The Behavior and Determinants of Illiquidity in the Non-Fungible Tokens (NFTs) Market *

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Abstract

We provide the first study of time-varying and cross-sectional properties of liquidity in the nascent and rapidly growing non-fungible token (NFT) marketplace. Using transaction-level data, we document important intra-day and weekday patterns in NFT liquidity. Despite the decentralized nature and infancy of the marketplace, we show the overall determinants of NFT liquidity have several parallels with highly developed financial markets. We then study how the arrival of new information impacts NFT marketplace liquidity. By reducing information frictions, NFT news increases overall liquidity, especially when the media source tends to provide more specific or technical information about NFTs. Overall, our findings deepen our understanding of how liquidity impacts newly developed marketplaces.

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

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1. Introduction

An essential role of financial markets is to provide liquidity to investors (O'Hara, 2003). An asset is considered to be liquid when market participants can transact quickly with little price impact Liu (2006). Thus, an asset's liquidity is paramount to the development and functioning of efficient markets.[1] Given the vital role of liquidity, there exists substantial literature on the properties of liquidity in well-developed markets, such as those for stocks and bonds.[2] However, far less is known about the evolution of liquidity in the markets for emerging asset classes.

In this paper, we study the liquidity of the nascent and rapidly growing non-fungible token (NFT) marketplace.[3] Our analysis contributes to the literature on liquidity in emerging markets in the following ways. First, we provide descriptive evidence on the cross-sectional and time varying liquidity characteristics of the NFT market. Second, we identify the key drivers of the NFT market liquidity overall, daily, and intra-day. Finally, we examine how the arrival of new information impacts the liquidity of the NFT market.

Examining the determinants and characteristics of liquidity in the NFT market is important. As stated in Chordia et al. (2001), marketplaces, investors, and regulators can benefit from the knowledge of what factors affect liquidity and trading activity. This benefit is all the more important in nascent markets that are just developing. One such setting is the very young NFT marketplace that experienced an explosive growth in recent years. For example, as detailed in White et al. (2022), from 2017 to 2021, the number of total NFTs generated increased from 1,108 to 4,029,005, the number of NFT trades increased from 1,286 to 7,368,296, and NFT dollar volume per trade increased from \$119.50 to \$1,621.57. By doc-

[1]For instance, the unexpected decline in liquidity is an important reason for the stock market crash of October 1987 (Amihud et al., 1990) and the May 6, 2010, Flash Crash (Kirilenko et al., 2017). On May 6, 2010, the price of E-mini S&P 500 futures dropped by five percent in five minutes (Easley et al., 2011).

[2]See Le and Gregoriou (2020), Schestag et al. (2016), and Goyenko et al. (2009) for reviews of the literature on liquidity.

[3]An NFT is a digital asset stored on a blockchain, a form of digital ledger, that can be sold and traded. NFTs differ from fungible tokens, such as Bitcoin, in that they are unique, irreplaceable, and cannot be exchanged for an identical asset.

umenting trends and factors that affect liquidity in the fast growing NFT market, our study can be beneficial for NFT traders, NFT exchanges, academics, and regulators.[4]

In addition, an examination of liquidity in this emerging market allows us to compare liquidity characteristics in a market that is always open with liquidity characteristics in well developed markets (e.g., stock market, bond market). Specifically, extant literature examines intraday patterns in stock liquidity (McInish and Wood (1992); Vo (2007); Upson and Van Ness (2017)), determinants of stock market liquidity (McInish and Wood (1992); Chordia et al. (2001)), and media impact on stock market liquidity (Shyu et al. (2020)). By studying similar dimensions of NFT market liquidity, our findings increase our understanding of liquidity in quickly evolving modern financial markets. A better understanding of determinants of liquidity can increase investor confidence in price discovery and financial markets (Chordia et al. (2001)). Thus our findings can enhance investors' understanding, confidence, and participation in NFT markets leading to continued NFT market growth.

Our first focus is to investigate the trends in liquidity in the NFT market. While we are the first to our knowledge to examine liquidity in the NFT market, intraday patterns in stock liquidity are well documented in the literature. In U.S. equity markets, McInish and Wood (1992) report a U-shaped pattern in intraday liquidity. Similarly, Vo (2007) finds that spreads follow a U-shaped intraday pattern in the Toronto stock exchange. However, using a sample of New York Stock Exchange (NYSE) firms in 2012, Upson and Van Ness (2017) show that the intraday pattern of liquidity is now an S-shape, with higher spreads at the open and lower spreads at the close. Using the stock market liquidity trends research as a comparison, we examine the intraday and day-of-week trends of NFT market liquidity.

We study trends and determinants of NFT liquidity using a sample of NFT trades from 2017 to 2021.[5] We document day-of-week and intraday patterns in NFT liquidity. NFT

[4]Though, NFTs are currently not regulated, there are certain legal considerations about NFT markets and how they should be addressed. See a detailed discussion for legal considerations about NFTs at https://www.jonesday.com/en/insights/2021/04/nfts-key-us-legal-considerations-for-an-emerging-asset-class.

[5]We measure NFT illiquidity with an intraday version of Amihud (2002) illiquid metric (see section 4.1.1 for details). Amihud outperform other measures when estimating liquidity levels and reliably identifies

liquidity is the highest on Monday and decreases throughout the week. The day-of-week pattern in NFT liquidity is similar to the documented day-of-week liquidity pattern in the stock market; stock market liquidity tends to increase on Tuesday and decline on Friday (Chordia et al. (2001)). In terms of intraday patterns, we find that NFT liquidity is decreasing in the first half of trading day and is increasing in the second half of the trading day. This intraday pattern is similar to the stock market liquidity intraday S-shape pattern, with lower liquidity at the open and higher liquidity at the close (Upson and Van Ness (2017)). Overall, day-of-week and intraday patterns in NFT liquidity indicate that week-of-day and time-of-day preference for trading in NFT markets and stock market may be similar. The fact that we find similar patterns in liquidity between the stock market and the NFT market is quite surprising when you consider that the NFT market is decentralized, deregulated, and always open for trading. These results are the first in describing a deregulated, decentralized, and always open market.

Second, we examine the determinants of liquidity in the NFT market. We start by identifying variables in the NFT market that are related to those variables identified by the existing literature on stock market liquidity: activity, information, risk, and competition (Schwartz (1988); McInish and Wood (1992)). Specifically, we proxy for trading activity with number of trades. Consistent with findings of related literature (e.g., McInish and Wood (1992)), we expect trading activity to improve NFT liquidity. Existing studies document that issue size and age of bonds are associated with bond trading activities and liquidity (Bao et al. (2011); Edwards et al. (2007)); hence we control for NFT issue size and age. We expect to find that similar to bonds there is a positive relationship between NFT size and liquidity but a negative relationship between age and liquidity.

In order to control for alternative investing opportunities and the relationships between cryptocurrency and NFTs, we include Bitcoin, stock market, and Ethereum returns. Since crypto and financial market returns can positively affect NFT returns (Borri et al. (2022)),

liquidity differences between trading venues Brauneis et al. (2021).For the purposes of this paper we will focus on describing everything in terms of liquidity instead of illiquidity where appropriate.

we expect Bitcoin, Eteheruem, and stock market returns to improve NFT liquidity. The fact that most NFTs are minted on the Ethereum blockchain suggest that as Ethereum returns increase, NFTs may be become more valuable as well and lead to more trading in NFTs. Alternatively, if the return on Ethereum is increasing, investor may delay placing their NFTs trades which will reduce NFT liquidity and vice versa. Since competition between trading venues can affect liquidity (e.g., McInish and Wood (1992); Bessembinder (1999); Chung et al. (2001)), we also control for NFT platforms. We expect competition to improve NFT liquidity.

We document a negative age-liquidity relationship in the NFT market; older NFTs are more liquid than newer NFTs. This finding is opposite of positive age-liquidity relation documented in U.S. corporate bond markets (Edwards et al. (2007); Bao et al. (2011)). Similar to the findings in the U.S. corporate bond markets, we find that NFTs with a larger initial issue price are more liquid than NFTs with lower issue price. In line with determinants of stock liquidity studies (e.g., McInish and Wood (1992)), we also find that NFT liquidity is positively related to the number of transactions in an NFT. In terms of marketplaces, our findings indicate that NFT liquidity varies across platforms. LarvaLabs has the highest NFT liquidity relative to OpenSea and Rarible. We find OpenSea has the highest number of NFT trades and NFTs but has the lowest NFT liquidity.

Our final tests examine how the arrival of new information impacts NFT marketplace liquidity. Although prior work shows that media coverage has no direct impact on stock liquidity (Shyu et al. (2020)), we posit that NFT news can impact liquidity by removing information frictions on a nascent market. For information arrival, we use NFT media coverage (i.e., NFT related news articles).[6] NFT news can expand market participants information set and thus reduce their risk (White et al., 2022). We therefore expect information flow through NFT news to be positively related with NFT liquidity.

Indeed, our results indicate that media coverage has a direct and large impact on NFT

[6]Note that NFT media coverage is also related to NFT risk.

liquidity. We find that information flow through NFT media coverage is an important determinant of NFT liquidity. Specifically, a 10% increase in the number of NFT articles decreases NFT illiquidity by about 3.5%. Additionally, we categorize NFT news based on news source type and examine the impact of different news source types on liquidity. We use news source type as a proxy for the technical details or sophistication of the articles published. We would expect more sophisticated articles to increase liquidity through including more information that could be useful for price discovery. We find all news sources increase the liquidity of the NFT market. However, news from a Crypto based publication sources increase liquidity significantly more than from Financial, National, or Local news sources. This aligns with our conjecture as Financial, National, and Local news sources publishes NFT articles that simply explain what NFTs are while Crypto news sources provide nuanced information to market participants.

This paper contributes to two strands of research. First, we add to the literature on determinants of liquidity in financial markets by being the first paper to document trends and determinants in NFT liquidity. While factors that affect liquidity are extensively examined in stock markets (McInish and Wood (1992); Chordia et al. (2001); Vo (2007); Upson and Van Ness (2017)) and bond markets (Chakravarty and Sarkar (2003); Edwards et al. (2007); Bao et al. (2011)), empirical evidence on liquidity in markets for emerging asset classes is scarce.[7] Our study starts to fill this gap in the literature by identifying important factors and trends in NFT liquidity.

Second, our study contributes to the literature that explores the media's impact on financial markets. Under different settings, studies show that media coverage has an important roles in stock returns, (Tetlock (2007); Tetlock et al. (2008); Tetlock (2010); Dougal et al. (2012)), short selling (Engelberg et al. (2012)), and stock return anomalies (Engelberg et al. (2018)), but no direct effect on stock liquidity (Shyu et al. (2020)). Other literature shows

[7]A recent study Brauneis et al. (2021) examine how to measure liquidity in different cryptocurrency markets. However, our focus is different than theirs in that they focus on measuring liquidity in cryptocurrency markets and we study the determinants of liquidity in the NFT markets.

the relationship between news and NFT returns (White et al. (2022); Kapoor et al. (2022)). Our findings complement and extend this literature by showing that the arrival of news improves the liquidity of nascent NFT markets, especially when the news originates from sources that focus on digital assets.

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 results in Section 4. We conclude in Section 5.

2. Trading in NFT Markets

In this section, we provide an overview of NFT market and platform characteristics.[8] The NFT market has some similarities to other financial markets but also has a few operational differences from the stock, bond, or even cryptocurrency markets. These differences include: trading requirements, lack of regulations, trading hours, and data transparency.

Trading in the NFT market is more complicated than in the stock market where you can simply open an account and start trading. In order to trade in the NFT market, traders need a cryptowallet[9] and a specific cryptocurrency. A cryptocurrency such as Ethereum or Polygon is necessary because NFTs for the most part cannot yet be purchased directly with fiat currency.[10] The currency needed to purchase an NFT is determined by the blockchain on which the NFT was minted. Besides for dictating the currency needed to purchase the NFT the blockchain that the NFT was minted on matters for determining the gas (or transaction) fee. Different blockchains have different gas fees.[11] In order to sell an NFT you do not need

[8]An NFT is defined as a unique digital identifier that cannot be copied, substituted, or subdivided, that is recorded in a blockchain, and that is used to certify authenticity and ownership (as of a specific digital asset and specific rights relating to it). NFT, Retrieved April 10, 2022, from https://www.merriam-webster.com/dictionary/. White et al. (2022) provide detailed explanations for aspects of NFT markets that are related to NFT returns.

[9]An example of a cryptowallet would be MetaMask https://metamask.io/

[10]There are companies that are trying to solve the need to own cryptocurrency and make it even easier for people to enter the NFT market. Companies like Moonpay allow people to purchase NFTs directly with their credit card.https://www.moonpay.com/nft/how-to-buy-nfts Moonpay will also hold the purchased NFTs for the individual so they do not need to have a cryptowallet.

[11]https://medium.com/coinmonks/polygon-vs-ethereum-where-you-should-launch-your-nft-project-bdcb70a3e67c

to be registered with any government agency whereas with the stock or bond market you are trading through brokers. However, in the NFT market you can list or purchase an NFT on your own and all you need is a free account on one of numerous NFT exchanges. The NFT market also has similarities with the housing market in that both markets allow potential investors to bid on assets without requiring the seller to sell.

The NFT market is currently unregulated. As such, it is vulnerable to manipulation and fraud. This has not gone unnoticed by national governments. The government has convened a group to look into potential regulations for the crypto market to prevent the ongoing fraud.

Similar to the crypto market but unlike the stock and bond markets, the NFT market never closes. This allows market participants to transact in NFTs 24 hours a day, seven days a week. NFT transactions and ownership are tracked on the blockchain, which keeps a history of every transaction. Therefore all historical data is always available to the public. The buyers and sellers' wallets are identified, but not the identification of the person or company behind the wallet.

There are multiple platforms through which NFTs can be bought and sold.[12] These NFT platforms come in three different types: general NFT marketplaces, program specific NFT marketplaces, and NFT specific marketplaces. First, general NFT marketplaces like OpenSea sell all types of NFTs from LAND to Bored Apes yacht Club. Second, program specific markets places would be like Decentraland that sells LAND and other Decentralalnd specific NFTs in their marketplace. Some NFTs are available on both types of platforms. For example, programs like Decentraland sell their NFTs on their own market place and a general NFT marketplace like OpenSea. Third, NFT specific platforms only sell one specific collection of NFTs. Each platform is different not only in what they sell but in their rules governing trading. For example, these platform specific rules include transaction fees, trading incentives, and minting costs.

[12] We discuss NFT marketplaces in detail in Section 2. Data and Descriptive Statistics.

3. Data and Descriptive Statistics

We obtain NFT transaction data from Dune Analytics. The dataset reports NFT transactions on the Ethereum, Polygon, Binance Smart Chain, Gnosis Chain, and Optimism blockchains.[13] All transaction times and time periods are in Coordinated Universal Time (UTC). We focus on Ethereum-based NFT trades, which account for approximately 86% of NFT transactions in 2021. Our sample period is from June 23, 2017 to December 31, 2021. Our sample includes 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. OpenSea has the largest market share during our sample period, representing more than 60% of NFT sales in 2021. Our initial sample includes 8,989,371 observations. Like prior work (e.g., Schaar and Kampakis (2022); White et al. (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 Table 1. Our final NFT sample includes 7,569,287 NFT trades and the NFT illiquidity measure is defined for 1,879,880 NFT trades over 2017 to 2021. The reduction in final sample is due to the requirement that NFTs need five prices over the sample period to be included in the datset.

{Insert Table 1: Sample Selection}

Table 2 summarizes NFT distributions of number of NFT trades, number of NFTs, and NFT dollar volume per trade across intraday intervals, weekdays, years, and marketplaces. In panel A, we observe high NFT trading activity and dollar volume in the early and late intraday intervals. In panel B, we find the highest number of NFT trades on Monday and Sunday. Highest dollar volume is found on Monday while the lowest dollar volume is found on Saturday. Panel C shows evolution of NFT trades and volume across years. There is a

[13] See detailed descriptions of the NFT data at https://docs.dune.com/

significant growth in number of NFT trades and trading volume across years. The growth in number of NFT trades from 2017 to 2021 is about 572,862%. Average NFT dollar volume per trade increased from \$119 in 2017 to \$1,621 in 2021. In panel D, we examine NFT trading activities across four NFT marketplaces. In terms of NFT marketplaces, OpenSea has the highest number of NFT trades and NFTs. While SuperRare has the lowest number of NFT trades and NFTs. LarvaLabs has the highest average dollar volume and SuperRare has the lowest dollar volume. Overall, our results in Table 2 indicate that NFT trading activity can vary across intraday intervals, weekdays, and platforms.

{Insert Table 2: NFT Trading Activity}

3.1. Descriptive Statistics

3.2. Intraday and NFT Level Variables

To calculate intraday variables, we first divide each trading day into eight intervals. Each interval is three hours. We measure NFT liquidity with an intraday version of the Amihud (2002) illiquidity measure. This measure is conceptually based on the Kyle (1985) model and relates to the price impact of trades, i.e., the price change measured as a return, to the trade volume measured in US dollars (Friewald et al. (2013)). A larger Amihud measure indicates higher price impact of a trade and reflects lower liquidity. The illiquidity measure is commonly used in stock market liquidity (e.g., Goyenko et al. (2009)) and bond market liquidity studies (e.g., Friewald et al. (2013); Crotty (2013)). Brauneis et al. (2021) show that the Amihud (2002) illiquidity ratio outperforms other measures when estimating liquidity levels. The Amihud estimator is also reliable in identifying liquidity differences between trading venues. The illiquid measure is calculated as the average trade-by-trade absolute value of return divided by the dollar volume of the trade. Then we take the average of the illiquid measure for each intraday interval for each NFT. Our illiquid calculation process is similar to other studies (e.g., Friewald et al. (2013); Crotty (2013)). An additional intraday variable is the number of trades. Number of trades is the total number of trades in each intraday interval.

We also include two additional determinants of NFT liquidity that are NFT level variables: issuance and age. We define issuance as the dollar amount of an NFT at first issuance. Age is defined as the number of days since the NFT was first minted.[14]

3.2.1. Descriptive Statistics for Intraday and NFT Level Variables

Table 3 summarizes descriptive statistics for intraday variables and NFT illiquidity overall, across days, marketplaces, and intraday intervals. Overall the sample mean NFT illiquidity and average NFT illiquidity across days does not vary too much. However, we observe the highest NFT illiquidity on Sunday and Saturday and lowest NFT illiquidity on Monday. Volatility in NFT illiquidity is higher than volatility in the overall sample on Saturday and Sunday. In terms of liquidity across platforms, we find on average OpenSea has the highest NFT illiquidity while LarvaLabs has the lowest illiquidity. In terms of intraday intervals, lower NFT illiquidity is observed in the first and the last three intraday intervals. The results in Table 3 indicate that NFT liquidity may have daily and intraday patterns.

{Insert Table 3: Descriptive Statistics for Intraday and NFT Level Variables}

3.3. Day Level Variables

We follow White et al. (2022) in creating news measures for all NFT news and measures based on media type. News related variables are obtained from RavenPack. We calculate Bitcoin, stock market, and Ethereum returns at the daily level. Bitcoin returns are calculated using open and close Bitcoin prices. Stock market return is defined as the daily CRSP value-weighted market return. Missing CRSP return values are set to zero. Ethereum returns are calculated using open and close Ethereum prices. We separate Ethereum return into

[14]Appendix gives detailed variable definitions.

negative and positive returns. Negative (positive) Ethereum return is the Ethereum daily return if it is negative (positive), and zero otherwise.

3.3.1. Descriptive Statistics for Day Level Variables

Table 4 presents descriptive statistics of our day level variables. For all NFT news, each NFT news article is assigned into one of five media categories: Local, National, Financial, Technology, and Crypto media. The number of NFT articles is highest in Financial media followed by Crypto media. The lowest number of NFT news is from Technology media and Local media. During our sample period average Bitcoin return and CRSP value weighted index returns are about 0.30% and 0.10%, respectively. Negative and Positive Ethereum mean returns are about -1.514% and 1.916%.

{Insert Table 4: Descriptive Statistics for Day Level Variables}

3.4. Trends in Liquidity

Figure 1 presents the intraday and daily liquidity trends. Panel (a) shows that without controlling for other factors liquidity in the NFT market is the highest on Monday and decreases through the end of the week. This day-of-week pattern in NFT liquidity is comparable to the day-of-week pattern in stock market liquidity; stock market liquidity tends to increase on Tuesday and decline on Friday (Chordia et al. (2001)).

In examining trends of returns[15] and trades over days of the week in panels (b) and (c), we see there is not an immediate relationship between NFT liquidity and returns or trades. We examine this relationship closer in Table 5. However, we do see that returns and number of trades for NFTS seem to be at their highest when liquidity is high.

We also examine these patterns on an intraday level in Panels (d)–(f). It is important to keep in mind that liquidity is measured over three hour intervals that are in UTC time.

[15] We use the same returns data as in White et al. (2022) for daily data and calculate the returns at an intraday level using the same methodology.

The NFT market is a 24 hour market, so we need to consider how UTC times relate to time zones in which the majority of participants may be living. New York is four hours behind UTC time and LA is seven hours behind UTC. Considering New York and LA time zones, we see that liquidity is decreasing over the evening for market participants from the United States and increasing during normal stock market trading hours. This intraday pattern is similar to the stock market liquidity intraday S-shape pattern, with lower liquidity at the open and higher liquidity at the close (Upson and Van Ness, 2017). Panels (e) and (f) show the relationship between liquidity and returns or number of trades at the intraday level. We find a positive relationship between liquidity and returns or trades. Overall, day-of-week and intraday patterns in NFT liquidity indicates that day-of-week and time-of-day preference for trading in NFT markets and stock market may be similar. The additional days and times the NFT market are open do have trading activity but seem to have lower liquidity than at standard stock market times. Figure 1 shows the trends on a daily and intraday level but to understand determinants of liquidity we need to examine additional variables. In next section, we further examine the determinants of liquidity in a multivariate setting.

{Insert Figure 1: Liquidity Trends}

4. Empirical Tests and Results

4.1. Determinants of NFT Illiquidity

We examine determinants of NFT liquidity with a multivariate approach similar to McInish and Wood (1992). Specifically, we estimate the following equation:

$$
\begin{aligned}
Illiquid_{i,k,t} = \alpha_1 + &\beta_1 \cdot (News_{t-1}) + \gamma_1 \cdot (Issuance_{i,k-1,t}) + \gamma_2 \cdot (Age_{i,k-1,t}) \\
&+ \gamma_3 \cdot (NumberofTrades_{i,k-1,t}) + \psi_1 \cdot (PlatformDummyVariables) \\
&+ \psi_2 \cdot (IntradayDummyVariables) + \psi_3 \cdot (WeekdayDummyVariables) \\
&+ \omega_1 \cdot NegativeEthereumReturn_{t-1} + \omega_2 \cdot PositiveEtherReturn_{t-1} \\
&+ \omega_3 \cdot BitcoinReturn_{t-1} + \omega_4 \cdot CRSPReturn_{t-1} + \epsilon_t,
\end{aligned}
\tag{1}
$$

The dependent variable is the natural logarithm of the Amihud illiquidity measure for NFT i in interval k on day t. Detailed definitions of all variables are given in the Appendix. We use the natural logarithms of illiquidity, age, NFT news, and number of trades to approximately conform to normality. Intraday variables are lagged by one interval and daily measures are lagged by one day. Standard errors used to compute t-statistics are adjusted for heteroscedasticity and within-NFT clustering.[16]

In Table 5, we examine determinants of NFT liquidity by estimating equation 1. We run four different models each represented by a different column in Table 5. Column (1) includes all the controls mentioned above minus any day-of-week or intraday controls. Column (2) includes all the controls from column (1) and introduces intraday controls. Column (3) includes all the controls of column (1) and controls for the day-of-week. The last column, column (4), includes all our controls from column (1) plus intraday and day-of-week-controls.

In terms of intraday determinants of NFT liquidity, our results show that for all specifications issuance amount, age, and number of trades are important determinants of NFT liquidity. The negative and significant coefficient on age variable indicate that older NFTs are more liquid than newer NFTs. Conversely, in the U.S. corporate bond market, newer bonds have higher liquidity (e.g., lower transaction costs) than older bonds (Edwards et al. (2007); Bao et al. (2011)). The negative and significant coefficients on issue size indicate

[16]For brevity, we do not report t-statistics but the results are available upon request.

that the NFTs with larger initial issue price are more liquid than NFTs with lower issue price. This result is consistent with findings of Edwards et al. (2007) and Bao et al. (2011) that large bond issues are more liquid than small bond issues. In addition, we find a negative a nd statistically significant relationship between the number of trades and NFT illiquidity. This results is Consistent with findings in the stock market liquidity literature (e.g., McInish and Wood (1992)).

In each regression specification, our NFT news proxy is the number of all NFT related articles. The estimated coefficient on NFT news is negative and statistically significant for all specifications. This result indicates that information dissemination through NFT media coverage negatively affects NFT illiquidity and therefore improves NFT liquidity. Our results are also economically significant. Specifically, in model 4, a one percent increase in the number of NFT articles decreases NFT illiquidity by about 0.35%. Our findings show that the impact of media coverage on NFT liquidity is different than on stock liquidity. For example, Shyu et al. (2020) find that media coverage has no direct effect on stock liquidity. In their analysis, impact of media coverage on stock liquidity is significant only when conditioned on earnings dispersion. Thus, their results indicated that impact of media on stock liquidity is indirect. They conclude media-exacerbated earnings dispersion reduces liquidity provided by individual investor but does not affect liquidity provided by institutional investors. On the other hand, our findings indicate that media coverage has direct positive impact on NFT liquidity.

Our competition related results are also interesting. We find that there is a negative relation between negative Ethereum returns and NFT illiquidity, while positive Ethereum returns are positively associate with NFT illiquidity. Specifically, our findings indicate that the impact of Ethereum returns on NFT illiquidity is asymmetric. While NFT illiquidity increases following positive and negative Ethereum markets, the impact for positive markets is greater. Chordia et al. (2001) document a similar relation between stock market movements and stock liquidity. They find that when in down markets stock market liquidity decreases.

On the other hand, the impact of up markets on stock market liquidity is mixed. In equally weighted portfolios, Chordia et al. (2001) find in up markets that liquidity improves. However, in value weighted portfolios they find the opposite or statistically insignificant results. Our findings also indicate that as Bitcoin returns increase NFT illiquidity decreases. Impact of stock market returns on NFT illiquidity is mostly statistically insignificant.

We also find that NFT marketplaces are significant determinants of NFT liquidity. Specifically, compared to LarvaLabs, NFT illiquidity on OpenSea and Rarible is higher.[17] Among these three platforms, the lowest NFT liquidity is observed on OpenSea even though OpenSea has the highest number of NFT trades and NFTs. These findings indicate that when examining NFT liquidity one must consider additional factors, not only the number of NFTs or NFT trades.

The day-of-week dummy variables document day patterns in NFT liquidity. We set Sunday as our base, thus coefficients on day-of-week dummy variables are interpreted relative to Sunday. The coefficients on all weekday variables are significant and positive except the coefficient on Monday, which is negative and significant. The highest NFT liquidity is observed on Monday and the lowest liquidity is observed on Friday. While Chordia et al. (2001) suggest that stock market liquidity increases on Tuesday, our findings indicate that NFT liquidity is highest on Monday. Similar to Chordia et al. (2001), we find NFT liquidity declines on Friday but unlike in the stock market liquidty in the NFT market continues to decline over the weekend.

The coefficients on the intraday dummy variables reveal a S-shape pattern. NFT illiquidity is increasing in the first half of trading day (in the first four intervals) and decreasing in the second half of the trading day. NFT illiquidity is starting to increase in the interval from 03:00-06:00 and we observe highest illiquidity during 09:00-12:00. In the interval from 12:00-15:00 illiquidity is starting to decrease and the lowest illiquidity is in the interval from 15:00-18:00. In the intervals from 18:00-21:00 and 21:00-24:00, illiquidity starts to increase

[17]While we have SuperRare in our original dataset, we do not have any observation from SuperRare that satisfy our filters to calculate NFT illiquidity measure.

but is still lower than illiquidity in the first half of the trading day. While previous studies of intraday stock liquidity studies document a U-shape pattern in stock market (e.g.McInish and Wood (1992); Vo (2007)), in a sample of NYSE firms from 2012, Upson and Van Ness (2017) show that the intraday pattern of liquidity is now an S-shape, with higher illiquidity at the open and lower illiquidity at the close. Our intraday NFT illiquidity patterns are similar to the ones documented by Upson and Van Ness (2017). Thus, it is possible that the time-of-day preference for trading in both markets may be similar.

{Insert Table 5: Determinants of NFT Illiquidity}

4.2. Further Analysis of NFT Illiquidity

To further examine the link between information dissemination through media-coverage and NFT market liquidity, we investigate news and NFT liquidity through five subsamples based on the source of NFT news. In the source subsamples, each NFT news article is assigned as being from one of five media sources: Local, National, Financial, Technology, and Crypto media.[18] These five subsamples are then used to estimate equation 1 by replacing news proxy with news articles categorized by their source types. All other model specifications and controls are the same as equation 1.

In Table 6, we report the results from our examination of the link between NFT liquidity and news source. Consistent with our main results, in all models, the impact of NFT news articles on NFT illiquidity is negative and statistically significant. Thus, regardless of their sources, NFT news improves NFT liquidity. While the local media coverage provides the lowest liquidity improvement (Column 1), Crypto media coverage provides the highest liquidity improvement (Column 5). NFT news coming from a crypto source is likely to be more sophisticated and more specific. The sophistication and specificity of an article is more likely to enhance liquidity. The second highest liquidity improvement is found in Financial

[18]We follow White et al. (2022) for separating the sources into the appropriate subsample.

media coverage regression (Column 3). The impacts of technology media and national media on NFT liquidity are close to each other but are different from each other.

{Insert Table 6: NFT Illiquidity by News Source Type}

In Table 7, we examine if the differences between the coefficients on the impact of NFT news sources on NFT liquidity are statistically significant. Interestingly, we find that NFT news from Crypto sources is statistically significantly different from local, national, and technology media outlets. Therefore, news from a Crypto source improves NFT liquidity more than NFT news from Local, National, and Technology sources. The differences are statistically significant at the 1% level. The difference between the impact of NFT news from Crypto and Financial outlets is statistically insignificant. This is consistent with the idea that Crypto and Financial news would be the more sophisticated news sources in discussing NFTs. We also find that the difference between impact of NFT news from Financial and National media outlets is not significant. At the same time, impacts of news from National and Financial outlets are greater than the impact of news from Technology and Local media outlets. Overall, the findings in Table 7 indicate that news from Crypto, Financial, and National media outlets improves NFT liquidity more compared to news from Local and Technology media outlets.

{Insert Table 7: Differences in Impact of NFT News Source Type on NFT Illiqudity}

5. Conclusion

Existing literature documents trends and determinants of liquidity in stock and bond markets. However, there is an absence of research that considers the trends and determinants of liquidity in fast growing financial markets. In this study, we address this issue and study liquidity in NFT markets. We document several trends and determinants of NFT liquidity. Specifically, we document strong day-of-week, and day-of-time patterns in NFT liquidity.

Similar to the findings in the stock market, NFT liquidity is the highest on Monday and decreases through the rest of the week. The intraday pattern in NFT liquidity is also comparable to that found in stock market liquidity. NFT liquidity decreases in the first half of trading day and increases in the second half of the trading day. These day and intraday patterns in NFT liquidity indicate investors may have time preferences for NFT trading.

In addition, we find that NFT issue size, NFT age, number of trades, Ethereum returns, Bitcoin returns, and NFT marketplace play significant role in determining NFT liquidity. NFT liquidity increases with issue size, age, and number of trades. Furthermore, we find NFT marketplaces have significant impact on NFT liquidity, as well. Among LarvaLabs, OpenSea, and Rarible, LarvaLabs has the highest NFT liquidity. OpenSea has the lowest NFT liquidity but the highest number of NFT trades.

Furthermore, we examine the impact of news on liquidity in the NFT market.Our results show that information flow through media coverage has direct and positive effect on NFT liquidity. Specifically, a 10% increase in number of NFT articles decreases NFT illiquidity by about 3.5%. In further analysis, we show that the positive impact of information dissemination with NFT news on NFT liquidity is robust to NFT news source types. While all news source types improves NFT liquidity, news from Crypto, Financial, and National media outlets increases NFT liquidity more than news from Local and Technology media outlets.

The determinants of NFT liquidity we investigated in this study are significant and explain around 30 percent of variations in NFT liquidity. Explanatory power of our tests are comparable to related studies such as (Chordia et al., 2001) that focus on factors that affect stock market liquidity. Chordia et al. (2001) state that "liquidity begets liquidity" and thus trends in liquidity are important for traders' market participation. By documenting important determinants and trends in NFT liquidity, our findings deepen our understanding of NFT liquidity and provide essential tools for NFT traders, marketplaces, and other market participants.

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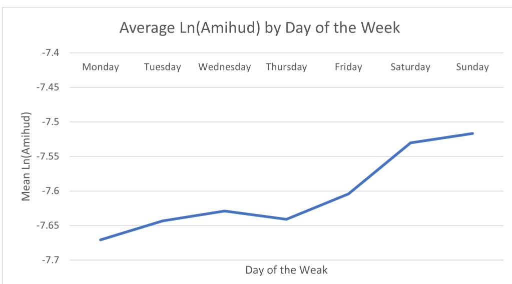
Appendix: Variable Definitions

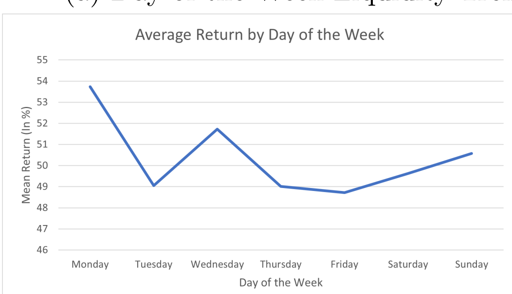
Variable	Definition
Intra-day and NFT Level	
Time Interval	Each day is divided into 8 intervals (k=1 ... 8). Each interval is three hours.
Amihud$_{i,j,k}$	Trade level illiquidity variable. Similar to Crotty (2013) and Friewald et al. (2013), we define illiquid as the absolute return on trade j, divided by dollar volume of trade j for NFT i. Then, we calculate average of illiquid for each intraday interval k for each NFT i.
NFT Issuance$_i$	Dollar value of NFT i at issuance.
NFT Trades$_{i,k}$	Number of trades is the sum of number of trades in each intraday interval k for each NFT i.
NFT Age$_{i,t}$	Number of days since NFT i issuance.
Day Level	
All NFT News$_t$	Natural 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.
Local NFT News$_t$	All NFT News$_t$ from local news sources. E.g., news source is a local TV, newspaper, or radio.
National NFT News$_t$	All NFT News$_t$ from national news sources. E.g., news source is a national TV or newspaper.
Financial NFT News$_t$	All NFT News$_t$ from financial news sources. E.g., news source is a financial media outlet.
Technology NFT News$_t$	All NFT News$_t$ from technology news sources. E.g., news source is a technology media outlet.
Crypto NFT News$_t$	All NFT News$_t$ from Crypto news sources. E.g., news source is a Crypto media outlet.
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.
Negative Ether Return$_t$	The Ethereum daily return (ETH) if it is negative, and zero otherwise.
Positive Ether Return$_t$	The Ethereum daily return (ETH) if it is positive, and zero otherwise.
Stock Return$_t$	Return of the CRSP value-weighted market on day t. Non-trading days are set to zero.

Fig. 1. **Liquidity Trends**

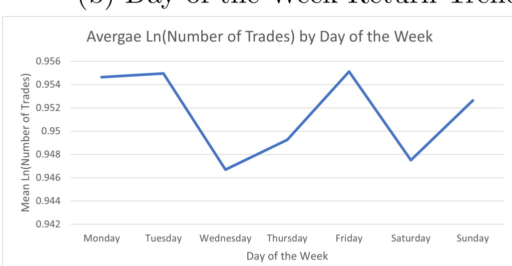
This figure depicts the time trends for the Amihud measure, returns, and number of trades in the NFT market over our sample. Panels (a)–(c) represent the trends over the days of the week while Panels (d)–(f) represent the trends over three hour intervals based on UTC time. We calculate the Amihud meausre trade by trade for each NFT. Then we calculate an average Amihud measure in each interval for each NFT. Ln(Amihud) is natural log of average Amihud measure for each day-of-week or intraday interval. Return (%) is the average return in each day-of-week or intraday interval. Number of trades is the sum of number of trades in each day-of-week or intraday interval.



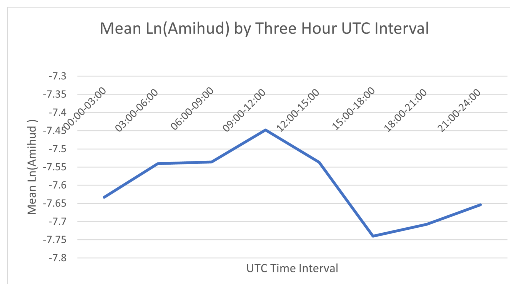
(a) Day of the Week Liquidity Trends



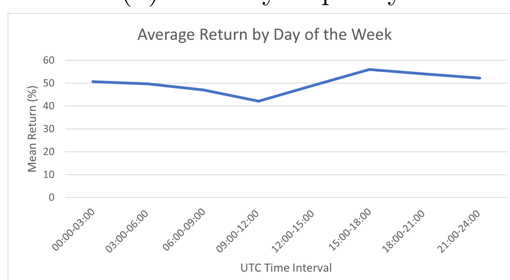
(b) Day of the Week Return Trends



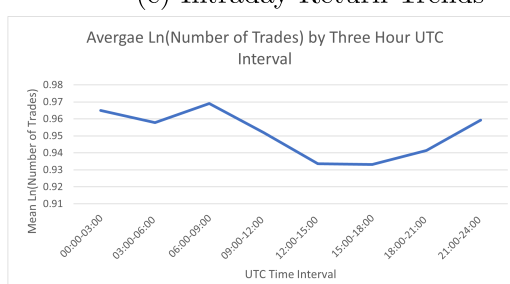
(c) Day of the Week Trade Trends



(d) Intraday Liquidity Trends



(e) Intraday Return Trends



(f) Intraday Trade Trends

Table 1: **Sample Selection**

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. Filter 6 is used for the Amihud measure calculation as discussed in (Crotty, 2013)

	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)
(6) Less NFTs with less than five prices	(5,689,407)
Final sample	1,879,880

Table 2: **Distribution of NFT Trading Activity**

This table presents distribution of NFT dollar volume per trade across intraday intervals, weekdays, years, and platforms. Each interval is a three hour window in UTC time.

Panel A: Intra-Day Dollar Volume

3-Hour Interval	NFT Trades	Number of NFTs	Mean ($)	Volatility_i	P25 ($)	P50 ($)	P75 ($)
00:00-03:00	1,080,205	581,792	1,550.19	3,751.06	167.82	439.43	1,162.65
03:00-06:00	1,048,064	550,952	1,517.38	3,695.68	156.62	428.42	1,159.00
06:00-09:00	839,706	445,511	1,449.04	3,610.02	142.63	409.14	1,101.77
09:00-12:00	711,869	373,610	1,349.79	3,472.32	122.33	360.17	1,008.51
12:00-15:00	781,799	400,995	1,530.25	3,802.02	142.42	403.63	1,139.47
15:00-18:00	922,427	493,526	1,793.10	4,124.17	190.25	507.84	1,378.70
18:00-21:00	1,057,454	565,070	1,764.09	4,048.08	188.93	508.77	1,371.60
21:00-24:00	1,127,763	617,549	1,619.76	3,823.27	172.84	467.21	1,263.01

Panel B: Weekday Dollar Volume

Day of the Week	NFT Trades	Number of NFTs	Mean ($)	Volatility_i	P25 ($)	P50 ($)	P75 ($)
Sunday	1,110,479	591,903	1,601.81	3,973.82	144.28	413.43	1,156.09
Monday	1,145,416	619,300	1,683.49	3,965.78	189.00	465.47	1,251.87
Tuesday	1,097,579	590,504	1,571.86	3,814.99	166.77	445.95	1,170.74
Wednesday	1,045,252	552,269	1,582.24	3,737.89	168.55	456.30	1,249.22
Thursday	1,041,023	547,505	1,601.84	3,817.61	165.81	453.63	1,235.83
Friday	1,055,730	559,619	1,549.31	3,711.10	157.61	449.72	1,229.77
Saturday	1,073,808	567,905	1,485.92	3,625.90	144.01	421.17	1,163.73

Panel C: Yearly Dollar Volume

Years	NFT Trades	Number of NFTs	Mean ($)	Volatility_i	P25 ($)	P50 ($)	P75 ($)
2017	1,286	1,108	119.50	240.06	51.44	71.45	99.74
2018	4,887	4,437	60.28	345.45	2.49	8.45	35.34
2019	70,082	57,630	77.87	338.82	2.60	14.87	55.23
2020	124,736	93,032	160.23	757.66	3.00	15.16	67.15
2021	7,368,296	3,872,798	1,621.57	3,852.79	174.79	463.79	1,242.21

Panel D: Marketplace Dollar Volume

Platform	NFT Trades	Number of NFTs	Mean ($)	Volatility_i	P25 ($)	P50 ($)	P75 ($)
LarvaLabs	17,454	6,418	18,210.93	14,432.77	357.28	20,178.25	33,027.06
OpenSea	7,475,287	3,991,854	1,544.86	3,669.97	161.82	443.75	1,198.09
Rarible	69,641	24,806	1,387.00	2,922.49	110.83	373.79	1,372.84
SuperRare	6,905	5,927	3,107.48	5,274.62	200.24	931.40	3,332.10

Table 3: **Descriptive Statistics for Intraday and NFT Level Variables**
This table presents descriptive statistics of intraday variables used in our analysis. Low ln(Amihud) indicates low illiquidity. Detailed variable definitions are given in Appendix.

Panel A: Intraday Summary Statistics

Weekday	Observations	Mean	Volatility_i	P25	P50	P75
Variable	N (intra-days)	Mean	S.D.	P25	P50	P75
Overall Sample						
Ln(Amihud)	710,438	-7.60	2.81	-9.52	-7.69	-5.83
Ln(Issuance)	710,438	5.28	1.96	3.98	5.30	6.62
Ln(Numtrades)	710,438	0.95	0.53	0.69	0.69	1.10
Ln(Age)	710,438	2.79	1.57	1.61	3.09	4.04

Panel B: Intra-Day Ln(Amihud)

Interval	Observations	Mean	Volatility_i	P25	P50	P75
00:00 - 03:00	94,626	-7.63	2.77	-9.52	-7.72	-5.89
03:00 - 06:00	95,093	-7.54	2.82	-9.48	-7.63	-5.76
06:00 - 09:00	81,148	-7.54	2.89	-9.52	-7.63	-5.71
09:00 - 12:00	76,773	-7.45	2.88	-9.41	-7.52	-5.62
12:00 - 15:00	84,282	-7.54	2.84	-9.47	-7.61	-5.74
15:00 - 18:00	87,599	-7.74	2.76	-9.64	-7.84	-5.99
18:00 - 21:00	94,406	-7.71	2.75	-9.57	-7.78	-5.99
21:00 - 24:00	96,511	-7.65	2.76	-9.55	-7.75	-5.90

Panel C: Weekday Ln(Amihud)

Weekday	Observations	Mean	Volatility_i	P25	P50	P75
Sunday	105,726	-7.52	2.89	-9.51	-7.62	-5.68
Monday	102,119	-7.67	2.75	-9.53	-7.75	-5.96
Tuesday	99,625	-7.64	2.76	-9.51	-7.72	-5.89
Wednesday	98,060	-7.63	2.76	-9.50	-7.72	-5.88
Thursday	98,920	-7.64	2.79	-9.54	-7.74	-5.88
Friday	100,546	-7.60	2.80	-9.53	-7.68	-5.83
Saturday	105,442	-7.53	2.88	-9.51	-7.61	-5.70

Panel D: Marketplaces Ln(Amihud)

Platforms	Observations	Mean	Volatility_i	P25	P50	P75
LarvaLabs	4,193	-10.20	2.63	-11.49	-11.49	-9.07
OpenSea	688,990	-7.58	2.77	-9.47	-7.66	-5.82
Rarible	17,255	-8.01	3.95	-10.35	-8.58	-6.27

Table 4: **Descriptive Statistics for Day Level Variables**

This table reports descriptive statistics of day level variables used in our analysis. For each measure of NFT news, we compute the natural logarithms of the count of news articles on that day plus 1. *Bitcoin Return*, *Negative Ether Return*, *Positive 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.

Daily Summary Statistics

Interval	Observations	Mean	Volatility$_i$	P25	P50	P75
Variable	N (days)	Mean	S.D.	P25	P50	P75
News						
All NFT News	1,055	1.382	1.861	0.000	0.000	3.091
Local News	1,055	0.700	1.224	0.000	0.000	1.099
National News	1,054	0.743	1.244	0.000	0.000	1.386
Financial News	1,055	0.949	1.443	0.000	0.000	2.079
Tech News	1,054	0.462	0.864	0.000	0.000	0.693
Crypto News	1,054	0.827	1.140	0.000	0.000	1.792
Controls						
Bitcoin Return	1,055	0.003	0.039	-0.014	0.002	0.020
Negative Ether Return	1,055	-0.015	0.030	-0.019	0.000	0.000
Positive Ether Return	1,055	0.019	0.031	0.000	0.003	0.030
Stock Return	1,055	0.001	0.012	-0.001	0.000	0.004

Table 5: **Determinants of NFT Illiquidity**

This table reports the estimates of Equation (1), where the dependent variable is the natural log of Amihud illiquidity measure for NFT i in interval k on day t. Each column represents the estimates of Equation (1) where *News* is based on the tone type of News. We define all variables in the Appendix. We use natural logarithms of illiquidity, age, NFT news, and number of trades measures to approximately conform to normality. Intraday variables are lagged by one interval and daily measures are lagged by one day. All regressions control of day-of-week fixed effects and standard errors used to compute t-statistics are adjusted for heteroscedasticity and within-NFT clustering. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable = Illiquidity$_{tk}$			
News$_{t-1}$	-0.227^{***}	-0.228^{***}	-0.348^{***}	-0.350^{***}
Ln(Issuance)$_i$	-0.761^{***}	-0.760^{***}	-0.752^{***}	-0.751^{***}
Ln(Trades)$_{k-1}$	-0.267^{***}	-0.268^{***}	-0.267^{***}	-0.268^{***}
Ln(Age)$_{i,t}$	-0.115^{***}	-0.115^{***}	-0.109^{***}	-0.109^{***}
Negative Ether Return$_{t-1}$	-2.845^{***}	-2.858^{***}	-0.956^{***}	-0.959^{***}
Positive Ether Return$_{t-1}$	2.743^{***}	2.751^{***}	2.013^{***}	2.020^{***}
Stock Return$_{t-1}$	2.122^{***}	2.145^{***}	0.300	0.316
Bitcoin Return$_{t-1}$	-1.062^{***}	-1.058^{***}	-1.533^{***}	-1.537^{***}
OpenSea	1.185^{***}	1.183^{***}	1.321^{***}	1.319^{***}
Rarible	0.860^{***}	0.856^{***}	0.993^{***}	0.989^{***}
03:00-06:00		0.0521^{***}		0.0520^{***}
06:00-09:00		0.0224^{*}		0.0252^{**}
09:00-12:00		0.0564^{***}		0.0589^{***}
12:00-15:00		0.0058		0.0061
15:00-18:00		-0.0596^{***}		-0.0613^{***}
18:00-21:00		-0.0363^{***}		-0.0396^{***}
21:00-24:00		-0.0125		-0.0152
Monday			-0.0486^{**}	-0.0500^{**}
Tuesday			0.366^{***}	0.366^{***}
Wednesday			0.424^{***}	0.423^{***}
Thursday			0.398^{***}	0.398^{***}
Friday			0.425^{***}	0.426^{***}
Saturday			0.367^{***}	0.370^{***}
Constant	-3.343^{***}	-3.342^{***}	-3.265^{***}	-3.263^{***}
Number of observations	710,438	710,438	710,438	710,438
R^2	0.296	0.296	0.299	0.299

Table 6: **NFT Illiquidity by NFT News Source Type**

This table reports the estimates of Equation (1), where the dependent variable is the natural log of Amihud illiquidity measure for NFT i in interval k on day t. Each column represents the estimates of Equation (1) where *News* is based on the media type of News. We define all variables in the Appendix. We use natural logarithms of illiquidity, age, NFT news, and number of trades measures to approximately conform to normality. Intraday variables are lagged by one interval and daily measures are lagged by one day. All regressions control of day-of-week fixed effects and standard errors used to compute t-statistics are adjusted for heteroscedasticity and within-NFT clustering. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively.

Determinants of NFT Illiquidity

	Dependent variable =Illiquidity$_{tk}$				
Media Type:	Local	National	Financial	Tech	Crypto
News$_{t-1}$	-0.115^{***}	-0.294^{***}	-0.347^{***}	-0.234^{***}	-0.408^{***}
Ln(Issuance)$_i$	-0.772^{***}	-0.749^{***}	-0.756^{***}	-0.765^{***}	-0.764^{***}
Ln(Trades)$_{k-1}$	-0.274^{***}	-0.274^{***}	-0.268^{***}	-0.270^{***}	-0.257^{***}
Ln(Age)$_{i,t}$	-0.120^{***}	-0.107^{***}	-0.112^{***}	-0.120^{***}	-0.130^{***}
Negative Ether Return$_{t-1}$	-1.722^{***}	-2.140^{***}	-1.054^{***}	-1.868^{***}	-0.942^{***}
Positive Ether Return$_{t-1}$	2.315^{***}	1.565^{***}	1.693^{***}	2.274^{***}	2.070^{***}
Stock Return$_{t-1}$	0.690	1.436^{***}	$0.871*$	$1.361**$	-0.698
Bitcoin Return$_{t-1}$	-1.112^{***}	-0.646^{***}	-1.456^{***}	-1.096^{***}	-0.792^{***}
OpenSea	1.008^{***}	1.259^{***}	1.271^{***}	1.062^{***}	1.142^{***}
Rarible	0.686^{***}	0.914^{***}	0.949^{***}	0.727^{***}	0.809^{***}
3:00-6:00	0.0496^{***}	0.0522^{***}	0.0527^{***}	0.0515^{***}	0.0500^{***}
6:00-9:00	0.0200^{*}	0.0278^{**}	0.0247^{**}	0.0233^{*}	0.0214^{*}
9:00-12:00	0.0534^{***}	0.0627^{***}	0.0586^{***}	0.0584^{***}	0.0555^{***}
12:00-15:00	0.00403	0.00926	0.00734	0.00902	0.00863
15:00-18:00	-0.0545^{***}	-0.0604^{***}	-0.0600^{***}	-0.0556^{***}	-0.0555^{***}
18:00-21:00	-0.0285^{***}	-0.0403^{***}	-0.0373^{***}	-0.0305^{***}	-0.0352^{***}
21:00-24:00	-0.00610	-0.0155	-0.0141	-0.00925	-0.0104
Monday	$-0.0241**$	-0.0645^{***}	-0.00669	$-0.0195*$	-0.0743^{***}
Tuesday	0.0740^{***}	0.236^{***}	0.432^{***}	0.268^{***}	0.304^{***}
Wednesday	0.0978^{***}	0.267^{***}	0.467^{***}	0.305^{***}	0.385^{***}
Thursday	0.0965^{***}	0.218^{***}	0.444^{***}	0.285^{***}	0.355^{***}
Friday	0.120^{***}	0.277^{***}	0.468^{***}	0.289^{***}	0.392^{***}
Saturday	0.0772^{***}	0.208^{***}	0.366^{***}	0.250^{***}	0.385^{***}
Constant	-3.804^{***}	-3.779^{***}	-3.586^{***}	-3.915^{***}	-3.384^{***}
Number of observations	710,438	710,437	710,438	710,437	710,438
R^2	0.292	0.298	0.298	0.294	0.297

Table 7: **Difference in Impact of NFT News Source Type on NFT Illiqudity**

This table reports the differences between coefficients on *News* variables in Table 6 and their t-statistics. ***, ** and * represent significance at the 1%, 5%, and 10% level, respectively.

Difference between coefficients by news source

Types	Difference between Coefficients	t-statistics
Crypto (5) - Local (1)	−0.29308	-9.29^{***}
Crypto (5) - National (2)	−0.11392	-3.17^{***}
Crypto (5) - Financial (3)	−0.06147	−1.54
Crypto (5) - Tech (4)	−0.17367	-5.14^{***}
Tech(4) - Local (1)	−0.11941	-5.26^{***}
Tech(4) - National (2)	0.05975	2.10^{**}
Tech(4) -Financial (3)	0.11219	3.37^{***}
Financial (3) - Local (1)	−0.23161	-7.47^{***}
Financial (3) - National (2)	−0.05244	−1.48
National (2) - Local (1)	−0.17916	-6.94^{***}