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Herding behavior in conventional cryptocurrency market, non-fungible tokens, and DeFi assets.

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ABSTRACT

We examine the static and time-varying herding behavior in three cryptocurrency classes: 'conventional' cryptocurrencies, non-fungible tokens, and DeFi assets during the most recent cryptocurrency bubble of 2021. While static herding analysis failed to demonstrate any evidence of herding, the time-varying herding has been identified in conventional cryptocurrencies and DeFi assets for the short investment horizons. The herding asymmetry analysis reveals that herding is not evident in conventional cryptocurrencies and NFT during up/down market, high/low volatility days, and high/low trading days. We only find herding in DeFi assets during the low volatility days.

1. Introduction

The decentralized finance has attracted significant attention from investors, media and government; however, the technology is still widely misunderstood (Harvey and Reule, 2020). The digital assets ecosystem is rapidly evolving providing new opportunities for speculators and entrepreneurs. There are many papers that suggest that cryptocurrency markets are not homogeneous (Corbet et al., 2020; Benedetti and Nikbakht, 2021; Katsiampa et al., 2022). In comparison to conventional cryptocurrencies, such as Bitcoin and Ethereum, that are fungible/interchangeable, non- fungible tokens (NFTs) are rare, unique, and not interchangeable digital assets on blockchain technology. NFTs can be anything digital, like artwork, music, videos, photo, tweet, and digital land (Dowling, 2021a; Yousaf and Yarovaya, 2022a). Decentralized Finance (DeFi) assets are fungible within their specific categories, and the term refers to the financial services functioning in a peer-to-peer fashion without the central authority, based on blockchain technology. These financial services include lending, borrowing, online wallets, spot trading, and derivatives.

According to Wang et al. (2022) NFT and DeFi markets behaved differently during the period of cryptocurrency markets explosivity, specifically, NFTs bubbles had been more volatile and had higher average explosive magnitudes that DeFi bubble during the 'DeFi boom' of 2021 ((Wang et al., 2022)Lucey et al., 2022), when the cryptocurrency market capitalization increased from $256 billion in May 2020 to $2313 in May 2021. Both DeFi assets and NFTs have largely contributed to this growth of overall cryptocurrency market capitalization and prices of conventional cryptocurrencies. Thus, in this paper, we hypothesize that new DeFi assets and NFT markets will exhibit higher level of herding than conventional cryptocurrencies, since many investors will follow the crowd and

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Table 1
Descriptive statistics.

Panel A. Conventional cryptocurrencies								
	Bitcoin	Ethereum	Binance_Coin	Dogecoin	Tether	XRP	Bitcoin_Cash	Litecoin
Mean	0.0045	0.0082	0.0099	0.0147	0.0000	0.0053	0.0046	0.0055
Maximum	0.1720	0.2323	0.5298	1.7658	0.0146	0.4391	0.4240	0.1656
Minimum	−0.1428	−0.2117	−0.2684	−0.5069	−0.0199	−0.5476	−0.2308	−0.2071
Std. Dev.	0.0353	0.0473	0.0633	0.1346	0.0024	0.0778	0.0601	0.0523
Skewness	0.1328	−0.0893	1.8637	6.7470	−1.5492	0.3655	0.7622	−0.2156
Kurtosis	6.155	5.642	17.590	83.663	24.438	15.662	12.108	5.115
Panel B. NFTs								
	THETA	CHILIZ	DECENTRALAND	ENJIN_COIN	DIGIBYTE	ORIGIN_PROTOCOL	WAX	ERC20
Mean	0.0112	0.0103	0.0096	0.0068	0.0044	0.0056	0.0048	−0.0170
Maximum	0.2600	0.7115	0.3878	0.4072	0.3680	0.4968	0.4948	1.2656
Minimum	−0.2067	−0.4321	−0.2034	−0.2414	−0.2295	−0.3479	−0.3007	−2.0592
Std. Dev.	0.0739	0.1105	0.0759	0.0730	0.0748	0.0925	0.0901	0.2286
Skewness	0.3652	1.1313	1.1528	1.2196	0.9972	0.9681	0.5113	−3.1999
Kurtosis	3.6255	10.7286	6.6929	8.8131	6.2682	7.4558	6.5090	38.8341
Panel C. Defi Assets								
	CHAINLINK	WRAPPED_BITCOIN	TERRA	DAI	THORCHAIN	MAKER	SYNTHETIX	BAT
Mean	0.0069	0.0046	0.0123	0.0000	0.0143	0.0074	0.0089	0.0050
Maximum	0.2472	0.1763	0.6293	0.0134	0.3331	0.4194	0.1908	0.3040
Minimum	−0.2194	−0.1528	−0.6086	−0.0246	−0.2478	−0.1905	−0.2468	−0.2469
Std. Dev.	0.0664	0.0358	0.0953	0.0030	0.0874	0.0653	0.0737	0.0643
Skewness	0.1931	0.0434	0.3293	−0.7399	0.2590	1.8332	0.0863	0.6353
Kurtosis	4.3673	6.2811	17.7011	19.7635	3.2061	11.3060	3.1842	6.7142

Notes: Std. Dev.-Standard deviation. BAT- Basic attention token.

emerging investment trends rather than conduct their own analysis of these new investment assets.

While cryptocurrency as an asset class is typically considered as speculative and risky assets due to their high volatility (Makarov and Schoar, 2020), high cyberattack risk, and lack of quality information or universally accepted regulation (Corbet et al., 2019); we further assume that crypto investors follow each other rather than depend on their own analysis due to lack of information or fear of loss, where herding behavior can be intensified during the extreme fear episodes of crisis or bubbles (Galariotis et al., 2015). Herding behavior influences the risk-return tradeoff and has implications for asset pricing (Yao et al., 2014), therefore extreme herding behavior leads to high market volatility, explosivity, or crises (Bouri et al., 2019), resulting in market instability, which, therefore, entails important implications for policymakers.

In this paper, we assess both static and time-varying herding behavior in top eight most tradable cryptocurrencies in three different categories: DeFi assets, NFTs and conventional cryptocurrencies for the period from 16/05/2020 to 15/05/2021, and specifically during the most recent cryptocurrency bubble, i.e. from 01/01/2021 to 15/05/2021 (Lucey et al., 2021)Lucey et al., 2022 Wang et al., 2022; Wang, 2022). By this analysis, we aim to answer the question: *Does herding behavior in DeFi, NFT, and conventional cryptocurrency markets intensify during the cryptocurrency bubble period?*

Academic literature on NFTs is rapidly growing following the increased attention to this new type of digital asset. Wang (2022) offers a comprehensive summary of NFT literature and introduce a novel NFT attention index (NFTsAI) that offers a tracking tool for analysis of behavior of NFTs during key events in cryptocurrency space, including periods of explosivity. However, currently, there is no paper assessing the differences in herding behavior among NFTs, DeFi, and conventional cryptocurrencies during the bubble-like periods. Thus, our paper contributes to three main strands in literature. First, we provide the most recent evidence on herding behavior in conventional cryptocurrencies (e.g., Bouri et al., 2019; Youssef, 2020; Papadamou et al., 2021; Yarovaya et al., 2021) providing novel evidence for NFT and DeFi markets. Second, this paper adds to the emerging field of NFTs and DeFi research, and to date these assets are rarely explored in the academic world (e.g., Dowling, 2021a; Corbet et al., 2021; Wang et al., 2022; Wang, 2022). Dowling (2021a) explores the volatility transmission between NFTs pricing and conventional cryptocurrencies pricing and finds the lower level of spillovers between both markets. Yousaf and Yarovaya (2022a) look at the connections between the returns, volatility, and trading volumes of the non-fungible tokens. Dowling (2021b) examines the pricing efficiency in NFTs (specifically Decentraland) and concludes the pricing inefficiency. Corbet et al. (2021) examine the return and volatility transmission between the DeFi assets and conventional cryptocurrencies. Yousaf and Yarovaya (2022b) explore the linkages among conventional Defi, and NFTs, and other asset classes including oil, gold, stock, and Bitcoin. They report that these new asset classes are de-coupled from the other asset classes. Yousaf et al. (2022) test the connectedness between Defi assets and fiat currencies and conclude the weak connections among them.

Third, our results contribute to enhancing understanding of financial market efficiency (Fama, 1970), and recent body of work that shows inefficiency in cryptocurrency markets due to the static or time-varying investor's herding (e.g., Bouri et al., 2019; Vidal-Tomás et al., 2019; Ballis and Drakos, 2020). Static analysis performed using a well-known Chang et al. (2000) model did not show any evidence of herding in three cryptocurrency classes during full sample and bubble periods. The herding asymmetry analysis reveals that herding in Defi assets is evident only during the low volatility days. However, the time-varying herding is identified in conventional cryptocurrencies and DeFi assets, providing evidence of time-varying inefficiency in these two cryptocurrency classes.

The remainder of this paper is structured as follows: Section 2 provides the data and methodology, Section 3 presents the empirical findings, and Section 4 concludes.

2. Data and methodology

2.1. Data description

We use the daily data of three categories of cryptocurrencies from 16/05/2020 to 15/05/2021: (i) conventional cryptocurrencies; (ii) non-fungible tokens, and (iii) DeFi assets. Table 1 displays the descriptive statistic for selected assets. For each category of cryptocurrency, we collect the data of top eight cryptocurrencies[1] based on market capitalization, whose data is available for at least one year. The data of cryptocurrencies are taken from coinmarketcap.com. Following Yousaf and Yarovaya (2022b), we further examine herding during the most recent cryptocurrency bubble from 01/01/2021 to 15/05/2021, which is consistent with (Lucey et al., 2022). Besides, similar periods of market explosivity have been identified by Wang et al. (2022), specifically for DeFi and NFT markets.

[1] Defi and NFTs are relatively new markets compared to the conventional cryptocurrencies. Majority of Defi and NFTs tokens have been introduced at the end of 2020 or start of 2021, therefore we find very few Defi and NFTs with a high market cap and data availability for at least one year on May 15, 2021 (end of sample period). We selected the cryptocurrencies based on two criteria: (1) cryptocurrency's data should be available for at least one year; and (2) the cryptocurrency should have the highest market capitalization. Ultimately, we chose the data of the most capitalized eight cryptocurrencies as a representative of each category (Conventional, Defi, NFTs) based on the availability of at least one year data. We further removed the assets from each category if data were available for less than one year on May 15, 2021. The final sample includes cryptocurrencies have the highest market capitalization in their categories as per May 15, 2021. The market capitalization of 24 selected cryptocurrencies is 72 percent of the total cryptocurrency market capitalization on May 15, 2021, hence the selected cryptocurrencies represent the major proportion of cryptocurrency market. Ballis and Drakos (2020), and Stavroyiannis and Babalos (2019) also use the sample of 6 and 8 cryptocurrencies, respectively, to detect herding in cryptocurrency market.

Table 2
Herding during full sample period (Eq. (2)).

	Conventional		Non-fungible tokens		Defi assets	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
α_0	0.014***	0.000	0.045***	0.000	0.023***	0.000
α_1	0.232***	0.000	−0.095	0.307	0.402***	0.000
α_2	3.150***	0.000	4.468***	0.000	0.318	0.600

Notes: Coeff.-coefficient. ***, **, * denote the 1%, 5%, and 10% level of significance, respectively.

2.2. Methodology

This study uses the model of Chang et al. (2000) to estimate herding behaviour in the cryptocurrency markets. According to this model, if the relationship between the dispersion of individual asset returns and market returns is non-linear, this could be interpreted as evidence of herding behaviour in the market. The cross-sectional absolute deviation (CSAD) is used as the measure of dispersion, defined as:

$$CSAD_t = \frac{\sum_{i=1}^{N} | R_{it} - R_{mt}|}{N} \tag{1}$$

where i denotes the cryptocurrency, t the time period, and N the number of cryptocurrencies. R_{it} indicates the returns of cryptocurrency i at time t, R_{mt} denotes the returns of the market (cross-sectional average returns of N cryptocurrencies) at time t. Chang et al. (2000) propose the following model to estimate herding in the market:

$$CSAD_t = \alpha_0 + \alpha_1 |R_{mt}| + \alpha_2 (R_{mt})^2 + e_t \tag{2}$$

This model indicates herding in the market if α_2 is found to be negatively significant. Hence, a negative and non-linear association between the CSAD and market returns indicates herding behaviour in the asset market.

Chang et al. (2000) suggest the following equations to detect herding during up and down-market conditions:

$$CSAD_t^{Up} = \alpha_0 + \alpha_1^{UP} R_{mt}^{UP} + \alpha_2^{UP} \left(R_{mt}^{UP}\right)^2 + e_t \tag{3}$$

$$CSAD_t^{Down} = \alpha_0 + \alpha_1^{Down} \left|R_{mt}^{Down}\right| + \alpha_2^{Down} \left(R_{mt}^{Down}\right)^2 + e_t \tag{4}$$

where R_{mt}^{UP} (R_{mt}^{Down}) indicates positive (negative) market returns on day t. $CSAD_t^{Up}$ ($CSAD_t^{Down}$) refers to the $CSAD_t$ when market returns are positive (negative) on day t.

Following equations can be used to estimate herding during high and low market volatility:

$$CSAD_t^{\sigma^2-High} = \alpha_0 + \alpha_1^{\sigma^2-HIGH} \left|R_{m,t}^{\sigma^2-High}\right| + \alpha_2^{\sigma^2-HIGH} \left(R_{m,t}^{\sigma^2-High}\right)^2 + \varepsilon_t \tag{5}$$

$$CSAD_t^{\sigma^2-Low} = \alpha_0 + \alpha_1^{\sigma^2-LOW} \left|R_{m,t}^{\sigma^2-Low}\right| + \alpha_2^{\sigma^2-LOW} \left(R_{m,t}^{\sigma^2-Low}\right)^2 + \varepsilon_t \tag{6}$$

where $\sigma^2 - High$ and $\sigma^2 - Low$ denote high and low volatility in markets, respectively. Following Tan et al. (2008), we define high and low volatility as “If the volatility of day t is greater than the moving average of the last 30 days’ volatility, then volatility is high, and vice versa”.

Following equations can be used to estimate herding during high and low trading volumes:

$$CSAD^{V-HIGH} = \alpha_0 + \alpha_1^{V-HIGH} \left|R_{m,t}^{V-HIGH}\right| + \alpha_2^{V-HIGH} \left(R_{m,t}^{V-HIGH}\right)^2 + \varepsilon_t \tag{7}$$

$$CSAD^{V-LOW} = \alpha_0 + \alpha_1^{V-LOW} \left|R_{m,t}^{V-LOW}\right| + \alpha_2^{V-LOW} \left(R_{m,t}^{V-LOW}\right)^2 + \varepsilon_t \tag{8}$$

where V-HIGH and V-LOW indicate high and low trading volumes, respectively. If the trading volume of day t is greater than the moving average of the last 30 days’ trading volume, then the trading volume is high, and vice versa.

Following notations provided by Galariotis et al. (2015) Eq. 9 describes the regression to estimate herding during the bubble period (01/01/2021 – 15/05/2021):

$$CSAD_t = \alpha_0 + \alpha_1 |R_{mt}| + \alpha_2 (R_{mt})^2 + \alpha_3 (R_{mt})^2 * DM_t^{bubble\ period} + e_t \tag{9}$$

For the bubble period, $DM_t^{bubble\ period}$ is a dummy variable equal to 1 during the days of the bubble period (01/01/2021 – 15/05/2021) and 0 otherwise. There is evidence of herding if α_3 is negative and significant. Finally, following Stavroyiannis and Babalos (2017), we estimate the time-varying herding using the rolling window approach.

Table 3
Herding asymmetries.

	Conventional Coeff.	P-value	Non-fungible tokens Coeff.	P-value	Defi assets Coeff.	P-value
Panel A: Up market (Eq. (3))						
α_0	0.012***	0.000	0.047***	0.000	0.025***	0.000
α_1	0.434***	0.000	−0.077	0.664	0.352***	0.001
α_2	2.812***	0.000	4.731***	0.000	1.503	0.103
Panel B: Down market (Eq. (4))						
α_0	0.013***	0.000	0.044***	0.000	0.022***	0.000
α_1	0.227*	0.073	−0.216*	0.091	0.315***	0.002
α_2	1.068	0.285	4.805***	0.000	0.318	0.684
Panel C: High Volatility (Eq. (5))						
α_0	0.022***	0.000	0.054*	0.000	0.023***	0.000
α_1	0.098	0.289	−0.307**	0.021	0.399***	0.001
α_2	3.579***	0.000	5.229***	0.000	0.419	0.620
Panel D: Low Volatility (Eq. (6))						
α_0	0.011***	0.000	0.030***	0.000	0.023***	0.000
α_1	0.331**	0.036	0.429**	0.037	0.486***	0.001
α_2	2.185	0.330	1.276	0.414	**−1.670**	**0.034**
Panel E: High Volume (Eq. (7))						
α_0	0.024***	0.000	0.039***	0.000	0.025***	0.000
α_1	0.045	0.631	0.292*	0.094	0.413***	0.000
α_2	3.795***	0.000	1.616	0.113	0.311	0.739
Panel F: Low Volume (Eq. (8))						
α_0	0.006***	0.001	0.044***	0.000	0.022***	0.000
α_1	0.677***	0.000	−0.176	0.182	0.313***	0.001
α_2	−1.531	0.408	5.179***	0.000	0.474	0.537

Notes: Coeff.-coefficient. ***, **, * denote the 1%, 5%, and 10% level of significance, respectively.

Table 4
Herding during the bubble period (Eq. (9)).

	Conventional Coeff.	P-value	Non-fungible tokens Coeff.	P-value	Defi assets Coeff.	P-value
α_0	0.011***	0.000	0.043***	0.000	0.022***	0.000
α_1	0.112*	0.053	−0.169*	0.071	0.392***	0.000
α_2	3.459***	0.000	4.574***	0.000	0.330	0.585
α_3	0.016***	0.000	0.014***	0.000	0.004**	0.028

Notes: Coeff.-coefficient. ***, **, * denote the 1%, 5%, and 10% level of significance, respectively.

3. Empirical findings

3.1. Static herding

Table 2 presents the results of static herding behavior in three types of cryptocurrencies during full sample period, i.e., conventional cryptocurrencies, Non-Fungible Tokens (NFTs), and DeFi assets. The coefficient α_1 is significantly positive in conventional cryptocurrency and Defi assets markets, indicating that the $CSAD_t$ is an increasing function of absolute market returns $|R_{mt}|$. According to CCK model, the herding is only evident if the coefficient α_2 is found to be statistically significant and negative. The coefficient α_2 is statistically significant and positive in all three types of cryptocurrencies, showing the anti-herding behavior.

Table 3 provides the herding results during different types of asymmetries, i.e., up/down market, high/low volatility, and high/low volumes. In panel A and B, the significant positive values of coefficient α_2 are providing evidence of anti-herding in all three types of cryptocurrencies. Refers to the Panel C and D, the obtained coefficients on α_2 are positive and statistically significant in conventional cryptocurrencies and non-fungible tokens during high and low volatility days. However, the value of coefficient α_2 is negative and statically significant in Defi assets during the low volatility days. Finally, refers to panel E and F, the coefficients on α_2 also show the anti-herding behavior in all three types of cryptocurrencies during high and low volume/trading days.

Table 4 provides the results of herding during the bubble period. The herding is only evident during the bubble period if the coefficient α_3 is found to be statistically negative. The results reveal that the coefficients on α_3 are statistically positive and significant, which provides evidence of anti-herding in all cryptocurrency markets during the bubble period.

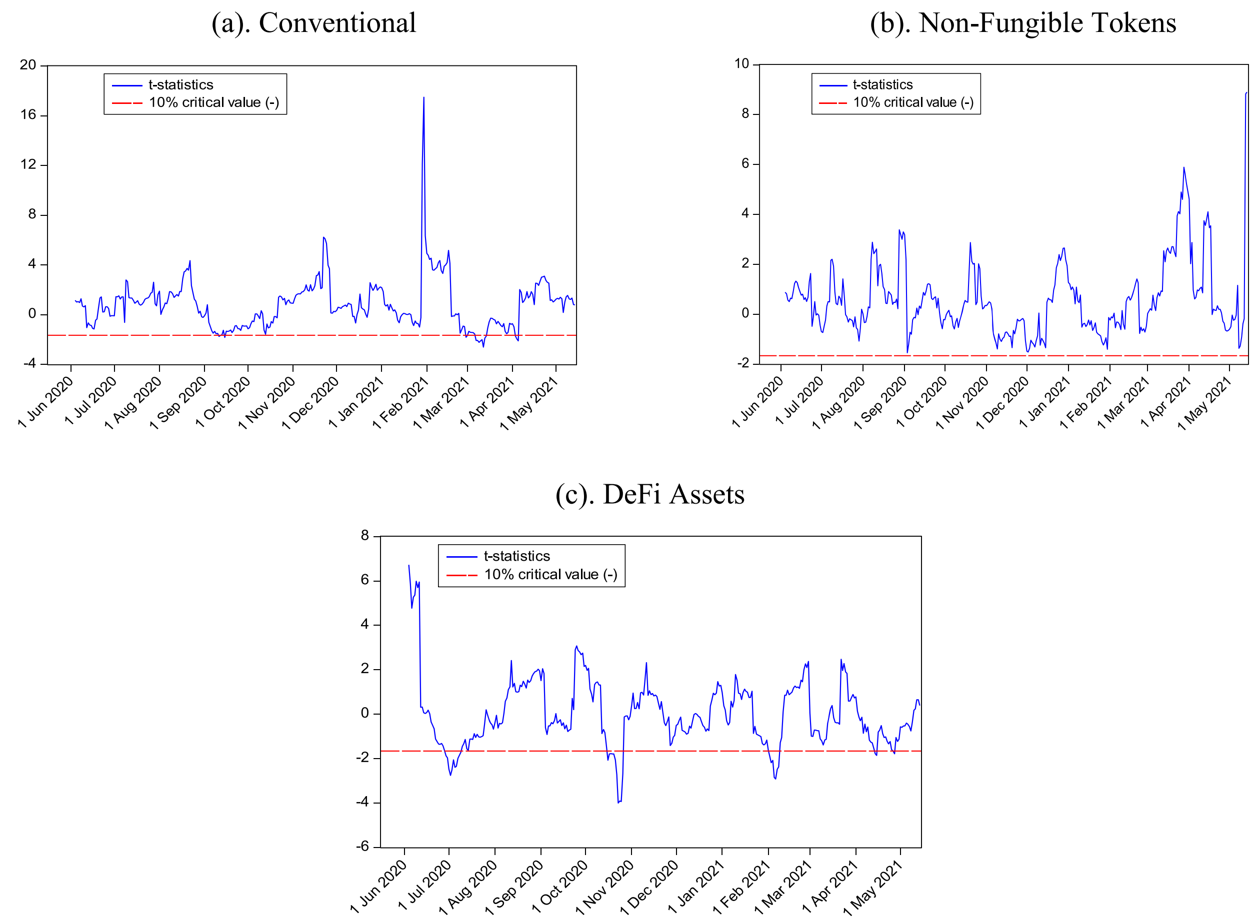

Fig. 1. Time-varying herding.

3.2. Time-varying herding

Fig. 1 illustrates the time-varying herding in three types of cryptocurrencies during the full sample period, i.e., conventional cryptocurrencies, Non-Fungible Tokens (NFTs), and DeFi assets. The length of rolling window is 20 days.[2] In these figures, if t-statistics are below the negative critical value-line (in other words, negative α_2 becomes statistically significant) then it shows the herding behavior. Fig. 1(a) reveals that the time-varying t-statistics values are above the critical value line in most of the sample period. However, the t-statistics of coefficient α_2 is lower than the critical value in conventional cryptocurrencies over 04/03/2021 – 15/03/2021 and 03/04/2021 – 05/04/2021, these timeframes coincide with the bubble period providing evidence of time-varying herding in conventional cryptocurrencies during the bubble period of 2021.

Refers to Fig. 1(b), the t-statistics of coefficient α_2 is above the critical value line in NFTs over the full sample period, showing the time-varying anti-herding behavior in NFTs. Finally, refers to Fig. 1(c), the t-statistics of coefficient α_2 is lower than the critical value in four timeframes, primarily from 28/06/2020 to 09/07/2020, 16/10/2020 to 27/10/2020, 30/01/2021 to 09/02/2021, 13/04/2021 to 16/04/2021, and 25/04/2021 to 28/04/2021. Hence, the time-varying herding is evident in DeFi assets during 2020 and 2021.

4. Conclusion

We estimate the static and time-varying herding in three categories of cryptocurrency markets, namely conventional cryptocurrencies, non-fungible tokens, and DeFi assets. The static herding is not evident during the full sample period, asymmetries (up/down market, high/low volatility, high/low trading days), and bubble period in all three types of cryptocurrencies, except for the DeFi assets. Herding is only detected during low volatility days in DeFi assets. The time-varying results provide the evidence of herding in conventional cryptocurrency market and Defi assets for shorter timeframes, indicating that the investors behaviors are dynamic and

[2] The findings are robust to little expanding or shrinking the currently used rolling window. These results are not reported here due to space constraints.

not always rational in these two categories of markets. It implies that investors cannot get sufficient diversification benefits by investing in conventional cryptocurrencies and Defi assets only. For policymakers, the shorter horizons-based time-varying herding is the signal of high volatility and market instability in conventional cryptocurrency and Defi assets markets, therefore they should design policies in such a way that their market becomes less prone to the short-term herding in these markets. . The static and time-varying anti-herding in NFTs show that the non-fungible tokens market is more efficient than conventional cryptocurrencies and Defi markets, implying that the greater portfolio diversification benefits can be achieved by investing in NFTs.

CRediT authorship contribution statement

Imran Yousaf: Conceptualisation; data collection and analysis; Software; writing.
Larisa Yarovaya: Conceptualisation; literature review; writing and editing.

Declaration of Competing Interest

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

Data Availability

Data will be made available on request.

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