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Herding in the non-fungible token (NFT) market[☆]

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In this study, we empirically examine the existence and dynamics of herding in the burgeoning market of non-fungible tokens (NFT) with transaction-level data from November 23, 2017 to April 27, 2021. We adopt both macro- and micro-approaches to detect herding and find supportive evidence of the existence of herding in this market, the dynamics of which appears to be event-driven. A large inflow of newcomers or inexperienced investors can serve as a trigger of herding. Herding in the NFT market tends to arise when the return on Ethereum increases, but it tends to diminish as the return on Bitcoin increases. Meanwhile, unlike in traditional asset markets, herding in NFT markets does not appear to happen across submarkets (*OpenSea, Atomic, Cryptokitties, Godsunchained*, and *Decentraland)*. Active investors herd to trade NFTs within different collections and follow the market consensus when they are making investment decisions on NFTs listed on OpenSea. Results from macro- and micro-approaches validate and complement one another, plotting a profile on how investors herd in the NFT market.

1. Introduction

As a new species of cryptographic asset based on blockchain technology, the non-fungible token (NFT) came into prominence and attracted attention from academia and practitioners in early 2021. Unlike cryptocurrencies, which are primarily treated as currencies, NFTs are blockchain-recorded digital assets that can be anything digital, e.g., images, videos, and songs (Dowling, 2022b). As the forerunner, Dowling (2022a) finds that the pricing of digital assets, LAND, a rapidly growing type of NFT in Decentraland,[1] is inefficient, possibly due to its abrupt price soaring at the beginning of 2021. As NFTs generate trivial cash flow, the soaring prices of NFTs are sometimes considered speculative bubbles.[2] In this sense, some argue that participants in the NFT market expect to make money by purchasing overvalued digital assets and then reselling these assets to the next batch of "greater fools" (see Polasik et al., 2015 for the example of "greater fool theory" in the cryptocurrency market). An updraft in prices encourages more people to buy assets and draws more media coverage (Umar et al., 2021), and in turn causes even more people to buy, creating considerable profits for earlier generation of players (Lo and MacKinlay, 2011; Janssen et al., 2019). This strategy works as long as enough newcomers are willing to take over the assets at even higher prices. Can we ascribe the soaring and volatile pricing of NFT to market bubbles? Does investors' herding mentality play a role in this price boost? This research provides the first set of empirical evidence on herding in the NFT market.

Herding is defined as individuals' suppressing their own beliefs and basing their investment decisions solely on the collective actions of the market, even when they disagree with the majority of others' predictions (Christie and Huang, 1995; Batten and Wagner, 2014; Asparouhova et al., 2015). With herding, individual market participants' private information fails to be reflected by market prices, leading to deviation from the rational fundamental value. High correlation in investors' belief and decisions magnifies the volatility of asset prices. Herding is a potential mechanism

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[1] Decentraland is one of the newly generated virtual worlds, which is built on the blockchain. As a citizen in this virtual world, you need to buy LAND, and you can use your LAND arbitrarily, such as hosting a game or giving a promotion (Ordano et al., 2017).

[2] Many news reports question the rationality of the NFT pricing and ascribe it to the market bubble. You may see *Has the NFT Art Bubble Finally Burst? Not Yet, New Data Suggests* (https://www.theartnewspaper.com/2022/06/06/has-the-nft-art-bubble-finally-burst-not-yet-new-data-suggests) and *Is the NFT Bubble Finally Bursting?* (https://www.jumpstartmag.com/is-the-nft-bubble-finally-bursting/) as examples.

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explaining the extreme return and instability in the NFT market, and we will investigate how media coverage and herding may cause instability in the NFT market.

Although some literature claims that the necessary conditions for the emergence of herding include the uncertain fundamental value and varied private information among investors (Avery and Zemsky, 1998; Bikhchandani et al., 1992; Corazzini and Greiner, 2007; Nöth and Weber, 2003),[3] which seems contradictory to the zero fundamental value of the NFT according to the standard valuation method (Nicholas Taleb, 2021), recent studies manage to extend the discussion to the case of NFT. As proposed by Arieli (2017) and Song and Zhang (2020), if an agent obtains additional utility from taking identical actions by others (payments externality),[4] then herding could also emerge. Similar to cryptocurrency, the more prevalently NFTs are used, the more benefited holders of NFTs would be from the larger community of NFTs (network effects by Ante, 2022; Kong and Lin, 2021), thus creating a positive payment externality. In this paper, we propose to investigate whether herding exists in the NFT market and explore its dynamics,[5] as well as the possible spillover across NFT submarkets.

We conduct analyses on herding using both macro- and micro-approaches, and results from all the approaches provide evidence supporting the existence of herding in the NFT market. Firstly, we use the macro-approach by Chang et al. (2000) to detect herding. There are three waves of herding: the first two are when *CryptoPunks* was released and when submarkets of NFT were launched, and the third is when NFT was intensively covered by media at the second half of 2020 as the NFT market started to proliferate from July 2020.[6] During these three periods, the daily market return became higher and more volatile than usual. Further, we investigate whether and how trading experience is associated with herding. We find that as the proportion of "newcomers" (those participating in the NFT market only once) increases, herding is more likely to emerge. In addition, investors' attention, driven by media exposure, also rises when herding arises. Besides, herding in the NFT market tends to arise when the return on Ethereum increases, but it tends to diminish as the return on Bitcoin increases. One potential explanation is that NFTs are usually traded using Ethereum, while Bitcoin is a major competitor of Ethereum in the cryptocurrency market. Lastly, since the five submarkets: *OpenSea, Atomic, Cryptokitties, Godsunchained*, and *Decentraland* that offer tokens with different underlying characteristics, we proceed to analyze the cross-submarket herding among these submarkets. We find that while herding is prominent in all submarkets, traders in one submarket do not imitate (or herd to) investors' behavior in other submarkets. To validate our results from the micro level, we adopt the micro-approaches by Choi and Sias (2009) and Uwilingiye et al. (2019). Since NFTs belonging to the same collection are similar in characteristics, investors can refer to other investors' investment decision on the same collection to trade and the transparency of trading history for each investor on blockchain allow them to do so. We find that herding exists among active investors and some of those investors herd to trade NFTs within different collections. We also examine whether active investors would herd to enter or leave the same submarket. It is shown that 37% of the 198 most active investors herd when making investment decisions on NFTs listed on the submarket of OpenSea.

Our study contributes to the burgeoning literature on NFT and herding as the first one to examine investors' herding in the NFT market, different from previous studies mainly focusing on the pricing efficiency of NFT (Aharon and Demir, 2022; Ante, 2022; Borri et al., 2022; Kireyev and Lin, 2021; Kong and Lin, 2021; Umar et al., 2022). Besides, the transaction level data from the NFT market provide us with the chance to examine herding using both micro- and macro-approach on the same group of investors. Because of the limit on the availability of transaction level data in traditional asset markets, previous literature on herding with the micro-approaches and that with the macro-approaches generally derive results based on different sources of data, making their conclusions incommensurable. However, the NFT market is special or even unique in that data on both prices and transaction details are publicly available. It offers an opportunity to conduct herding analyses using micro- and macro-approaches and draw direct comparison between them. Therefore, we contribute to the literature by highlighting the NFT market as a context in which the dichotomy between the micro- and macro-approaches can be shrunken. The remainder of this paper is organized as follows: in Section 2 we review literature on NFT and the market, Section 3 presents data and methodologies we adopt, Section 4 reports the empirical evidence of herding, and Section 4 concludes.

2. Literature review on the NFT market

As the NFT market is still at its early development stage, the size of the literature on this topic is smaller than those on markets of traditional assets. While most of the existing literature focuses on constructing the market index and addressing the relationship of return with other assets, a few studies proceed to examine individual investors' behavior.

To construct the market index, since NFTs are illiquid and imperfect substitution of each other, comparable with those unique assets like real estate and fine arts, the repeat-sales regression (RSR) models (Borri et al., 2022) and hedonic regression models (Kong and Lin, 2021) are adopted generally, while Kireyev and Lin (2021) note the biasedness of the hedonic regression model in this context to develop a new approach based on the structural model. Considering returns between NFT and other assets, Ante (2022), Borri et al. (2022), and Kong and Lin (2021) find that the NFT return exposes to both the stock market return and the return of cryptocurrency based on which NFT is traded,[7] but Scharnowski et al. (2021) propose a different view that stock returns and NFT returns are unrelated. Divergence in opinions also exist on the effect of investors' attention on NFT return performance: while Kong and Lin (2021) show attention has explanatory power on NFT returns, Borri et al. (2022) hold the opposite view.[8] As the existing studies have not reached an agreement on how to estimate the market index, in this study, we just use the arithmetic average across individual NFTs' returns as the market return. Meanwhile, the market situation tends to be dynamic rather than static, so contradictory conclusions in the existing literature may also be driven by the usage of different samples.

[3] In these studies, the emergence of information cascades is examined, in which case market price does not reflect fundamental value as private information is impeded from flowing into the market.

[4] Here the case of NFT reveals positive payment externality, and there are also cases with negative payment externality, such as bank runs, which could also lead to herding (Diamond and Dybvig, 1983).

[5] As is addressed by Fu and Wu (2021), Chen and Kawaguchi (2018), and Li et al. (2018), herding in the asset market emerge to be time-varying rather than static.

[6] See *Non-fungible tokens quarterly report Q1 2021* (https://nonfungible.com/reports/2021/en/q1-quarterly-nft-market-report) for the rapid growth of the NFT market in the second half of 2020, and Appendix A.1 contains the list of events and the corresponding news reports in the NFT market.

[7] Dowling (2022b) examines the pricing correlation between NFT and the cryptocurrency market but is inconclusive, as results from different methods lead to controversy.

[8] For cryptocurrencies, it is generally agreed that investors' attention can generate momentum and forecast future return (Liu and Tsyvinski, 2021).

Oh et al. (2022) are the first to study NFT return performance with investors' profiles considered. They label investors as experienced and inexperienced with the activity level upon certain time points as the criterion. It is found that experienced investors earned higher returns for each unit of Ethereum (ETH)[9] invested, in which case inexperienced investors purchase NFT with a higher average price than experienced investors, implying the same pattern in our study. Besides considering investors' historical activities, Ante (2022) and Kong and Lin (2021) propose the network effect, which is discussed in cryptocurrency literature in the adoption of a new token. This effect is essential for the success of digital platforms and initial coin offerings and is usually proxied by wallet user growth, active address growth, transaction count growth, and payment count growth (Liu and Tsyvinski, 2021). Kong and Lin (2021) provide empirical evidence that NFT prices could be driven by the network effect, proving the importance of newcomers in affecting NFT prices from another perspective and giving us the basis for using the proliferation of newcomers to explain the emergence of herding.

In addition, Nadini et al. (2021) and White et al. (2022) address the network of interactions among investors. Since transaction recordings on the chain contain information about the trading counterparties, including wallet addresses, data are available for researchers to investigate how traders interact with each other. Nadini et al. (2021) and White et al. (2022) reach similar conclusions: traders typically specialize in NFTs associated with similar objects and form tight clusters with other traders to exchange the same objects. Traders' tendency to stick to a particular category of NFT provides a potential explanation for our finding that investors in each submarket imitate the behavior of others trading only in this submarket while would not imitate the behavior of investors in other submarkets. Considering the data availability of wallet addresses, von Wachter et al. (2022) conducted research on the potential wash trading in the NFT market, given the ease with which agents can control multiple addresses. Thus far, little research focuses on investors' behavior in the NFT market, while none of them has examined the possibility of herding.

3. Data and methodology

We use the dataset provided by Nadini et al. (2021). The dataset is publicly available at https://osf.io/wsnzr/?view_only=319a53cf1bf542bbbe538aba37916537. The raw dataset contains over 6 million lines of transaction recording in five NFT submarkets: *OpenSea, Atomic, Cryptokitties, Godsunchained*, and *Decentraland*,[10] from 23rd Nov. 2017 to 27th Apr. 2021. Daily returns of individual NFTs are calculated in a sense of continuous compounding, the details of which can be found in Appendix C. When minted, an NFT is grouped into certain collection according to certain characteristics, so the NFTs in the same collection share similarities.[11] The descriptive statistics for NFTs and collections in our sample are reported in Table 1.

The methods for investigating herding empirically are generally divided into two large categories. The first one includes the macro-approaches (Chang et al., 2000; Christie and Huang, 1995), which use the cross-sectional correlation dispersion to quantify the average proximity of individual returns to the realized market consensus. The second category includes micro-approaches (Choi and Sias, 2009; Sias, 2004; Uwilingiye et al., 2019), which test herding by examining investors' position change. Considering the potential conflicting results from different testing methods, e.g., as noted by Demirer et al. (2010), we adopt methodologies from both two paths in this study.

The reason for us to consider both approaches is as the following: previous studies on herding use micro-approaches with position data from institutional investors to examine herding among institutional investors, thus corresponding to a subset of investors in the whole market. Even though we have the transaction level data from all the investors in the NFT market, the micro-approaches are still more suitable for only a subset of investors, i.e., those with the higher frequency of transactions. Most of the investors traded so infrequently that they did not provide us with enough information to test whether they herd or not at the individual level. Therefore, we adopt the macro-approach by Chang et al. (2000) in addition to the micro-approaches by Uwilingiye et al. (2019) and Choi and Sias (2009) because the macro-approach can provide results based on the whole sample. Moreover, Bikhchandani and Sharma (2001) classify herding into intentional herding and spurious herding. While spurious herding is induced by investors' similar investment decisions reacting to commonly known public information, intentional herding is driven by investors' cognitive bias to follow the actions of others, which is what we are mainly interested in our study. Using the approach by Chang et al. (2000), we cannot distinguish investors' intentional herding and spurious herding, but the micro-approaches can help factor out spurious herding. Thus, incorporating both micro- and macro-approaches of herding testing can help us to cross-validate our findings, and these approaches are in general complements instead of substitutes to each other.

3.1. The macro-approach by Chang et al. (2000)

3.1.1. Testing measurements and specification

Chang et al. (2000) (CCK) demonstrate that under rational asset pricing model, the return dispersions are predicted to be linear, which is not hold when herding happen. Since assets have different sensitivity to the market return, the dispersion will increase as the absolute value of the market return rises. However, when herding exist, investors will base on the collective action of the market to make their decision, the asset returns will deviate less to the market return than estimated. Under such situation, CCK facilitate the detection of herding by using the cross-sectional absolute deviation (CSAD) of returns as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right|, \quad (1)$$

where $R_{i,t}$ denotes the return on the individual asset i while $R_{m,t}$ denotes the return of the market portfolio at time t.[12] With herding, investors are willing to suppress their beliefs and follow the market consensus, and thus individual asset returns converge to the market average. To capture this convergence, CCK proposes the following specification:

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R_{m,t}^2 + \varepsilon_t. \quad (2)$$

The convergence would be grasped by a negative and statistically significant γ_2 coefficient, and thus the existence of herding would also be revealed by this significantly negative γ_2, which can be regarded as the herding indicator.

Yao et al. (2014) and Fu and Wu (2021) show that since a high level of serial correlation is expected to exist in high-frequency time series market data, failure to consider this issue

[9] Transactions on NFT are generally based on Ethereum.

[10] According to Nadini et al. (2021), the five submarkets are APIs where data are downloaded from, and the summary of characteristics of the five submarkets is contained in Appendix B.

[11] You may refer to the list of collections on OpenSea as an example: https://opensea.io/rankings/trending.

[12] The daily market return ($R_{m,t}$) is calculated by taking equally weighted arithmetic average of daily returns of individual NFTs.

Table 1
Descriptive statistics for our dataset.

	Statistics					
	N	Mean	Median	Minimum	Maximum	Std. dev.
Number of trading days in the sample	1252	–	–	–	–	–
Number of collections	4625	–	–	–	–	–
Number of NFTs	4040920	–	–	–	–	–
Number of NFTs in a collection	–	1313	6	1	1290146	28178
Number of NFTs traded each day	–	4849	1522	143	154445	12534
Number of collections traded each day		66	26	1	686	118

Notes: (a) This table presents the descriptive statistics for NFTs and the corresponding collections from 23rd Nov. 2017 to 27th Apr. 2021.

$$CSAD_t = \begin{cases} \alpha + \gamma_{1,1}\left|R_{m,t}\right| + \gamma_{2,1}R^2_{m,t} + \gamma_3 CSAD_{t-1} + \varepsilon_{1,t}\varepsilon_{1,t} \sim N\left(0,\sigma_1^2\right) \text{ if } s_t = 1, \\ \alpha + \gamma_{1,2}\left|R_{m,t}\right| + \gamma_{2,2}R^2_{m,t} + \gamma_3 CSAD_{t-1} + \varepsilon_{2,t}\varepsilon_{2,t} \sim N\left(0,\sigma_2^2\right) \text{ if } s_t = 2, \end{cases} \quad (4)$$

$$P\left(s_{t+1} = i | s_t = j\right) = p_{ij}, \quad i, j \in \{1, 2\}$$

Box I.

will result in biased estimates. According to the specifications in Yao et al. (2014) and Fu and Wu (2021), we add a 1 day lag of the dependent variable ($CSAD_t$) as a regressor into Eq. (2):

$$CSAD_t = \alpha + \gamma_1\left|R_{m,t}\right| + \gamma_2 R^2_{m,t} + \gamma_3 CSAD_{t-1} + \varepsilon_t. \quad (3)$$

3.1.2. Dynamics of herding

To examine the dynamics of herding in the NFT market, we employ the fixed transition probabilities MS model (FTP-MS) by Diebold and Rudebusch (1999). According to Fu and Wu (2021), we propose two regimes of the market, one with herding while the other without, and the basic specification is as follows (see Eq. (4) which is given in Box I) where we set the constant term α as a non-switching parameter indicating the long-run average of $CSAD_t$ and $P\left(s_{t+1} = i | s_t = j\right)$ is the transition probability between the two states. The unobservable state variable, s_t, evolves according to the first-order Markov-switching process:

$$P = \begin{pmatrix} P_{1,1} & 1 - P_{2,2} \\ 1 - P_{1,1} & P_{2,2} \end{pmatrix},$$

where $P\left(s_{t+1} = i | s_t = j\right) = p_{ij}$ and $0 < P_{i,i} < 1$; $0 < P_{j,j} < 1$. If we set regime 1 ($s_t = 1$) as the regime with herding (negative $\gamma_{2,1}$) and regime 2 ($s_t = 2$) as the regime without herding (positive or insignificant $\gamma_{2,2}$), $1 - P_{2,2}$ denotes the probability in which herding would emerge. Moreover, we can estimate the probability of the existence of herding at every point in time, thus addressing the dynamics of herding in the NFT market.

Assuming that the coefficients in Eq. (3) are smooth functions of another single variable we are interested in, following Hastie and Tibshirani (1993) and Rios-Avila (2020), we can estimate a smooth varying-coefficient model and plot the estimated coefficient on $R^2_{m,t}$ to visualize its change against the single variable of interest. We propose the following specification:

$$CSAD_t = \beta_0(z) + \beta_1(z)\left|R_{m,t}\right| + \beta_2(z) R^2_{m,t} + \beta_3(z) CSAD_{t-1} + \varepsilon_t, \quad (5)$$

where all coefficients (βs) are assumed to be smooth functions of the single variable (z).[13] The coefficients are estimated using local linear kernel-weighted regression following Li and Racine (2007). In this sense, we can illustrate the association between the emergence of herding and the other variable (z), which measures the characteristics of the market situation.

Table 2 provides the summary of descriptive statistics of the daily market return ($R_{m,t}$) and $CSAD_t$ of the NFT market,[14] while Fig. 1 plots the dynamics of $R_{m,t}$ and $CSAD_t$. In Fig. 1, $CSAD_t$ is proportional to $R_{m,t}$, a pattern noted by Chang et al. (2000) that rational asset-pricing models imply a linear relationship between the dispersion in individual asset returns and the return on the market portfolio, but the emergence of herding mitigates part of this effect, as we would illustrate in the next section.

3.2. The micro-approaches

Current studies on herding in the micro-approaches are generally based on holding data, i.e., position, to detect herding. The approaches proposed by Sias (2004) and Choi and Sias (2009) are based on the correlation of the changes in asset positions across investors in two adjacent periods. Those methods show that institutional investors follow both their own prior decisions and other institutional investors in the same industry. However, they do not differentiate spurious herding and intentional herding. Using Geweke (1982) type of causality tests, Uwilingiye et al. (2019) proposed an approach that can disentangle spurious herding and intentional herding. In this study, we adopt both the approach by Choi and Sias (2009) and that by Uwilingiye et al. (2019).

3.2.1. The micro-approach by Choi and Sias (2009)

Choi and Sias (2009) test herding by calculating the cross-sectional correlation between institutional investors' industry demand in this quarter and in the previous quarter. In the context of NFT market, each NFT belongs to a certain collection while NFTs in the same collection are similar in characteristics. Thus, we test herding on the level of NFT collections. However, unlike the case of the stock market, our dataset includes transactions from all the investors rather than solely the institutional investors. For a certain collection of NFT, the number of buyers would be equal to the number of sellers at any time point, so the aggregate position change from all the investors is equal to zero, impeding the usage of this method to detect herding for all the investors. Therefore, we test herding for investors with relatively high trading frequencies. There are two reasons to do so. Firstly, traders with high trading frequencies provide us with enough

[13] In this study, z is set to be the proportion of newcomers into the market, investors' attention towards NFT, and the returns on Bitcoin and Ethereum respectively in the following sections.

[14] The daily market return ($R_{m,t}$) is calculated by taking equally weighted arithmetic average of daily returns of individual NFTs.

Table 2
Descriptive statistics of R_m and $CSAD_t$.

Variables	Mean	Std	Skewness	Kurtosis	Jarque-Bera	ADF	ACF at lag			
							1	2	5	20
$R_{m,t}$	0.0306	0.0759	3.7141	36.0826	$(5.9973 \times 10^4)^{***}$	$(-19.8237)^{***}$	0.5035	0.5241	0.3618	0.0352
$CSAD_t$	0.1389	0.0921	2.4615	16.9022	$(1.1347 \times 10^4)^{***}$	$(-8.9298)^{***}$	0.6632	0.5941	0.4966	0.3266

Notes: *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

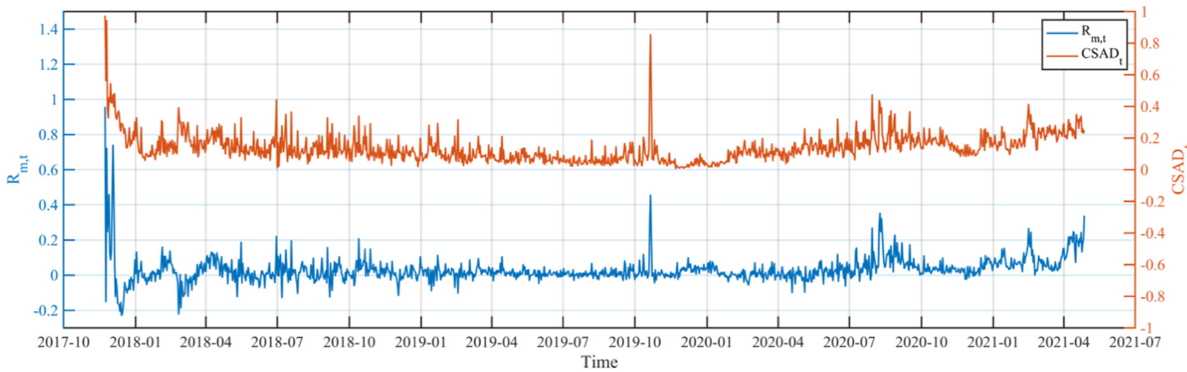

Fig. 1. The $R_{m,t}$ and $CSAD_t$.In this figure, $R_{m,t}$ (in blue, the left Y-axis) and $CSAD_t$ (in red, the right Y-axis) are plotted from Nov. 2017 to Apr. 2021.

information to examine their behavior. We cannot measure an investor's demand change if she trades only once during our sample period. Secondly, traders with relatively high trading frequencies have more experienced in trading, and dominate the market in most of the time, as shown in Appendix D. Thus focusing on those investors provides an examination of herding on active players in the market.

We define investor n as purchasing collection k if this investor is the buyer in a certain transaction on an NFT belonging to collection k. Similarly, investor n is labeled as a seller of collection k if she is the seller in a certain transaction on an NFT belonging to collection k. Following Choi and Sias (2009), we define collection demand as the ratio of the number of investors buying collection k in period t to the number of investors trading collection k in period t:

$$\Delta_{k,t} = \frac{\#\ buyers\ of\ \ collection\ kinperiodt}{\#\ buyers\ of\ \ collection\ k\ in\ period\ t{+}\#\ sellers\ of\ \ collection\ k\ in\ period\ t}, \tag{6}$$

where we select investors with the highest 30% cumulative number of transactions[15] in calculation and define each period as a quarter, i.e., 90 days. There are totally 4624 collections in the NFT market.

If herding exists on the collection level, investors' collection demand this quarter would be correlated with that in the last quarter. Investors can follow their own decisions made in the last quarter or follow the behavior of traders investing NFTs in the same collection last quarter, both inducing positive correlation in collection demand between this and last quarter. Therefore, following Choi and Sias (2009), we decompose the correlation in collection demand between this quarter and the last into two parts:

$$\begin{aligned}
&\rho\left(\Delta_{k,t}, \Delta_{k,t-1}\right) \\
&= \left[\frac{1}{(K)\sigma\left(\Delta_{k,t}\right)\sigma\left(\Delta_{k,t-1}\right)}\right] \\
&\times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}}\left(\frac{D_{n,k,t}-\overline{\Delta_{k,t}}}{N_{k,t}}\cdot\frac{D_{n,k,t-1}-\overline{\Delta_{k,t-1}}}{N_{k,t-1}}\right)\right] \\
&+ \left[\frac{1}{(K)\sigma\left(\Delta_{k,t}\right)\sigma\left(\Delta_{k,t-1}\right)}\right] \\
&\times \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}}\sum_{m=1,m\neq n}^{N_{k,t-1}}\left(\frac{D_{n,k,t}-\overline{\Delta_{k,t}}}{N_{k,t}}\cdot\frac{D_{m,k,t-1}-\overline{\Delta_{k,t}}}{N_{k,t-1}}\right)\right],
\end{aligned} \tag{7}$$

where K denotes the number of collections ($K = 4624$), $N_{k,t}$ denotes the number of investors trading collection k in quarter t, $\sigma\left(\Delta_{k,t}\right)$ and $\overline{\Delta_{k,t}}$ denotes the cross-sectional standard deviation and average collection demand in quarter t respectively, and $D_{n,k,t}$ equal one if investor n buys collection k in quarter t and zero if investor n sells collection k. In Eq. (7), the first term represents the part of correlation induced by investors following their own lag demand last quarter, and the second term represents the part driven by investors following the lag demand of other investors last quarter.

Table 3 reports the time-series mean of the cross-sectional quarterly descriptive statistics on active investors, i.e., investors with the highest 30% cumulative number of transactions. A collection has 258 active investors on average in each quarter, with a minimum of 6 and maximum of 59496. The large standard deviation of 1422 reflects that the number of investors varies dramatically across different collections, so investors' preference is heterogeneous among different collections. The average 65.11% collection demand indicates that averagely active investors are more likely to be buyers. Since which collection an NFT belongs to is predetermined by its miner when this NFT was created, the number of member NFTs can vary hugely from collection to collection. The average collection has 1313 NFTs from a minimum of 1 to a maximum of 129046.

3.2.2. *The micro-approach by Uwilingiye et al. (2019)*

Instead of using changes in industry demand to test herding, the approach proposed by Uwilingiye et al. (2019) tests herding on the level of individual institutional investors and technology stocks. Uwilingiye et al. (2019) test herding among the top 115 institutional investors with the highest scale of fund management.

[15] The detailed analysis of the cumulative number of transactions for investors can be found in Appendix D.

Table 3
Active investors and collection characteristics.

	Statistics				
	Mean	Median	Minimum	Maximum	Std. dev.
Number of investors trading on a collection	258	24	6	59496	1422
$\#Buyers/(\#Buyers + \#Sellers)$	65.11%	66.67%	0%	100%	29.29%
Number of NFTs in a collection	1313	6	1	1290146	28178

Notes:
(a) NFTs are classified each quarter (90 days) into one of the 4624 collections. Since we only focus on active investors, i.e., investors with the highest 30% cumulative number of transactions, descriptive statistics in this table are specific to this subgroup of investors.
(b) This table reports the time-series average of the cross-sectional descriptive statistics each quarter for Number of investors trading on each collection and the ratio of buyers.

Accordingly, we focus on the 200 most active traders (the top 200 traders with the highest cumulative number of transactions) and NFTs in the OpenSea market. In practice, we can evaluate any group of investors with this approach as long as we have their position data. We select the 200 most active traders as a sample of the active traders, and we can provide testing results with larger sample size upon request, e.g., the 500 most active traders or the 1000 most active traders. Since the individual transaction history for each investor is publicly accessible, having a large number of transactions could be a signal of experienced,[16] thus attracting other investors to follow. We particularly focus on the OpenSea market as it is the world's first and largest web3 marketplace for NFTs and crypto collectibles, attracting most of the coverage by the media.

The method by Uwilingiye et al. (2019) tests herding by examining the linear feedback (causality) in individual institutional investors' position change and the aggregate position change of all the institutional investors considered. Thus, in our case, we examine the linear feedback in each of the 200 most active traders' position changes on NFTs listed on OpenSea and the change in the 200 traders' aggregate position. According to Geweke (1982), the linear dependence and feedback between two time series X and Y can be decomposed into three parts:

$$F_{X,Y} = F_{X\rightarrow Y} + F_{Y\rightarrow X} + F_{X\cdot Y},$$

where $F_{X,Y}$ denotes the total linear association between X and Y, $F_{X\rightarrow Y}$ denotes the linear feedback from X to Y (X Granger cause Y), $F_{Y\rightarrow X}$ denotes the linear feedback from Y to X (Y granger cause X), and $F_{X\cdot Y}$ represents the instantaneous feedback between X and Y. Uwilingiye et al. (2019) argues that we can use the Geweke (1982) causality approach to factor out spurious herding, as investors' common reaction to the same fundamental information can be captured by the instantaneous feedback between individual investors' position change and the change in the aggregate position of all the investors considered. In our context, if X is a series of position change on OpenSea for one of the 200 investors and Y is the series of change in the aggregate position of all the 200 investors, $F_{X\rightarrow Y}$ indicates the existence of informed traders that other traders follow, resulting in causality from this individual investor to the others. The causal relationship from the aggregate position change to individual position change ($F_{Y\rightarrow X}$) can be a manifestation of intentional herding, since the individual investor makes her decision based on the market consensus. Lastly, The part of instantaneous causality ($F_{X\cdot Y}$) captures spurious herding. In this study, we calculate the position change in the frequency of half a month (15 days) so that we expect investors to have enough time to make rational decisions, a necessary setting that instantaneous causality can be used to capture spurious herding according to Uwilingiye et al. (2019). With this setting, we evaluate how many of the investors among the most active 200 herd to trade NFTs listed on OpenSea.

Fig. 2 shows the daily change in the aggregate position on OpenSea for the most active 200 investors. It is shown that at the end of 2019 those investors increased their holding on OpenSea while at the beginning of 2021 they decreased their holding. Both of the two periods of intensive position change coincident with the periods of herding revealed by the method of CCK as illustrated in the next section.

4. Empirical results and discussion

4.1. Results based on the macro-approach by Chang et al. (2000)

4.1.1. Herding detection and its dynamics

Table 4 presents the estimation results based on the macro-approach by Chang et al. (2000). Both the AIC and BIC of the estimated FTP-MS model (shown in the (5) and (6) columns in Table 1) are smaller than those of the basic model Eq. (3), suggesting the higher level of fitting and explanatory power of the FTP-MS model.

As is shown in Table 4, the significantly negative estimated value of γ_2 (-0.7081) is considered indication of the existence of herding in the NFT market. Further, the FTP-MS model successfully isolates the period during which herding occurs. In column (5), the herding indicator is negative for regime 1 ($\gamma_{2,1}$) while positive for regime 2 ($\gamma_{2,2}$), suggesting that herding happens only during the time of regime 1. We can see that the estimated conditional variance in regime 1 (σ_1^2) is considerably higher than that in regime 2 (σ_2^2) so the market becomes more volatile when herding emerges than usual.

In Fig. 3, the series of market returns is plotted together with the periods of regime 1 over time, indicated by the shadowed areas. We also add tags to indicate big events in the NFT market in Fig. 3. During the time of regime 1, $R_{m,t}$ fluctuates more dramatically than usual, in accord with the higher conditional variance of $CSAD_t$ when herding emerges. Besides, $R_{m,t}$ tends to jump up during the periods of herding, suggesting the co-existence of herding and price soaring.[17] As is shown in Fig. 3, the FTP-MS model identifies three major periods when herding exists, i.e., from Nov. 2017 (the beginning of our sample) to Oct. 2018, from Dec. 2019 to Feb. 2020, and from Aug. 2020 to Apr. 2021(the end of our sample). Launches of several early submarkets, i.e., *Opensea*, *Cryptokitties*, and *Godsunchained*, and the release of the leading collection of NFT *CryptoPunks* at the end of 2017 coincidence with the first period. The second period is near the time when the other two submarkets, *Atomic* and *Decentraland*, were launched, while the latest period is during the time when NFT was intensively covered by media at the second half of 2020 as the NFT market started to proliferate from July

[16] As an example, see the transaction history of a investor on OpenSea: https://opensea.io/vEmpireDDAO/activity.

[17] As is shown in Appendix A.2, the average daily market return $R_{m,t}$ during the periods when herding emerge is significantly higher than usual.

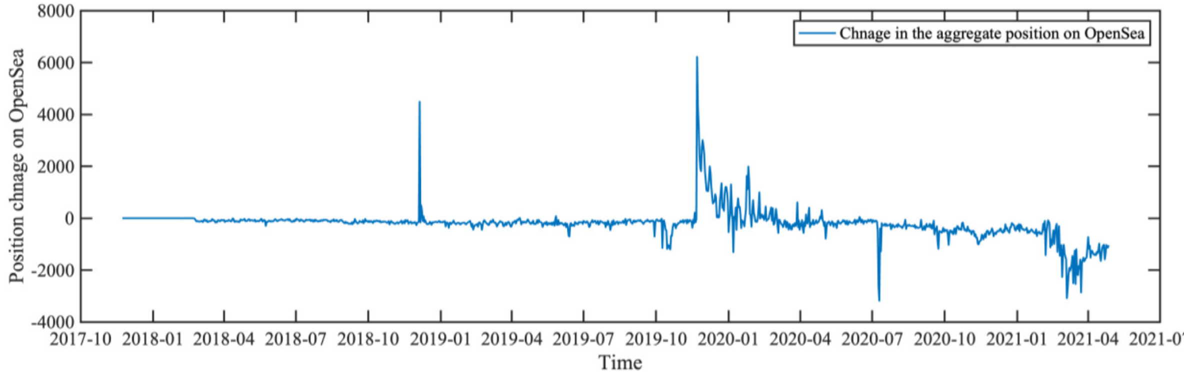

Fig. 2. Change in the aggregate position on OpenSea for the most active 200 investors.
The blue line present daily change in the aggregate position on OpenSea for the most active 200 investor, based on whom we test herding using the micro-approach by Uwilingiye et al. (2019).

Table 4
Parameter estimation results of Eqs. (3) and (4).

Parameter	Eq. (2)		Eq. (3)		Eq. (4)	
	Estimation (1)	p-value (2)	Estimation (3)	p-value (4)	Estimation (5)	p-value (6)
α	0.0788***	0.000	0.0426***	0.000	0.0439***	0.000
γ_1	1.3632***	0.000	1.0890***	0.000	–	–
γ_2	−**0.6085***	0.000	−**0.7081***	0.000	–	–
γ_3	–	–	0.3559***	0.000	0.2989***	0.000
$\gamma_{1,1}$	–	–	–	–	1.1288***	0.000
$\gamma_{1,2}$	–	–	–	–	1.0394***	0.000
$\gamma_{2,1}$	–	–	–	–	−**0.7399***	0.000
$\gamma_{2,2}$	–	–	–	–	**1.9883***	0.000
σ_1^2	–	–	–	–	0.0046***	0.000
σ_2^2	–	–	–	–	0.0009***	0.000
$P_{1,1}$	–	–	–	–	0.95***	0.000
$P_{2,2}$	–	–	–	–	0.98***	0.000
Log Likelihood	1852	–	2041	–	2183	–
AIC	−3698	–	−4074	–	−4345	–
BIC	−3683	–	−4054	–	−4294	–

Notes:
(a) This table presents estimated coefficients for Eqs. (2), (3), and (4) with data from the five submarkets in total.
(b) The sample size for each regression is 1252.
(c) We estimate Eq. (4) with the Matlab package by Perlin (2015).
(d) *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.
(e) Considering the potential heteroscedasticity and autocorrelation, we report the estimation results for Eqs. (2) and (3) with the p-values calculated using Newey and West (1987) standard errors in Appendix A.3 (Table A.3). 05/08/2023 01:43:00

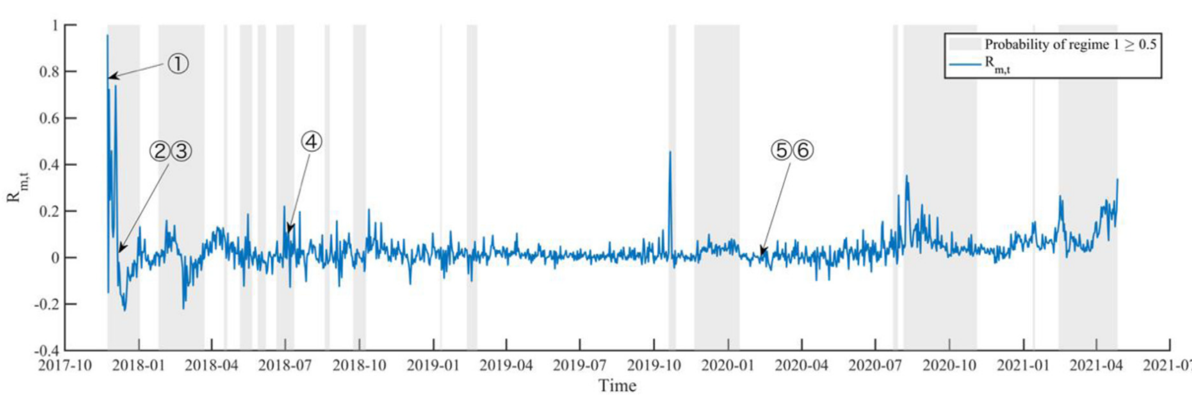

Fig. 3. Dynamics of herding and big events in NFT market.
In this figure, the shadow region corresponds to the period with probability of regime 1 ≥ 0.5. Tags in the figure correspond to the following events: ① Launch of *CryptoPunks* in June, 2017 (Kong and Lin, 2021); ② Launch of *Opensea* in Dec. 2017 (https://opensea.io/about); ③ Launch of *Cryptokitties* in Nov. 2017 (https://www.prnewswire.com/news-releases/cryptokitties-the-worlds-first-ethereum-game-launches-today-660494083.html); ④ Launch of *Godsunchained* in Jul. 2018 (https://godsunchained.fandom.com/wiki/Release_date); ⑤ Launch of *Atomic* in Feb. 2020 (https://www.cryptowisser.com/nft-marketplace/atomic-hub-marketplace/); ⑥ Launch of *Decentraland* in Feb. 2020 (https://decentraland.org/blog/announcements/decentraland-announces-publich-launch/).

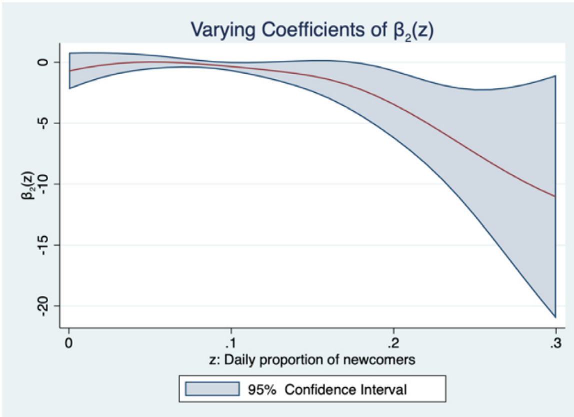

Fig. 4. Time varying coefficient of β_2 in Eq. (5) and the daily proportion of Newcomers in the NFT market.

2020.[18] The pattern in Fig. 3 can therefore be regarded as event-driven. In the following sections, we would further investigate the possible driving forces and mechanisms of herding in the NFT market.

4.1.2. The newcomers and investors' attention with herding formation

4.1.2.1. Newcomers and herding. Oh et al. (2022) note that in the NFT market experienced investors earned higher returns for each unit of Ethereum (ETH)[19] invested than those inexperienced, possibly because inexperienced investors purchase NFT with a higher average price than experienced investors.[20] Most newcomers have traded only once and are not familiar with the market situation. They are therefore more likely to follow the market consensus and thus fuel the formation of herding. Thus, we conjecture that when newcomers flow into the NFT market, herding is more likely to occur. To test this conjecture, we select the proportion of investors in the group who have traded only once (the cumulative number of transactions = 1) as the proxy for the newcomer proportion. We adopt the smooth varying-coefficient model in Eq. (5) with coefficients smooth functions of the newcomer proportion. Fig. 4 illustrates the association between the daily proportion of newcomers and the estimate of β_2. In Fig. 4, β_2 becomes negative when the daily proportion of newcomers goes large, suggesting the emergence of herding when more newcomers participate, who bear higher costs of purchasing while pushing up prices.

4.1.2.2. The effect of investors' attention on herding. Fortune-made stories in the NFT market spread to the public, either by word of mouth, by news media, or by social media, driving people to participate and then fostering the development of the NFT market, a case of *Narrative Economics* (Shiller, 2017). Following Kong and Lin (2021), we employ Google search frequency (Search Volume Index, SVI) on the topic of "Ethereum" as the proxy of investors' attention towards NFT, because NFTs are mostly traded on the Ethereum blockchain.[21] We obtain the data from Google Trends and adjust the original weekly data on daily basis, which is plotted in Fig. 5. In Fig. 5, Google SVI rose accordingly when the market went into the regime of herding (the shadow area) around Jul. 2020, while it also comoved with the proportion of traders who are newcomers (shown by the black line).[22]

To evaluate whether herding arises when investors' attention towards NFT increases, we also adopt the smooth varying-coefficient model with coefficients smooth functions of Google SVI. Therefore, in Eq. (5), (z) here stands for Google SVI, which is the proxy of investors' attention on NFTs. Fig. 6 shows that as investors' attention towards NFTs increases (Google SVI increase), the coefficient before $R^2_{m,t}$ (β_2) becomes negative, and the threshold is around 30. Therefore, herding emerges when investors pay more attention to NFTs, and the pattern together with that of the newcomers configurates a story, in which newcomers urged by the overwhelmed reporting by media come into the NFT market and push up prices, and herding emerges accordingly.

4.1.3. Herding in the NFT market and the performance of cryptocurrencies

While NFTs are regarded as alternative assets to Bitcoin (Kong and Lin, 2021), investors willing to purchase NFTs need to convert their fiat money to Ethereum firstly. To buy NFTs, an investor can choose to sell Bitcoin and buy in Ethereum. Therefore, Ethereum, which is necessary in trading NFTs, may perform differently with Bitcoin when herding arises in the NFT market. To examine how these two cryptocurrencies correlate with herding in the NFT market, we adopt the smooth varying-coefficient model in Eq. (5) with coefficients smooth functions of the daily return on Ethereum and Bitcoin, respectively.

Figs. 7 and 8 illustrate the association between the estimate of β_2 and the daily returns on Ethereum and Bitcoin, respectively. While herding in the NFT market tends to emerge as the return on Ethereum increases, it tends to diminish as the return on Bitcoin rises. This result is compelling for investors with portfolios on both NFTs and cryptocurrencies for diversification, as they can adjust their portfolio accordingly to avoid the harm of herding on diversification.[23]

Our finding can be partially explained by the negative relationship between assets' short-term and long-term returns induced by herding. While Singh (2013) documents the positive abnormal return of assets contemporaneous with institutional herding and the long-term reversals when herding ceases, Dasgupta et al. (2011) rationalize this empirical finding with a theoretical model: prices of assets increase above their real value when institutional investors herd to buy, and the prices reverse back in the long run. In our context, herding push up the prices of NFTs, which are positively correlated with the return on Ethereum. However, in the long run, herding ceases with the negative return on NFTs, making investors in the NFT market flow into the Bitcoin market, pushing up the Bitcoin price.

4.1.4. Within- and cross-submarkets herding

In the traditional financial market, investors always trade on multi-platform or different instruments simultaneously. Investors in stock markets usually follow news about the global market. For example, Chiang and Zheng (2010) note that investors in

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18 See *Non-fungible tokens quarterly report Q1 2021*(https://nonfungible.com/reports/2021/en/q1-quarterly-nft-market-report) for the rapid growth of the NFT market in the second half of 2020, and Appendix A.1 contains the list of events and the corresponding news reports in the NFT market.

19 Transactions on NFT are generally based on Ethereum.

20 You can refer to Appendix D for the detailed analysis on investors' dynamics with different level of trading experience.

21 In this paper, the SVI on the topic of "Ethereum" also captures the trend of searching for the topics related to "Ethereum", such as Non-fungible Token and NFT, and thus is broader than solely on "NFT". Therefore, SVI on "Ethereum" can capture people's attention on relevant topics of NFT as much as possible.

22 We have conducted the Granger Causality Test to examine the relationship between Google SVI and daily proportion of newcomers (investors in the group with $CumTran$ = 1), which you can find in Appendix E. It is shown that the change in Google SVI Granger-cause the change in daily proportion of newcomers, while the reversed relationship does not hold.

23 Herding makes it difficult for the investors to achieve the same degree of diversification, as assets tend to comove (Christie and Huang, 1995).

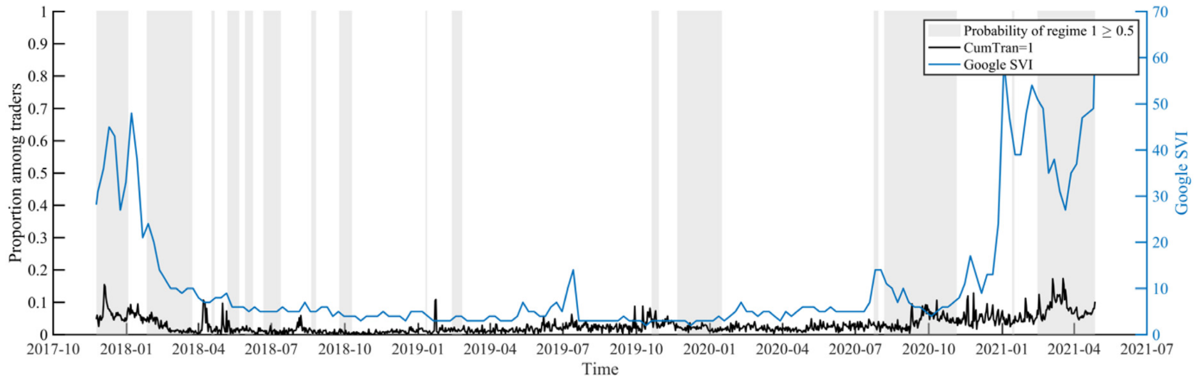

Fig. 5. Google SVI and dynamics of herding.
The blue line present Google search volume index (SVI) with the search topic related to "Ethereum", which is obtained from Google Trend. The black line present daily proportion of investors in the group with CumTran = 1 (newcomers).

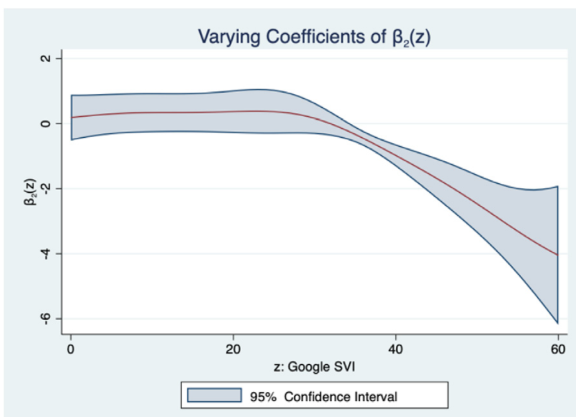

Fig. 6. Time varying coefficient of β_2 in Eq. (5) and Google SVI.

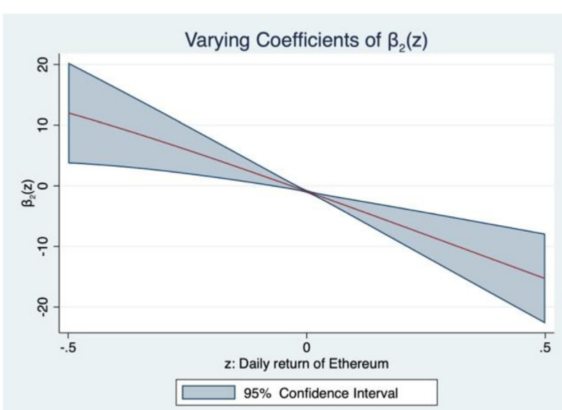

Fig. 7. Time varying coefficient of β_2 in Eq. (5) and the daily return on Ethereum.

all of the major markets, including those in Asia, Latin America, and Europe, imitate the actions of investors in the US market, a case of herding across markets. Herding across markets is due to the cost of information and the free-of-charge information revealed by investors' actions in other markets. Therefore, we wonder conjecture that herding exists across different NFT submarkets (*OpenSea*, *Atomic*, *Cryptokitties*, *Godsunchained*, and *Decentraland*), in which case investors in one submarket would follow the investing decision by investors in other submarkets.

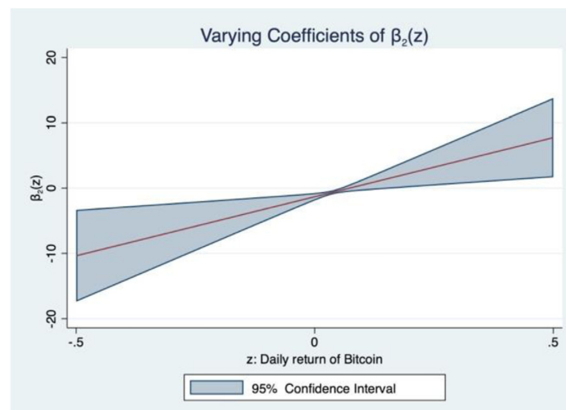

Fig. 8. Time varying coefficient of β_2 in Eq. (5) and the daily return on Bitcoin.

To examine the herding across submarkets, we adopt the specification by Chiang and Zheng (2010), in which case the daily market return of the second submarket that investors in certain submarket herd to[24] is added to Eq. (3):

$$CSAD_t = \alpha + \gamma_1 \left|R_{m,t}\right| + \gamma_2 CSAD_{t-1} + \gamma_3 R_{m,t}^2 + \gamma_4 R_{m,t}^{*2} + \varepsilon_t, \tag{8}$$

where $R_{m,t}^*$ denotes the daily market return in another submarket that investors in a certain submarket may herd to. For example, if we want to examine whether investors in *Atomic* herd to investors in *Cryptokitties*, data of $CSAD_t$, $R_{m,t}$, and $CSAD_{t-1}$ should be from *Atomic* while those of $R_{m,t}^*$ should be from *Cryptokitties*. The estimation results are reported in Table 5,[25] and the only case in which herding happens across submarkets is for *Decentraland*. Investors in *Decentraland* imitate actions by their peers in their own submarket while also imitating actions by investors in *Atomic* at the same time, as indicated by the significantly negative estimated coefficient before $R_{m,A,t}^2$ (−0.1138) under 10% significance level. In all the other cases, γ_4 is either positive or insignificant, suggesting that herding across submarkets rarely

[24] Here "investors in one certain submarket herd to the second submarket" means that those investors follow the actions by investors in the second submarket, in which case investors in the first submarket herd to the information revealed by the actions of investors in the second submarket.

[25] The descriptive statistics of $R_{m,t}$ and $CSAD_t$ for the five submarkets are summarized in Table B.2 of Appendix B.

Table 5
Parameter estimation results of Eq. (6) for the five submarkets.

Submarket	Constant	$\lvert R_{m,t}\rvert$	$CSAD_{t-1}$	$R^2_{m,A,t}$	$R^2_{m,C,t}$	$R^2_{m,D,t}$	$R^2_{m,G,t}$	$R^2_{m,O,t}$
Atomic	0.0424***	1.3194***	−0.0474***	**−0.8301***	–	–	–	–
	0.0424***	1.3195***	−0.0474***	−0.8301***	−0.0009	–	–	–
	0.0427***	1.3242***	−0.0497***	−0.8345***	–	−0.0069	–	–
	0.0419***	1.3219***	−0.0476	−0.8319***	–	–	0.0016	–
	0.0432***	1.3177***	−0.0474	−0.8292***	–	–	–	−0.0681
Cryptokitties	0.0825***	1.6030***	0.0408	0.02925	−1.3135***	–	–	–
	0.0826***	1.2513***	0.1134***	–	**−0.5206***	–	–	–
	0.0819***	1.2748***	0.0974***	–	−0.5225***	0.0511***	–	–
	0.0888***	1.6329***	0.0494**	–	−1.3317***	–	0.0021	–
	0.0821***	1.2861***	0.0968***	–	−0.5309***	–	–	0.0118
Decentraland	0.1055***	1.1359***	0.2433***	−0.1138*	–	−0.3410***	–	–
	0.0335***	1.0670***	0.3194***	–	−0.0027	−0.3254***	–	–
	0.0335***	1.0671***	0.3194***	–	–	**−0.3254***	–	–
	0.0564***	1.2273***	0.2830***	–	–	−0.3675***	0.0271*	–
	0.0338***	1.1659***	0.2989***	–	–	−0.3564***	–	−0.0027
Godsunchained	−0.0099	1.0700***	0.0106	−0.0034	–	–	−0.3331***	–
	0.0049	0.3881***	0.0100	–	−0.0032	–	−0.0774***	–
	0.0018	0.4842***	0.0119	–	–	−0.0015	−0.1176***	–
	0.0048***	0.3883***	0.0100***	–	–	–	**−0.0774***	–
	0.0018	0.4842***	0.0118	–	–	–	−0.1177***	−0.0004
OpenSea	0.0623***	0.5188***	0.1081**	−0.0382	–	–	–	1.0012***
	0.0303***	0.8012***	0.2694***	–	0.0210	–	–	−0.4634***
	0.0310***	0.8002***	0.2644***	–	–	0.0591	–	−0.4626***
	0.0391***	0.9391***	0.2771***	–	–	–	0.0003	−0.5085***
	0.0308***	0.8008***	0.2701***	–	–	–	–	**−0.4632***

Notes:
(a) This table presents estimated coefficients for Eq. (6) to test the herding across markets.
(b) The sample size for each regression is 1252.
(c) $R_{m,A,t}$, $R_{m,C,t}$, $R_{m,D,t}$, $R_{m,G,t}$, and $R_{m,O,t}$ denotes the average daily market return in the submarket of *OpenSea, Atomic, Cryptokitties, Godsunchained*, and *Decentraland,* respectively.
(d) *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

happens in general.[26] This result concords with Nadini et al. (2021) and White et al. (2022) that investors in the NFT market tend to focus on a limited number of tokens, while the trading counterparties also are in small constrained groups, deterring their attention to other submarkets.

4.2. Results based on the micro-approach by Choi and Sias (2009)

Table 6 reports the testing results based on the micro-approach by Choi and Sias (2009). Every row in Table 6 presents the correlation of cross-sectional collection demand between two subsequent quarters and the decomposition of the correlation with Eq. (7). We split our data into 14 quarters, so there are 13 cross-sectional correlation coefficients. The last row in Table 6 reports the time-series average of the 13 cross-sectional correlation coefficients, and it shows that on average active investors' demand for an collection this quarter is positively related to their demand the next quarter, with the average cross-sectional correlation 34.57% and significant at 1% level. The third and fourth columns report the portion of correlation induced by investors following their own lag industry demand and the portion driven up by investors following other investors' lag industry demand. Both parts of the correlation are significant at 1% for every 13 pair of adjacent quarters, and averagely 63% of the correlation arises from active investors following others trading on the same collection, i.e., shown in the last row of the fifth column. It is worth noting that the portion of correlation arising from investors following others is higher in the second half of our sample period, suggesting that investors' tendency to mimic other' decision increases over time.

[26] Herding within one submarket is prominent in all the five submarkets, and you can refer to Appendix F for detailed discussion.

4.3. Results based on the micro-approach by Uwilingiye et al. (2019)

Following the micro-approach by Uwilingiye et al. (2019), we examine the change in certain investor's position of NFTs listed on OpenSea and the change in the aggregate position of all the 200 most active investors with this investor excluded. To satisfy the requirement of the Geweke (1982) causality approach, we exclude the 2 cases that fail the Augmented Dickey Fuller (ADF) test, so our conclusion would be based on the remaining 198 cases. The Geweke (1982) causality test results are reported in Table 7. In the second column, it reports the χ^2 statistics under the null hypothesis that *Individual position change does not Granger cause change in the aggregate position*. We can reject this null hypothesis in 40 out of 198 cases (20%) at 10% significance level, indicating the presence of informed traders. Moreover, the third column reports the χ^2 statistics under the null hypothesis that *Change in the aggregate position does not Granger cause Individual position change*, and we can reject the null hypothesis in 73 out of 198 cases (37%) at 10% significance level,[27] suggesting the existence of intentional herding as this direction of causality can be induced by investors' basing the market consensus to make decisions. Spurious herding is captured by the instantaneous causality, the test result of which is reported in the fourth column. Spurious herding presents in 74 out of 198 cases (37%), indicating that some of the investors among the most active 200 would make the same investment decision on NFTs listed on OpenSea according to the commonly known fundamental information.

[27] The same null hypothesis is rejected in 142 out of 497 cases (29%) at 10% significance level among the 500 most active investors, and in 192 out of 997 cases (19%) at 10% significance level among the 1000 most active investors. Details in the results for testing on other groups of investors can be provided upon request.

Table 6
Tests of herding on collections with the micro-approach by Choi and Sias (2009).

Periods	Partitioned correlation coefficient			Percentage of correlation arising from investors following other investors
	Correlation coefficient	Investors following their own lag industry demand	Investors following other investors' lag industry demand	
23/11/2017–20/02/2018 and 21/02/2018–21/05/2018	0.4131 (7.94)***	0.2921 (2.97)***	0.1210 (6.91)***	29%
21/02/2018–21/05/2018 and 22/05/2018–19/08/2018	0.5802 (15.15)***	0.3662 (10.45)***	0.2140 (17.12)***	37%
22/05/2018–19/08/2018 and 20/08/2018–17/11/2018	0.2200 (5.57)***	0.1662 (4.60)***	0.0538 (7.54)***	24%
20/08/2018–17/11/2018 and 18/11/2018–15/02/2019	0.1833 (11.79)***	0.0686 (5.86)***	0.1147 (9.10)***	63%
18/11/2018–15/02/2019 and 16/02/2019–16/05/2019	0.5295 (6.20)***	0.1305 (4.65)***	0.3990 (7.43)***	75%
16/02/2019–16/05/2019 and 17/05/2019–14/08/2019	0.1332 (3.90)***	0.0368 (9.09)***	0.0964 (10.04)***	72%
17/05/2019–14/08/2019 and 15/08/2019–12/11/2019	0.4845 (5.03)***	0.2837 (6.78)***	0.2008 (22.37)***	41%
15/08/2019–12/11/2019 and 13/11/2019–10/02/2020	0.3326 (2.62)***	0.0359 (4.99)***	0.2967 (10.62)***	89%
13/11/2019–10/02/2020 and 11/02/2020–10/05/2020	0.3120 (4.18)***	0.0156 (3.23)***	0.2964 (6.28)***	95%
11/02/2020–10/05/2020 and 11/05/2020–08/08/2020	0.2901 (4.69)***	0.0619 (5.55)***	0.2282 (6.45)***	79%
11/05/2020–08/08/2020 and 09/08/2020–06/11/2020	0.3459 (6.90)***	0.1077 (5.73)***	0.2382 (7.29)***	69%
09/08/2020–06/11/2020 and 07/11/2020–04/02/2021	0.3385 (7.75)***	0.0534 (10.55)***	0.2851 (5.99)***	84%
07/11/2020–04/02/2021 and 05/02/2021–27/04/2021	0.3306 (8.90)***	0.1260 (13.66)***	0.2046 (10.32)***	62%
Average	0.3457 (6.97)***	0.1342 (6.78)***	0.2115 (9.80)***	63%

Notes:
(a) This table reports the testing results based on the micro-approach by Choi and Sias (2009) and the decomposition of the correlation by Eq. (7).
(b) We split our sample into 14 quarters with each quarter 90 days from 23rd Nov. 2017 to 27th Apr. 2021.
(c) Every row presents the correlation of cross-sectional collection demand between two subsequent quarters.
(d) We report Newey–West t-statistics in the parentheses.
(e) *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

5. Discussion and conclusion

Using data provided by Nadini et al. (2021), this study is the first to examine the existence of herding in the NFT market. We adopt both the macro- and micro-approach to detect herding.

Our empirical evidence based on the macro-approach by Chang et al. (2000) shows that herding exists and is more likely to arise when market return surged, as well as the price. Besides, herding is more likely to occur when big events happened, e.g., the launch of the NFT submarkets and the release of the leading NFT collection *CryptoPunks*. We have also investigated the agents whose behavior correlates with herding. As new-comers step into the market, herding is more likely to emerge, and the emergence of herding correlates with investors' attention, which is mainly driven by media coverage. Therefore, it is very likely that newcomers were attracted by the reporting on media and then participated in the NFT market as a result, pushing up prices as they lack knowledge of the market situation. Ethereum returns are positively correlated with herding in NFT markets, while Bitcoin returns are negatively correlated with herding in NFT markets. In addition, we find that investors in different submarkets do not herd to other submarkets in general.

To cross-validate our finding based on the macro-approach, we also test herding with the micro-approaches by Choi and Sias (2009) and that by Uwilingiye et al. (2019). We find that herding exists both at the aggregate market level and among the most active investors, i.e., investors with relatively high cumulative number of transactions, and they herd to trade NFTs listed on OpenSea as well as within different collections. Herding is found to be still significant after we factor out spurious herding.

Because NFTs are evaluated to be low-correlation assets, they are recommended for diversification (Dowling, 2022b). However, herding makes it difficult for the investors to achieve the same degree of diversification. With the existence of herding, observed behavior patterns that are correlated across individuals make the correlation between assets high (Bikhchandani et al., 1992). A good news is that we find investors generally do not herd across submarkets. Therefore, to obtain efficient level of diversification

Table 7
Test of herding on NFTs listed on OpenSea with the micro-approach by Uwilingiye et al. (2019).

	Granger causation χ^2 (*p-value*)		Instantaneous causality χ^2 (*p-value*)	Total correlation χ^2 (*p-value*)	ADF test
Trader index	Individual to aggregate	Aggregate to individual			
1	5.405 (0.067)*	1.000 (0.606)	25.701 (0.000)***	32.106 (0.000)***	−1.287 (0.181)
2	5.072 (0.079)*	12.367 (0.002)***	39.835 (0.000)***	57.274 (0.000)***	−4.128 (0.000)***
3	0.002 (0.999)	5.377 (0.068)*	2.680 (0.102)	8.059 (0.153)	−4.732 (0.000)***
4	3.723 (0.155)	3.415 (0.181)	0.010 (0.919)	7.148 (0.210)	−2.276 (0.023)**
5	1.711 (0.425)	0.921 (0.631)	0.690 (0.406)	3.322 (0.650)	−1.602 (0.102)
6	8.045 (0.018)**	29.528 (0.000)***	21.225 (0.000)***	58.798 (0.000)***	−5.299 (0.000)***
7	0.079 (0.961)	3.353 (0.187)	1.935 (0.164)	5.367 (0.373)	−4.483 (0.000)***
8	5.796 (0.055)*	17.754 (0.000)***	10.116 (0.001)***	33.666 (0.000)***	−8.625 (0.000)***
9	0.522 (0.770)	10.364 (0.006)***	1.559 (0.212)	12.445 (0.029)**	−3.668 (0.000)***
10	4.088 (0.130)	0.283 (0.868)	0.382 (0.537)	4.753 (0.447)	−3.364 (0.000)***
11	5.053 (0.080)*	2.984 (0.225)	0.701 (0.402)	8.739 (0.120)	−3.372 (0.000)***
12	1.249 (0.536)	5.850 (0.054)*	41.163 (0.000)***	48.261 (0.000)***	−4.057 (0.000)***
13	4.254 (0.119)	8.442 (0.015)**	9.258 (0.002)***	21.954 (0.001)***	−4.985 (0.000)***
14	0.233 (0.890)	4.446 (0.108)	0.349 (0.555)	5.028 (0.413)	−4.101 (0.000)***
15	0.249 (0.883)	3.406 (0.182)	10.158 (0.001)***	13.813 (0.017)**	−7.322 (0.000)***
16	35.590 (0.000)***	0.072 (0.965)	3.361 (0.067)*	39.023 (0.000)***	−6.535 (0.000)***
17	2.884 (0.236)	5.891 (0.053)*	0.982 (0.322)	9.757 (0.082)*	−6.048 (0.000)***
18	2.854 (0.240)	0.017 (0.992)	2.543 (0.111)	5.414 (0.367)	−8.713 (0.000)***
19	0.047 (0.977)	2.328 (0.312)	0.030 (0.862)	2.406 (0.791)	−5.220 (0.000)***
20	0.044 (0.978)	9.451 (0.009)***	3.308 (0.069)*	12.803 (0.025)**	−7.011 (0.000)***
21	1.213 (0.545)	2.527 (0.283)	9.193 (0.002)***	12.933 (0.024)**	−4.881 (0.000)***
22	1.361 (0.506)	3.140 (0.208)	21.215 (0.000)***	25.716 (0.000)***	−5.119 (0.000)***
23	6.312 (0.043)**	21.623 (0.000)***	8.994 (0.003)***	36.930 (0.000)***	−6.991 (0.000)***
24	4.106 (0.128)	0.824 (0.662)	0.601 (0.438)	5.532 (0.354)	−2.497 (0.013)**
25	0.415 (0.812)	3.205 (0.201)	0.345 (0.557)	3.965 (0.554)	−6.798 (0.000)***
26	0.219 (0.896)	0.000 (1.000)	0.001 (0.981)	0.220 (0.999)	−2.037 (0.041)**
27	1.820 (0.403)	11.486 (0.003)***	0.816 (0.366)	14.121 (0.015)**	−4.101 (0.000)***
28	0.740 (0.691)	0.381 (0.827)	0.001 (0.979)	1.121 (0.952)	−3.512 (0.000)***
29	2.682 (0.262)	0.399 (0.819)	5.276 (0.022)**	8.356 (0.138)	−3.891 (0.000)***
30	4.749 (0.093)*	24.076 (0.000)***	2.334 (0.127)	31.159 (0.000)***	−4.950 (0.000)***
31	0.030 (0.985)	2.569 (0.277)	0.994 (0.319)	3.593 (0.609)	−2.247 (0.025)**
32	0.404 (0.817)	4.629 (0.099)*	9.101 (0.003)***	14.134 (0.015)**	−5.790 (0.000)***
33	2.107 (0.349)	0.073 (0.964)	0.457 (0.499)	2.637 (0.756)	−5.213 (0.000)***
34	2.180 (0.336)	2.706 (0.258)	2.254 (0.133)	7.141 (0.210)	−5.141 (0.000)***
35	8.085 (0.018)**	0.176 (0.916)	0.730 (0.393)	8.991 (0.109)	−3.873 (0.000)***
36	1.086 (0.581)	5.590 (0.061)*	0.653 (0.419)	7.329 (0.197)	−3.757 (0.000)***
37	6.663 (0.036)**	1.122 (0.571)	0.444 (0.505)	8.229 (0.144)	−2.460 (0.014)**
38	7.979 (0.019)**	1.011 (0.603)	9.193 (0.002)***	18.182 (0.003)***	−4.594 (0.000)***
39	3.114 (0.211)	2.235 (0.327)	0.083 (0.773)	5.433 (0.365)	−3.044 (0.003)***
40	0.648 (0.723)	1.954 (0.377)	26.442 (0.000)***	29.044 (0.000)***	−3.009 (0.004)***
41	0.722 (0.697)	16.118 (0.000)***	8.862 (0.003)***	25.702 (0.000)***	−6.658 (0.000)***
42	1.611 (0.447)	0.190 (0.910)	1.561 (0.212)	3.362 (0.644)	−1.932 (0.051)*
43	0.425 (0.809)	5.978 (0.050)*	0.496 (0.481)	6.899 (0.228)	−6.421 (0.000)***
44	1.645 (0.439)	22.205 (0.000)***	0.018 (0.893)	23.869 (0.000)***	−3.018 (0.004)***
45	5.306 (0.070)*	10.128 (0.006)***	5.717 (0.017)**	21.152 (0.001)***	−5.161 (0.000)***
46	0.328 (0.849)	4.127 (0.127)	0.287 (0.592)	4.742 (0.448)	−5.665 (0.000)***
47	1.461 (0.482)	1.250 (0.535)	0.595 (0.441)	3.306 (0.653)	−2.703 (0.008)***
48	2.509 (0.285)	21.612 (0.000)***	4.207 (0.040)**	28.328 (0.000)***	−10.119 (0.000)***
49	0.568 (0.753)	26.231 (0.000)***	5.816 (0.016)**	32.615 (0.000)***	−4.899 (0.000)***
50	0.274 (0.872)	0.782 (0.677)	1.376 (0.241)	2.431 (0.787)	−4.002 (0.000)***
51	0.492 (0.782)	3.115 (0.211)	0.015 (0.903)	3.622 (0.605)	−3.045 (0.003)***
52	2.149 (0.341)	36.119 (0.000)***	4.184 (0.041)**	42.452 (0.000)***	−5.884 (0.000)***
53	1.516 (0.468)	1.982 (0.371)	7.649 (0.006)***	11.148 (0.049)**	−4.467 (0.000)***
54	6.582 (0.037)**	23.436 (0.000)***	16.625 (0.000)***	46.643 (0.000)***	−5.402 (0.000)***
55	0.564 (0.754)	1.159 (0.560)	1.739 (0.187)	3.462 (0.629)	−7.062 (0.000)***
56	0.059 (0.971)	6.469 (0.039)**	2.650 (0.104)	9.178 (0.102)	−3.288 (0.002)***
57	0.234 (0.889)	0.877 (0.645)	0.072 (0.788)	1.183 (0.946)	−7.621 (0.000)***
58	0.239 (0.887)	2.975 (0.226)	1.591 (0.207)	4.805 (0.440)	−5.731 (0.000)***
59	7.795 (0.020)**	28.854 (0.000)***	2.680 (0.102)	39.329 (0.000)***	−5.023 (0.000)***
60	1.102 (0.576)	6.742 (0.034)**	3.589 (0.058)*	11.434 (0.043)**	−2.656 (0.009)***
61	0.411 (0.814)	0.033 (0.984)	0.009 (0.926)	0.452 (0.994)	−5.692 (0.000)***
62	0.393 (0.822)	2.027 (0.363)	2.033 (0.154)	4.453 (0.486)	−2.663 (0.009)***
63	9.117 (0.010)**	24.146 (0.000)***	1.394 (0.238)	34.656 (0.000)***	−6.192 (0.000)***
64	1.956 (0.376)	3.148 (0.207)	0.026 (0.871)	5.130 (0.400)	−3.348 (0.000)***
65	4.878 (0.087)*	0.303 (0.860)	5.494 (0.019)**	10.674 (0.058)*	−3.889 (0.000)***
66	0.208 (0.901)	16.308 (0.000)***	0.923 (0.337)	17.439 (0.004)***	−5.956 (0.000)***
67	2.053 (0.358)	0.120 (0.942)	0.704 (0.401)	2.877 (0.719)	−3.215 (0.002)***
68	13.045 (0.001)***	0.235 (0.889)	3.192 (0.074)*	16.472 (0.006)***	−2.122 (0.033)**
69	2.259 (0.323)	0.077 (0.962)	2.466 (0.116)	4.803 (0.440)	−8.034 (0.000)***
70	2.596 (0.273)	35.576 (0.000)***	3.720 (0.054)*	41.892 (0.000)***	−5.148 (0.000)***

(*continued on next page*)

Table 7 (*continued*).

Trader index	Granger causation χ^2 (*p-value*)		Instantaneous causality χ^2 (*p-value*)	Total correlation χ^2 (*p-value*)	ADF test
	Individual to aggregate	Aggregate to individual			
71	3.947 (0.139)	41.408 (0.000)***	3.990 (0.046)**	49.344 (0.000)***	−8.867 (0.000)***
72	1.661 (0.436)	0.718 (0.698)	0.077 (0.781)	2.457 (0.783)	−3.555 (0.000)***
73	0.650 (0.723)	0.389 (0.823)	0.213 (0.645)	1.252 (0.940)	−3.882 (0.000)***
74	0.343 (0.842)	1.602 (0.449)	0.847 (0.357)	2.792 (0.732)	−4.857 (0.000)***
75	0.027 (0.986)	2.043 (0.360)	0.414 (0.520)	2.485 (0.779)	−4.416 (0.000)***
76	0.350 (0.839)	0.100 (0.951)	0.261 (0.609)	0.711 (0.982)	−4.222 (0.000)***
77	1.091 (0.580)	31.286 (0.000)***	0.977 (0.323)	33.354 (0.000)***	−5.547 (0.000)***
78	0.074 (0.964)	7.129 (0.028)**	0.491 (0.484)	7.693 (0.174)	−7.254 (0.000)***
79	0.544 (0.762)	0.093 (0.955)	0.833 (0.361)	1.471 (0.916)	−5.918 (0.000)***
80	0.411 (0.814)	0.041 (0.980)	0.957 (0.328)	1.410 (0.923)	−5.584 (0.000)***
81	4.315 (0.116)	17.444 (0.000)***	26.019 (0.000)***	47.777 (0.000)***	−3.653 (0.000)***
82	5.103 (0.078)*	12.192 (0.002)***	35.951 (0.000)***	53.245 (0.000)***	−5.008 (0.000)***
83	0.794 (0.672)	0.456 (0.796)	1.417 (0.234)	2.667 (0.751)	−6.244 (0.000)***
84	17.990 (0.000)***	1.851 (0.396)	32.191 (0.000)***	52.032 (0.000)***	−4.737 (0.000)***
85	14.485 (0.001)***	44.838 (0.000)***	0.421 (0.517)	59.744 (0.000)***	−5.004 (0.000)***
86	0.242 (0.886)	0.196 (0.907)	0.936 (0.333)	1.374 (0.927)	−5.509 (0.000)***
87	10.302 (0.006)***	0.135 (0.935)	12.008 (0.001)***	22.444 (0.000)***	−2.786 (0.006)***
88	6.092 (0.048)**	1.208 (0.547)	0.994 (0.319)	8.294 (0.141)	−3.008 (0.004)***
89	0.580 (0.748)	19.137 (0.000)***	0.918 (0.338)	20.634 (0.001)***	−5.229 (0.000)***
90	0.013 (0.993)	0.019 (0.991)	0.016 (0.901)	0.048 (1.000)	−5.684 (0.000)***
91	3.421 (0.181)	1.071 (0.586)	6.102 (0.013)**	10.594 (0.060)*	−4.706 (0.000)***
92	0.231 (0.891)	3.467 (0.177)	2.087 (0.149)	5.786 (0.328)	−6.110 (0.000)***
93	1.203 (0.548)	0.383 (0.826)	1.298 (0.255)	2.883 (0.718)	−5.428 (0.000)***
94	0.963 (0.618)	0.237 (0.888)	7.289 (0.007)***	8.489 (0.131)	−3.660 (0.000)***
95	1.443 (0.486)	7.548 (0.023)**	6.266 (0.012)**	15.257 (0.009)***	−5.559 (0.000)***
96	0.255 (0.880)	1.054 (0.590)	0.071 (0.790)	1.381 (0.926)	−6.971 (0.000)***
97	0.259 (0.879)	1.673 (0.433)	1.235 (0.266)	3.167 (0.674)	−3.707 (0.000)***
98	0.078 (0.962)	3.826 (0.148)	2.416 (0.120)	6.320 (0.276)	−7.787 (0.000)***
99	2.276 (0.320)	5.850 (0.054)*	8.612 (0.003)***	16.739 (0.005)***	−4.226 (0.000)***
100	0.338 (0.844)	0.208 (0.901)	0.210 (0.647)	0.756 (0.980)	−3.255 (0.002)***
101	2.280 (0.320)	35.483 (0.000)***	3.877 (0.049)**	41.640 (0.000)***	−7.938 (0.000)***
102	0.226 (0.893)	1.123 (0.570)	0.073 (0.787)	1.422 (0.922)	−5.912 (0.000)***
103	0.954 (0.621)	18.538 (0.000)***	21.811 (0.000)***	41.303 (0.000)***	−3.858 (0.000)***
104	1.410 (0.494)	1.846 (0.397)	0.836 (0.360)	4.092 (0.536)	−8.592 (0.000)***
105	0.065 (0.968)	0.020 (0.990)	0.321 (0.571)	0.406 (0.995)	−8.154 (0.000)***
106	1.840 (0.398)	0.036 (0.982)	0.052 (0.819)	1.928 (0.859)	−2.137 (0.032)**
107	0.123 (0.940)	2.950 (0.229)	5.086 (0.024)**	8.159 (0.148)	−5.193 (0.000)***
108	0.429 (0.807)	3.198 (0.202)	0.228 (0.633)	3.855 (0.570)	−5.020 (0.000)***
109	2.050 (0.359)	6.367 (0.041)**	0.013 (0.908)	8.431 (0.134)	−2.944 (0.004)***
110	11.109 (0.004)***	6.124 (0.047)**	37.347 (0.000)***	54.580 (0.000)***	−8.485 (0.000)***
111	0.420 (0.811)	0.473 (0.789)	0.374 (0.541)	1.267 (0.938)	−2.969 (0.004)***
112	10.193 (0.006)***	31.407 (0.000)***	11.246 (0.001)***	52.846 (0.000)***	−6.209 (0.000)***
113	7.735 (0.021)**	4.556 (0.103)	40.027 (0.000)***	52.317 (0.000)***	−6.056 (0.000)***
114	0.293 (0.864)	0.028 (0.986)	0.006 (0.937)	0.328 (0.997)	−2.542 (0.012)**
115	0.206 (0.902)	1.698 (0.428)	0.055 (0.814)	1.959 (0.855)	−6.713 (0.000)***
116	0.093 (0.955)	0.075 (0.963)	0.191 (0.662)	0.358 (0.996)	−5.038 (0.000)***
117	1.075 (0.584)	0.456 (0.796)	1.587 (0.208)	3.118 (0.682)	−8.181 (0.000)***
118	5.290 (0.071)*	4.190 (0.123)	0.387 (0.534)	9.867 (0.079)*	−5.950 (0.000)***
119	0.449 (0.799)	0.045 (0.978)	0.193 (0.661)	0.687 (0.984)	−5.820 (0.000)***
120	1.963 (0.375)	6.564 (0.038)**	0.000 (0.986)	8.527 (0.129)	−2.366 (0.018)**
121	4.620 (0.099)*	14.080 (0.001)***	16.394 (0.000)***	35.094 (0.000)***	−4.176 (0.000)***
122	1.618 (0.445)	0.695 (0.706)	0.008 (0.927)	2.321 (0.803)	−5.101 (0.000)***
123	1.446 (0.485)	8.470 (0.014)**	23.940 (0.000)***	33.856 (0.000)***	−5.137 (0.000)***
124	0.257 (0.879)	1.093 (0.579)	0.073 (0.788)	1.423 (0.922)	−7.483 (0.000)***
125	8.978 (0.011)**	1.777 (0.411)	30.284 (0.000)***	41.040 (0.000)***	−7.115 (0.000)***
126	0.201 (0.904)	8.517 (0.014)**	1.698 (0.193)	10.416 (0.064)*	−4.394 (0.000)***
127	1.787 (0.409)	43.506 (0.000)***	3.861 (0.049)**	49.153 (0.000)***	−6.660 (0.000)***
128	3.758 (0.153)	10.330 (0.006)***	0.095 (0.758)	14.182 (0.014)**	−4.028 (0.000)***
129	2.024 (0.363)	1.902 (0.386)	0.239 (0.625)	4.166 (0.526)	−6.368 (0.000)***
130	1.772 (0.412)	0.047 (0.977)	1.385 (0.239)	3.205 (0.668)	−4.034 (0.000)***
131	2.434 (0.296)	35.970 (0.000)***	4.302 (0.038)**	42.706 (0.000)***	−8.684 (0.000)***
132	0.121 (0.941)	4.587 (0.101)	0.043 (0.835)	4.751 (0.447)	−7.527 (0.000)***
133	4.770 (0.092)*	1.431 (0.489)	14.750 (0.000)***	20.952 (0.001)***	−8.175 (0.000)***
134	4.399 (0.111)	2.834 (0.242)	3.376 (0.066)*	10.609 (0.060)*	−4.123 (0.000)***
135	0.707 (0.702)	0.788 (0.674)	0.212 (0.645)	1.707 (0.888)	−3.545 (0.000)***
136	2.533 (0.282)	4.694 (0.096)*	2.592 (0.107)	9.819 (0.081)*	−4.374 (0.000)***
137	2.101 (0.350)	32.030 (0.000)***	2.890 (0.089)*	37.022 (0.000)***	−5.700 (0.000)***
138	0.707 (0.702)	1.493 (0.474)	10.504 (0.001)***	12.704 (0.026)**	−4.759 (0.000)***
139	0.004 (0.998)	0.860 (0.651)	0.288 (0.591)	1.152 (0.949)	−6.145 (0.000)***
140	0.201 (0.904)	0.016 (0.992)	0.039 (0.843)	0.257 (0.998)	−5.282 (0.000)***

(*continued on next page*)

Table 7 (*continued*).

Trader index	Granger causation χ^2 (*p-value*) Individual to aggregate	Aggregate to individual	Instantaneous causality χ^2 (*p-value*)	Total correlation χ^2 (*p-value*)	ADF test
141	0.179 (0.914)	0.726 (0.696)	0.188 (0.664)	1.094 (0.955)	−7.057 (0.000)***
142	0.388 (0.824)	0.378 (0.828)	0.156 (0.693)	0.922 (0.969)	−3.823 (0.000)***
143	0.696 (0.706)	0.730 (0.694)	0.023 (0.880)	1.449 (0.919)	−3.377 (0.000)***
144	2.151 (0.341)	11.457 (0.003)***	0.041 (0.839)	13.649 (0.018)**	−5.178 (0.000)***
145	0.016 (0.992)	0.587 (0.746)	0.005 (0.945)	0.607 (0.988)	−3.762 (0.000)***
146	1.408 (0.495)	0.117 (0.943)	0.013 (0.909)	1.538 (0.909)	−5.355 (0.000)***
147	3.147 (0.207)	35.439 (0.000)***	2.058 (0.151)	40.644 (0.000)***	−6.747 (0.000)***
148	2.155 (0.340)	14.648 (0.001)***	4.809 (0.028)**	21.612 (0.001)***	−4.275 (0.000)***
149	0.119 (0.942)	1.557 (0.459)	0.011 (0.917)	1.686 (0.891)	−7.566 (0.000)***
150	5.582 (0.061)*	0.665 (0.717)	14.767 (0.000)***	21.014 (0.001)***	−7.078 (0.000)***
151	1.349 (0.509)	22.904 (0.000)***	2.890 (0.089)*	27.143 (0.000)***	−7.793 (0.000)***
152	2.299 (0.317)	0.412 (0.814)	3.383 (0.066)*	6.094 (0.297)	−5.706 (0.000)***
153	1.316 (0.518)	3.510 (0.173)	29.758 (0.000)***	34.584 (0.000)***	−4.221 (0.000)***
154	2.927 (0.231)	40.507 (0.000)***	4.436 (0.035)**	47.870 (0.000)***	−6.346 (0.000)***
155	0.319 (0.853)	0.430 (0.806)	0.004 (0.947)	0.753 (0.980)	−3.770 (0.000)***
156	11.736 (0.003)***	42.529 (0.000)***	7.658 (0.006)***	61.924 (0.000)***	−6.584 (0.000)***
157	0.734 (0.693)	1.920 (0.383)	0.397 (0.528)	3.052 (0.692)	−5.468 (0.000)***
158	1.708 (0.426)	1.428 (0.490)	0.317 (0.574)	3.453 (0.631)	−4.721 (0.000)***
159	0.239 (0.887)	0.049 (0.976)	0.001 (0.975)	0.288 (0.998)	−7.612 (0.000)***
160	0.514 (0.773)	14.893 (0.001)***	6.677 (0.010)***	22.085 (0.001)***	−5.786 (0.000)***
161	1.889 (0.389)	3.207 (0.201)	0.266 (0.606)	5.362 (0.373)	−3.389 (0.000)***
162	7.368 (0.025)**	18.665 (0.000)***	32.515 (0.000)***	58.549 (0.000)***	−5.257 (0.000)***
163	0.361 (0.835)	8.410 (0.015)**	1.694 (0.193)	10.466 (0.063)*	−6.484 (0.000)***
164	0.860 (0.650)	2.815 (0.245)	1.956 (0.162)	5.631 (0.344)	−4.828 (0.000)***
165	2.577 (0.276)	1.138 (0.566)	0.012 (0.913)	3.726 (0.589)	−3.788 (0.000)***
166	35.587 (0.000)***	0.181 (0.914)	2.208 (0.137)	37.976 (0.000)***	−5.787 (0.000)***
167	5.766 (0.056)*	25.872 (0.000)***	16.320 (0.000)***	47.958 (0.000)***	−5.647 (0.000)***
168	8.455 (0.015)**	16.003 (0.000)***	0.143 (0.705)	24.601 (0.000)***	−4.124 (0.000)***
169	0.286 (0.867)	0.023 (0.989)	0.034 (0.854)	0.343 (0.997)	−5.811 (0.000)***
170	0.114 (0.945)	1.492 (0.474)	0.055 (0.815)	1.661 (0.894)	−4.802 (0.000)***
171	13.288 (0.001)***	1.011 (0.603)	0.868 (0.352)	15.167 (0.010)***	−2.870 (0.005)***
172	8.521 (0.014)**	23.588 (0.000)***	6.750 (0.009)***	38.859 (0.000)***	−5.902 (0.000)***
173	0.128 (0.938)	12.378 (0.002)***	24.031 (0.000)***	36.537 (0.000)***	−5.402 (0.000)***
174	3.715 (0.156)	0.799 (0.671)	0.307 (0.579)	4.822 (0.438)	−5.473 (0.000)***
175	0.780 (0.677)	0.037 (0.982)	1.022 (0.312)	1.839 (0.871)	−3.108 (0.003)***
176	3.283 (0.194)	3.428 (0.180)	2.681 (0.102)	9.392 (0.094)*	−4.088 (0.000)***
177	1.786 (0.409)	0.065 (0.968)	1.242 (0.265)	3.092 (0.686)	−7.094 (0.000)***
178	1.364 (0.506)	0.792 (0.673)	0.360 (0.548)	2.516 (0.774)	−4.671 (0.000)***
179	0.086 (0.958)	4.338 (0.114)	2.917 (0.088)*	7.341 (0.197)	−6.589 (0.000)***
180	9.017 (0.011)**	38.520 (0.000)***	4.536 (0.033)**	52.073 (0.000)***	−4.957 (0.000)***
181	0.341 (0.843)	0.108 (0.948)	0.875 (0.349)	1.324 (0.932)	−3.820 (0.000)***
182	5.689 (0.058)*	0.298 (0.862)	41.289 (0.000)***	47.276 (0.000)***	−4.746 (0.000)***
183	2.596 (0.273)	2.912 (0.233)	1.126 (0.289)	6.634 (0.249)	−2.813 (0.006)***
184	1.217 (0.544)	1.405 (0.495)	4.244 (0.039)**	6.866 (0.231)	−3.498 (0.000)***
185	0.685 (0.710)	28.539 (0.000)***	2.609 (0.106)	31.832 (0.000)***	−5.791 (0.000)***
186	7.312 (0.026)**	0.915 (0.633)	22.665 (0.000)***	30.891 (0.000)***	−5.890 (0.000)***
187	1.815 (0.404)	6.533 (0.038)**	6.120 (0.013)**	14.468 (0.013)**	−3.610 (0.000)***
188	0.009 (0.996)	0.759 (0.684)	0.002 (0.965)	0.770 (0.979)	−7.142 (0.000)***
189	0.034 (0.983)	0.015 (0.992)	0.124 (0.724)	0.174 (0.999)	−5.182 (0.000)***
190	0.572 (0.751)	7.499 (0.024)**	0.831 (0.362)	8.902 (0.113)	−5.903 (0.000)***
191	0.849 (0.654)	14.625 (0.001)***	5.010 (0.025)**	20.485 (0.001)***	−6.545 (0.000)***
192	1.790 (0.409)	1.909 (0.385)	0.354 (0.552)	4.053 (0.542)	−4.343 (0.000)***
193	0.549 (0.760)	3.326 (0.190)	0.114 (0.736)	3.989 (0.551)	−4.225 (0.000)***
194	1.477 (0.478)	2.108 (0.348)	11.128 (0.001)***	14.713 (0.012)**	−4.931 (0.000)***
195	1.871 (0.392)	11.304 (0.004)***	2.805 (0.094)*	15.979 (0.007)***	−6.894 (0.000)***
196	2.332 (0.312)	39.101 (0.000)***	3.621 (0.057)*	45.054 (0.000)***	−8.495 (0.000)***
197	3.287 (0.193)	0.481 (0.786)	3.513 (0.061)*	7.281 (0.201)	−7.246 (0.000)***
198	0.771 (0.680)	1.736 (0.420)	0.015 (0.903)	2.522 (0.773)	−6.403 (0.000)***
199	1.378 (0.502)	15.502 (0.000)***	0.034 (0.854)	16.913 (0.005)***	−7.826 (0.000)***
200	2.860 (0.239)	26.745 (0.000)***	2.313 (0.128)	31.918 (0.000)***	−5.051 (0.000)***

Notes:
(a) The second and third columns report the χ^2 statistics (and the p-values in parentheses) under the null hypothesis that *Individual position change does not Granger cause change in the aggregate position* and *Change in the aggregate position does not Granger cause Individual position change*, respectively.
(b) The fourth column reports the χ^2 statistics (and the p-values in parentheses) under the null hypothesis that *No instantaneous causality between individual position change and change in the aggregate position.*
(c) The fifth column reports the χ^2 statistics (and the p-values in parentheses) under the null hypothesis that *No linear association between individual position change and change in the aggregate position.*
(d) The sixth column reports the statistics for the ADF test for the series of position change of each of the 200 investors accordingly, as the implementation of Geweke (1982) causality approach requires the time-series to be stationary.
(e) *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.
(f) In this table, each trader index corresponds to one investor among the 200 most active. You can find those investors' address in Appendix G.

using the least number of NFTs, investors should choose the ones from different submarkets to minimize the negative effect of herding on diversification.

In addition, since the existence of herding indicates market inefficiencies, which can be mitigated by increasing information transparency, regulators of the NFT markets could redesign their platforms so that it can be easier for newcomers to access and understand market information. Therefore, enhancing information transparency can partly alleviate the market inefficiencies due to herding driven by newcomers.

There are a few limitations of our work. For example, we cannot obtain data on how close the investors track media reporting, so it is difficult for us to provide evidence on the relationship between attention to media coverage and herding at individual level. We leave this task for further works when more detailed data is available.

Declaration of competing interest

The undersigned declares no conflict of interest. No commercial interests were involved, and financial support was entirely academic, governmental, or from not-for-profit foundations.

Appendix A

A.1.

See Table A.1.

Table A.1
Evens in the NFT market and the corresponding news reporting in chronological order.

Year	Month	Day	Events and the corresponding reports	Source
2019	March	25th	NEO adds support for NFT	https://medium.com/o3-labs/introducing-non-fungible-tokens-on-neo-928002b35641
	April	23rd	0xcert Framework supports cross-chain ERC721 with Wanchain	https://0xcert.org/news/0xcert-framework-1.4.0-integrated-with-wanchain/
	May	4th	Ethereum Name Service becomes ERC721 compatible	https://medium.com/the-ethereum-name-service/ens-nft-emoji-75259145314f
		5th	VeChain VIP-181 NFT standard accepted	https://github.com/vechain/VIPs/blob/master/vips/VIP-181.md
		7th	EOS dGoods v1	https://medium.com/dgoods/dgoods-v1-0-public-beta-release-72f896ad7aed
	June	17th	ERC1155 Multi-Token Standard Final Status	https://blog.enjincoin.io/erc-1155-the-final-token-standard-on-ethereum-a83fce9f5714
	August	26th	Cosmos adds an NFT module	https://github.com/cosmos/cosmos-sdk/issues/4046
	October	10th	Phantasma Chain Adds Support for NFT	https://medium.com/phantasticphantasma/phantasma-sdk-update-cf3bcb0b0f6e
2020	March	10th	Zynga's co-founder's Gala Games Announced	https://venturebeat.com/business/zynga-cofounder-creates-blockchain-game-partners-for-decentralized-gaming/
		19th	The Sandbox raises $2MM	https://venturebeat.com/business/the-sandbox-raises-2-million-more-to-build-out-blockchain-based-game-world/
		26th	Bullionix brings gold to NFT	https://medium.com/@bullionix/first-look-at-bullionixs-gold-backed-3d-nfts-launching-march-30-ca75cc371605
		27th	ATARI Token presale announced	https://www.globenewswire.com/news-release/2020/03/27/2007876/0/en/Atari-Launch-of-the-Atari-Token.html
	May	20th	The Godfather's NFT is visible in Terra Virtua	https://www.altcoinbuzz.io/blockchain-gaming/game-launches-updates/the-godfather-official-nfts-are-out/
	June	17th	Ubisoft's Rabbids launched	https://venturebeat.com/games/ubisoft-launches-blockchain-based-rabbids-collectibles-to-raise-money-for-unicef/
	July	2nd	NFT sales hit $100 Million	https://decrypt.co/34364/nft-token-sales-hit-100-million-as-virtual-economy-booms
		13th	Ubisoft supports Nine Chronicles	https://decrypt.co/35375/ubisoft-backs-blockchain-game-nine-chronicles
		15th	Garbage Pail Kids announced on WAX	https://www.globenewswire.com/news-release/2020/07/16/2062972/0/en/Topps-GPK-Goes-Exotic-Digital-Trading-Cards-Makes-Blockchain-History-on-WAX-Selling-Out-in-67-Minutes.html
		16th	Sorare raises3.5MM€	https://www.eu-startups.com/2020/07/paris-based-sorare-raises-e3-5-million-to-accelerate-the-growth-of-its-global-fantasy-football-game/
	August	6th	Dapper Labsraises$12MM from VC	https://cointelegraph.com/news/dapper-labs-raises-12m-from-vc-firms-and-nba-players-nets-12m-in-nft-sales
		14th	Doctor Who: Worlds Apart announced	https://decrypt.co/38640/doctor-who-crypto-trading-card-game-puts-daleks-on-blockchain
		15th	Korean Chat App "KakaoApp" bets on NFT	https://cointelegraph.com/news/major-south-korean-chat-app-bets-big-on-nft-based-stock-trading
	September	8th	Activision patent for blockchain gaming	https://finance.yahoo.com/news/activision-patent-envisions-drawing-player-145857930.html
		10th	Coinfund invests in Rarible	https://thetokenizer.io/2020/09/10/rarible-secures-funding-from-coinfund-to-build-community-governed-nft-marketplace/
		14th	PolyientGames raises $4.8MM in PGFK sale	https://cointelegraph.com/news/polyient-games-innovative-dual-state-token-sale-kicks-off-tomorrow
		16th	Turner Sports announces Blocklete Games	https://pressroom.warnermedia.com/us/media-release/turner-sports/turner-sports-launches-blocklete-games-unique-sports-gaming-brand

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Table A.1 (*continued*).

Year	Month	Day	Events and the corresponding reports	Source
	October	2nd	NBA Top Shot launching open beta	https://cointelegraph.com/news/nba-topshot-opens-to-public-after-closed-beta-drives-2m-in-nft-sales
		10th	Dapper Labs raises $18MM in Flow ICO	https://decrypt.co/44545/cryptokitties-team-raise-18-million-in-flow-blockchain-token-sale
		12nd	Christies' auction using blockchain	https://news.artnet.com/market/christies-artory-blockchain-pilot-1370788
		29th	The Sandbox partners with The Smurfs	https://www.animocabrands.com/the-sandbox-partners-the-smurfs
	November	3rd	NIFTEX Raises $500K to Build Out NFT Trading Platform	https://www.coindesk.com/business/2020/11/03/niftex-raises-500k-to-build-out-nft-trading-platform/
		5th	Terra Virtua raises $2.5MM to create the first mass-market NFT Ecosystem	https://medium.com/terravirtua/terra-virtua-raises-2-5m-to-create-first-mass-market-nft-ecosystem-e0facb62de38
		16th	IBM patent for blockchain MMO	https://www.theblock.co/linked/84736/ibm-patent-gaming-mmo-blockchain
		19th	Axie Infinity enters Binance Launchpad	https://www.coindesk.com/business/2020/11/19/nft-game-axie-infinity-raises-860k-in-governance-token-sale/
		19th	Mintbase Raises $1M Seed Round	https://www.coindesk.com/business/2020/11/18/mintbase-raises-1m-seed-round-to-bring-nfts-to-near-protocol/
	December	5th	Artist 'Beeple' raised$3.5MM through Nifty Gateway	https://news.bitcoin.com/acclaimed-nft-artists-blockchain-backed-digital-art-auction-raises-3-5-million/
		10th	AnRXKEYraises$1.2MM	https://www.altcoinbuzz.io/cryptocurrency-news/finance-and-funding/anrkey-x-raises-1-2-million-to-merge-defi-esports-nfts/
		15th	DJ Deadmau5 launches $100,000 worth of NFT Collectibles	https://www.globenewswire.com/news-release/2020/12/15/2145434/0/en/First-ever-deadmau5-digital-collectibles-to-be-released-on-WAX-Blockchain.html
		18th	FC Barcelona Footballer Invests $4.3MM in Sorare	https://www.coindesk.com/business/2020/12/18/fc-barcelona-footballer-invests-43m-in-fan-token-platform-sorare/
2021	January	4th	Telos Launches NFTs That Act Like U.S. Treasury Bonds	https://chainbulletin.com/telos-launches-t-bond-nfts
		8th	Topps Is Bringing High-End Pop Culture Brands to Blockchain	https://gizmodo.com/topps-is-bringing-high-end-pop-culture-brands-to-blockc-1845906715
		16th	K-Pop Stars to Mint Digital Collectibles on Polkadot	https://www.coindesk.com/mamamoo-non-fungible-tokens-nft-xeno
		21st	Rick and Morty Creator Sells NFT Art Collection for Over $1 M	https://news.bitcoin.com/rick-and-morty-creator-sells-nft-art-collection-for-over-1-million-in-ether/
		31st	Mark Cuban released 5 digital collectibles on Mintable	https://www.issuewire.com/mark-cuban-released-5-digital-collectibles-on-mintable-a-blockchain-based-marketplace-1690383071079903
	February	11th	Microsoft and EnjinBring NFTs to Minecraft	https://www.coindesk.com/minecraft-enjin-microsoft-nfts
		12th	NBA Top Shot poised to net $250 million in round	https://www.theblockcrypto.com/daily/94772/dapper-labs-nba-topshot-fundraise-250-million?utm_source=rss&utm_medium=rss
		20th	Original Nyan Cat GIF sold for $600k	https://sea.mashable.com/tech/14620/nyan-cat-gif-sells-for-us600k-worth-of-ether-and-theres-definitely-no-bubble
		21st	Logan Paul Raises $3.5 Million in One Day from NFT Sales	https://beincrypto.com/logan-paul-raises-3-5-million-in-one-day-from-nft-sales/
		23rd	NonFungible.com Yearly Report published	https://nonfungible.com/reports/2020/en/yearly-nft-market-report-free?nocache=
	March	2nd	Musician 3LAU sells an NFT album, making $11.6 million	https://www.businessinsider.com/
		9th	Original Banksy burnt then sold as an NFT	https://www.bbc.com/news/technology-56335948
		11th	The luxury brand tracking provenance Arianee raises $9.5MM	https://www.coindesk.com/arianee-early-pioneer-of-nfts-for-luxury-provenance-raises-9-5~m
		11th	Artist Beeple sold an NFT at Christie's for $69MM	https://www.christies.com/features/Monumental-collage-by-Beeple-is-first-purely-digital-artwork-NFT-to-come-to-auction-11510-7.aspx
		12th	Kings of Leon NFT sales generated over $2MM	https://www.nme.com/news/music/kings-of-leon-have-generated-2million-from-nft-sales-of-their-new-album-2899349
		18th	Opensea raises $23MM from a16z	https://techcrunch.com/2021/03/18/nft-marketplace-opensea-raises-23-million-from-a16z
		23rd	Jack Dorsey's first-ever tweet sells for $2.9MM	https://www.bbc.com/news/business-56492358
		26th	Dragonfly Capital invests $225MM in DeFI & NFTs	https://www.theblockcrypto.com/linked/99557/dragonfly-capital-new-225-million-fund-defi-nft
		30th	Dapper Labs raises $305MM	https://www.kob.com/business-news/dapper-labs-creators-of-nba-top-shot-get-305m-in-funding/6057600/?cat=602
		30th	Forest Road raises $20MM to turn IP movies into NFT	https://deadline.com/2021/03/forest-road-nft-for-studios-independent-producers-non-fungible-digital-tokens-beeple-1234724685/

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Table A.1 (*continued*).

Year	Month	Day	Events and the corresponding reports	Source
	April	8th	Playboy is getting into the NFT market	https://www.marketwatch.com/story/playboy-is-getting-into-the-nft-market-with-plans-to-create-digital-art-from-its-own-photography-11617817952
		17th	Edward Snowden's NFT sold for $5.5 million at an auction for charity	https://www.engadget.com/edward-snowden-nft-sold-for-55-million-080508241.html
		18th	Auction brings Hall of Famer Ted Williams to NFT market	https://apnews.com/article/sports-baseball-general-news-8ab5a9c6bf8dd7908af4fc365aefc872
		26th	Eminem sold original beats as part of his first NFTs drop	https://musically.com/2021/04/26/eminem-sold-original-beats-as-part-of-his-first-nfts-drop/
		28th	Kurt Cobain's 'The Last Session' Photoshoot Will Be Sold as an NFT	https://www.rollingstone.com/pro/news/kurt-cobain-nirvana-last-session-photoshoot-nft-1161975/

Notes:
(a) Events in this table are summarized from *Quarterly NFT Market Report Q1 · 2021* (https://nonfungible.com/reports/2021/en/q1-quarterly-nft-market-report), *Quarterly NFT Market Report Q2 · 2021* (https://nonfungible.com/reports/2021/en/q2-quarterly-nft-market-report), *Yearly NFT Market Report 2020* (https://nonfungible.com/reports/2020/en/yearly-nft-market-report), and *Yearly NFT Market Report 2019* (https://nonfungible.com/reports/2019/en/yearly-nft-market-report). NFT is scarcely covered in media before 2019 so this table starts with the year 2019.
(b) As our data of NFT transactions are *from 23rd Nov. 2017 to 27th Apr. 2021*, in this table, we summarize the events until April 2021.

Table A.2
Parameter estimation results of Eq. (A.1).

Coefficient	Estimation	Std. Err.	t-stat	*p*-value
α_0	0.0204***	0.0026	7.97	0.000
α_1	0.0313***	0.0045	6.97	0.000

Notes:
(a) This table presents estimated coefficients for Eq. (A.1).
(b) *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

A.2.

To examine whether the market return $R_{m,t}$ during the periods when herding emerges is higher than usual in average, we adopt the following specification:

$$R_{m,t} = \alpha_0 + \alpha_1 Herding_t + \varepsilon_t, \tag{A.1}$$

where $Herding_t = 1$ if t indicates a day when herding emerges, and $Herding_t = 0$ otherwise. The regression results are reported in Table A.2, which shows that the average daily market return during the time when herding emerges is significantly higher than usual (significant α_1 at the level of 1%). The daily market return $R_{m,t}$ is estimated to be 0.0204 during usual time while is 0.0517 (0.0204+0.0313) in average during the time when herding emerges.

A.3.

See Table A.3.

Table A.3
Parameter estimation results of Eqs. (3) and (4) with p-values derived using Newey–West *t*-statistics.

Parameter	Eq. (2)		Eq. (3)	
	Estimation (1)	p-value (2)	Estimation (3)	p-value (4)
α	0.0765***	0.000	0.0426***	0.000
γ_1	1.4491***	0.000	1.0890***	0.000
γ_2	−**0.9231****	0.011	−**0.7082****	0.032
γ_3	–	–	0.3558***	0.000

Notes:
(a) This table presents estimated coefficients for Eqs. (2) and (3) with data from the five submarkets in total.
(b) The sample size for each regression is 1252.
(c) The p-values are calculated with Newey and West (1987) heteroscedasticity and autocorrelation consistent standard errors.
(d) *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

Appendix B

See Table B.1.

Appendix C

The token is mainly priced with Ethereum in each transaction, while an equivalent US dollar value is provided. For consistency, we adopt the US dollar value of each transaction in return calculation.

Without any market maker in the NFT market, transactions are based on the agreement between sellers and buyers after several rounds of bargaining. Therefore, the price is revealed only on the days when transactions happened, in which case a certain token's price is unavailable on most days due to the lack of transactions, leaving us an unbalanced pricing table (if we construct the pricing table with rows denoting dates while columns denoting tokens). Moreover, the number of within-day transactions also varies across time. Because in practice, we are going to calculate daily returns of tokens, for those cases with multiple within-day transactions, we select the price of the first transaction on a certain day as the open price of that day while the last as the end price. We treat returns as continuous compounding and employ the following way to calculate the return of token i on day $t'-1$ for cross-day return:

$$R_{i,t'-1} = \frac{\log\left(\overline{P_{t'}}\right) - \log(\underline{P_t})}{t'-t}, \tag{C.1}$$

where $\overline{P_{t'}}$ and $\underline{P_t}$ denote the open price of day t' and the end price of day t respectively, and between the two days t and t', there is not any other transaction happening. For the within-day return of token i on t, we adopt the following way:

$$R_{i,t} = \log\left(\underline{P_t}\right) - \log\left(\overline{P_t}\right), \tag{C.2}$$

where $\underline{P_t}$ and $\overline{P_t}$ denote the end and open price of token i on day t. In practice, if $t'-1 = t$ while both $R_{i,t'-1}$ and $R_{i,t}$ exist, we select $R_{i,t}$ as the return of token i on day t. In this way, we can construct daily returns of tokens with the highest level of information utilized.

To illustrate, consider the example of the pricing table (Table C.1). On day *t*, if we sort the price with respect to transaction time, we can have a set of prices $\{P_{t1}, P_{t2}, \ldots, P_{tk}\}$, where P_{t1} denotes the price of the first transaction on day t. In Table C.1,

Table B.1
Summary of properties of the five NFT submarkets.

Property	*Atomic*	*Cryptokitties*	*Decentraland*	*Godsunchained*	*OpenSea*
Date of launch	Feb. 2020	June. 2017	Feb. 2020	Jul. 2018	Dec. 2017
Number of tokens	2743879	595695	8346	219464	1120983
Number of Collections	1973	1	1	1	2819
Number of investors participating	117616	98957	3334	2528	179560
Average number of transactions per investor	27	7	5	93	11
Number of days when the transaction happened	297	1252	1109	588	1102
Highest transaction price (in US dollar)	90069	173559	296355	22506	7501893
Lowest transaction price (in US dollar)	3.6800×10^{-10}	8.4779×10^{-16}	0.0204	1.5143×10^{-16}	2.2646×10^{-16}

Notes:
(a) The statistics reported in this table are based on the dataset posted by Newey and West (1987), and thus reflect the market situation from Nov. 2017 to Apr. 2021.
(b) Since only NFTs with transactions are recorded in the dataset, the statistics in this table do not reflect those NFTs that have never been traded.

Table B.2
Descriptive statistics of $R_{m,t}$ and $CSAD_t$ in the five submarkets.

Variables	Mean	Std	Skewness	Kurtosis	Jarque-Bera	ADF	ACF at lag			
							1	2	5	20
Panel A: Atomic market										
$R_{m,t}$	0.2060	0.2208	7.3057	83.2383	82315***	−11.9341***	0.3327	0.1668	0.2822	−0.0255
$CSAD_t$	0.2433	0.1576	2.3790	13.3106	1596***	−6.7667	0.2643	0.2128	0.1620	−0.0856
Panel B: Cryptokitties market										
$R_{m,t}$	0.0596	0.1381	3.9413	33.7299	52504***	−24.5950***	0.2467	0.1746	0.0712	0.0716
$CSAD_t$	0.1987	0.1418	2.6083	15.2182	9207***	−13.1955***	0.2583	0.2089	0.1101	0.0990
Panel C; Decentraland market										
$R_{m,t}$	0.0009	0.1586	−9.2712	189.0423	1615200***	−28.1947***	−0.0508	0.0422	−0.0312	−0.0167
$CSAD_t$	0.1422	0.1527	3.5536	26.3534	27535***	−14.6129***	0.3917	0.3632	0.3370	0.2472
Panel D: Godsunchained market										
$R_{m,t}$	−0.0018	0.1917	−3.5754	93.5945	202330***	−33.1982***	−0.2484	0.0441	0.0522	−0.0117
$CSAD_t$	0.0231	0.1070	18.0782	378.3260	3483300***	−22.9341***	0.0096	0.0104	0.0291	0.0295
Panel E; OpenSea market										
$R_{m,t}$	0.0161	0.1767	−1.0827	45.8228	84417***	−31.6424***	0.0387	−0.0347	0.1087	−0.0597
$CSAD_t$	0.1113	0.1242	3.3992	22.2125	19071***	−15.1056***	0.3315	0.3074	0.2548	0.1568

Notes:
(a) In Section 4.3, we use $R_{m,A,t}$, $R_{m,C,t}$, $R_{m,D,t}$, $R_{m,G,t}$, and $R_{m,O,t}$ to denote the average daily market return in the submarket of *OpenSea, Atomic, Cryptokitties, Godsunchained*, and *Decentraland*, respectively.
(b) *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

Table C.1
Pricing table example.

Date	Open price	End price
1	P_{11}	P_{11}
2	P_{21}	P_{22}
3	–	–
4	P_{41}	P_{41}
5	–	–
6	P_{61}	P_{63}
7	P_{71}	P_{74}

Table C.2
Return table example.

Date	Return
1	$\text{Log}(P_{11}) - \text{Log}(P_{11})$
2	$\text{Log}(P_{22}) - \text{Log}(P_{21})$
3	$(\text{Log}(P_{41}) - \text{Log}(P_{22}))/2$
4	$\text{Log}(P_{41}) - \text{Log}(P_{41})$
5	$(\text{Log}(P_{61}) - \text{Log}(P_{41}))/2$
6	$\text{Log}(P_{63}) - \text{Log}(P_{61})$
7	$\text{Log}(P_{74}) - \text{Log}(P_{71})$

only one transaction happened on day 1, so the open price is equal to the end price of day 1 (P_{11}). Whereas on day 6, 3 transactions happened, and thus the end price is P_{63} and the open price is P_{61}. Then using Eqs. (C.1) and (C.2), as well as the selection rule when $t' - 1 = t$, we can construct the return table of Table C.2.

Appendix D

Fig. D.1 plots the relationship between the cumulative dollar value of transactions and the cumulative number of transactions for each trader, and every point therefore stands for an individual trading account. Ideally, as the trader has more experience in transactions, he would cumulate higher dollar values of transactions so that the points would locate higher on the right-hand-side than the left-hand-side in plotting. However, in Fig. D.1, more of the investors with less experience have a higher level of the cumulative value of transactions than those with more experience. We also conduct a regression of the logarithmic cumulative value of transactions (ln(CumVal)) on the cumulative number of transactions (CumTran) with the following specification:

$$\ln(\text{CumVal}) = \delta_0 + \delta_1 \text{CumTran} + \varepsilon, \tag{D.1}$$

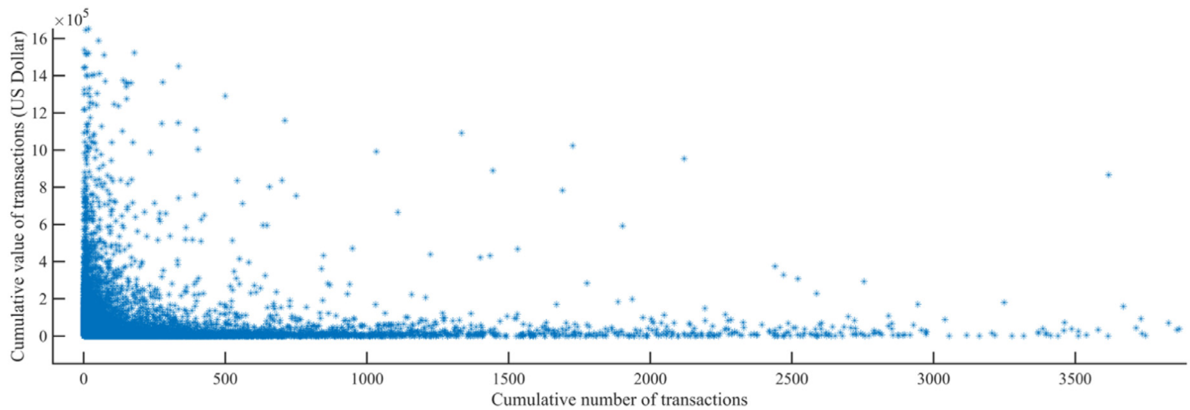

Fig. D.1. Relationship between cumulative number of transactions and cumulative value of transactions.
In this figure, Y-axis indicates the cumulative dollar value of transactions while x-axis indicates the cumulative number of transactions, with each point standing for one individual account.

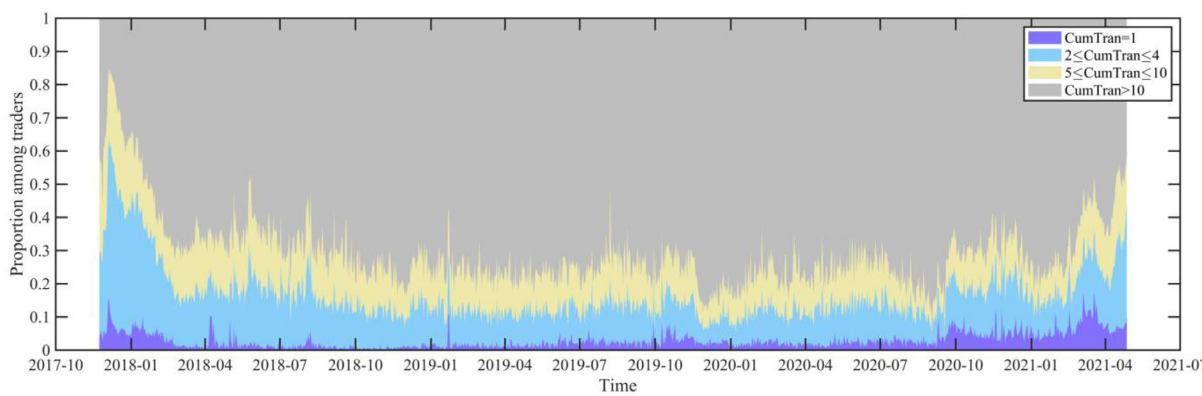

Fig. D.2. Stacked plot of investors' proportion with respect to trading experience.
We split traders into four groups with different cumulative number of transactions (CumTran): CumTran = 1, 2 ≤ CumTran ≤ 4, 5 ≤ CumTran ≤ 10, CumTran > 10. The proportion of traders in each of the four groups is plotted over time.

Table D.1
Parameter estimation results of Eq. (D.1).

Coefficient	Estimation	Robust Std. Err.	t-stat	p-value
δ_0	4.1131***	0.0097	324.28	0.000
δ_1	0.0008	0.0005	1.58	0.113

Notes:
(a) This table presents estimated coefficients for Eq. (D.1)
(b) *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

Considering heteroskedasticity, we obtain the heteroskedasticity robust standard errors as is shown in Table D.1. It reveals that the average cumulative value of transactions does not increase (in logarithmic form) as the cumulative number of transactions goes large, indicating that those newcomers with less experience (with a small cumulative number of transactions) are more likely to buy tokens at an extremely high price, similar with the results by Oh et al. (2022).

To illustrate, we divide investors into four groups according to their cumulative number of transactions (CumTran): CumTran = 1, 2 ≤ CumTran ≤ 4, 5 ≤ CumTran ≤ 10, and CumTran > 10. Figs. D.2 and D.3 plot the dynamics of change in the proportion of traders from the four groups and show that although investors with more experience (CumTran > 10) dominate the market most of the time (the gray area in Fig. D.2), the proportion of investors with less experience (CumTran ≤ 10) jumps during the periods when herding emerges (the shadowed periods in Fig. D.3). Here we divide investors into four groups only for illustration, and you can refer to the frequency table (Table D.2) for information about the distribution of investors with different cumulative number of transactions.

Appendix E

Here we use DPICT1 to denote the Daily Proportion of Investors in the group with CumTran = 1. To see the relationship between DPICT1 and Google SVI, we use their changing rate to ensure stationarity. The changing rates of DPICT1 and Google SVI, denoted as $\Delta DPICT1$ and $\Delta GoogleSVI$, are calculated continuously,[28] and the descriptive statistics are presented together with those of DPICT1 and Google SVI in Table E.1. We conduct the Granger Causality Test to see the relationship between $\Delta DPICT1$ and $\Delta GoogleSVI$, which is reported in Table E.2, and there exists Granger-causality from $\Delta GoogleSVI$ to $\Delta DPICT1$, indicated by the statistically significant F-statistics, as well as the Chi2-statistics at a lag of 4 in Panel A. However, the causality in reversed direction ($\Delta DPICT1$ Granger-cause $\Delta GoogleSVI$) is not supported, as is shown in Panel B of Table E.2.

[28] Here we adopt the following way to calculate changing rate of the underlying variable X: $\Delta X_t = (\log(X_t) - \log(X_{t-\Delta t}))/\Delta t$, where Δt denotes the time periods passed from $X_{t-\Delta t}$ to X_t.

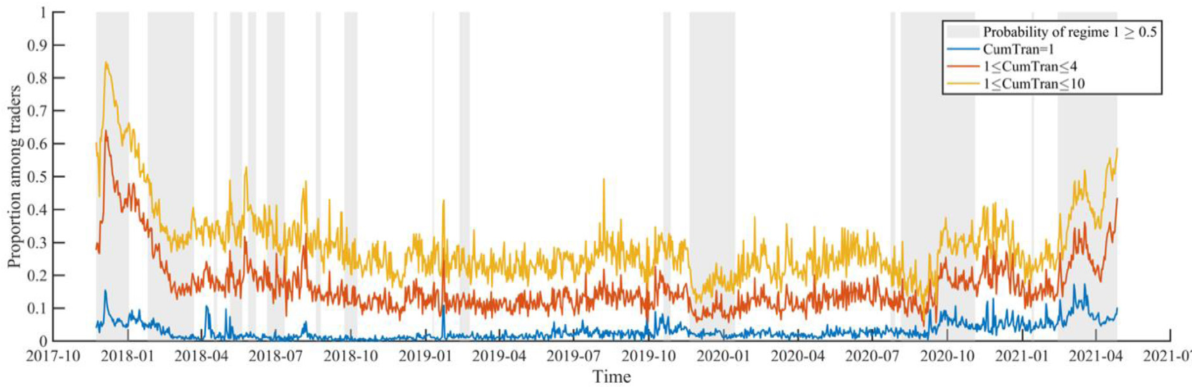

Fig. D.3. Investors' dynamic with respect to trading experience.
In this figure, each line presents the cumulative proportion of investors in the corresponding group with certain level of cumulative number of transactions (CumTran).

Table D.2
Frequency table for traders with different cumulative numbers of transactions.

	Cumulative number of transactions												
	1	2	3	4	5	6	7	8	9	10	11	12	> 12
Frequency	83690	75270	52218	31565	18749	14652	9000	8291	5490	5293	3974	3778	46379
Percentage	23.35	21.00	14.57	8.81	5.23	4.09	2.51	2.31	1.53	1.48	1.11	1.05	12.94
Cumulative Percentage	23.35	44.35	58.92	67.73	72.96	77.05	79.56	81.87	83.40	84.88	85.99	87.04	100

Notes: Because of limited space, we summarize the frequency of those with a cumulative number of transactions higher than 12 in the right-most column (> 12), and the range of a cumulative number of transactions is from 1 to 46379.

Table E.1
Descriptive statistics of *DPICT1* and *Google SVI*.

Variables	Mean	Std	Skewness	Kurtosis	Jarque-Bera	ADF	ACF at lag			
							1	2	5	20
DPICT1	0.0301	0.0258	1.7887	7.0429	1492***	−6.9054***	0.8114	0.7376	0.6776	0.5359
Google SVI	10.9959	13.1353	1.9950	5.6862	1185***	2.9699	0.9915	0.9822	0.9495	0.7726
*△DPICT*1	0.0006	0.6223	0.1000	4.5396	123***	−53.4246***	−0.3990	−0.1084	0.0094	0.0568
△GoogleSVI	0.0007	0.0400	−1.1247	17.1220	10463***	−11.5709***	0.7948	0.6244	0.1892	0.0045

Notes: *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

Table E.2
Granger Causality Test of *△DPICT*1 and *△GoogleSVI*.

H_0	Lag	F-stat	p-value (*Prob > F*)	Chi2-stat	*p*-value (*Prob > Chi2*)	AIC	BIC
Panel A:							
△GoogleSVI does not Granger-cause *△DPICT*1	1	0.91	0.3405	0.91	0.3392	1196.43	1210.26
	2	1.60	0.2028	3.22	0.1998	1050.46	1073.27
	3	1.54	0.2040	4.66	0.1988	984.29	1015.87
	4	**2.08***	**0.0813**	**8.46***	**0.0762**	**919.74**	**959.86**
Panel B:							
*△DPICT*1 does not Granger-cause *△GoogleSVI*	1	0.30	0.5851	0.30	0.5851	−3353.71	−3339.88
	2	0.26	0.7714	0.52	0.7699	−3166.31	−3143.49
	3	0.15	0.9264	0.47	0.9264	−2977.93	−2946.35
	4	0.58	0.6784	2.35	0.6723	−2792.94	−2752.82

Notes: *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

Appendix F

To examine whether herding exists within submarkets of NFT, we repeat the estimation of Eqs. (3) and (4) in the five submarkets, and the results are reported in Table F.1. Table F.1 shows that the coefficients before $R^2_{m,t}$ (γ_2) in the five NFT submarkets are all significantly negative, revealing the existence of herding in all the five submarkets. However, the FTP-MS model successfully captures the herding dynamics only in the submarkets of *Atomic* and *OpenSea*, for their opposite signs before the estimation of $\gamma_{2,1}$ and $\gamma_{2,2}$. Both the estimation of $\gamma_{2,1}$ and $\gamma_{2,2}$ for the case of *Cryptokitties* and *Decentraland* are negative, implying the homogeneous existence of herding during the whole sample period in these two submarkets. Meanwhile, the estimation of $\gamma_{2,1}$ and $\gamma_{2,2}$ for the case of *Godsunchained* are both positive, indicating the weakness of herding in this submarket.

Appendix G

See Table G.1.

Table F.1
Parameter estimation results of Eqs. (3) and (4) for submarkets.

Parameter	Atomic		Cryptokitties		Decentraland		Godsunchained		OpenSea	
	Eq. (3)	Eq. (4)	Eq. (3)	Eq. (4)	Eq. (3)	Eq. (4)	Eq. (3)	Eq. (4)	Eq. (3)	Eq. (4)
α	0.0424***	0.0343***	0.0826***	0.0912***	0.0335***	0.0255***	0.0048***	0.0097***	0.0308***	0.0254***
γ_1	1.3194***	–	1.2513***	–	1.0671***	–	0.3883***	–	0.8008***	–
γ_2	**−0.8301*****	–	**−0.5206*****	–	**−0.3254*****	–	**−0.0774*****	–	**−0.4632*****	–
γ_3	−0.0474***	0.1349***	0.1134***	−0.0032	0.3194***	0.1687***	0.0100***	0.0068*	0.2701***	0.2415***
$\gamma_{1,1}$	–	0.9237***	–	1.3735***	–	1.3021***	–	0.9394***	–	0.7043***
$\gamma_{1,2}$	–	0.6609***	–	1.2645***	–	1.8387***	–	−0.0048	–	0.7626***
$\gamma_{2,1}$	–	**0.3298*****	–	**−0.4866*****	–	**−0.3699*****	–	**0.2273**	–	**−0.4127*****
$\gamma_{2,2}$	–	**−0.1766*****	–	**−0.4641*****	–	**−1.1517*****	–	**0.0001**	–	**1.2404*****
σ_1^2	–	0.0017***	–	0.0028***	–	0.0020***	–	0.0094***	–	0.0248***
σ_2^2	–	0.0488***	–	0.031***	–	0.0438***	–	0.0001***	–	0.0010***
$P_{1,1}$	–	1***	–	0.96***	–	0.92***	–	0.19***	–	0.65***
$P_{2,2}$	–	1***	–	0.92***		0.74***	–	0.89***	–	0.86***
Log Likelihood	267	433	1566	–	851	1275	535	1602	1005	1448
AIC	−528	−847	−3113	–	−1696	−2529	−1064	−3186	−2004	−2876
BIC	−517	−810	−3062	–	−1681	−2479	−1051	−3142	−1989	−2826

Notes:
(a) This table presents estimated coefficients for Eqs. (3) and (4) with data from the five submarkets in total.
(b) The sample size for each regression is 1252.
(c) We estimate Eq. (4) with the Matlab package by Perlin (2015).
(d) *, **, and *** indicate level of significance at 10%, 5%, and 1% respectively.

Table G.1
Trader address for the 200 most active investors.

Trader index	Trader address	Trader index	Trader address
1	0x327305a797d92a39cee1a225d7e2a1cc42b1a8fa	101	0x9254f7f72bc6294ad6569d1ab78139121db880f6
2	0x76481caa104b5f6bccb540dae4cefaf1c398ebea	102	0xfcc5f5b71994b6d300f8b49120c0a24eb4d7d664
3	0x0008d343091ef8bd3efa730f6aae5a26a285c7a2	103	0xf0f54196b9d51200bdd00b7aa0db993510db951c
4	0x4fabda075e15e9245ed7cfb5db398b4683bfcf54	104	0xee402489d83e2b22d496910f8c810d35a3ad7b25
5	0xfc624f8f58db41bdb95aedee1de3c1cf047105f1	105	0x0acb5378a717c5b040f326720bb09e573905c2d3
6	0xf33bd4edc6dcd7240966f20401014ad0018d065b	106	0xe2ffab08ca7406f14b52645e095e6bccb44a5c75
7	0x023c74b67dfcf4c20875a079e59873d8bbe42449	107	0x2e9ce539d7e316468dfa447685a8e761ba639c1f
8	0x9e8c66c743723b1ffe4feb99b5bbcd67d391f6fe	108	0x5eda42ebd6172c7c18247c46842ac95601c3eb29
9	0xa0a0eaa4760d99f9173003185d0efa5bed675e78	109	0x6b4cfc4061800d6e097f8a5fa64878c7fadbf2bd
10	0xd387a6e4e84a6c86bd90c158c6028a58cc8ac459	110	0x4baf4a6a4d4ebc50319e92bc885846ba164e5f80
11	0xb367b96bd9af396dc5281cfdcd9e9571f670832f	111	0xe307c2d3236be4706e5d7601ee39f16d796d8195
12	0xb04239b53806ab31141e6cd47c63fb3480cac908	112	0xe2f033468adc8b1931541ef712bf750b318c4aed
13	0x161b930a6e782d90e591a97547a60e3c9bb0f274	113	0x53e77261fdd7187cbb5b427f6c39c72e675b29d1
14	0x84ecb387395a1be65e133c75ff9e5fcc6f756db3	114	0x1f38ebcffb0be993b981225a917aaa8a6d6a4e52
15	0x23b2bcae8dec395afd931f49ea8387937e515ca1	115	0x1d936d78b16bf83e67eb1f151222216e4c88f68e
16	0x0904dac3347ea47d208f3fd67402d039a3b99859	116	0x3b41008e6c8693be95531e3d4df6bb5185fb6d07
17	0x0ed70f92b87ceced51a9e472fcd8d93a54a11835	117	0xcaef3aae37c2506916fa791648b0fe3356342e33
18	0x9e6e344f94305d36ea59912b0911fe2c9149ed3e	118	0x61592a6f682bbabfd743aa7596ee269e7448212c
19	0xf748879edbe8cca140940788163d7be4d2a2e46a	119	0xe5c4c41194901047523108bb47eb109781a1a86a
20	0xbc9ca5bd0f07700929f8d538233b0a9e60f4ddc5	120	0xa15ef0101ea50e2bf6a35f0c0186f63d514c6263
21	0x1723edbfbb1f2c4c2fbbee572c146c1831676063	121	0x8b3ad493c077e894a034db7eb53e8285560298fd
22	0x95a08c297ad5861734c4440fd5ac6b80a8bf9228	122	0x2e0ce5513f4b3a48a8a4e30ff69e24714f5cd5fa
23	0xa3ac984451 4b96bb502627ca9dceb57c4be289e3	123	0xf862c9413f2cc21ebfda534ecfa6df4f59f0b197
24	0xfbde72a013b10d0735831c6f8d898f5a0b41974a	124	0x87d346216360e1e9c6e9e81a733bcb6c03c288a1
25	0xc78c5564333bfc50172904cdf484952e0576cfd9	125	0x0544fbed9b72aa036517b21d1db50201a17d09ce
26	0xa21037849678af57f9865c6b9887f4e339f6377a	126	0xd81be2dd1fe5e3f9aada3ffea6d64e62506edacc
27	0x48c94e8f4c0f0a125bed72e292c8dc84673e4dfc	127	0x2c5968ee5ce21ad7324c97014fcb99f87f7fec6f
28	0x864c56caf3797abeb010c4e8be54973f1cc93d20	128	0xb241fdbee4b2b9c56a6e222a73093bbd3e7a0717
29	0x9e315e9701908501f6dc68a2af6e28a20c75d970	129	0x9af756e7be065dca83674ec17f3703579a544da1
30	0x450629e1d26c57ce62aa15265aa6c0bd97a5490a	130	0x75771dedde9707fbb78d9f0dbdc8a4d4e7784794
31	0x2d891ed45c4c3eab978513df4b92a35cf131d2e2	131	0xa8fef13a53ec1503e00bfbedacb3566d778e5d27
32	0xa20c32005968d0af6ef2dd8be949da175c0c8a8e	132	0x51fd346ffd1b2678ff76ba92b19e5710be8abfe5
33	0x7045540552d1fcc2ab1eb64e1f868aeb490606fa	133	0xd08866c9153142c90ccd1d3105f751d060f13894
34	0x1df4c50410e20c2210b60b95cd845672cbd437a7	134	0x9016c9cbacc47b07ad14fa7c226429ffb69e4507
35	0xcfee1c9c3a4e8e709e2f177770febae79875c531	135	0xcb7e9e305fa4afa4cf5b414120c560ad3ed75a53
36	0xf52393e120f918ffba50410b90a29b1f8250c879	136	0x872395adec14b3bcc87f9cd112d509c960314645
37	0x42cec1efe742be293cdf8df2a89f48814cf084ff	137	0xa0fec1a6b8453873041c7529906de5c1acc1b26a
38	0xcb322d24121c62ebce620eaffba821370567bed7	138	0x2f261a227480b7d1802433d05a92a27bab645032
39	0x07be7d2abb1373cb4d0cbac8807dc853f9dd9286	139	0xa2e08e1d550e557d72e2ca6f9e023e36281bfcf0
40	0x22d1a32a0be51f71702f8f64c56e51c7560b2f4c	140	0x9a96812ff78123f01f7be3cf3fa12b949130a288
41	0x69b4f1d198783baca5da8bb69f4447514ffa26df	141	0x5492e0112e49e5fed0a7b1278c76df655e509a99
42	0x09191d18729da57a83a9afc8ace0c8d7d104e118	142	0xbae25a69a6eb7341ee834be7635e247e22a1e57a
43	0x2c00d05ff7ffe93d77145dfe12aa56e622ae6f40	143	0x12e0c5e484ea663e567ad4c20f71ae58b23175c8
44	0xd1b3db7201d8c0c320aee20e1a106c9b0812057d	144	0x8ed4d3c67ee1a73f5df8ca3e10698f1cd4c5b14c
45	0xd04b5f64cc6f01b89bcf05c8d2286e9ba744ef85	145	0xca97a04e562a71d6fc95f335cb6adc5e07e2e8d8

(continued on next page)

Table G.1 (*continued*).

Trader index	Trader address	Trader index	Trader address
46	0x69323bea116b59ebc0bbc89b93b997e8b1f0d633	146	0xcb5c0d33d92e4910daa24825db8af9b64e17c33c
47	0x774ae05c60a3bb52bf5b4c137d59192ee7c310ef	147	0x671a2d53ae15314610ca5126b257c22a80aa4111
48	0x5c035bb4cb7dacbfee076a5e61aa39a10da2e956	148	0x722e74b104292b6e95040bdc0c8192a82b133199
49	0x93b7e47db71372cfaa56686d46183ce01ad0a3ad	149	0x74383b4aafd78d0458917b54c0a1ef278d938d6a
50	0xc35a5fec6be6957899e15559be252db882220b37	150	0xab5853ddb6b5a8b0dcfbe9a9d034b45ef703f5be
51	0xc2be9e536eee410a720c6440cbac293f4358451c	151	0xf604d313a43f87b7d19de1477c9cc4a2c9d7ea8e
52	0x445394622fc3e31a18401745ca6b0c4a16cefae9	152	0x6d33e7d18a3b0a837a1f92b6dc3a4781929f3fbe
53	0x8de12bca6a79caf05ded82308f5b35ea9e230f17	153	0x55a9c5180dcafc98d99d3f3e4b248e9156b12ac1
54	0x3b02692ab73431e2e263421b1b6ecf89cdb6714c	154	0xab88432dcca57d5ff22e9cc6b932b1221001284b
55	0xd965a4f8f5b49dd2f5ba83ef4e61880d0646fd00	155	0x88b7e1814a23943e0b87f370f80114bb3ab044f8
56	0x6a00ef8a35bce729b40887e2aabec3bccae16e83	156	0x2b9bac82406a387746f951eaa6458493d23f725c
57	0x459a5af4fae179425a0bf9b2c4717f4b214207fc	157	0x869a681d47519497b8c3a03190ce5757f2e6c3f2
58	0x42a60d2f2ffa2150c568010a8d425f0aad284fd2	158	0x75dffacbce225b30f0c9644e94e0092295322c4e
59	0x2c7f17acb3549a8d2232bdb9f59313a80257d057	159	0x1589e6b7465f94a5bfcc09a1f64865e366cdbc6b
60	0x6880add29b5e84c543ff745856a0f3368e58f165	160	0xc8a974a97f6a7f57b6ce09aed5905d5547039f11
61	0x29ecaa773f052d14ec5258b352ee7304f57aabc3	161	0xf089678b4aaeeed0b9fcecf0cf8bf480875c9877
62	0x95a437e4cf18cf243a3a46d3798904b635e25d81	162	0xb95ab1da009bd1facbd54858014af8edf9cab8f7
63	0x51de9878f78da56c853b22374656b32aa1d86b5a	163	0x075b2a494c57efcac188d613e5e98a38e70ae5df
64	0xabdb1a71f300759917a45684a78192265e6a0d18	164	0x442dccee68425828c106a3662014b4f131e3bd9b
65	0x188ae4ee04957e754d1c654d47035dfb529b7163	165	0x4ea5ca0eb9552b00e130f51a7564f1b3d748df74
66	0x8b709b40fe42eb31589ad5b012da7d6204b7402a	166	0xb98cdacd006b9d47c37ca63cc86f916ee23fc550
67	0x41308f0538d32dae052e3524c82f47eae2e560f1	167	0x7f282ed81c7041069676e447ac683ead21e0d857
68	0x37ca19f8d7c5b7ba854c3ea678a9ee27bb05d72b	168	0xeeadc5701b5fd25fbcc7fbf04b048cdb1fff1c65
69	0xb6d820e80a2a7c49f94c9d6c8ea08dccedc9ce4c	169	0xbe314949e2b9d14c27fa6785323f7cfc9250f92a
70	0x2e3dda0639e7766af544859d182b91aea65cd612	170	0xcadc64f9f974f810b68a714e9001ce4800719b86
71	0x9ed285aa1dfd8b5f4c61ec1f6b11d007ffa54708	171	0x9ffcbd14db24054a141c23633f7b32cb3330e7b2
72	0xb358bf9c59c3f839429056de665e99d50a25090d	172	0x1aff1e0f1d5f76f92145a278d8c31af9ade783dd
73	0xb81b0c63f9ff610e2edd4b2fe05a1cedcc12fe58	173	0x8870628aa0fef5cf92374a092ae42c8999a58471
74	0xa096b47ebf7727d01ff4f09c34fc6591f2c375f0	174	0xbce3bd3b206946abbe094903ae2b4244b52fb4e9
75	0xd914a19f0e1420ace988b01863cf68a85c4ae554	175	0x137d9174d3bd00f2153dcc0fe7af712d3876a71e
76	0x68b42e44079d1d0a4a037e8c6ecd62c48967e69f	176	0xd68c2b3086f9d0e278b0e0aea23ed361fa7c28e1
77	0x1fecb2e6ed1e930879d86d4734489442f2f80952	177	0xf249bfd75e8af55008a76f4e2c80df2de503fdda
78	0xbb6b5e1377a36a668995b889b5b57aeb84018b4c	178	0x5f1088110edcba27fc206cdcc326b413b5867361
79	0x330ed0f002d34343c09f668516e21915a3349aa2	179	0x0a00f2a39633e4106ad37cc4c4e10c7f30d77c23
80	0x1d5c30676ca03adae00257568b830c8d424a1e53	180	0x61603b1cbed9879045e02ffcf17f8a0148d76f4c
81	0xe0fb7622091e3d9ef9b438471b10b9ea88c7cf6b	181	0xcfb586d08633fc36953be8083b63a7d96d50265b
82	0xa1e47487271702d1fd94d5650ce8bac33c951557	182	0xfd5873b0e11dfa1f848995e34fc017de9f5a3d98
83	0x678e2da2e8be98c58dc54df92c6b88b5b52eabc8	183	0x8eec2c10adc20749d226493677fe253e1c13ff1e
84	0xb379db134fac891d11b1942fe29df1978d84fc83	184	0xb2815298bb6f8cec3b1faacf81b4f1ad0b111918
85	0x5a1929628b4d0c511a6f29855229c78ea27c42f8	185	0x613b909325e0f7bf25beefb6254187f6d9ec7309
86	0x5161e1380cd661d7d993c8a3b3e57b059ad8d7a4	186	0xeace206af7039fe91f5fd047f03118d4d7d4f8ba
87	0xc77dce01a98ebc40f76b2d1f403e52d55b74fded	187	0x312e4826a495a707d64c9c96f5eab7d24ee23e4f
88	0x83bb781a2a2ca1fec0350f178c911848811cc440	188	0x8e668a4582d0465accf66b4e4ab6d817f6c5b2dc
89	0xfee776fe84388ca9a38b286ff40e11db967917ed	189	0xf97eecd48a5c412775070272b3e4af81c8aa940b
90	0x8820a512ce3b3b51c0340a81930941d3339d3eda	190	0xf957a0d48ffda04d80e829f92ca0b5199d908349
91	0x84957e6c9f6ccfed9c35c850c3903732ed90858a	191	0xb8c2a8ca44e96d970802dfd9261662c81c17f47d
92	0x30c41bed20645d229d78168078975fdbb7bfa555	192	0x3401ea5a8d91c5e3944962c0148b08ac4a77f153
93	0x0927661d9790d58087f045c2e84aa38024365a91	193	0xcd4fec10c8ad4873e209062b31defb684ff8cb7c
94	0x8fc339425b2c5be02035c00ef311fda7d1fa9ab7	194	0x0f25c5ac5cbed4ff15aab4ca3639f87a453b9ab8
95	0xf34953841d09bd0833b67640f80a3afdb7e2184b	195	0x0c6fc5083f7f4ec4a3b2de37ccef88a72b64fa1a
96	0xc213e80da9d81baeb7338aaea044d9784ab5dff8	196	0x2ce0fb9a765ba7f55d43897dd404c8d92e9c0708
97	0xfadae26458902e6eaf1415ec02151470a68f8137	197	0xcf0e9b4746cfb97bae329fe5f696969f6564566a
98	0x70e5984850a52fd802704731f52b671dfdbcc1ac	198	0x16205a6048b6af17f1ac1a009bbf2ed9289e6921
99	0xd95c9809b6e7f404488d52c8d82e6d095b37a190	199	0x220d04c2c3b0cc065d1c4a43a58e33e469546797
100	0x2642b53770a0331014a186c79e0b1a1d40015b32	200	0x480c896bd09d0ba7d4522f9349d8e10ef36686f8

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