Finance Research Letters 46 (2022) 102382

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Herding intensity and volatility in cryptocurrency markets during the COVID-19

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A R T I C L E I N F O

JEL codes:
G11
G14
G15
G40

Keywords:
Herding
Bitcoin
Cryptocurrencies
Behavioral finance
COVID-19

A B S T R A C T

This paper investigates whether herding is present before and during the COVID-19 pandemic, analyzing intraday data of Bitcoin and eight altcoins. The herding intensity measure of Patterson and Sharma (2006) is calculated for the first time for cryptocurrency markets. Furthermore, we employed a novel Granger causality methodology with a Fourier approximation to determine the relationship between herding and volatility, considering the structural breaks. Our results indicate a significant herding behavior, concentrating during the COVID-19 outbreak. The causality test results show that herding has a significant effect on market volatility. Our results do not support the efficient market hypothesis.

1. Introduction

Cryptocurrencies (CCs) have become a popular topic of discussion among investors, portfolio managers, policymakers, and academics due to their different characteristics and high performance recently. As of February 2021, there are 299 exchanges with a total market capitalization of $ 1.16 trillion worldwide, with 4010 CCs being traded[1]. Although in the beginning, they emerged as secure "payment tools" in which Blockchain technology was used, with the realization of their potential to generate high returns, they turned into rapidly growing speculative "investment tools" (Baur et al., 2018). Their low correlation with traditional investment tools (Bouri et al., 2017 and Corbet et al., 2018), lower transaction costs than traditional currencies (Stavroyiannis and Babalos, 2019), and their functioning as a safe haven, especially in times of economic uncertainty (Bouri et al. 2019), have increased their popularity. However, more recent papers, such as Drożdż et al. (2020) and Watorek et al. (2021), argued that the CC market has become coupled to traditional markets such as currencies, stocks, and commodities during the COVID-19 pandemic. The CC markets have failed in maturing and deepening, suffered from a lack of legal regulations and quality information, thus fluctuating excessively compared to traditional investment tools. On the other hand, Drożdż et al. (2018) stated that CCs had carried the potential of becoming a regular market.

The efficient market theory (EMT) suggests that price formation in markets is based on fundamental factors; however, the theory cannot explain the volatility in speculative markets (Javaira and Hassan, 2015). Therefore, the excessive volatility in CC markets might

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[1] Bitcoin is the largest CC, with a market value of about $ 716 billion, and Binance is the largest CC exchange with a daily transaction volume of around $ 21 billion. (coinmarketcap.com, February 4, 2021).

https://doi.org/10.1016/j.frl.2021.102382
Received 21 February 2021; Received in revised form 8 June 2021; Accepted 15 August 2021
Available online 17 August 2021
1544-6123/

be explained by behavioral factors, such as herding[2]. Herding refers to the investor's tendency to mimic the behavior of other investors. It is essential to study the herding behavior in CC markets since the value of CCs heavily relies on the beliefs and decisions of individuals rather than fundamental factors (Kumar, 2020). Furthermore, studying herding is vital since it may lead to bubbles or market crashes (Lux, 1995).

The Cross-Sectional Standard Deviation (CSSD) and Cross-Sectional Absolute Deviation (CSAD) proposed by Christie and Huang (1995) and Chang et al. (2000), respectively, are standard techniques used to measure herding in financial markets. These are the static measures that are based on returns' dispersion. Since they do not consider structural breaks and nonlinearities in data, many researchers have included dynamic models in their analysis. Among these studies, Bouri et al. (2019) examined herding for 14 CCs and found no significant herding under static models but evidenced herding after applying rolling window techniques. Besides, they argued that the tendency to herd increased as uncertainty increased. In contrast, Stavroyiannis and Babalos (2019) examined eight CCs by employing these two static models and the time-varying parameter regression model proposed by Nakajima (2011). They found that herding was no longer present when a more sophisticated model was used. Calderón (2018) examined asymmetric herding for 100 CCs and found herding when the market exhibited positive returns under static models. However, their Markov regime-switching results indicated herding under extreme market declines. Haryanto et al. (2020) found herding in both up and down periods and suggested that herding moves along the market trends. Vidal-Tomas et al. (2019) examined asymmetric herding for 65 CCs using these two static models and observed herding only during down markets. They also found that the smallest CCs were herding with the largest ones. Similarly, Ballis and Drakos (2020) examined asymmetric herding for six major CCs; in contrast to the findings of Vidal-Tomas et al. (2019), they found the presence of herding during up movements[3].

In addition to the CSSD and CSAD models, da Gama Silva et al. (2019) employed the beta herding model developed by Hwang and Salmon (2004) that supported the presence of herding, where the others failed. However, Kaiser and Stöckl (2020) employed the same measures, all of which supported herding. Also, they showed that Bitcoin was the "transfer currency" that herding measures centered around. Raimundo Júnior et al. (2020) employed the state-space model from Hwang and Salmon (2004), adapting the standardized-beta methodology by Hwang et al. (2018). They found a strong correlation between herding parameters and market stress (high volatile days), suggesting that herding is potentially higher in market stress. Similarly, the findings of Kumar (2020) and Jalal et al. (2020) supported the existence of herding under high volatility after they employed the CSAD measure.

This paper examines herding behavior in CC markets and its causal linkages with realized volatility. We contribute the related literature in several aspects. First, the herding intensity measure of Patterson and Sharma (2006) is calculated for the first time for Bitcoin and eight other altcoins, Cardano (ADA), Binance Coin (BNB), EOS.io (EOS), Ethereum (ETH), Litecoin (LTC), Tron (TRX), Stellar (XLM), and Ripple (XRP). The herding intensity measure at daily frequency is built upon intraday data, containing valuable information about the dynamics of such markets where drastic price changes in CCs are usual. We analyze a large dataset containing intraday orderbook information of the selected CCs traded in Binance to calculate the herding intensity statistics. Second, we examine the herding behavior in the CCs during the COVID-19 pandemic, which has altered investing behavior in the markets due to the halted industrial production process and precautions taken by policymakers. Chauhan et al. (2020) argue that investors follow the crowd decision by suppressing their private information during the turbulent period of uncertainty. Here, we consider the COVID-19 pandemic period as an uncertainty period and divide our sample period into two, before and during the pandemic, to mention any difference[4]. The remarkable price increase observed in bitcoin and other CCs, especially during the pandemic period, motivated us to do this research[5]. Third, given that the sample period between December 2018 and January 2021 covers the COVID-19 outbreak, we employ an econometric framework considering structural breaks in the data. The multiple break procedure of Bai and Perron (2003) is employed to detect the structural break dates in the herding activity. Fourth, we extend the studies of Raimundo Júnior et al. (2020), Kumar (2020), and Jalal et al. (2020), examining the relationship between herding and volatility by implementing a Granger causality methodology with Fourier approximation, capturing nonlinearities in the data.

The paper is organized as following the introduction; the second section consists of methodology; the third section presents data and empirical results; the last section concludes the paper.

2. Methodology

The Patterson and Sharma (2006) statistics measuring herding intensity is based on the following random variable:

$$\chi(i,j,t) = \frac{(r_i + 1/2) - np_i(1 - p_i)}{\sqrt{n}} \tag{1}$$

where r_i is the actual number of runs of type i (positive, negative, or zero returns); ½ is a discontinuity adjustment parameter; n is the

[2] A few researchers show that investors tend to herd more when the CC market is highly volatile (see, Raimundo Júnior et al., 2020; Kumar, 2020; and Jalal et al., 2020).

[3] According to Bouri et al. (2018) selling pressure in the cryptocurrency market might be limited since short selling is not allowed on most cryptocurrencies.

[4] COVID-19 was recognized as a pandemic by the World Health Organization (WHO) on January 30, 2020.

[5] After the announcement of the COVID-19 as pandemic by the WHO, following declines in stock markets, the price of Bitcoin has begun to decrease and reached to the lowest level of the year as $3,850 on March 2020. Then, its price increased almost 12 times and has reached to $47,545 at the mid of February 2021.

Table 1
Total Number of Trades and Runs ('000).

	Total Trades	Positive Trades	Negative Trades	Zero Trades	Positive Runs	Negative Runs	Zero Runs
ADA	38,470	12,347	12,681	13,442	7,815	7,814	6,863
BNB	80,683	30,163	31,432	19,088	15,821	15,685	10,216
BTC	429,641	147,662	149,786	132,193	83,796	83,843	60,457
EOS	53,854	19,305	19,763	14,786	11,257	11,295	8,533
ETH	165,258	53,688	54,489	57,081	34,237	34,269	29,071
LTC	55,955	16,641	16,958	22,356	11,446	11,457	10,856
TRX	29,829	6,943	6,992	15,894	5,724	5,712	6,066
XLM	30,095	9,801	9,957	10,337	6,161	6,133	5,078
XRP	94,463	32,342	33,362	28,759	19,634	19,677	14,995

Table 2
Herding Intensity Statistics, Median.

	Dec 2018 - Jan 2021			Dec 2018 - Dec 2019			Jan 2020 - Jan 2021		
	H^n	H^p	H^z	H^n	H^p	H^z	H^n	H^p	H^z
ADA	-14.352	-14.149	-19.909	-8.802	-8.681	-16.155	-18.927	-19.536	-25.66
BNB	-26.67	-28.343	-94.242	-23.818	-23.534	-73.889	-28.789	-31.751	-128.242
BTC	-14.912	-15.328	-206.936	7.132	6.141	-160.615	-123.17	-123.352	-260.889
EOS	-11.414	-10.363	-49.873	-6.539	-5.435	-53.992	-17.685	-16.165	-45.821
ETH	-7.037	-5.971	-57.989	12.371	12.228	-53.537	-37.875	-36.783	-65.115
LTC	-12.053	-12.038	-11.568	-7.642	-6.427	-14.428	-18.674	-19.107	-9.366
TRX	-22.998	-23.365	-12.747	-12.129	-12.389	-10.989	-29.91	-30.669	-14.677
XLM	-8.727	-8.821	-25.157	-4.614	-3.967	-26.271	-13.643	-14.43	-23.967
XRP	-10.64	-10.154	-54.15	6.517	6.799	-59.848	-24.488	-22.576	-48.128

total number of trades in CC *j* on date *t*; *p* is the probability of a run from type *i*. $\chi(i, j, t)$ has an asymptotic normal distribution with zero mean and variance $\sigma^2(i,j,t) = p_i(1-p_i) - 3p_i^2(1-p_i)^2$. The herding intensity measure can be calculated as:

$$H(i,j,t) = \frac{\chi(i,j,t)}{\sqrt{\sigma^2(i,j,t)}} \rightarrow N(0,1) \tag{2}$$

We calculate three herding intensity measures: Buyer-initiated (positive returns, H^p), seller-initiated (negative returns, H^n), and zero tick (zero return, H^z). For large samples, such as those analyzed in this paper, $H(i, j, t)$ follows a normal distribution and variance of one. Average (median) $H(i, j, t)$ statistics taking value larger than the critical value of -1.96 imply a statistically significant herding intensity at the 5% level.

For causality testing, we apply the augmented TY procedure with a Fourier approximation, considering structural shifts, relaxing the assumption that the intercepts are constant over time Nazlioglu et al. (2019):

$$y_t = \alpha(t) + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \ldots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \tag{3}$$

where y_t is a vector of *k* endogenous variables, *d* is the maximum degree of integration, ε_t is a vector of error terms, and β is the matrix of parameters, $\alpha(t)$ is the Fourier approximation:

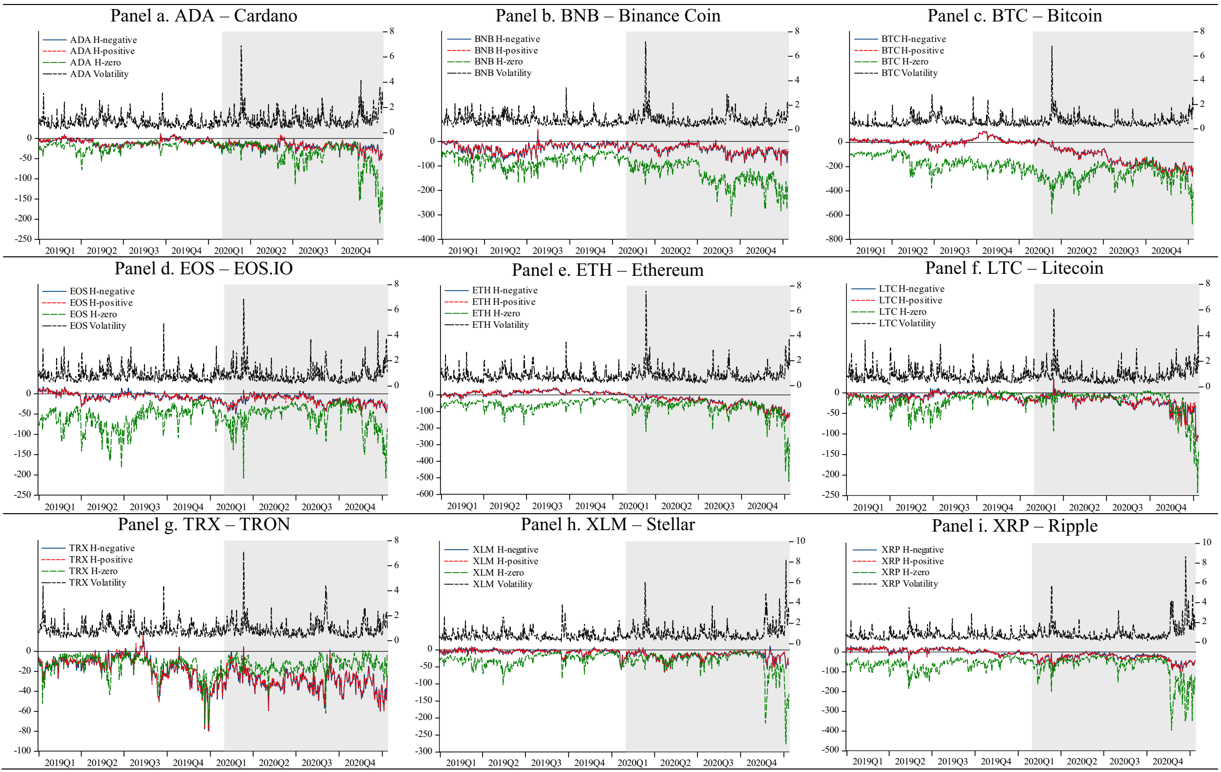
$$\alpha(t) \cong \alpha_0 + \sum_{k=1}^{n} \alpha_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \beta_k \cos\left(\frac{2\pi kt}{T}\right) \tag{4}$$

where *n* is the number of frequencies; *k* is a particular frequency; α_k and β_k, respectively, measure the amplitude and displacement of the frequency; *T* is the number of observations (Enders and Lee, 2012, p. 197; Nazlioglu et al., 2019). We estimate the model with cumulative frequencies, setting *n* greater than unity. For d=0, Eq. 3 simplifies to the VAR model with the Fourier approximation developed by Enders and Jones (2016) to test Granger causality between stationary, *I*(0), variables. By imposing zero restriction on the first *p* parameters in (3), we obtain *Wald* statistics following χ^2 distribution, with *p* degrees of freedom, under the null hypothesis of Granger non-causality against the alternative hypothesis of Granger causality.

3. Data and empirical results

We obtain the orderbook containing intraday-trading data from the Binance exchange[6] for Bitcoin (BTC) and eight other altcoins, Cardano (ADA), Binance Coin (BNB), EOS.io (EOS), Ethereum (ETH), Litecoin (LTC), Tron (TRX), Stellar (XLM), and Ripple (XRP). The

[6] https://www.binance.com/



Note: The shaded areas denote the NBER-based recession period and the COVID-19 outbreak, beginning from late January 2020.

Fig. 1. Herding Intensity and Volatility
Note: The shaded areas denote the NBER-based recession period and the COVID-19 outbreak, beginning from late January 2020.

Table 3
Bai and Perron (2003) Multiple Break Analysis.

Asset	Break-1	Break-2	Subsample-1	Subsample-2	Subsample-3
ADA-H^n	9/20/2019	1/9/2020	-2.156 [a]	-1.073 [a]	-2.957 [a]
ADA-H^p	4/27/2019	7/8/2020	-1.420 [a]	-2.345 [a]	-3.141 [a]
ADA-H^z	7/21/2019	4/23/2020	-3.120 [a]	-2.632 [a]	-3.622 [a]
BNB-H^n	7/23/2019	8/16/2020	-3.333 [a]	-2.824 [a]	-3.852 [a]
BNB-H^p	7/23/2019	8/26/2020	-3.253 [a]	-2.847 [a]	-3.798 [a]
BNB-H^z	2/5/2020	7/6/2020	-4.314 [a]	-4.580 [a]	-5.131 [a]
BTC-H^n	3/1/2020	7/9/2020	0.690 [a]	-4.121 [a]	-5.247 [a]
BTC-H^p	3/1/2020	7/9/2020	0.711 [a]	-4.170 [a]	-5.242 [a]
BTC-H^z	5/9/2019	1/6/2020	-4.581 [a]	-5.244 [a]	-5.564 [a]
EOS-H^n	9/5/2019	8/9/2020	-0.479 [a]	-2.233 [a]	-3.137 [a]
EOS-H^p	4/21/2019	8/9/2020	0.110	-2.087 [a]	-3.180 [a]
EOS-H^z	8/6/2019	1/9/2020	-4.267 [a]	-3.674 [a]	-3.896 [a]
ETH-H^n	2/3/2020	7/22/2020	1.752 [a]	-3.129 [a]	-4.207 [a]
ETH-H^p	2/3/2020	7/22/2020	1.712 [a]	-3.140 [a]	-4.227 [a]
ETH-H^z	9/4/2019	7/22/2020	-4.154 [a]	-3.842 [a]	-4.542 [a]
LTC-H^n	11/3/2019	8/11/2020	-1.377 [a]	-2.381 [a]	-3.466 [a]
LTC-H^p	11/9/2019	8/10/2020	-1.686 [a]	-2.451 [a]	-3.441 [a]
LTC-H^z	4/21/2019	8/10/2019	-2.856 [a]	-3.522 [a]	-2.180 [a]
TRX-H^n	5/9/2019	8/28/2019	-2.504 [a]	-1.461 [a]	-3.336 [a]
TRX-H^p	5/9/2019	8/28/2019	-2.491 [a]	-1.539 [a]	-3.331 [a]
TRX-H^z	8/22/2019	8/17/2020	-2.244 [a]	-2.816 [a]	-2.349 [a]
XLM-H^n	5/5/2019	1/19/2020	-0.917 [a]	-1.531 [a]	-2.779 [a]
XLM-H^p	5/11/2019	1/19/2020	-0.981 [a]	-1.653 [a]	-2.737 [a]
XLM-H^z	7/2/2019	1/16/2020	-3.595 [a]	-2.891 [a]	-3.260 [a]
XRP-H^n	11/5/2019	7/30/2020	1.504 [a]	-2.705 [a]	-3.512 [a]
XRP-H^p	11/2/2019	2/21/2020	1.454 [a]	-2.200 [a]	-3.319 [a]
XRP-H^z	7/27/2019	9/24/2020	-4.293 [a]	-3.866 [a]	-4.482 [a]

Note: H^n, H^p, and H^z are Herding Intensity measures, buyer-initiated, seller-initiated, and neutral. a, b, and c denote the statistical significance at the 1%, 5%, and 10% levels, respectively. The break dates are determined based on the Bai and Perron (2003) procedure.

Table 4
Unit Root Test Results, Enders and Lee, 2012.

	Level			First Diff.		
	ADF-stat	Freq.	Lag	ADF-stat	Freq.	Lag
ADA-H^n	-5.840 [a]	3	2	-17.399 [a]	3	4
ADA-H^p	-6.040 [a]	3	2	-23.015 [a]	3	2
ADA-H^z	-5.356 [a]	1	2	-26.002 [a]	2	1
ADA-Vol	-8.137 [a]	3	3	-17.179 [a]	2	5
BNB-H^n	-10.161 [a]	3	1	-16.749 [a]	3	6
BNB-H^p	-10.040 [a]	3	1	-15.923 [a]	3	7
BNB-H^z	-3.828 [b]	1	5	-17.971 [a]	2	4
BNB-Vol	-10.066 [a]	3	2	-17.569 [a]	2	5
BTC-H^n	-3.562 [c]	1	4	-21.456 [a]	2	3
BTC-H^p	-2.524	3	4	-17.003 [a]	2	5
BTC-H^z	-2.395	3	6	-17.482 [a]	3	5
BTC-Vol	-7.771 [a]	3	3	-17.259 [a]	3	5
EOS-H^n	-3.751 [b]	2	4	-17.111 [a]	3	5
EOS-H^p	-3.524 [b]	3	6	-18.573 [a]	3	5
EOS-H^z	-5.070 [a]	1	3	-22.221 [a]	2	2
EOS-Vol	-8.318 [a]	3	3	-27.052 [a]	2	2
ETH-H^n	-4.517 [a]	1	4	-19.818 [a]	1	3
ETH-H^p	-4.355 [a]	1	12	-9.458 [a]	1	11
ETH-H^z	-4.420 [a]	1	3	-22.450 [a]	1	2
ETH-Vol	-8.433 [a]	3	3	-17.434 [a]	2	5
LTC-H^n	-5.065 [a]	1	3	-26.764 [a]	3	2
LTC-H^p	-6.070 [a]	1	2	-23.778 [a]	3	2
LTC-H^z	-4.582 [a]	1	3	-23.702 [a]	2	2
LTC-Vol	-8.212 [a]	2	2	-17.119 [a]	2	5
TRX-H^n	-5.285 [a]	1	4	-17.954 [a]	3	4
TRX-H^p	-5.723 [a]	1	3	-18.241 [a]	3	4
TRX-H^z	-6.611 [a]	1	5	-21.129 [a]	1	3
TRX-Vol	-7.882 [a]	3	3	-24.989 [a]	1	2
XLM-H^n	-8.253 [a]	1	3	-20.552 [a]	3	3
XLM-H^p	-5.245 [a]	3	4	-21.076 [a]	3	3
XLM-H^z	-5.037 [a]	2	2	-24.181 [a]	2	1
XLM-Vol	-9.338 [a]	3	2	-12.632 [a]	2	11
XRP-H^n	-3.964 [b]	1	4	-11.658 [a]	2	11
XRP-H^p	-4.217 [b]	1	3	-20.572 [a]	2	3
XRP-H^z	-5.193 [a]	1	2	-21.293 [a]	1	2
XRP-Vol	-6.917 [a]	1	2	-16.775 [a]	2	5

Note: H^n, H^p, and H^z are Herding Intensity measures, buyer-initiated, seller-initiated, and neutral. Vol is the realized volatility, following the Parkinson's (1980) method. a, b, and c denote the statistical significance at the 1%, 5%, and 10% levels, respectively. Fourier frequencies (Freq.) and lags are determined based on the Schwarz Information Criterion.

orderbook data cover the period December 31, 2018 – January 12, 2021. The data are in terms of Tether (USDT), a base cryptocurrency fluctuating close to one US dollar. We report the summary statistics regarding the total number of trades and runs in Table 1, indicating that Bitcoin has the highest trading volume, with more than 400 million orders over the sample period.

In the first stage of the analysis, following the procedures described in Patterson and Sharma (2006), we construct daily herding intensity statistics for all CCs. Table 2 reports the median of the herding intensity statistics over the full-sample period and two subsamples determined by the COVID-19 outbreak in January 2020. Median herding intensity statistics take negative values during the full-sample period, ranging from -206.94 to -5.97, suggesting statistically significant herding behavior at the 1% level. We observe different behavior across subsamples. The buyer- and (H^p) seller-initiated (H^n) herding measures in the earlier subsample period, December 2018-December 2019, suggest no evidence of herding for Bitcoin, Ethereum, and Ripple. The herding intensity statistics are smaller (more negative) during the second subsample period, January 2020-January 2021, than those of the first subsample, suggesting a greater probability of herding for all CCs during the latter subsample. Overall, the results suggest significant herding behavior intensified during the COVID-19 period, illustrated in Fig. 1.

Given the changing trader behavior across arbitrarily determined subsamples, we check endogenously detected structural breaks in the herding intensity measures, employing the Bai and Perron (2003) multiple structural change procedure, allowing up to two breaks given the length of the sample period. Table 3 reports that the parameters are mostly negative, changing across the subsamples and more negative in the last subsamples, supporting the previous analysis that herding behavior intensified in 2020. The tests detect the most breaks in the third quarter of 2020, followed by the breaks clustered around the beginning of 2020. The H^Z series for Bitcoin and most altcoins are more reactive to the increases in volatility, taking lower values than H^p and H^n. Investors tend to split large trades into small ones due to widening bid-ask spreads, further increasing volatility (Madhavan et al., 1997), and reducing efficiency (Habermeier and Kirilenko, 2003). Investors' such decisions, particularly during high volatility periods, might be reflected in the zero-tick sequences, stimulated by the market microstructure where the minimum tick size approaching zero reduces market resiliency (Foucault et al., 2005). Overall, the detected herding behavior in the CC markets is not consistent with the EMT.

Table 5
Causality between Herding Intensity and Realized Volatility.

	Herding $\neq>$ Volatility				Volatility $\neq>$ Herding			
	Wald Stat	Bootstrap p-value	Lag	Freq.	Wald Stat	Bootstrap p-value	Lag	Freq.
ADA-H^n	47.582 [a]	0.000	2	3	2.734	0.249	2	3
ADA-H^p	67.272 [a]	0.000	3	3	3.118	0.377	3	3
ADA-H^z	487.416 [a]	0.000	2	3	3.467	0.184	2	3
BTC-H^n	86.576 [a]	0.000	3	3	10.689 [b]	0.016	3	3
BTC-H^p	81.427 [a]	0.000	3	3	8.448 [b]	0.046	3	3
BTC-H^z	554.221 [a]	0.000	2	3	32.617 [a]	0.000	2	3
BNB-H^n	116.887 [a]	0.000	2	3	2.235	0.325	2	3
BNB-H^p	113.856 [a]	0.000	2	3	2.823	0.222	2	3
BNB-H^z	545.944 [a]	0.000	3	3	23.042 [a]	0.000	3	3
EOS-H^n	27.405 [a]	0.000	3	3	9.543 [b]	0.028	3	3
EOS-H^p	34.055 [a]	0.000	1	3	0.081	0.786	1	3
EOS-H^z	731.840 [a]	0.000	2	3	26.288 [a]	0.000	2	3
ETH-H^n	57.634 [a]	0.000	1	3	1.905	0.174	1	3
ETH-H^p	70.305 [a]	0.000	2	3	10.000 [a]	0.010	2	3
ETH-H^z	773.328 [a]	0.000	2	3	26.377 [a]	0.000	2	3
LTC-H^n	1.714	0.202	1	3	0.188	0.667	1	3
LTC-H^p	0.134	0.712	1	3	0.698	0.421	1	3
LTC-H^z	235.189 [a]	0.000	3	3	16.407 [a]	0.001	3	3
TRX-H^n	0.225	0.647	1	3	1.119	0.287	1	3
TRX-H^p	2.166	0.132	1	3	3.389 [c]	0.063	1	3
TRX-H^z	31.442 [a]	0.000	1	3	0.547	0.476	1	3
XLM-H^n	55.182 [a]	0.000	1	3	8.413 [a]	0.003	1	3
XLM-H^p	67.255 [a]	0.000	1	3	6.763 [b]	0.012	1	3
XLM-H^z	462.034 [a]	0.000	2	3	12.869 [a]	0.001	2	3
XRP-H^n	151.019 [a]	0.000	3	3	5.745	0.118	3	3
XRP-H^p	157.487 [a]	0.000	2	3	9.605 [a]	0.009	2	3
XRP-H^z	1066.888 [a]	0.000	3	3	10.936 [b]	0.013	3	3

Note: H^n, H^p, and H^z are Herding Intensity measures, buyer-initiated, seller-initiated, and neutral. a, b, and c denote the statistical significance at the 1%, 5%, and 10% levels, respectively. Fourier frequencies (Freq.) and lags are determined based on the Schwarz Information Criterion.

In the second stage of the analysis, we investigate the Granger causality between herding intensity statistics and volatility. The daily (annualized) volatility (*Vol*) for CC *j* at date *t* is calculated following Parkinson (1980), using the daily high (P_{jt}^{High}) and low (P_{jt}^{Low}) prices (USDT) obtained from Binance:

$$Vol = 100\sqrt{365 \times \left(0.361\left[\ln\left(P_{jt}^{High} \middle/ P_{jt}^{Low}\right)\right]^2\right)} \tag{5}$$

We analyze the natural logarithm of the time-series, applying the log-modulus transformation of John and Draper (1980).

The results of the ADF unit root test, augmented with a Fourier approximation by Enders and Lee (2012), are reported in Table 4. The tests suggest rejecting the null hypothesis of unit root at the conventional levels for the series, except the buyer-initiated and zero-tick herding intensity for Bitcoin. The integrated time-series become stationary after they are first-differenced, denoting that they are integrated of order one, and the remaining series are stationary at their levels.

Having determined the maximum degree of integration (*d*), we estimate bi-variate VAR models using one of three herding intensity measures and volatility for each CC. Table 5 shows the Fourier Granger causality testing results. The Wald statistics suggest rejecting the null hypothesis of no causality from herding to volatility at the 1% level, or better, for all cases, except the buyer- and seller-initiated herding intensity measures for Litecoin and Tron. We can reject the null hypothesis of no causality from volatility to (at least) one of the herding measures for all cases at the 10% level, or better, except for Cardano. Even though the results suggest a bi-directional feedback relationship between herding and volatility for most of the CCs, we reach relatively more robust causality running from herding to volatility. Our results agree with those of Raimundo Júnior et al. (2020), Kumar (2020), and Jalal et al. (2020), supporting the notion that herding behavior causes volatility in the markets.

4. Conclusion

The above methodology is applied for the first time in CC markets. Using the herding intensity measure of Patterson and Sharma (2006), we detect significant herding behavior intensified by the COVID-19 outbreak. The herding behavior contradicts the EMT, denoting an irrational price formation in the CC markets. Moreover, the causality-testing results suggest that herding behavior has a significant impact on market volatility.

Our results are of importance for investors, policymakers, and academics. Investors should be aware of the herding behavior, which may adversely affect their portfolio values due to changing volatility structure in the markets. One possible reason for increased herding behavior by COVID-19 may be the excessive monetary expansion and (miss-)allocation of resources (e.g., pandemic-related incentives, stimulus checks) created by policymakers. The policymakers should make more sound decisions regarding the legal structure of CC markets and their integration with the conventional financial markets. Regarding market microstructure, cryptocurrency exchange platforms might adjust minimum tick sizes to prevent trading activities from reducing market resiliency. Academics may conduct future research on the drivers of herding behavior in the CC markets, mainly focusing on the social media-based investor sentiment to gain more detailed insight into their trading structure.

CRediT authorship contribution statement

Pinar Evrim Mandaci: Writing – original draft, Formal analysis, Conceptualization, Supervision, Validation, Writing – review & editing. **Efe Caglar Cagli:** Writing – original draft, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – review & editing.

Declarations of Competing Interest

None.

References

Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. J. Appl. Econom. 18, 1–22. https://doi.org/10.1002/jae.659.

Ballis, A., Drakos, K., 2020. Testing for herding in the cryptocurrency market. Financ. Res. Lett. 33, 101210 https://doi.org/10.1016/j.frl.2019.06.008.

Baur, D.G., Hong, K.H., Lee, A.D., 2018. Bitcoin: Medium of exchange or speculative assets? J. Int. Financ. Markets Inst. Money 54, 177–189. https://doi.org/10.1016/j.intfin.2017.12.004.

Bouri, E., Gupta, R., Roubaud, D., 2019. Herding behaviour in cryptocurrencies. Financ. Res. Lett. 29, 216–221. https://doi.org/10.1016/j.frl.2018.07.008.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L.I., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Financ. Res. Lett. 20, 192–198. https://doi.org/10.1016/j.frl.2016.09.025.

Calderón, O.P., 2018. Herding Behavior In Cryptocurrency Markets. Universitat Autònoma de Barcelona. Department of Applied Economics Spain. Working Paper.

Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. J. Bank. Financ. 24, 1651–1679. https://doi.org/10.1016/S0378-4266(99)00096-5.

Chauhan, Y., Ahmad, N., Aggarwal, V., Chandra, A., 2020. Herd behaviour and asset pricing in the Indian stock market; Herd behavior and asset pricing. IIMB Manag. Rev. 32, 143–152. https://doi.org/10.1016/j.iimb.2019.10.008.

Christie, W.G., Huang, R.D., 1995. Following the pied piper: do individual returns herd around the market? Financ. Anal. J. 51, 31–37. https://doi.org/10.2469/faj.v51.n4.1918.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L., 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. Econ. Lett. 165, 28–34. https://doi.org/10.1016/j.econlet.2018.01.004.

da Gama Silva, P.V.J., Klotzle, M.C., Pinto, A.C.F., Gomes, L.L., 2019. Herding behavior and contagion in the cryptocurrency market. J Behav. Exp. Finance 22, 41–50. https://doi.org/10.1016/j.jbef.2019.01.006.

Drożdż, S., Gębarowski, R., Minati, L., Oświęcimka, P., Wątorek, M., 2018. Bitcoin market route to maturity? Evidence from return fluctuations, temporal correlations and multiscaling effects featured. Chaos 28, 071101. https://doi.org/10.1063/1.5036517.

Drożdż, S., Kwapień, J., Oświęcimka, P., Stanisz, T., Wątorek, M., 2020. Complexity in Economic and Social Systems: Cryptocurrency Market at around COVID-19. Entropy 22, 1043. https://doi.org/10.3390/e22091043.

Enders, W., Jones, P., 2016. Grain prices, oil prices, and multiple smooth breaks in a VAR. Stud. Nonlinear Dyn. E. 20, 399–419. https://doi.org/10.1515/snde-2014-0101.

Enders, W., Lee, J., 2012. The flexible Fourier form and Dickey-Fuller type unit root tests. Econ. Lett. 117, 196–199. https://doi.org/10.1016/j.econlet.2012.04.081.

Foucault, T., Kadan, O., Kandel, E., 2005. Limit order book as a market for liquidity. Rev. Financ. Stud. https://doi.org/10.1093/rfs/hhi029.

Haryanto, S., Subroto, A., Ulpah, M., 2020. Disposition effect and herding behavior in the cryptocurrency market. J. Ind. Bus. Econ. 47, 115–132. https://doi.org/10.1007/s40812-019-00130-0.

Habermeier, K., Kirilenko, A.A., 2003. Securities transaction taxes and financial markets. IMF Staff Pap 501 (50), 165–180. https://doi.org/10.2307/4149921, 2003.

Hwang, S., Rubesam, A., Salmon, M., 2018. Overconfidence, sentiment and beta herding: a behavioral explanation of the low-beta anomaly. SSRN Electr. J., 3224321

Hwang, S., Salmon, M., 2004. Market stress and herding. J. Empir. Finance 11, 585–616. https://doi.org/10.1016/j.jempfin.2004.04.003.

Jalal, R.N.U.D., Sargiacomo, M., Sahar, N.U., Fayyaz, U.E.R., 2020. Herding behavior and cryptocurrency: market asymmetries, inter-dependency and intra-dependency. J. Asian Financ. Econ. Bus. 7, 27–34. https://doi.org/10.13106/jafeb.2020.vol7.no7.027.

Javaira, Z., Hassan, A., 2015. An examination of herding behavior in Pakistani stock market. Int. J. Emerg. Mark. 10, 474–490. https://doi.org/10.1108/IJoEM-07-2011-0064.

John, J.A., Draper, N.R., 1980. An alternative family of transformations. Appl. Stat. 29, 190–197. https://doi.org/10.2307/2986305.

Kaiser, L., Stöckl, S., 2020. Cryptocurrencies: Herding and the transfer currency. Financ. Res. Lett. 33, 101214 https://doi.org/10.1016/j.frl.2019.06.012.

Kumar, A., 2020. Empirical investigation of herding in cryptocurrency market under different market regimes. Rev. Behav. Financ. https://doi.org/10.1108/RBF-01-2020-0014.

Lux, T., 1995. Herd behaviour, bubbles and crashes. Econ. J. 105, 881–896. https://doi.org/10.2307/2235156.

Madhavan, A., Richardson, M., Roomans, M., 1997. Why do security prices change? A transaction-level analysis of NYSE stocks. Rev. Financ. Stud. 10, 1035–1064. https://doi.org/10.1093/rfs/10.4.1035.

Nakajima, J., 2011. Time-varying parameter VAR model with stochastic volatility: an overview of methodology and empirical applications. Monet. Econ. Stud. 29, 107–142.

Nazlioglu, S., Gormus, A., Soytas, U., 2019. Oil prices and monetary policy in emerging markets: structural shifts in causal linkages. Emerg. Mark. Financ. Trade 55, 105–117. https://doi.org/10.1080/1540496X.2018.1434072.

Parkinson, M., 1980. The extreme value method for estimating the variance of the rate of return. J. Bus. 53, 61–65. https://doi.org/10.1086/296071.

Patterson, D.M., Sharma, V., 2006. Do Traders Follow Each Other At The NYSE? University of Michigan-Dearborn. Working Paper.

Raimundo Júnior, G.D.S., Palazzi, R.B., Tavares, R.de S., Klotzle, M.C., 2020. Market stress and herding: a new approach to the cryptocurrency market. J. Behav. Financ. https://doi.org/10.1080/15427560.2020.1821688.

Stavroyiannis, S., Babalos, V., 2019. Herding behavior in cryptocurrencies revisited: novel evidence from a TVP model. J. Behav. Exp. Financ. 22, 57–63. https://doi.org/10.1016/j.jbef.2019.02.007.

Vidal-Tomás, D., Ibáñez, A.M., Farinós, J.E., 2019. Herding in the cryptocurrency market: CSSD and CSAD approaches. Financ. Res. Lett. 30, 181–186. https://doi.org/10.1016/j.frl.2018.09.008.

Wątorek, M., Drożdż, S., Kwapień, J., Minati, L., Oświęcimka, P., Stanuszek, M., 2021. Multiscale characteristics of the emerging global cryptocurrency market. Phys. Rep. 901, 1–82. https://doi.org/10.1016/j.physrep.2020.10.005.