the chi-squared values on the sum of the lagged coefficients are not significant.

Overall, the results in Tables 6, 7, and 8 generally support H2 in that news impacts NFT market activity in terms of trading, minting, and the number of participants. The overall relation appears to be stronger when news is positive or neutral in tone. Thus, our results indicate that media coverage can boost NFT marketplace activity, especially when the news does not contain negative sentiment.

5.6. News and Return Volatility

We next turn to tests of H3 by estimating Equation (1), where the dependent variable is the NFT return *volatility* on day t. The results are summarized in Table 9.

[Insert Table 9 here]

News has an immediate negative impact on return volatility on the next day. Indeed, the coefficients on *all news*, *positive news*, and *neutral news* on day *t-1* are negative and significant at the 5% level or better. Moreover, there is evidence that *all news* Granger causes declines in volatility. Non-negative news also has a long-lasting effect as the sum of the coefficients are negative and significant in chi-squared tests at the 10% level or better. The coefficient on negative news is negative and significant for *t-2*. However, the chi-squared tests fail to support Granger causality for news with a negative tone. These results provide initial evidence that the media educates market participants rather than generating hype.

5.7. News and Returns

Our second test of H3 further examines the role of the media by measuring the relation between news and seller returns. We estimate Equation (1), where the dependent variable is NFT *returns* on day t, and report our results in Table 10.

[Insert Table 10 here]

The results show that news negatively relates to next day returns, especially when the tone is negative or neutral. Specifically, the coefficients on *news* on day $t+1$ are negative and significant at the 10% level or better. However, we find no evidence of Granger causality using chi-squared tests of the joint coefficients during the trading week. The sum of the coefficients on negative news is less than zero and significant at the 10% level in chi-squared tests. Thus, there is marginal evidence that relation between negative news and lower returns is long lasting.

Taken together, the results in Tables 9 and 10 are inconsistent with the notion that the primary role of the media in speculative markets is to generate hype. Instead, we find evidence that NFT news Granger causes lower return volatility and has a mostly negative or non-Granger causal relation with seller returns. These results are consistent with the explanation that the media plays an information gatekeeper role in speculative markets.

6. Additional Tests

6.1. News Source

In this subsection, we examine whether the source of NFT news has a differential influence on market participation. To do so, we assign each news story into one of five media categories: *Local*, *National*, *Financial*, *Tech*, and *Crypto*. For each media type, we examine the distribution of NFT news and re-estimate our tests of Equation (1).

Local media includes local radio stations (e.g., Wisconsin Public Radio), television stations (e.g., CBS Miami), and regional newspapers (e.g., St. Louis Post-Dispatch). *National* media includes sources such as CNN, Fox News, and ABC News. *Financial* media includes sources such as CNBC, Bloomberg News, and Seeking Alpha. *Tech* sources include news organizations such as The Verge, WIRED, Gizmodo, and CNET News. *Crypto* media includes outlets such as BitcoinInsider, CoinDesk, Cointelegraph, and Decrypt.

Panel A of Table 11 presents a frequency distribution by media type. *Financial* media provide the greatest proportion of NFT news articles at 34% of the sample. These articles stem from 170 unique sources. Just over 1,200 *Local* sources furnish 22% of the news articles, followed by 20% of news published by 74 *National* sources. A total of 36 *Crypto* sources provide 16% of news articles, while 110 *Tech* media outlets provide the remaining 7%.

[Insert Table 11 here]

Panel B summarizes the tone of news articles by media type. Overall, there are some statistical differences in the sentiment across categories. *Financial* media tend to be more positive in tone when covering NFTs, while *National* and *Tech* media tends to be more neutral. *Local* media tends to be more negative in their NFT news stories. While one might expect *Crypto* news sources to have a relatively more positive tone, we find no statistical differences in the tone of NFT news for *Crypto* versus non-Crypto sources.

Next, we re-estimate Equation (1) for each subsample of media type to determine their influence on market participation and the properties of returns. We present the results in Panels A to E of Table 12.

[Insert Table 12 here]

NFT news by *National* and *Tech* media Granger cause market activity. Indeed, the chi-squared tests of the joint coefficients on news by these sources are significant in tests of *trades*, *minting*, and *participation*. There is some evidence that *Crypto* media news Granger causes *trades* and *participants*. *Local* media, however, have no Granger relation with marketplace activity. These results could stem from a couple of factors. First, the negative tone of *Local* NFT news could discourage participation. Second, the demographics of *Local* media readership might differ from those that are likely to participate in NFT markets.

In Panel D, we examine the relation between news media type and return volatility. Although the coefficients are negative and significant on day $t-1$ for all media types except *Local*, none of the chi-squared tests on the joint lags are significant. Thus, no particular media type drives the reduction in return volatility observed in Table 9.

The results are similar in tests of news and returns by media type in Panel E. Of note, NFT news by Crypto media on day $t-1$ is negatively related to seller returns on day t. This result is also inconsistent with the notion that media hypes NFT markets—including those media that focus on the digital asset space.

Taken together, the results suggest that NFT news by *National* and *Tech* media drive market activity and lead to informed rather than hyped outcomes. *Crypto*-focused show no abnormal tendency to hype NFT markets based on the tone of their coverage and relation with returns. *Local* media sources tend to provide more negative coverage of NFTs but do not influence participation or returns.

6.2. Alternative VAR Analysis

In our tests, we follow Tetlock (2007) in estimating the VAR model using OLS and conducting chi-squared tests to establish Granger causality. An alternative approach is to run a traditional VAR and report the corresponding Granger causality Wald tests (e.g., Kumar et al., 2012). In the Internet Appendix, we report results from this alternative VAR approach.

The results are similar for tests of *news* as the dependent variable. In tests where the lags of *news* are the variable of interest, we obtain similar results for Granger causality tests of *trades* and *minting*. However, the Granger causality tests of *news* on *participants* misses significance (p-value $= 0.174$). Thus, there is more robust evidence that the media influences trading and minting of existing participants versus attracting new participants. The relation between *news* and both *volatility* and *returns* are similar with the alternative VAR approach.

7. Conclusion

Prior work shows that news impact financial markets and investor returns. Some argue that the media reduces information frictions and allows participants to make informed decisions by educating investors on the risks of emerging technologies. Others present evidence that, in speculative markets, the media often focuses on extreme growth and returns, thereby enhancing the salience of this information. In this setting, the media can hype speculative assets and exacerbate irrational behavior.

We revisit the role of the media in speculative markets by studying news about NFTs, which represent an emerging technology and nascent asset class. We first present evidence that the NFT space is characterized by extreme growth, highly skewed returns, and uncertainty for market participants. A market with such characteristics is a natural laboratory for studying the influence of the media in speculative markets.

Building upon prior literature and substantial anecdotal evidence, we then develop a conceptual framework of the role of the media in covering NFT markets. Using a VAR approach, we first identify the drivers of media coverage. We then show that NFT news is linked to (i.e., Granger causes) marketplace activity. To test whether the news reflects a media role of hype or education, we study the relation of news with NFT returns. We find strong evidence that news results in a swift, strong, and sustained reduction in price volatility. Moreover, we find some evidence that seller returns decline after news, which is inconsistent with hyping a fast growing market.

Overall, our study contributes to the literature on the role of the media in speculative and unregulated markets. We show that journalists play an important investor protection role by producing informative content on new and risky assets. Thus, we also contribute the strands of literature that examine information frictions in speculative markets. Our findings, therefore, should be of interest to academics, regulators, and market participants.

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Appendix: Variable Definitions

Variable	Definition
NFT News	
All News$_t$	Log transformed number of NFT news articles on day t plus 1. We identify NFT news articles as those with the word *fungib** or *NFT** in the headline.
Positive News$_t$	Log transformed number of positive NFT news articles on day t plus 1. Positive articles have a composite sentiment score (CSS) in RavenPack between 0.01 and 1.00.
Neutral News$_t$	Log transformed number of neutral NFT news articles on day t plus 1. Neutral articles have a CSS in RavenPack equal to 0.00.
Negative News$_t$	Log transformed number of negative NFT news articles on day t plus 1. Negative articles have a CSS in RavenPack between -1.00 and -0.01.
NFT Properties	
Trades$_t$	Log transformed number of NFT trades on day t plus 1.
Minting	Log transformed number of NFTs minted on day t plus 1.
Seller Wallets$_t$	Number of unique seller wallets on day t plus 1.
Buyer Wallets$_t$	Number of unique buyer wallets on day t plus 1.
Participants$_t$	Log transformed number of buyer plus seller wallets on day t plus 1.
Volatility$_t$	Detrended squared residuals of *NFT Return*. We first demean *NFT Returns* to obtain a residual and then square this residual. We then subtract the past 15-day moving average of this squared residual (Tetlock, 2007).
Returns$_t$	Value-weighted average returns for NFTs on day t.
Controls	
Bitcoin Return$_t$	Daily Bitcoin (BTC) return using the earliest and latest price on day t, from CoinMarketCap.
Ether Return$_t$	Daily Ether (ETH) return using the earliest and latest price on day t, from CoinMarketCap.
Stock Return$_t$	Return of the CRSP value-weighted market on day t. Non-trading days are set to zero.

Table 1: Yearly Distribution of NFT Trading

Panel A: Activity

Years	New Minting	Total Minting	Trades	Dollar Volume ($)	Buyer Wallets	Seller Wallets
2017	1,108	1,108	1,286	153,686	103	45
2018	4,437	5,545	4,887	292,699	480	358
2019	57,630	63,175	70,082	5,348,987	4,192	4,421
2020	93,032	156,207	124,736	18,964,920	11,267	8,802
2021	3,872,798	4,029,005	7,368,296	11,950,205,425	774,214	376,412

Panel B: Returns

Years	Return_i Mean (%)	Return_i P25 (%)	Return_i Median (%)	Return_i P75 (%)	Volatility_i
2017	158.18	1.18	56.74	125.05	341.29
2018	119.44	-36.57	11.38	102.8	329.59
2019	97.45	-17.55	9.51	68.3	294.87
2020	114.26	-26.52	2.67	79.46	338.26
2021	70.39	-12.44	0.98	56.61	238.88

Panel C: Marketplaces

Platform	First Sample Year	Minting	Trades	Dollar Volume ($)	Buyer Wallets	Seller Wallets
LarvaLabs	2017	6,418	17,454	325,567,703	1,824	1,323
Opensea	2018	3,991,854	7,475,287	11,531,432,392	768,705	379,312
SuperRare	2019	5,927	6,905	21,516,470	569	760
Rarible	2021	24,806	69,641	96,449,152	19,158	8,643
Sum (2017-2021)		4,029,005	7,569,287	11,974,965,717	790,256	390,038

This table summarizes non-fungible token (NFT) trading across years and platforms. Panel A presents the yearly distribution of market activity. Panel B computes yearly values for measures of NFT returns. Panel C highlights trading information for NFT marketplaces in our sample.

Table 2: Time Trends in NFT News

	News			
Year-Quarter	All	Positive	Neutral	Negative
2017-Q3	0	0	0	0
2017-Q4	0	0	0	0
2018-Q1	3	3	0	0
2018-Q2	9	0	9	0
2018-Q3	0	0	0	0
2018-Q4	14	2	12	0
2019-Q1	9	3	6	0
2019-Q2	13	6	7	0
2019-Q3	8	5	3	0
2019-Q4	15	6	6	3
2020-Q1	20	12	8	0
2020-Q2	17	4	4	9
2020-Q3	50	24	23	3
2020-Q4	207	60	134	13
2021-Q1	3,006	1,253	1,509	244
2021-Q2	5,134	1,889	2,722	523
2021-Q3	5,748	2,680	2,698	370
2021-Q4	11,679	4,560	5,872	1,247
Total	25,932	10,507	13,013	2,412

This table presents a count of the number of non-fungible token (NFT) news articles by calendar quarter over the third quarter of 2017 to the fourth quarter of 2021. We present the data for *all news* articles and separated by NFT news type. *Positive news* articles have a composite sentiment score (CSS) in RavenPack between 0.01 and 1.00. *Neutral news* articles have a CSS in RavenPack equal to 0.00. *Negative news* articles have a CSS in RavenPack between −1.00 and −0.01.

Table 3: Textual Analysis of NFT News Headlines

Rank	Phrase	% Headlines	Word	% Headlines
1	nft marketplace	6.09	art	7.08
2	nft collection	3.81	launches	7.91
3	nft platform	3.67	marketplace	7.74
4	nft market	1.93	ethereum	7.45
5	nft art	1.65	platform	7.21
6	nft project	1.65	launch	6.91
7	fungible tokens	1.45	blockchain	5.85
8	launches nft	1.43	crypto	5.66
9	nft drop	1.29	collection	5.77
10	nft craze	1.15	announces	5.30
11	bored ape	1.11	digital	5.15
12	digital art	1.11	world	4.75
13	nft sales	0.98	million	4.90
14	announces nft	0.89	market	4.59
15	nft game	0.87	metaverse	3.54
16	exclusive nft	0.79	game	3.33
17	nft auction	0.77	auction	3.26
18	nft space	0.76	project	3.16
19	launch nft	0.74	artist	3.11
20	artist beeple	0.72	defi	2.81
21	selling nft	0.71	tokens	2.55
22	art nft	0.70	release	2.49
23	bored ape yacht club	0.70	sells	2.47
24	digital collectibles	0.69	partners	2.45
25	nft launches	0.63	gaming	2.34

This table reports the 25 most frequent phrases and words in the headlines of non-fungible token (NFT) *news* articles. We also report the percent (%) of all headlines containing each phrase and word.

Table 4: Summary Statistics

Variable	N (days)	Mean	S.D.	P25	P50	P75
NFT News						
All	1,081	1.251	1.803	0.000	0.000	2.485
Positive	1,081	0.907	1.445	0.000	0.000	1.609
Neutral	1,081	0.984	1.534	0.000	0.000	1.792
Negative	1,081	0.439	0.864	0.000	0.000	0.693
NFT Properties						
Trades	1,081	5.093	2.320	3.466	4.043	6.858
Minting	1,081	5.985	1.754	4.779	5.403	6.378
Participants	1,081	4.521	1.954	3.091	3.738	5.638
Volatility	1,081	-0.186	10.992	-2.369	-0.466	0.489
Returns	1,081	2.250	2.070	0.854	1.767	2.938
Controls						
Bitcoin Return	1,081	0.003	0.039	-0.014	0.002	0.019
Ether Return	1,081	0.004	0.050	-0.019	0.003	0.030
Stock Return	1,081	0.001	0.012	-0.001	0.000	0.004

This table reports descriptive statistics of daily variables used in our analysis. *Trades* is the natural logarithm of number of NFT trades in a given day plus 1. *Minting* and *participants* are the log transformed value of the number of unique non-fungible tokens (NFTs) created and market participants in a given day plus 1. *Return* is the value weighted average of individual NFT returns in a given day, where individual return is the difference between two trades based on U.S. dollar amount. *Volatility* is the detrended squared NFT return residuals. For each measure of news, we compute the natural logarithms of the count of NFT news articles on that day plus 1. *Positive news*, *negative news*, and *neutral news* have a composite sentiment score (CSS) in RavenPack between 0.01 and 1.00, -1.00 and -0.01., and equal to 0.00, respectively. *Bitcoin return*, *Ether return*, and *stock return* are daily returns on Bitcoin, Ethereum, and the CRSP value-weighted market portfolio. The details of variable calculations are given in the Appendix.

Table 5: Determinants of NFT News

NFT News Type:	All	Positive	Neutral	Negative
News				
$\chi^2(7)$ [*Joint*]	875.785***	501.097***	850.790***	189.723***
p-value	(0.000)	(0.000)	(0.000)	(0.000)
Sum of 1 to 7	0.838	0.790	0.845	0.721
χ^2 (1) [Sum]	610.231***	366.228***	583.078***	109.903***
p-value	(0.000)	(0.000)	(0.000)	(0.000)
Trades				
χ^2 (7) [Joint]	16.841**	12.523*	13.627*	4.830
p-value	(0.018)	(0.085)	(0.058)	(0.681)
Sum of 1 to 7	0.106	0.136	0.057	0.028
χ^2 (1) [Sum]	8.381***	8.945***	2.848*	0.402
p-value	(0.003)	(0.002)	(0.091)	(0.526)
Minting				
χ^2 (7) [Joint]	20.233***	7.671	15.148**	11.464
p-value	(0.005)	(0.198)	(0.034)	(0.119)
Sum of 1 to 7	−0.132	−0.081	−0.104	−0.183
χ^2 (1) [Sum]	9.400***	4.259**	6.362**	5.042**
p-value	(0.002)	(0.039)	(0.012)	(0.024)
Participants				
χ^2 (7) [Joint]	15.746**	7.946	15.641**	12.282*
p-value	(0.028)	(0.337)	(0.029)	(0.091)
Sum of 1 to 7	0.135	0.054	0.137	0.151
χ^2 (1) [Sum]	5.213**	0.822	5.547**	4.379**
p-value	(0.022)	(0.364)	(0.018)	(0.036)
Volatility				
χ^2 (7) [Joint]	8.780	2.696	8.079	5.963
p-value	(0.261)	(0.911)	(0.325)	(0.544)
Sum of 1 to 7	0.005	0.002	0.002	0.004
χ^2 (1) [Sum]	1.111	0.487	0.324	4.077**
p-value	(0.291)	(0.485)	(0.569)	(0.043)
Return				
χ^2 (7) [Joint]	11.353	4.313	19.634***	7.594
p-value	(0.124)	(0.743)	(0.006)	(0.369)
Sum of 1 to 7	−0.012	−0.012	−0.014	−0.045
χ^2 (1) [Sum]	0.626	0.995	1.289	4.808**
p-value	(0.429)	(0.318)	(0.256)	(0.028)

This table reports the chi-squared (χ^2) values from an estimate of Equation (1), where the dependent variable is NFT *news* on day *t*. We use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. We fully tabulate the coefficients in the Internet Appendix. To test for Granger causality, we calculate the chi-squared test statistics and report the associated *p*-value in parentheses. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively. We define all variables in the Appendix.

Table 6: Determinants of NFT Trades

	Dependent variable = $Trades_t$			
NFT News Type:	All	Positive	Neutral	Negative
$News_{t-1}$	−0.019	−0.012	−0.009	−0.013
$News_{t-2}$	0.047***	0.047***	0.034*	0.016
$News_{t-3}$	0.022	0.000	0.033**	−0.001
$News_{t-4}$	0.000	0.019	−0.017	0.012
$News_{t-5}$	0.020	−0.003	0.029	0.004
$News_{t-6}$	−0.004	0.017	−0.012	0.006
$News_{t-7}$	−0.024	−0.032*	−0.024	−0.017
$\chi^2(7)$ [*Joint*]	23.324***	19.832***	20.413***	5.050
p-value	(0.001)	(0.006)	(0.005)	(0.653)
Sum of 1 to 7	0.042	0.036	0.034	0.007
$\chi^2(1)$ [*Sum*]	3.786*	1.899	2.185	0.039
p-value	(0.051)	(0.168)	(0.139)	(0.842)
Other controls	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.983	0.982	0.982	0.982

This table reports estimates of Equation (1), where the dependent variable is NFT *trades* on day t. We use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. We fully tabulate the coefficients in the Internet Appendix. To test for Granger causality, we calculate the chi-squared test statistics and report the associated p-value in parentheses. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively. We define all variables in the Appendix.

Table 7: Determinants of NFT Minting

	Dependent variable = Minting_t			
NFT News Type:	All	Positive	Neutral	Negative
News_{t-1}	−0.017	−0.019	−0.012	−0.020
News_{t-2}	0.018	0.026	0.016	0.012
News_{t-3}	0.035^{**}	0.018	0.018	0.020
News_{t-4}	−0.013	−0.002	−0.009	0.021
News_{t-5}	0.040^{**}	0.005	0.043^{**}	0.010
News_{t-6}	−0.030	0.007	−0.032	−0.015
News_{t-7}	−0.021	−0.020	−0.027	−0.010
$\chi^2(7)$ [*Joint*]	19.039^{***}	8.961	16.889^{**}	0.621
p-value	(0.008)	(0.255)	(0.018)	(0.516)
Sum of 1 to 7	0.012	0.015	−0.003	0.018
$\chi^2(1)$ [*Sum*]	0.305	0.451	0.015	0.293
p-value	(0.581)	(0.501)	(0.901)	(0.587)
Other controls	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.974	0.974	0.974	0.974

This table reports the estimates of Equation (1), where the dependent variable is NFT *minting* on day t. We use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. We fully tabulate the coefficients in the Internet Appendix. To test for Granger causality, we calculate the chi-squared test statistics and report the associated p-value in parentheses. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively. We define all variables in the Appendix.

Table 8: Determinants of NFT Participants

	Dependent variable = Participants_t			
NFT News Type:	All	Positive	Neutral	Negative
News_{t-1}	-0.002	-0.013	0.015	0.001
News_{t-2}	0.032^{*}	0.047^{***}	0.024	0.021
News_{t-3}	0.029	0.007	0.026^{*}	0.004
News_{t-4}	-0.005	0.012	-0.013	0.005
News_{t-5}	0.000	-0.018	0.018	0.018
News_{t-6}	-0.003	0.009	-0.015	-0.002
News_{t-7}	-0.026	-0.021	-0.035^{*}	-0.022
$\chi^2(7)$ [*Joint*]	16.399^{**}	15.852^{**}	17.549^{**}	5.913
p-value	(0.021)	(0.026)	(0.014)	(0.549)
Sum of 1 to 7	0.025	0.023	0.020	0.025
$\chi^2(1)$ [*Sum*]	1.369	0.901	0.897	0.718
p-value	(0.242)	(0.342)	(0.343)	(0.396)
Other controls	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.977	0.977	0.977	0.977

This table reports the estimates of Equation (1), where the dependent variable is NFT *participants* on day t. We use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. We fully tabulate the coefficients in the Internet Appendix. To test for Granger causality, we calculate the chi-squared test statistics and report the associated p-value in parentheses. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively. We define all variables in the Appendix.

Table 9: Determinants of NFT Return Volatility

	Dependent variable = Volatility$_t$			
NFT News Type:	All	Positive	Neutral	Negative
News$_{t-1}$	-2.075^{***}	-1.338^{**}	-1.624^{**}	-0.533
News$_{t-2}$	0.221	0.444	-0.216	-0.724^{**}
News$_{t-3}$	-0.037	-0.564	0.272	0.482
News$_{t-4}$	-0.047	-0.577	0.004	0.223
News$_{t-5}$	0.758	0.254	0.751	0.035
News$_{t-6}$	-1.528^{**}	-0.512	-1.131^{*}	-0.573
News$_{t-7}$	0.995	0.666	0.500	-0.173
$\chi^2(7)$ [*Joint*]	14.693^{**}	9.341	10.451	6.471
p-value	(0.040)	(0.229)	(0.164)	(0.485)
Sum of 1 to 7	-1.713	-1.627	-1.444	-1.263
$\chi^2(1)$ [*Sum*]	4.906^{**}	3.024^{*}	3.899^{**}	1.687
p-value	(0.027)	(0.082)	(0.048)	(0.193)
Other controls	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.063	0.054	0.058	0.051

This table reports the estimates of Equation (1), where the dependent variable is NFT *volatility* on day t. We use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. We fully tabulate the coefficients in the Internet Appendix. To test for Granger causality, we calculate the chi-squared test statistics and report the associated p-value in parentheses. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively. We define all variables in the Appendix.

Table 10: Determinants of NFT Returns

	Dependent variable = Returns_t			
NFT News Type:	All	Positive	Neutral	Negative
News_{t-1}	-0.286^{**}	-0.125	-0.267^{**}	-0.149^{*}
News_{t-2}	0.028	0.050	-0.008	-0.142^{**}
News_{t-3}	0.039	-0.076	0.082	0.079
News_{t-4}	0.000	-0.067	-0.052	0.042
News_{t-5}	0.069	-0.026	0.132	-0.047
News_{t-6}	-0.143	-0.003	-0.134	-0.058
News_{t-7}	0.124	0.042	0.080	-0.010
$\chi^2(7)$ [*Joint*]	8.367	4.936	8.905	7.201
p-value	(0.301)	(0.667)	(0.259)	(0.408)
Sum of 1 to 7	-0.169	-0.205	-0.167	-0.285
$\chi^2(1)$ [*Sum*]	2.022	2.148	2.102	3.278^{*}
p-value	(0.154)	(0.142)	(0.147)	(0.070)
Other controls	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.3468	0.343	0.347	0.345

This table reports estimates of Equation (1), where the dependent variable is NFT *returns* on day t. We use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. We fully tabulate the coefficients in the Internet Appendix. To test for Granger causality, we calculate the chi-squared test statistics and report the associated p-value in parentheses. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively. We define all variables in the Appendix.

Table 11: NFT News Sources

Panel A: Number of Articles

Media Type	Articles	Percent	Unique Sources	Examples
Local	5,785	22.3	1,210	CBS Miami
National	5,246	20.2	74	CNN
Financial	8,784	33.9	170	CNBC
Tech	1,864	7.2	110	CNET
Crypto	4,253	16.4	36	Coindesk
All	25,932	100	1,600	

Panel B: Tone of Articles

	Percent of Articles			Difference vs. sample		
Media Type	Positive	Neutral	Negative	Positive	Neutral	Negative
Local	40.4	47.2	12.3	-0.1	-3.8^{***}	3.9^{***}
National	39.0	52.1	8.9	-1.9^{**}	2.5^{***}	-0.6
Financial	41.4	50.7	7.8	1.4^{**}	0.8	-2.2^{***}
Tech	38.8	53.4	7.8	-1.8	3.5^{***}	-1.6^{**}
Crypto	41.4	49.3	9.4	1.0	-1.1	0.1
All	40.5	50.2	9.3			

This table presents distribution statistics for NFT *news* articles by media type. Panel A presents the number of articles by type. Panel B presents the tone by type. In Panel B, we also test for statistical differences in the tone versus other media types using standard two-tailed t-tests. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table 12: Market Participation by NFT News Source

Panel A: Determinants of Trades

	Dependent variable = Trades_t				
Media Type:	Local	National	Financial	Tech	Crypto
News_{t-1}	0.006	−0.016	−0.004	−0.014	−0.013
News_{t-2}	0.021^{*}	0.031	0.030^{*}	0.022	0.044^{***}
News_{t-3}	0.012	0.031	0.030^{*}	0.027	0.006
News_{t-4}	0.007	−0.003	−0.013	0.002	0.019
News_{t-5}	0.008	0.011	0.029	0.013	0.000
News_{t-6}	−0.016	0.007	−0.009	0.004	0.027
News_{t-7}	-0.024^{*}	-0.048^{***}	−0.024	−0.025	-0.041^{***}
$\chi^2(7)$ [*Joint*]	10.459	21.951^{***}	20.377^{***}	21.716^{***}	17.470^{**}
p-value	(0.163)	(0.002)	(0.004)	(0.002)	(0.015)
Other controls	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081	1081
R^2	0.982	0.982	0.982	0.982	0.982

Panel B: Determinants of Minting

	Dependent variable = Minting_t				
Media Type:	Local	National	Financial	Tech	Crypto
News_{t-1}	0.000	−0.020	−0.020	-0.035^{*}	−0.010
News_{t-2}	0.013	0.013	0.030^{*}	0.025	0.007
News_{t-3}	0.027^{***}	0.068^{***}	0.009	0.036^{***}	0.021
News_{t-4}	0.005	−0.019	−0.003	0.003	0.005
News_{t-5}	0.005	0.021	0.020	0.019	0.042^{***}
News_{t-6}	−0.022	−0.016	−0.023	−0.009	−0.018
News_{t-7}	-0.030^{***}	−0.033	−0.010	−0.010	−0.029
$\chi^2(7)$ [*Joint*]	9.657	20.259^{***}	7.312	15.674^{**}	9.750
p-value	(0.208)	(0.005)	(0.397)	(0.028)	(0.203)
Other controls	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081	1081
R^2	0.974	0.974	0.974	0.974	0.974

Panel C: Determinants of Participants

	Dependent variable = Participants_t				
Media Type:	Local	National	Financial	Tech	Crypto
News_{t-1}	0.012	−0.011	−0.016	0.010	0.021
News_{t-2}	0.023^{*}	0.029	0.046^{***}	0.030^{*}	0.016
News_{t-3}	0.014	0.045^{***}	0.017	0.034^{***}	0.033
News_{t-4}	0.009	−0.004	−0.015	0.008	0.000
News_{t-5}	−0.005	0.009	0.012	0.023	0.000
News_{t-6}	-0.025^{***}	0.007	−0.011	−0.001	0.003
News_{t-7}	−0.021	-0.047^{***}	−0.018	-0.035^{*}	-0.041^{***}
$\chi^2(7)$ [*Joint*]	9.999	32.267^{***}	19.632^{***}	36.606^{***}	12.592^{*}
p-value	(0.189)	(0.000)	(0.006)	(0.000)	(0.083)
Other controls	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081	1081
R^2	0.977	0.977	0.977	0.977	0.977

Table 12: Continued

Panel D: Determinants of Return Volatility

	Dependent variable = Volatility_t				
Media Type:	Local	National	Financial	Tech	Crypto
News_{t-1}	−0.305	−1.109*	−1.133*	−0.895***	−2.158***
News_{t-2}	−0.201	−0.088	−0.608	−0.586*	0.248
News_{t-3}	−0.257	−0.296	0.186	0.015	0.027
News_{t-4}	−0.096	0.491	0.291	−0.061	−1.028
News_{t-5}	−0.065	−0.059	−0.134	−0.070	1.554***
News_{t-6}	−0.158	−0.706	−0.925*	−0.344	−1.229*
News_{t-7}	0.025	0.477	0.634	0.062	0.388
$\chi^2(7)$ [*Joint*]	3.976	6.009	11.383	8.520	10.423
p-value	(0.782)	(0.538)	(0.122)	(0.288)	(0.165)
Other controls	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081	1081
R^2	0.049	0.051	0.055	0.051	0.060

Panel E: Determinants of Returns

	Dependent variable = Returns_t				
Media Type:	Local	National	Financial	Tech	Crypto
News_{t-1}	−0.025	−0.185*	−0.181*	−0.118	−0.273***
News_{t-2}	−0.029	−0.044	−0.083	−0.124*	0.027
News_{t-3}	−0.077	−0.014	0.066	0.075	0.022
News_{t-4}	0.017	−0.025	−0.046	−0.101	−0.077
News_{t-5}	−0.080	0.063	0.054	0.031	0.162
News_{t-6}	0.022	−0.084	−0.123	−0.056	−0.116
News_{t-7}	−0.024	0.072	0.101	−0.014	0.029
$\chi^2(7)$ [*Joint*]	5.992	5.155	7.631	7.487	6.521
p-value	(0.540)	(0.640)	(0.366)	(0.379)	(0.480)
Other controls	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081	1081
R^2	0.343	0.344	0.345	0.344	0.346

This table reports the estimation of Equation (1) by media type, where the dependent variables are non-fungible (NFT) *trades*, *minting*, *participants*, *volatility*, and *returns* on day t. We use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. We fully tabulate the coefficients in the Internet Appendix. To test for Granger causality, we calculate the chi-squared test statistics and report the associated p-value in parentheses. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively. We define all variables in the Appendix.

Internet Appendix to

"The role of the media in speculative markets: Evidence from non-fungible tokens (NFTs)"

Table IA-1: Sample Selection

	N
(1) All NFT data over June 23, 2017, to December 31, 2021	8,989,371
(2) Less missing NFT token identification or address	(792,786)
(3) Less NFTs linked to multiple items	(80,302)
(4) Less NFT transfers	(271,641)
(5) Less NFT trades with duplicate identification, amount, and timestamp	(275,355)
Final sample	7,569,287

This table presents our sample selection process. We begin with all NFT data and apply the listed filters. Note that the filters are not mutually exclusive, so the number removed in each step depends on its ordering.

Table IA-2: Correlation Matrix

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
[1] All News	1.00											
[2] Positive News	0.97***	1.00										
[3] Neutral News	0.98***	0.94***	1.00									
[4] Negative News	0.86***	0.83***	0.85***	1.00								
[5] Trades	0.91***	0.89***	0.89***	0.76***	1.00							
[6] Minting	0.82***	0.81***	0.81***	0.70***	0.94***	1.00						
[7] Participants	0.89***	0.87***	0.88***	0.76***	0.98***	0.95***	1.00					
[8] Volatility	−0.02	−0.01	−0.01	0.00	0.00	0.01	0.00	1.00				
[9] Returns	0.06	0.03	0.05	0.00	0.06	−0.02	0.06*	0.61***	1.00			
[10] Bitcoin Return	−0.02	−0.01	−0.03	−0.03	0.00	−0.01	−0.00	−0.02	−0.01	1.00		
[11] Ether Return	0.02	0.03	0.01	0.01	0.01	−0.00	0.01	−0.05	−0.01	0.80***	1.00	
[12] Stock Return	0.00	0.01	−0.01	0.01	0.00	−0.01	−0.01	0.00	0.01	0.25***	0.25***	1.00

This table presents a pairwise correlation matrix of the key variables in our analysis. Variable definitions are presented in the Appendix. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Table IA-3: Unit Root Test

	ADF Test	PP Test
NFT News		
All	-10.157^{***}	-8.603^{***}
Positive	-11.957^{***}	-10.960^{***}
Neutral	-10.536^{***}	-9.079^{***}
Negative	-16.301^{***}	-16.934^{***}
NFT Properties		
Trades	-5.258^{***}	-3.662^{**}
Minting	-4.675^{***}	-3.229^{*}
Participants	-5.656^{***}	-3.719^{**}
Volatility	-29.390^{***}	-29.374^{***}
Returns	-21.965^{***}	-23.884^{***}
Controls		
Bitcoin Return	-35.868^{***}	-35.753^{***}
Ethereum Return	-36.425^{***}	-36.285^{***}
Stock Return	-39.492^{***}	39.128^{***}

This table presents tests of unit roots using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. All unit root tests regressions include an intercept and a time trend variable. ***, ** and * represent statistical significance at the 1%, 5%, and 10% level, respectively, based on the MacKinnon approximation. In these tests, statistical significance rejects the null of a unit root and supports the alternative that the data are stationary.

Table IA-4: Selection-Order Criteria

Lag	LL	LR	df	p-value	FPE	AIC	HQIC	SBIC
0	-8050.0				0.200088	15.418	15.429	15.447
1	-4528.6	7042.9	36	0	0.000254	8.748	8.823	8.947
2	-4269.6	517.9	36	0	0.000166	8.321	8.461	8.690*
3	-4158.8	221.8	36	0	0.000143	8.178	8.382	8.718
4	-4074.7	168.2	36	0	0.000131	8.086	8.355	8.796
5	-4020.5	108.3	36	0	0.000126	8.051	8.385	8.932
6	-3902.2	236.7	36	0	0.000108	7.893	8.292	8.945
7	-3799.4	205.6*	36	0	0.000095*	7.765*	8.229*	8.988
8	-3778.3	42.1	36	0.223	0.000098	7.794	8.322	9.187
9	-3761.3	34.1	36	0.561	0.000101	7.830	8.423	9.394
10	-3737.4	47.9	36	0.089	0.000104	7.853	8.511	9.588

This table presents the lag selection-order criteria test. We follow Kumar et al. (2012) in estimating the log likelihood (LL) and modified Likelihood Ratio (LR) test, Final Prediction Error (FPE), Akaike's information criterion (AIC), Hannan and Quinn information criterion (HQIC), and Schwarz's Bayesian information criterion (SBIC) results. The optimal lag under each selection criteria is denoted by *. We report the degrees of freedom (df) and *p-value* for the Likelihood Ratio test. Kumar et al. (2012) note that when there is disagreement among the tests, the optimal lag length is chosen using the Likelihood Ratio test. In our study, the optimal lag length is seven trading days or one week.

Table IA-5: Determinants of NFT News

	Dependent variable = NFTs News_t			
News Type:	All	Positive	Neutral	Negative
News_{t-1}	0.336^{***}	0.335^{***}	0.340^{***}	0.275^{***}
News_{t-2}	-0.101^{***}	-0.084^{*}	-0.091^{**}	0.081^{*}
News_{t-3}	0.036	−0.012	0.055	0.096^{**}
News_{t-4}	0.041	0.074^{*}	0.005	−0.078
News_{t-5}	0.025	−0.041	0.039	0.067
News_{t-6}	0.172^{***}	0.191^{***}	0.162^{***}	0.095^{*}
News_{t-7}	0.329^{***}	0.327^{***}	0.335^{***}	0.185^{***}
Trades_{t-1}	0.054	0.099^{**}	0.012	0.006^{**}
Trades_{t-2}	0.002	−0.019	0.037	0.009
Trades_{t-3}	0.063	0.007	0.047	0.022
Trades_{t-4}	0.031	0.061	0.009	0.019
Trades_{t-5}	0.078	0.004	0.063	0.037
Trades_{t-6}	−0.068	0.013	-0.108^{***}	−0.059
Trades_{t-7}	−0.054	−0.029	−0.003	−0.006
Minting_{t-1}	−0.072	−0.086	−0.002	-0.142^{***}
Minting_{t-2}	−0.014	0.027	0.005	0.026
Minting_{t-3}	0.190^{**}	0.094	0.120^{**}	0.010
Minting_{t-4}	−0.072	−0.029	0.014	0.001
Minting_{t-5}	-0.127^{**}	-0.121^{*}	-0.111^{*}	−0.034
Minting_{t-6}	−0.040	0.036	−0.049	−0.035
Minting_{t-7}	0.003	−0.002	−0.081	−0.018
$\text{Participants}_{t-1}$	0.074	0.096^{*}	−0.037	0.108^{***}
$\text{Participants}_{t-2}$	0.001	−0.032	0.042	0.011
$\text{Participants}_{t-3}$	−0.043	0.031	−0.068	0.006
$\text{Participants}_{t-4}$	0.071	0.039	0.078	0.038
$\text{Participants}_{t-5}$	0.085	0.063	0.042	0.055
$\text{Participants}_{t-6}$	-0.102^{*}	-0.105^{*}	−0.023	−0.037
$\text{Participants}_{t-7}$	0.049	−0.038	0.103^{**}	−0.030
Volatility_{t-1}	0.001	0.000	0.002	0.001
Volatility_{t-2}	0.004^{*}	0.002	0.002	0.000
Volatility_{t-3}	−0.001	−0.001	−0.001	0.001
Volatility_{t-4}	−0.001	0.000	−0.000	0.000
Volatility_{t-5}	0.000	0.001	−0.002	−0.000
Volatility_{t-6}	−0.002	−0.001	−0.001	0.000
Volatility_{t-7}	0.004^{*}	0.001	0.003^{*}	0.002
Returns_{t-1}	−0.004	−0.015	−0.002	−0.006
Returns_{t-2}	-0.028^{**}	0.000	-0.033^{***}	−0.002
Returns_{t-3}	−0.005	0.000	−0.002	−0.011
Returns_{t-4}	0.011	0.002	0.004	0.000
Returns_{t-5}	0.004	−0.008	0.012	0.006
Returns_{t-6}	0.024^{**}	0.003	0.022^{**}	0.000
Returns_{t-7}	−0.014	0.006	−0.015	−0.011
Bitcoin Return_{t-1}	−0.689	−0.567	−0.984	−0.067
Ether Return_{t-1}	0.241	0.216	0.562	0.128
Stock Return_{t-1}	−0.253	−0.538	−0.498	−0.788
Constant	−0.098	-0.211^{**}	−0.093	−0.051
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.932	0.894	0.917	0.721

This table reports the estimation of Equation (1), where the dependent variable is NFT *news* on day t. Each coefficient represents the impact of a one standard deviation increase in the variable on the log transformed value of news. We define all variables in the Appendix. In our analysis, we use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively.

Table IA-6: Determinants of NFT Trades

	Dependent variable = NFT Trades_t			
NFT News Type:	All	Positive	Neutral	Negative
News_{t-1}	−0.019	−0.012	−0.009	−0.013
News_{t-2}	0.047***	0.047***	0.034*	0.016
News_{t-3}	0.022	0.000	0.033**	−0.001
News_{t-4}	0.000	0.019	−0.017	0.012
News_{t-5}	0.020	−0.003	0.029	0.004
News_{t-6}	−0.004	0.017	−0.012	0.006
News_{t-7}	−0.024	−0.032*	−0.024	−0.017
Trades_{t-1}	0.422***	0.425***	0.424***	0.429***
Trades_{t-2}	0.176***	0.174***	0.178***	0.176***
Trades_{t-3}	0.140***	0.144***	0.143***	0.146***
Trades_{t-4}	0.054	0.05	0.056	0.053
Trades_{t-5}	0.003	0.007	0.003	0.007
Trades_{t-6}	0.043	0.043	0.045	0.049
Trades_{t-7}	0.107***	0.111***	0.109***	0.114***
Minting_{t-1}	0.090**	0.089**	0.092**	0.088**
Minting_{t-2}	0.064	0.060	0.061	0.051
Minting_{t-3}	−0.005	−0.010	−0.012	−0.011
Minting_{t-4}	−0.074	−0.078	−0.079*	−0.079
Minting_{t-5}	−0.114**	−0.109**	−0.109**	−0.103**
Minting_{t-6}	0.010	0.013	0.012	0.016
Minting_{t-7}	0.053	0.046	0.050	0.038
$\text{Participants}_{t-1}$	0.029	0.032	0.027	0.03
$\text{Participants}_{t-2}$	−0.061	−0.062	−0.061	−0.056
$\text{Participants}_{t-3}$	−0.064	−0.064	−0.059	−0.063
$\text{Participants}_{t-4}$	0.153***	0.156***	0.154***	0.155***
$\text{Participants}_{t-5}$	0.021	0.019	0.018	0.016
$\text{Participants}_{t-6}$	−0.044	−0.041	−0.04	−0.039
$\text{Participants}_{t-7}$	−0.029	−0.025	−0.028	−0.018
Returns_{t-1}	0.017*	0.016*	0.017*	0.016*
Volatility_{t-1}	−0.001	−0.001	−0.002	−0.002
Volatility_{t-2}	−0.002	−0.002	−0.002	−0.002
Volatility_{t-3}	−0.002	−0.002	−0.002	−0.002
Volatility_{t-4}	0.003	0.003	0.003	0.003
Volatility_{t-5}	−0.003*	−0.002	−0.002*	−0.002*
Volatility_{t-6}	0.001	0.001	0.001	0.001
Volatility_{t-7}	0.001	0.001	0.001	0.002
Returns_{t-2}	0.007	0.007	0.008	0.008
Returns_{t-3}	0.014	0.015*	0.013	0.015*
Returns_{t-4}	−0.016	−0.017	−0.016	−0.018
Returns_{t-5}	0.006	0.006	0.006	0.005
Returns_{t-6}	0.005	0.005	0.005	0.005
Returns_{t-7}	−0.019**	−0.019**	−0.019**	−0.02**
Bitcoin Return_{t-1}	0.399	0.352	0.330	0.344
Ether Return_{t-1}	−0.949***	−0.923***	−0.924***	−0.970***
Stock Return_{t-1}	0.274	0.259	0.306	0.343
Constant	0.022	0.015	0.011	−0.021
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.983	0.982	0.982	0.982

This table reports the estimation of Equation (1), where the dependent variable is NFT *trades* on day *t*. We define all variables in the Appendix. In our analysis, we use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively.

Table IA-7: Determinants of NFT Minting

	Dependent variable = $Minting_t$			
NFT News Type:	All	Positive	Negative	Neutral
$News_{t-1}$	−0.017	−0.019	−0.012	−0.020
$News_{t-2}$	0.018	0.026	0.016	0.012
$News_{t-3}$	0.035**	0.018	0.018	0.020
$News_{t-4}$	−0.013	−0.002	−0.009	0.021
$News_{t-5}$	0.040**	0.005	0.043**	0.010
$News_{t-6}$	−0.030	0.007	−0.032	−0.015
$News_{t-7}$	−0.021	−0.020	−0.027	−0.010
$Trades_{t-1}$	0.017	0.019	0.021	0.022
$Trades_{t-2}$	−0.018	−0.021	−0.022	−0.022
$Trades_{t-3}$	0.048	0.051	0.053	0.053
$Trades_{t-4}$	−0.030	−0.038	−0.029	−0.036
$Trades_{t-5}$	−0.056	−0.052	−0.055	−0.054
$Trades_{t-6}$	0.063	0.065	0.066	0.069
$Trades_{t-7}$	0.018	0.017	0.017	0.018
$Minting_{t-1}$	0.606***	0.605***	0.606***	0.603***
$Minting_{t-2}$	0.068	0.068	0.069	0.063
$Minting_{t-3}$	0.072	0.065	0.063	0.067
$Minting_{t-4}$	0.059	0.057	0.056	0.059
$Minting_{t-5}$	0.000	0.001	0.001	0.007
$Minting_{t-6}$	0.088*	0.094**	0.093**	0.098**
$Minting_{t-7}$	0.069*	0.070*	0.065*	0.061
$Participants_{t-1}$	−0.038	−0.036	−0.038	−0.036
$Participants_{t-2}$	0.114**	0.117**	0.114**	0.118**
$Participants_{t-3}$	−0.001	−0.002	0.002	−0.002
$Participants_{t-4}$	−0.01	−0.011	−0.01	−0.012
$Participants_{t-5}$	0.025	0.024	0.024	0.018
$Participants_{t-6}$	−0.102**	−0.103**	−0.097**	−0.103**
$Participants_{t-7}$	−0.016	−0.017	−0.016	−0.013
$Volatility_{t-1}$	−0.002*	−0.002*	−0.002*	−0.002*
$Volatility_{t-2}$	0.000	0.000	0.000	0.000
$Volatility_{t-3}$	0.000	0.000	0.000	0.000
$Volatility_{t-4}$	−0.001	−0.001	−0.001	−0.001
$Volatility_{t-5}$	0.000	0.000	0.000	0.000
$Volatility_{t-6}$	0.003**	0.003**	0.003**	0.003**
$Volatility_{t-7}$	−0.002*	−0.002*	−0.002*	−0.002*
$Returns_{t-1}$	0.016**	0.016**	0.016**	0.016**
$Returns_{t-2}$	−0.012	−0.013	−0.013	−0.011
$Returns_{t-3}$	0.002	0.003	0.001	0.003
$Returns_{t-4}$	−0.004	−0.004	−0.004	−0.005
$Returns_{t-5}$	−0.005	−0.005	−0.006	−0.005
$Returns_{t-6}$	−0.010	−0.010	−0.010	−0.010
$Returns_{t-7}$	0.014	0.014	0.015	0.013
Bitcoin $Return_{t-1}$	0.370	0.373	0.292	0.375
Ether $Return_{t-1}$	−0.604*	−0.614**	−0.588*	−0.636**
Stock $Return_{t-1}$	0.058	0.072	0.106	0.095
Constant	0.139**	0.140**	0.122*	0.133**
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.974	0.974	0.974	0.974

This table reports the vector autoregression estimates of Equation (1), where the dependent variable is NFT *minting* on day t. We define all variables in the Appendix. In our analysis, we use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively.

Table IA-8: Determinants of NFT Participants

	Dependent variable = Participants_t			
NFT News Type:	All	Positive	Neutral	Negative
News_{t-1}	−0.002	−0.013	0.015	0.001
News_{t-2}	0.032*	0.047***	0.024	0.021
News_{t-3}	0.029	0.007	0.026*	0.004
News_{t-4}	−0.005	0.012	−0.013	0.005
News_{t-5}	0.000	−0.018	0.018	0.018
News_{t-6}	−0.003	0.009	−0.015	−0.002
News_{t-7}	−0.026	−0.021	−0.035*	−0.022
Trades_{t-1}	0.066	0.069	0.067	0.071
Trades_{t-2}	−0.009	−0.012	−0.009	−0.012
Trades_{t-3}	0.030	0.032	0.032	0.035
Trades_{t-4}	−0.072*	−0.074**	−0.069*	−0.071*
Trades_{t-5}	0.027	0.030	0.026	0.027
Trades_{t-6}	−0.013	−0.011	−0.013	−0.009
Trades_{t-7}	0.022	0.023	0.025	0.025
Minting_{t-1}	0.196***	0.195***	0.196***	0.194***
Minting_{t-2}	−0.072*	−0.075*	−0.074*	−0.081**
Minting_{t-3}	0.052	0.05	0.048	0.051
Minting_{t-4}	−0.045	−0.046	−0.048	−0.043
Minting_{t-5}	−0.061	−0.059	−0.057	−0.052
Minting_{t-6}	−0.018	−0.017	−0.014	−0.012
Minting_{t-7}	−0.013	−0.017	−0.015	−0.025
$\text{Participants}_{t-1}$	0.305***	0.307***	0.304***	0.306***
$\text{Participants}_{t-2}$	0.158***	0.159***	0.158***	0.161***
$\text{Participants}_{t-3}$	0.072	0.072	0.075	0.069
$\text{Participants}_{t-4}$	0.150***	0.151***	0.152***	0.149***
$\text{Participants}_{t-5}$	0.046	0.045	0.043	0.044
$\text{Participants}_{t-6}$	0.049	0.053	0.051	0.050
$\text{Participants}_{t-7}$	0.101***	0.101***	0.100***	0.105***
Volatility_{t-1}	0.000	0.000	0.000	−0.001
Volatility_{t-2}	−0.002	−0.002	−0.002	−0.002
Volatility_{t-3}	−0.002	−0.002*	−0.002	−0.002*
Volatility_{t-4}	0.001	0.001	0.001	0.001
Volatility_{t-5}	−0.001	−0.001	−0.001	−0.001
Volatility_{t-6}	0.001	0.001	0.001	0.001
Volatility_{t-7}	0.001	0.000	0.001	0.001
Returns_{t-1}	−0.001	−0.001	−0.001	0.000
Returns_{t-2}	0.006	0.005	0.006	0.007
Returns_{t-3}	0.016*	0.017*	0.016*	0.018**
Returns_{t-4}	−0.011	−0.011	−0.01	−0.011
Returns_{t-5}	0.008	0.008	0.008	0.007
Returns_{t-6}	0.002	0.002	0.002	0.002
Returns_{t-7}	−0.003	−0.002	−0.003	−0.003
Bitcoin Return_{t-1}	0.397	0.398	0.362	0.402
Ether Return_{t-1}	−0.678**	−0.671**	−0.667**	−0.702**
Stock Return_{t-1}	0.391	0.391	0.445	0.419
Constant	−0.024	−0.026	−0.027	−0.044
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.977	0.977	0.977	0.977

This table reports the vector autoregression estimates of Equation (1), where the dependent variable is NFT *participants* on day t. We define all variables in the Appendix. In our analysis, we use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively.

Table IA-9: Determinants of NFT Return Volatility

	Dependent variable = Volatility_t			
NFT News Type:	All	Positive	Neutral	Negative
News_{t-1}	-2.075^{***}	-1.338^{**}	-1.624^{**}	-0.533
News_{t-2}	0.221	0.444	-0.216	-0.724^{**}
News_{t-3}	-0.037	-0.564	0.272	0.482
News_{t-4}	-0.047	-0.577	0.004	0.223
News_{t-5}	0.758	0.254	0.751	0.035
News_{t-6}	-1.528^{**}	-0.512	-1.131^{*}	-0.573
News_{t-7}	0.995	0.666	0.500	-0.173
Trades_{t-1}	2.690^{**}	2.595^{*}	2.496^{*}	2.367^{*}
Trades_{t-2}	-1.342	-1.318	-1.487	-1.464
Trades_{t-3}	-0.425	-0.529	-0.292	-0.499
Trades_{t-4}	0.535	0.334	0.461	0.228
Trades_{t-5}	-0.081	0.063	-0.039	-0.030
Trades_{t-6}	0.642	0.437	0.536	0.415
Trades_{t-7}	-0.312	-0.159	-0.438	-0.335
Minting_{t-1}	-0.066	-0.095	-0.014	-0.099
Minting_{t-2}	-0.572	-0.435	-0.317	-0.287
Minting_{t-3}	-0.659	-0.869	-0.782	-0.813
Minting_{t-4}	0.275	0.046	0.204	0.145
Minting_{t-5}	0.077	0.164	0.138	0.235
Minting_{t-6}	0.544	0.947	0.740	0.984
Minting_{t-7}	-1.086	-0.772	-1.078	-0.953
$\text{Participants}_{t-1}$	-1.649	-1.477	-1.547	-1.456
$\text{Participants}_{t-2}$	0.109	0.088	-0.175	-0.085
$\text{Participants}_{t-3}$	1.137	0.966	1.148	1.148
$\text{Participants}_{t-4}$	1.056	1.115	1.023	1.032
$\text{Participants}_{t-5}$	0.852	0.699	0.927	0.696
$\text{Participants}_{t-6}$	-0.340	-0.556	-0.426	-0.624
$\text{Participants}_{t-7}$	-0.339	-0.452	-0.322	-0.303
Volatility_{t-1}	0.059	0.062	0.06	0.067
Volatility_{t-2}	0.013	0.008	0.014	0.009
Volatility_{t-3}	-0.043	-0.047	-0.045	-0.048
Volatility_{t-4}	0.007	0.001	0.007	0.003
Volatility_{t-5}	0.017	0.020	0.020	0.021
Volatility_{t-6}	-0.016	-0.009	-0.016	-0.011
Volatility_{t-7}	0.157^{*}	0.160^{*}	0.158^{*}	0.160^{*}
Returns_{t-1}	0.332	0.324	0.343	0.299
Returns_{t-2}	0.156	0.159	0.156	0.170
Returns_{t-3}	0.231	0.285	0.242	0.287
Returns_{t-4}	-0.403	-0.367	-0.406	-0.362
Returns_{t-5}	-0.467	-0.469	-0.485	-0.467
Returns_{t-6}	0.231	0.183	0.225	0.194
Returns_{t-7}	-0.735^{*}	-0.78^{**}	-0.728^{*}	-0.761^{*}
Bitcoin Return_{t-1}	-22.600^{*}	-23.150^{*}	-23.840^{*}	-22.650^{*}
Ether Return_{t-1}	17.900	17.040	17.760	17.610
Stock Return_{t-1}	-0.073	1.780	-2.354	-0.328
Constant	-0.560	-0.553	-0.341	0.900
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.063	0.054	0.058	0.051

This table reports the estimation of Equation (1), where the dependent variable is NFT *volatility* on day t. We define all variables in the Appendix. In our analysis, we use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively.

Table IA-10: Determinants of NFT Returns

	Dependent variable = $Returns_t$			
NFT News Type:	All	Positive	Neutral	Negative
$News_{t-1}$	-0.286^{**}	-0.125	-0.267^{**}	-0.149^{*}
$News_{t-2}$	0.028	0.050	-0.008	-0.142^{**}
$News_{t-3}$	0.039	-0.076	0.082	0.079
$News_{t-4}$	0.000	-0.067	-0.052	0.042
$News_{t-5}$	0.069	-0.026	0.132	-0.047
$News_{t-6}$	-0.143	-0.003	-0.134	-0.058
$News_{t-7}$	0.124	0.042	0.080	-0.010
$Trades_{t-1}$	0.316	0.316	0.301	0.290
$Trades_{t-2}$	-0.246	-0.249	-0.263	-0.260
$Trades_{t-3}$	0.086	0.080	0.103	0.081
$Trades_{t-4}$	0.000	-0.023	0.003	-0.029
$Trades_{t-5}$	-0.215	-0.195	-0.214	-0.205
$Trades_{t-6}$	-0.076	-0.099	-0.086	-0.100
$Trades_{t-7}$	0.176	0.206	0.164	0.185
$Minting_{t-1}$	0.202	0.203	0.215	0.199
$Minting_{t-2}$	-0.022	-0.012	0.003	-0.004
$Minting_{t-3}$	-0.128	-0.163	-0.147	-0.159
$Minting_{t-4}$	-0.281	-0.328	-0.293	-0.306
$Minting_{t-5}$	-0.145	-0.134	-0.136	-0.119
$Minting_{t-6}$	-0.021	0.048	0.001	0.032
$Minting_{t-7}$	0.021	0.045	0.009	0.007
$Participants_{t-1}$	-0.293	-0.265	-0.282	-0.268
$Participants_{t-2}$	-0.066	-0.076	-0.106	-0.085
$Participants_{t-3}$	0.195	0.180	0.202	0.211
$Participants_{t-4}$	0.313	0.325	0.313	0.326
$Participants_{t-5}$	0.413^{*}	0.391	0.423^{*}	0.393
$Participants_{t-6}$	-0.067	-0.095	-0.070	-0.083
$Participants_{t-7}$	-0.075	-0.071	-0.065	-0.045
$Volatility_{t-1}$	-0.023^{**}	-0.023^{**}	-0.023^{**}	-0.022^{**}
$Volatility_{t-2}$	0.001	0.000	0.001	0.001
$Volatility_{t-3}$	-0.018^{**}	-0.019^{**}	-0.019^{**}	-0.019^{**}
$Volatility_{t-4}$	-0.016^{*}	-0.017^{**}	-0.017^{*}	-0.017^{*}
$Volatility_{t-5}$	-0.010	-0.009	-0.009	-0.009
$Volatility_{t-6}$	-0.004	-0.004	-0.005	-0.004
$Volatility_{t-7}$	0.011	0.012	0.011	0.012
$Returns_{t-1}$	0.277^{***}	0.275^{***}	0.279^{***}	0.269^{***}
$Returns_{t-2}$	0.110^{*}	0.109^{*}	0.109^{*}	0.108^{*}
$Returns_{t-3}$	0.145^{***}	0.154^{***}	0.145^{**}	0.152^{***}
$Returns_{t-4}$	0.131^{**}	0.136^{**}	0.132^{**}	0.134^{**}
$Returns_{t-5}$	0.029	0.027	0.027	0.026
$Returns_{t-6}$	0.113^{**}	0.105^{**}	0.112^{**}	0.108^{**}
$Returns_{t-7}$	-0.029	-0.033	-0.027	-0.032
Bitcoin $Return_{t-1}$	-3.476^{*}	-3.645^{*}	-3.777^{*}	-3.810^{*}
Ether $Return_{t-1}$	1.877	1.729	1.902	1.962
Stock $Return_{t-1}$	11.100^{***}	11.370^{***}	10.770^{***}	11.260^{***}
Constant	0.667^{**}	0.632^{**}	0.656^{**}	0.765^{***}
Day-of-week FE	Yes	Yes	Yes	Yes
N (days)	1081	1081	1081	1081
R^2	0.348	0.343	0.347	0.345

This table reports the estimation of Equation (1), where the dependent variable is NFT *returns* on day *t*. We define all variables in the Appendix. In our analysis, we use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to seven lags. ***, **and * represent significance at the 1%, 5%, and 10% level, respectively.

Table IA-11: Summary of Granger Causality Wald Tests

Dependent Variable	Excluded	χ^2	p-value
News	Trades	14.344**	0.045
News	Minting	24.329***	0.001
News	Participants	10.587	0.157
News	Volatility	9.526	0.218
News	Return	8.979	0.254
News	ALL	83.881***	0.000
Trades	News	17.981**	0.012
Trades	Minting	19.646***	0.006
Trades	Participants	20.166***	0.005
Trades	Volatility	10.772	0.148
Trades	Returns	11.560	0.116
Trades	ALL	81.609***	0.000
Minting	News	15.075**	0.027
Minting	Trades	14.422**	0.044
Minting	Participants	17.227**	0.016
Minting	Volatility	11.394	0.122
Minting	Returns	7.785	0.351
Minting	ALL	77.305***	0.000
Participants	News	10.251	0.174
Participants	Trades	13.451*	0.061
Participants	Minting	32.158***	0.000
Participants	Volatility	5.305	0.622
Participants	Returns	8.719	0.273
Participants	ALL	78.904***	0.000
Volatility	News	16.174**	0.023
Volatility	Trades	5.779	0.565
Volatility	Minting	2.694	0.911
Volatility	Participants	2.989	0.886
Volatility	Returns	17.706**	0.013
Volatility	ALL	40.572	0.238
Returns	News	10.991	0.139
Returns	Trades	7.011	0.427
Returns	Minting	12.055*	0.098
Returns	Participants	13.580*	0.059
Returns	Volatility	33.881***	0.000
Returns	ALL	78.967***	0.000

This table reports Granger causality Wald tests. In each row, we test the null hypothesis that the coefficients on the lags of the excluded variable are jointly zero in tests of the dependent variable. A statistically significant chi-squared (χ^2) test statistic rejects the null hypothesis that the coefficients on all seven lags of an endogenous variable are jointly equal to zero and indicates that a variable Granger causes the measured dependent variable. ***, **and * denote significance at the 1%, 5%, and 10% level, respectively, based on the reported p-value. We define variables in the Appendix.