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Herding behavior in the cryptocurrency market during COVID-19 pandemic: The role of media coverage

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A B S T R A C T

This paper examines herding behavior in the cryptocurrency market during the COVID-19 pandemic using daily data and based on static and regime-switching models. Furthermore, we investigate whether herding behavior is affected by the coronavirus media coverage. Based on a sample of the top-43 cryptocurrencies in terms of market capitalization between 2013 and 2020, we find significant evidence of herding for the entire sample period only during high volatility state. Moreover, during the COVID-19 crisis, results suggest that investors in the cryptocurrency market follow the consensus. Finally, the impact of coronavirus media coverage is significant on herding among investors, explaining such behavior in the cryptocurrency market during the COVID-19 crisis. Our findings explain herding determinants that may help investors avoid such comportment, mainly during the crisis.

1. Introduction

After the global financial crisis, the cryptocurrency market has experienced rapid growth, which is suggested by the loss of confidence in the existing financial system (Paule-Vianez et al., 2020). Accordingly, cryptocurrencies have acquired a keen interest from academics and market participants due to their high investment benefits and hedging opportunities (Urquhart & Zhang, 2019; Mokni et al., 2020; Mokni, 2021). The main concern on this issue has been focused mainly on these assets' price determinants. Some studies investigate the impact of news on cryptocurrencies. For instance, Vidal-Tomás and Ibañez (2018) examine how Bitcoin responds to monetary policy and Bitcoin events and conclude that investors respond only to Bitcoin news. This result suggests that the Bitcoin market is efficient (semi-strong form) in relation to its own news, while it is inefficient when examining monetary policy events. Furthermore, Corbet et al. (2020a) prove that the price of cryptocurrency's reaction to the US monetary policy announcements varies across the type of digital assets. Academic researchers and professionals have also shown important attention to understand the behavior of investors operating in this new market. Indeed, Kristoufek (2013) detects a positive relationship between Bitcoin price and the search queries on Google Trends and Wikipedia as proxies of investors' interest and attention. Burggraf et al. (2020) claim that investors' sentiment drives the cryptocurrency price. A recent study by Naeem et al. (2021) use two online investor sentiment indexes: the Twitter Happiness sentiment index and the Financial and Economic Attitudes Revealed by Search of American households, to investigate whether online investor sentiment can predict cryptocurrency returns. Naeem et al. (2021) find a significant predictive ability of the two online investor sentiment proxies for six major cryptocurrency returns, confirming the inefficiency of

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cryptocurrencies. Moreover, Naeem et al. (2021) suggest that cryptocurrencies respond more to sentiment transmitted through social media than to macroeconomic news. Bouri et al. (2021) show that cryptocurrencies are used for hedging when investor sentiment is weak. Furthermore, Bouri et al.(2019a) issue an important result suggesting that explosivity in one cryptocurrency leads to explosivity in another. These findings may stem from a potential herding behavior among participants in the cryptocurrency market, which motivate us to investigate herding in the cryptocurrency market.

The cryptocurrency market has received more attention from researchers during the recent coronavirus outbreak (COVID-19), given its harmful impact on the financial markets. Some studies, including Zhang et al. (2020), and Haroon and Rizvi (2020), conclude that the coronavirus crisis enhances the market's volatility, and explain such results by the news that negatively influences the investors' sentiment during the pandemic stage. Indeed, since the emergence of the COVID-19 pandemic, the news was spread quickly, affecting investors' behavior. Zhang et al. (2022) and Mahdi and Al-Abdulla (2022) claim that COVID-19-related media coverage significantly affects some strategic assets, including Bitcoin. In the same line, studies by Rubbaniy et al. (2021) and Mandaci and Cagli (2021) argue that the news flow related to COVID–19 significantly affects investors' behavior in the cryptocurrency market. These findings could be attributable to an overreaction of these investors to such information during the period of stress (Akhtaruzzaman et al., 2021).

Notably, the COVID-19 has raised panic among investors, causing behavioral biases such as herding behavior. Herding behavior means that investors imitate the investment decisions of others without reference to fundamentals (Hwang & Salmon, 2004). This behavior can affect the stability of financial markets by increasing volatility and causing bubbles[1], leading to crushes and financial markets disequilibrium. Therefore, analyzing herding behavior becomes a crucial issue, especially in the cryptocurrency market. In fact, cryptocurrencies are characterized by extraordinary returns, extreme volatility, a weak legal framework, and a lack of quality information (Bouri et al. (2019b), suggest to co-explosivity (Bouri et al. (2019a)), with young participants that lack experience and sufficient knowledge and that trade according to sentiment transmitted via social media such as Google and Twitter (Naeem et al., 2021) rather than fundamentals, especially during the market stress periods. Particularly, over the COVID-19 pandemic, investors tend to be influenced by others regardless of their own analysis, which points to potential herding behavior, possibly intensified by the quantity of news related to this pandemic. Consequently, one can expect a significant relationship between herding and media coverage in the cryptocurrency market, mainly during the COVID-19 pandemic crisis.

Given the uncertainty generated by the ongoing COVID-19 crisis, our first goal in this study is to examine whether the COVID-19 pandemic contributes to herding behavior in the cryptocurrency market. To gain a deeper insight into this issue, our second goal is to explore the impact of coronavirus media coverage on herding behavior among investors in the cryptocurrency market. The cryptocurrency market is characterized by the presence of inexperienced investors (Bouri et al. (2019b) who are affected by media (Philippas et al., 2020). Moreover, cryptocurrencies are susceptible to bubbles and high volatility (Cheung et al., 2015) and exhibit anomalies Susana et al. (2020) (). On the other hand, cryptocurrencies offer a diversification opportunity and serve as a hedge and save haven due to their low correlation with other conventional assets. However, Conlon and McGee (2020) and Corbet et al. (2020b) suggest that cryptocurrencies fail to act as a hedge and safe haven during the COVID-19 pandemic. Therefore, we predict that the cryptocurrency market may exhibit herding behavior among investors during this health crisis. Besides, the investigation of the contribution of the COVID-19 media coverage on herding in the cryptocurrency market provides information to investors and policymakers on the factors influencing herding behavior in the cryptocurrency market. In fact, excessive media about the pandemic can alert market operators about the cryptocurrency prices' deviation from their fundamentals.

We contribute to the existing literature in three ways. First, motivated by previous studies investigating the influence of the COVID-19 on the investors' behavior (Zhang et al., 2020; Albulescu, 2020, Ali et al., 2020; Conlon & McGee, 2020; among others), we examine the impact of the new COVID-19 on the cryptocurrency market behavior. Therefore, we extend most of these studies by applying a regime-switching model that accounts for two different market states. Second, we add to the few studies examining the herding behavior among investors in the cryptocurrency market by considering a more updated period that includes the COVID-19 crisis and a higher number of cryptocurrencies. In fact, until now, only two studies have investigated the impact of the COVID-19 on herding in cryptocurrencies. Susana et al. (2020) identify herding behavior during the COVID-19 pandemic in Litecoin, Cardano, and Dash. Yarovaya et al. (2020), in a study that includes only an early stage of the COVID-19 crisis, show mixed findings on herding. Third, we attempt to explore the impact of coronavirus media coverage on herding among investors. To our knowledge, this study is the first to investigate the effect of coronavirus media coverage on herding in the cryptocurrency market. Hence, we shed more light on the determinants of herding in the cryptocurrency market by considering the coronavirus media coverage as a novel driver.

The findings of this study are multiples. First, by considering the whole period, we find evidence of herding during high volatility state. Second, when focusing on the COVID-19 crisis, results suggest that investors in the cryptocurrency market follow the consensus. Third, the coronavirus media coverage explains the herding behavior in the cryptocurrency market during the COVID-19 crisis. Our findings explain herding determinants that may help investors to avoid such behavior, mainly during the crisis.

The remainder of this paper is organized as follows. Section 2 presents a literature review. Section 3 describes data and methodology. Section 4 presents the empirical results. Section 5 concludes the paper.

[1] Bubbles mean that the prices deviate suddenly from their fundamentals.

2. Literature review

Several researchers have focused on the impact of coronavirus (COVID-19) on financial markets. Ashraf (2020) shows that stock markets respond negatively to the growth of COVID-19 confirmed cases. Albulescu (2020) suggests that the new coronavirus pandemic amplifies the US financial market's volatility. Shehzad et al. (2020) compare the impact of the global financial crisis (GFC) and COVID-19 on financial stock returns of the US, Germany, Italy, Japan, and China. Their empirical results show that the US and the European markets are more affected by the COVID-19 crisis than the GFC crisis. However, the Asian markets are more influenced by the GFC crisis. Recently, Akhtaruzzaman et al. (2021) argue that the COVID–19 media coverage index affects the volatility of environmental, social, and governance (ESG) leader indices from advanced and emerging equity markets. The COVID-19 pandemic has also affected the cryptocurrency market efficiency, as claimed by Ali et al. (2020), El Montasser et al. (2021), and Wang and Wang (2021).

On the other hand, many other studies have examined investors' behavior during market turmoil, particularly their tendencies to follow the market consensus, i.e., to herd. For instance, Mobarek et al. (2014) examine herding in the European stock markets during the 2001–2012 period. They find evidence of herding during the global financial crisis (GFC) and the Eurozone crisis. Economou et al. (2018) test the herding in three developed stock markets (the US, UK, and Germany) during the GFC period and report evidence of herding only for the UK stock market. Other studies, including Litimi et al. (2016) and BenSaida (2017), report herding evidence during turmoil periods in the US industries due to the investors' panic. A similar result was also found by BenMabrouk and Litimi (2018). They conclude that industry herding is evident during extreme oil market movements, and it is more pronounced during the down oil market. In an international level study, Chiang and Zheng (2010) consider 18 countries and prove evidence supporting herding during crisis periods in the US and Latin American markets. Balcilar et al. (2017) and Youssef and Mokni (2018) show that investors in Gulf Arab stock markets display herding during crisis periods. In the same context, Ulussever and Demirer (2017) conclude that herding behavior is more pronounced during market losses periods. Some other studies have concentrated on commodity markets, as Demirer et al. (2015), who provide evidence of herding in the grains sector during the high volatility state. In the same line, Youssef and Mokni (2020) and Youssef (2020) report that investors in commodity markets mimic their peers during and after the global financial crisis.

Recently, some studies have examined herding behavior in financial markets during the ongoing COVID-19 pandemic. Chang et al. (2020) examine herding in the energy stock prices of the USA, Europe, and Asia regions during the period covering the GFC, SARS, and COVID-19 pandemic. They conclude that herding is present during extreme downward movements in oil prices. Furthermore, the authors provide evidence of herding after the GFC but not during the coronavirus crisis. However, Espinosa-Méndez and Arias (2021) and Kizys et al.(2021) confirm the presence of herding during the coronavirus COVID-19 pandemic in international stock markets.

Despite many studies examining herding in stock and commodity markets, a few studies focus on the cryptocurrency market, especially over COVID-19. Ballis and Drakos (2020) investigate herding behavior in six major cryptocurrencies during 2015–2018. The CSAD model results indicate herding among investors in the top sector of the cryptocurrency market that becomes more strong during the up-market. A similar result is found by Kallinterakis and Wang (2019), who, by employing data for 296 cryptocurrencies, provide evidence of herding that intensifies during up-market, low volatility, and high volume days. Contrary to Ballis and Drakos's (2020) results, Vidal-Thomas et al. (2019) conclude that herding is present only during the down market by examining a set of 65 digital currencies. Bouri et al. (2019b) employ the CSAD static model, and the rolling windows approach to examine herding in 14 cryptocurrencies from 2013 to 2018. Their results from the CSAD model reveal no evidence of herding, while the rolling windows approach shows a significant herding behavior.

Furthermore, Bouri et al. (2019b) find that herding increases when the uncertainty measured by the US economic policy uncertainty (US EPU) increases. Da Gama Silva et al. (2019) test the presence of herding in 50 cryptocurrencies from 2015 to 2018 by using three different models, namely the CSAD model, the cross-sectional standard deviation (CSSD), and the beta-herding of Hwang and Salmon (2004). Empirical results by the CSSD model suggest the presence of herding during the down-market period. According to Hwang and Salmon (2004), the beta-herding state-space approach indicates the presence of herding and adverse-herding, while the CSAD model reveals weak evidence of herding.

Similarly, Kaiser and Stöckl (2020) use the CSAD and the beta-herding state space and confirm the existence of significant herding in a large sample of cryptocurrencies. Stavroyiannis and Babalos (2019) use a time-varying model and do not detect herding in the cryptocurrency market. However, by employing the same model, Youssef (2020) shows the presence of herding behavior in the cryptocurrency market over most of the study sample period. Moreover, the author confirms that investors are more likely to mimic their peers when the volatility, the S&P500, and the dollar index rise. Philippas et al.(2020) investigate whether informative signals drive herding among investors in 100 cryptocurrencies. Recently, Coskun et al. (2020) use the CSAD and the time-varying Markov-switching (TV-MS) for 14 cryptocurrencies but do not report evidence of herding. Susana et al. (2020) employ the CSSD approach and prove evidence of herding in the top ten cryptocurrencies during the pre-Covid 19 and Covid 19 pandemic. Yarovaya et al. (2020) report mixed results on herding in the cryptocurrencies during the Covid 19.

3. Data and methodology

3.1. Data

We use the daily data of the top-43 cryptocurrencies in terms of market capitalization as at end of 11th November 2020. Our sample runs from 04/28/2013 to 11/11/2020. We chose only the cryptocurrencies starting before 2018. After considering the 100 largest cryptocurrencies, we kept only 43 cryptocurrencies that their price data covers at least a 3-years period. As Bouri et al. (2019b)[2] we want a wider time span to analyze the role of the COVID-19 pandemic in the herding behavior. The closing prices of the 43 cryptocurrencies are obtained from https://coinmarketcap.com. The coronavirus media coverage index (MCI) is sourced from the Ravenpack finance.

3.2. The Cross-Sectional absolute deviation (CSAD) approach

To detect herding behavior, we first use the Cross-Sectional Absolute Deviation (CSAD) of returns, proposed by Chang et al. (2000) and calculated as follows:

$$CSAD_t = N^{-1}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{1}$$

Where:

$R_{i,t}$: the daily log-return for each cryptocurrency.$R_{m,t}$: is the average return of the equally weighted of the N cryptocurrencies available on day t. N is the number of traded cryptocurrencies on day t. To capture herding behavior, Chang et al. (2000) suggest the following regression:

$$CSAD_t = \alpha_0 + \alpha_1\left|R_{m,t}\right| + \alpha_2 R_{m,t}^2 + \varepsilon_t \tag{2}$$

A statistically significant negative parameter α_2 shows the presence of herding behavior in the cryptocurrency market. The Chang et al. (2000) model is based on a static structure, and hence its parameters are assumed to be constant over time. Consequently, the model of Chang et al. (2000) has been criticized since it ignores the dynamic nature of herding behavior. Studies in stock markets such as Balcilar et al.(2013, 2014), Balcilar et al. (2017), and commodity markets such as Demirer et al. (2015)[3] extend the static model to a regime-switching to take into account structure breaks when measuring herding behavior. They suggest that investors are more likely to herd during the high volatility period. To assess herding behaviour, we estimate a regime-switching model that differentiates between low and high volatility states presented as follows:

$$CSAD_t = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{m,t}\right| + \alpha_{2,S_t} R_{m,t}^2 + \varepsilon_{t,S_t}, \quad \varepsilon_{t,S_t}\ N\left(0, \sigma_{S_t}^2\right) \tag{3}$$

Where $S_t \in \{1, 2\}$ follows a two-state Markov process that represents normal (low volatility) or crisis (high volatility). A negative and statistically significant α_{2,S_t} implies the presence of herding in the cryptocurrency market during the state t.

3.3. Herding behaviour during the ongoing COVID-19 crisis

Mobarek et al. (2014), Economou et al.(2018), and Youssef and Mokni (2018) conclude that herding in the stock markets is influenced by crisis periods. In the context of the cryptocurrency market, Susana et al. (2020) show the presence of herding in the cryptocurrencies Litecoin, Cardano, and Dash. Moreover, Yarovaya et al. (2020) show that the COVID-19 crisis does not amplify the herding. We extend these studies by using a large number of cryptocurrencies, a longer coronavirus period, and employing two different methodologies to detect herding.

To explore the presence of herding behaviour in the cryptocurrency market during the ongoing COVID-19 crisis, we modify Eq. (2) and Eq. (3) by adding a dummy variable that highlights the COVID-19 crisis. We obtain the following equations:

$$CSAD_t = \alpha_0 + \alpha_1\left|R_{m,t}\right| + \alpha_2 R_{m,t}^2 + \alpha_3 D_t R_{m,t}^2 + \varepsilon_t \tag{4}$$

$$CSAD_t = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{m,t}\right| + \alpha_{2,S_t} R_{m,t}^2 + \alpha_{3,S_t} D_t R_{m,t}^2 + \varepsilon_{t,S_t}, \quad \varepsilon_{t,S_t}\ N\left(0, \sigma_{S_t}^2\right) \tag{5}$$

Where D_t is a dummy variable that takes one during the ongoing COVID-19 crisis (starting with January 1, 2020, until the end of the sample period) and 0 otherwise. Following Mobarek et al. (2014)[4], we use a crisis dummy instead of sub-samples period. Investors tend to adopt a herding behavior during the COVID-19 crisis if the α_3 is significantly negative.

[2] Bouri et al., 2019b consider the 50 largest cryptocurrencies and kept only 14 cryptocurrencies because their price data covers at least a 2-years period. their sample period runs from 2013 to 2018, however, the number of cryptocurrecies varies during the sample period.

[3] Demirer et al.(2015) show the presence of herding behavior in the grains sector during the high volatility regime.

[4] Mobarek et al.(2014) examine herding behavior during the global financial crisis and the Eurozone crisis in European stock markets.

Table 1
Descriptive statistics.

	Rm_t	$CSAD_t$
Mean	0.1548	3.7847
Median	0.2426	3.0360
Maximum	53.2046	36.5457
Minimum	−50.9424	0.0285
Std. Dev.	5.0493	2.7546

Table 1 reports some descriptive statistics for both the average of returns $R_{m,t}$ and CSAD $_t$, over the period from 04/28/2013 to 11/11/2020.

Table 2
herding behavior in the cryptocurrency market.

Variable	C	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	σ^2_ε	LL	AIC
Panel A: Static model						
Parameter	2.7131***	0.3258***	0.0004	5.9153	−6351.63	4.6165
t-statistics	(38.7610)	(15.7920)	(0.5608)			
Panel B: Regime Switching model						
Regime 1: low volatility state						
Parameter	2.4224***	0.1512***	−0.0002	1.1483		
t-statistics	(56.7515)	(11.3135)	(−0.3989)			
Regime 2: high volatility state					−5552.8040	4.0405
Parameter	3.7805***	0.7059***	−0.0041***	9.0682		
t-statistics	(17.3204)	(12.9127)	(−2.7160)			

Note: This table provides parameters estimation for both the static and regime-switching models given in Eqs. (2) and (3) for daily data from 04/28/2013 to 11/11/2020 for the cryptocurrency market. σ^2_ε is the variance of the residual term. LL and AIC are the log-likelihood value at the optimum and Akaike information criteria. *** denotes statistical significance at 1%.

3.4. The impact of media coverage on herding

Haroon and Rizvi (2020) suggest that news related to COVID-19 led to public panic, inducing volatility in equity markets. Moreover, Ashraf (2020) shows that stock market returns decrease as confirmed cases increase. Since the cryptocurrency market is dominated by inexperienced investors, which are largely affected by media, we predict that coronavirus media coverage can influence investors' behavior and be an important factor affecting the herding behavior in the cryptocurrency market. To explore the impact of coronavirus media coverage, we extend the model in Eq. (2) and Eq. (3) by introducing the media coverage index to obtain the following equations:

$$CSAD_t = \alpha_0 + \alpha_1\left|R_{m,t}\right| + \alpha_2 R^2_{m,t} + \alpha_3 MCI_t + \varepsilon_t \tag{6}$$

$$CSAD_t = \alpha_{0,S_t} + \alpha_{1,S_t}\left|R_{m,t}\right| + \alpha_{2,S_t} R^2_{m,t} + \alpha_{3,S_t} MCI_t + \ \varepsilon_{t,S_t}, \quad \varepsilon_{t,S_t}\ N\left(0, \sigma^2_{S_t}\right) \tag{7}$$

Where MCI_t is the coronavirus media coverage index that calculates the percentage of all news sources covering the novel coronavirus topic. Values range between 0 and 100, where a value of 60.00 means that 60 percent of all sampled news providers are currently covering stories about the COVID-19[5]. A statically significant and negative coefficient α_3 implies that the coronavirus media coverage amplifies herding among investors in the cryptocurrency market.

The models in Eqs. (2), (4), and (6) are estimated using the Newey-West (1987) 's heteroskedasticity and autocorrelation consistent standard errors.

4. Empirical results

4.1. Descriptive statistics

Table 1 presents descriptive statistics of the $R_{m,t}$ and the $CSAD_t$. Results indicate that the cryptocurrency market has positive mean returns (0.1548) and fluctuates during the sample period between −50.9424 and 53.2046. The standard deviation value is 5.0493,

[5] Source: Ravenpack finance.

Table 3
herding behavior during the ongoing COVID-19 crisis.

	C	$\|R_{m,t}\|$	$R^2_{m,t}$	D_t	σ^2_ε	LL	AIC
Panel A: Static model							
Parameter	2.7687***	0.2939***	0.0030***	−0.0067***		−6331.6420	4.6027
t-statistics	(39.5230)	(13.9326)	(3.4617)	(−6.3412)	5.8322		
Panel B: Regime Switching model							
Regime 1: low volatility state							
Parameter	2.4096***	0.1576***	−0.0006	0.0004	1.1485	−5546.4230	4.0610
t-statistics	(53.3609)	(9.5373)	(−0.6958)	(0.5530)			
Regime 2: high volatility state							
Parameter	3.7551***	0.7223***	−0.0045***	−0.1052***	8.8340		
t-statistics	(17.4657)	(13.4468)	(−3.0000)	(−2.7510)			

Note: This table provides parameters estimation for both the static and regime-switching models given in Eqs. (4) and (5) for daily data from 04/28/2013 to 11/11/2020 for the cryptocurrency market. σ^2_ε is the variance of the residual term. LL and AIC are the log-likelihood value at the optimum and Akaike information criteria. *** denotes statistical significance at 1%.

Table 4
The impact of media coverage on herding in the cryptocurrency market.

	C	$\|R_{m,t}\|$	$R^2_{m,t}$	MCI_t	σ^2_ε	LL	AIC
Panel A: Static model							
Parameter	2.8550***	0.3180***	0.0006	−0.0163***		−6321.7240	4.5955
t-statistics	(39.8636)	(15.5635)	(0.8258)	(−7.7704)	5.7903		
Panel B: Regime Switching model							
Regime 1: low volatility state							
Parameter	2.4893***	0.1503***	−0.0002	−0.0053***		−5528.8020	4.0246
t-statistics	(54.8328)	(10.9585)	(−0.3531)	(−4.7073)	1.1694		
Regime 2: high volatility state							
Parameter	3.9818***	0.6910***	−0.0039***	−0.0388***			
t-statistics	(17.5600)	(12.4742)	(−2.5732)	(−5.0798)	8.9014		

Note: This table provides parameters estimation for both the static and regime-switching models given in Eqs. (6) and (7) for daily data from 04/28/2013 to 11/11/2020 for the cryptocurrency market.σ^2_ε is the variance of the residual term. LL and AIC are the log-likelihood value at the optimum and Akaike information criteria. *** denotes statistical significance at 1%.

suggesting that the cryptocurrency market displays high volatility. Examining the CSAD, we observe an average value of 3.7847, indicating a high deviation of the cryptocurrencies from market consensus.

4.2. Herding behavior in the cryptocurrency market

Table 2 presents the estimation results for the CSAD in both static (Panel A) and regime-switching models (Panel B), expressed by Eqs. (2) and (3), respectively. Results from the static regression show no evidence of herding, as suggested by the positive and insignificant parameter α_2. Our results are consistent with those of Bouri et al. (2019b), and Youssef (2020)who report the absence of herding among investors in the cryptocurrency market based on the static approach. Regarding the regime-switching model, Table 2 reports that the variance σ^2_ε is different among states, indicating that regime-switching is more appropriate than the static model. Moreover, we observe a higher value of σ^2_ε for regime 2 compared to regime 1, indicating that state 2 is the high volatility state.

By examining results from the regime-switching, we observe a significant herding behavior only during high volatility periods (regime 2), given the significantly negative $\alpha_{2,2}$. Our finding is in line with Youssef (2020), who concludes that herding in the cryptocurrency market increases with volatility. These results may be explained because investors are more likely to mimic their peers during the stress period (Christie and Huang, 1995; Chang et al., 2000; Bikhchandani & Sharma, 2001; Demirer et al., 2015).

4.3. The impact of the ongoing COVID- 19 crisis on herding behavior in the cryptocurrency market

Table 3 presents the estimates for Eqs. (4) and (5) from static and regime-switching models, respectively. In this equation, observing a significant and negative value for α_3 implies the presence of herding in the cryptocurrency market.

Table 5
Estimation results of $\mathbf{CSAD_t}$ by the GARCH model.

Panel A: $CSAD_t = \alpha_0 + \alpha_1 \lvert R_{m,t} \rvert + \alpha_2 R^2_{m,t} + \varepsilon_t$ Eq. (2)						
	C	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	ARCH(Lag1)	GARCH(Lag1)	
Parameter	2.0610***	0.1813***	0.0002	0.3602*** (35.4316)	0.7522***	
t-statistics	(87.1384)	(24.1548)	(0.8671)		(151.0954)	
Panel B: $CSAD_t = \alpha_0 + \alpha_1 \lvert R_{m,t} \rvert + \alpha_2 R^2_{m,t} + \alpha_3 D_t R^2_{m,t} + \varepsilon_t$ Eq. (4)						
	C	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	D_t	ARCH(Lag1)	GARCH(Lag1)
Parameter	2.1107***	0.1499***	0.0034***	−0.0030***	0.3475***	0.7565***
t-statistics	(84.8721)	(17.1901)	(7.6476)	(−8.3299)	(33.7000)	(145.3007)
Panel C: $CSAD_t = \alpha_0 + \alpha_1 \lvert R_{m,t} \rvert + \alpha_2 R^2_{m,t} + \alpha_3 MCI_t + \varepsilon_t$ Eq. (6)						
	C	$\lvert R_{m,t} \rvert$	$R^2_{m,t}$	MCI_t	ARCH(Lag1)	GARCH(Lag1)
Parameter	2.1146***	0.1791***	0.0003	−0.0021***	0.3618***	0.7503***
t-statistics	(80.8776)	(23.2333)	(1.1505)	(−3.1395)	(35.4146)	148.7854

Note: *** denotes statistical significance at 1%.

The static model (Eq. (2)) in Table 2 reveals no evidence of herding in the cryptocurrency market. However, the augmented model with a crisis dummy (Eq. (4)) results in Table 3 show that the coefficient on D (α_3) is negative and statistically significant, suggesting that the COVID-19 crisis enhances herding in the cryptocurrency market. Not surprising, these results can be explainable by the nature of traders in the cryptocurrency market, that are young and that lack knowledge and experience, guided by market sentiment and hence tend to herd to avoid losses during stress periods. Examining results from the regime-switching model, Table 3 reports that the impact of the ongoing COVID-19 crisis on herding is significant only during the high volatility state (regime2), as indicated by a negative and significant estimate for $\alpha_{3,2}$.

Overall, our results suggest evidence supporting herding during the ongoing COVID-19 crisis. This finding is in line with Susana et al. (2020) and Yarovaya et al. (2020), who suggest the presence of herding during the COVID-19 pandemic.

4.4. *The impact of media coverage on herding behavior in the cryptocurrency market*

Table 4 presents results about the impact of media coverage on herding in the cryptocurrency market by using the static and switching regime models (Eqs. (6) and (7)). Observing a significant and negative value for α_3 (the estimates of the *MCI*) indicates that coronavirus media coverage contributes to herding in the cryptocurrency market.

First, by introducing the concept of media coverage, results from Table 4 show again evidence of herding during high volatility periods. Second, the estimates for MCI_t are negative and statistically significant in the static model (−0.0163) and regime-switching during both low volatility (−0.0053) and high volatility (−0.0388), suggesting a significant impact of media coverage on herding behaviour among investors in the crypto market. In relation to Haroon and Rizvi's (2020) findings, which show that the panic generated by news related to the COVID-19 pandemic increases the volatility, we find that news covering the novel coronavirus drive herding behavior among investors in the cryptocurrency market. This is not surprising for cryptocurrency participants guided by social media sentiment transmission. Third, our findings indicate that the influence of media coverage on herding is more prominent during high volatility periods. This may be due to investors' pessimism caused by the announcement of bad news. This result is predicted since the cryptocurrency market is dominated by inexperienced investors guided by social media sentiment transmission.

4.5. *Robustness analysis*

To insure about the results provided by this paper, we made a robustness analysis which is made into two steps. Firstly, we reestimate the CSAD models with GARCH effects to account for possible heteroscedasticity. Secound, we proceed by changing the selected samples of cryptocurrencies to control for the sensitivity of the results to the selected sample.

4.5.1. *CSAD model with GARCH effects*

Throughout our analysis, the CSAD models expressed by Eqs. (2), (4), and (6) are estimated using the Newey and West (1987)'s heteroskedasticity and autocorrelation consistent standard errors to solve any multicollinearity problem. As a robustness checking, Table 5 represents the results for using the Generalized Autoregressive Conditional heteroskedasticity model (GARCH) and, more specifically, a GARCH(1,1) for the estimation of Eqs. (2), (4), and (6).

Again, as observed in Panel A, the estimate for herding behavior $R^2_{m,t}$ is positive but not statically significant, suggesting no evidence of herding in the cryptocurrencies. Furthermore, our results support herding presence during the ongoing COVID-19 crisis since the coefficient of the dummy variable D_t is negative and statistically significant, as shown in Panel B. It is also observed that as the coronavirus media coverage index rises, herding on the cryptocurrencies increases, as suggested by the negative and statistically significant coefficient MCI_t in Panel C. These estimates corroborate our previous findings for herding in Table 2, herding during the ongoing COVID-19 crisis in Table 3, and the impact of media coverage in Table 4. Hence, both the Newey-West estimation and the

Table 6
Estimation results of $\mathbf{CSAD_t}$ using the largest 43, 100, 1000 and all cryptocurrencies.

	Dependent variable			
	CSAD			
	(1)	(2)	(3)	(4)
Number of cryptocurrencies	43	100	1000	ALL
constant	2.518*	3.620*	8.425*	8.419*
	(0.071)	(0.078)	(0.089)	(0.089)
R_{mt}	0.344**	0.289**	0.241**	0.242**
	(0.021)	(0.023)	(0.027)	(0.027)
R_{mt}^2	0.001***	0.001***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Adj-R^2	0.244	0.170	0.147	0.147

Note: * p<0.1; ** p<0.05; *** p<0.01

Table 7
Herding estimation equal weighted, value weighted and Bitcoin.

	(1) CSAD_equal weighted	(2) CSAD_value weighted	(3) CSAD_Bitcoin
constant	8.419*	8,801*	8,687*
	(0.089)	(0.092)	(0.091)
R_{mt}	0.242**	0.118**	0.192**
	(0.027)	(0.033)	(0.033)
R_{mt}^2	0.002***	0.005***	0.004***
	(0.001)	(0.002)	(0.002)
Adj-R^2	0.147	0.054	0.071

Note: * p < 0.1; ** p < 0.05; *** p < 0.01.

GARCH give similar findings. This indicates that our results are robust.

4.5.2. *Sensitivity to selected sample*

In this paper, Our data set includes 43 cryptocurrencies among the largest 100 cryptocurrencies, and their price data covers at least three years. The sample covers the period from 04/28/2013 to 11/11/2020. As a robustness method, we replicate the empirical analysis with other data by considering four different samples, including the 43 largest cryptocurrencies, the 100 largest cryptocurrencies, the 1000 largest cryptocurrencies, and all cryptocurrencies. Table 6 reports the estimation results for the static model, expressed by Eq. (2) for the different samples. The herding coefficients are positive and statically significant (at the 1% significance level) for the four larger samples suggesting no evidence of herding in the cryptocurrency markets. These findings are compatible with our findings presented in Table 2 (Panel A), showing no evidence of herding based on the static approach.

Throughout our analysis, we use the equal weighted average of stock returns on this particular day as a proxy for Rm,t. For robustness purposes, we calculate the value-weighted market portfolio returns based on their percentage of total market capitalization. Moreover, and following Kaiser and Stöckl (2020) and in order to take account of the concept of Bitcoin as a transfer of currency, we calculate the value-weighted market portfolio returns based on the Bitcoin. Table 7 report the result for the case of where an equally weighted market portfolio return is employed (column 1), the corresponding results using a value weighted market portfolio (column 2) and Bitcoin (column 3). The herding coefficients are positive and statically significant (at the 1% significance level) for the equal, value-weighted and Bitcoin measures, providing evidence of absence of herding in the three cases.

5. Conclusion

This study examines the impact of the ongoing COVID-19 crisis on herding behavior in the cryptocurrency market. Given the dramatic deterioration of markets and the increasing fear and panic during the COVID-19 crisis, we predict that investors in the cryptocurrency market may avoid losses by following the consensus. Furthermore, we explore the impact of coronavirus media coverage on herding behavior. To this end, we use the cross-sectional absolute deviation (CSAD) methodology of Chang et al. (2000) and the regime-switching model for better herding examination. While the CSAD model results do not report evidence supporting herding, those from the regime-switching suggest significant herding during high volatility regime.

Moreover, investors adopt herding behavior during the COVID-19 crisis as suggested by empirical results from both static model and high volatility regime. The impact of coronavirus media coverage on herding in the cryptocurrency market is significant. This result explains the presence of herding during the COVID-19 crisis. News related to the coronavirus increases panic and fear and affects the behavior of investors. Consequently, investors disregard their private information and follow others' investment decisions.

Cryptocurrencies may be preferable for investors to mitigate risk during crisis periods, given their hedging capabilities. However, investors in the cryptocurrency market should be more aware of assessing news flow related to COVID–19 and rely on their private information during crisis periods instead of copying their peers' decisions. During crisis periods, investors could avoid herding by consulting financial analysts with adequate knowledge and experience. Moreover, policymakers should establish some regulations that aim to enhance the efficiency of the cryptocurrency market, especially during the crisis period.

CRediT authorship contribution statement

Mouna Youssef: Estimation of the models, wrote the discussions of the results writing the introduction. **Sami Sobhi Waked:** Data conception, methodology, literature review, the conclusion, supervision.

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.

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