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INVESTOR ATTENTION AND HERDING IN THE CRYPTOCURRENCY MARKET DURING THE COVID-19 PANDEMIC

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Abstract

This study examines the relationship between investor attention and herding effect in the cryptocurrency market by employing the vector autoregression and quantile regression models. Furthermore, we examine whether the COVID-19 pandemic affected herding behaviour in cryptocurrencies. Using the daily closing price and Google search volume of the five leading cryptocurrencies, the paper finds that herding in the cryptocurrency market decreases with an increase in investor attention for the overall sample. The results for the COVID-19 period indicate that the impact of investor attention on the herding effect decreases due to increased attention to the pandemic. This study is one of the initial attempts to investigate the impact of investor attention on herding in cryptocurrencies.

Keywords: Investor attention, Herding, Cryptocurrency market, Coronavirus, COVID-19.

1. Introduction

The rapid spread of COVID-19, which is considered the third deadliest virus surge within the past 20 years period (Yang et al., 2020), led to a lot of havoc worldwide. As the COVID-19 outbreak resulted in disruptions in the equity and commodity markets across the globe with a declining trend in prices and a great level of uncertainty (Gupta et al., 2021), cryptocurrency markets also witnessed similar disturbances during 2020 (Naeem et al., 2021). Literature also highlights that the markets across the globe have not experienced such extreme volatile movements in prices in the past (Zhang et al., 2020; Haroon and Rizvi, 2020).

There exists a notion among investors about the hedging ability of Bitcoin during the downturn in the market (Dyhrberg, 2016). In the initial stage of the COVID-19 outbreak, investors considered Bitcoin as a hedging instrument which later resulted in more depletion in value than other assets. Most of the latest studies have looked into the damage caused by the COVID-19 crisis in the cryptocurrency market (James et al., 2021; Conlon et al., 2020). Bitcoin was found to have an amplifying impact on global financial markets rather than acting as a tool of diversification during this COVID-19 outbreak (Corbet et al., 2020; Conlon and McGee, 2020; Conlon et al., 2020). The cryptocurrency market has been negatively affected by the COVID-19 outbreak, diminishing its use as a diversification tool (Conlon and McGee, 2020).

The news related to the sudden increase in COVID-19 cases created an environment of uncertainty and resulted in a surge in panic and fear among the public (Salisu and Vo, 2020; Fernandez-Perez et al., 2020). With the increase in COVID-19 cases, investors searched for more details of the coronavirus on the internet (Lyócsa et al.,2020). Market participants face difficulty in making a concrete understanding of such information when exposed to a ton of news from varied sources. Barberis et al. (1998) postulate with psychological evidence that the market overreacts to such outpouring of news, although less weight should be given to this news.

Bikhchandani et al. (1992) and Sgroi (2002) point out that if there is a low-cost associated with the search of information, investors will have the incentive to gain information and exhibit herding behaviour. Herding results from the movement of a set of investors’ actions towards a particular direction by mimicking a few participants' behaviour. Theoretical literature has explained the interconnection between information and herd mentality (Sias, 2004; Nofsinger and Sias, 1999; Shleifer and Summers, 1990). Herding stems from the psychological biases of individuals and the phenomena of attention-seeking factors (Barber et al., 2009; Li et al., 2017).

There is a wide range of studies on herding behavior in the cryptocurrency market (Bouri et al., 2019; Vidal-Tomás et al., 2019). The Cryptocurrency market is characterised by the absence of proper legal structure and unavailability of adequate standard information (Ji et al., 2019). Less knowledgeable individuals use this information to trade in the cryptocurrency market without adequately comprehending the risk associated with such a venture. In most cases, they are driven by other participants' characteristics and actions in the market, making them exhibit herd mentality, which becomes more severe during turbulence and uncertain times (Naeem et al., 2021).

Analysing the herd mentality in the cryptocurrency market helps bring out valuable insights regarding the price variations (Corbet et al., 2019) and provides information regarding the connectedness and integration among the cryptocurrencies. However, the absence of strict fundamentals in proper valuation, along with the constant exposure of investors towards social networking sites, makes the cryptocurrency market vulnerable to an examination of behavioural aspects of investor actions (Corbet et al., 2019).

Several studies document the vulnerability of the cryptocurrency market towards behavioural elements such as sentiment from both media and markets (Weber, 2014), noise trading (Cheung et al., 2015; Fry and Cheah, 2016), and speculative bubbles (Cheah and Fry, 2015). However, Bouri et al. (2019) note that herd mentality is a time-varying phenomenon, and the market participants tend to base their decision on the performance of larger digital currencies as the smaller ones tend to follow the pattern of large cryptocurrencies (Vidal-Tomás et al., 2019).

Kahneman's (1973) proposition regarding the attention phenomenon highlights that it is a cognitive instinct that propels the decision to purchase an asset and can be considered as the linking element that explains the relation between media attention and bitcoin transactions. The concern of cognitive limitation (Kahneman, 1973) for investor attention has a far-reaching impact in the booming arena of virtual social networking and when there is larger uncertainty prevailing in the COVID-19 scenario around the globe.

Typically, “investor attention” is all about one’s conscious awareness about the reality of a kind of information relating to something. Google search volume is proxied for investor attention in many of the studies. Studies show that asset values get impacted by investor attention, and there is variation in its character with respect to time (Da et al., 2011). Prominent incorporation of news into asset prices is evident when market participants pay greater attention to the news, and it gets reflected in the prices (Huberman and Regev, 2001).

The relationship between investor attention and bitcoin is being studied using various proxies under multiple settings (Shen et al., 2019; Figa-Talamanca and Patacca, 2019; Dastgir et al., 2019). Within the sphere of our knowledge, there does not exist any study exploring the relationship between investor attention and herding behaviour in the cryptocurrency market. Therefore, we attempt to delve into the underlying variations in the cryptocurrency market's behaviour before the COVID-19 and how it got evolved along with the market turbulence in the pandemic. This study examines the relationship between investor attention and herding effect in the cryptocurrency market from August 7, 2015, to November 23, 2020, with a particular focus on the COVID-19 outbreak. We test the relationship between investor attention and herding effects across the entire period and two different regimes: the period before the COVID-19 outbreak (from August 7, 2015 to January 14, 2020) and the period after the COVID-19 outbreak (from January 15, 2020 to November 23, 2020). This helps us to distinguish the differences in investor attention on herding in cryptocurrencies across two distinct sentiment periods. Our study is one of the initial attempts to investigate the impact of investor attention on herding in cryptocurrencies. We use Google search volume as a proxy for investor attention, which acts as a free information source and measures investors' attention propensity.

The remainder of the paper is structured as follows. Section two discusses the data and methodology. Section three presents empirical results and some discussions, and Section four concludes the paper.

2. Data and Methodology

2.1 Cryptocurrency Data

We use the daily data of five major cryptocurrencies based on the market capitalization as of November 23, 2020. The prices of all cryptocurrencies (denominated in USD) are obtained from investing.com. The data span from August 7, 2015, to November 23, 2020. Table 1 reports the total market capitalization of cryptocurrencies. Bitcoin dominates the market with a share of 61.7%, followed by Ethereum (11.69%), Ripple (5.27%), Tether (3.27%), and Litecoin (0.99%). These cryptocurrencies account for 82.92% of the total market capitalization.

Table 1: The Market capitalization of cryptocurrencies

Name	Symbol	Market capt	Share
Bitcoin	BTC	3,52,39,37,69,773	61.71%
Ethereum	ETH	66,73,71,16,945	11.69%
Ripple	XRP	30,10,19,22,821	5.27%
Tether	USDT	18,66,76,90,992	3.27%
Litecoin	LTC	5,67,06,53,476	0.99%
The total market capitalization of the cryptocurrency market: $5,71,06,11,12,332			

2.2 Google Search Volume

We use Google search volume index (GSVI) as a proxy for investor attention obtained via Google Trends. It provides a time series of the volume of search queries. Google Trends provides the term-specific index that directly relates to the sentiment of google users. We use the following search keywords: 'Bitcoin,' 'Ethereum,' 'Litecoin,' 'XRP' (for Ripple), and 'USDT' (for Tether). The daily GSVI is obtained using a 3-month window. To avoid the possibility of unrelated noise in the search data, we employ the precise keyword for each cryptocurrency to capture only relevant information. Finally, to measure the aggregate investor attention, we take the average value by utilizing the daily GSVI of all the cryptocurrencies. Following Lin

(2021) and Baig et al. (2019) we scale the aggregate investor attention by 100 as shown below:

$$GSV_t = \frac{\left(\frac{1}{N}\left(\sum_{i=1}^{5} GSVI_{i,t}\right)\right)}{100} \tag{1}$$

GSV_t is the aggregate investor attention at time *t*; N is the number of cryptocurrencies and $GSVI_{i,t}$ is the Google search volume index for cryptocurrency *i* at time *t*.

2.3 Herding calculation method

In this study, we apply the Cross-Sectional Absolute Deviation (CSAD) method proposed by Chang et al. (2000) to measure the presence of herding in the cryptocurrency market. The CSAD statistic is measured as:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{2}$$

Where $R_{i,t}$ is the return of cryptocurrency i on day t and $R_{m,t}$ is the market return on day t. We use Cryptocurrency Index (CRIX) as a proxy for the market index, the data of which is obtained from http://data.thecrix.de.

Chang et al. (2000) argued that during extreme market movements (when the market is under stress), the relationship between CSAD and market return ($R_{m,t}$) is expected to be non-linear. If investors mimic each other during the market stress period, the CSAD decreases, which turns the relation between the square of market return and CSAD negative. The negative relation between the square of market return and CSAD is an indication of herding. The same is shown in the following equation:

$$CSAD_t = \alpha_0 + \beta_1|R_{m,t}| + \beta_2 R^2{}_{m,t} + \varepsilon_t \tag{3}$$

The presence of herding behaviour is tested as:

a) If $\beta_1 > 0$ *and* $\beta_2 = 0$, it means there is an absence of herding.
b) If $\beta_2 < 0$ and significant, it means herding behaviour exists.
c) If $\beta_2 > 0$, and significant it means anti-herding behaviour exists.

Table 2 shows the descriptive statistics and the stylized facts of investor attention (GSV) and herding effect (CSAD). We can see that the mean value of CSAD and GSV has increased during the COVID-19 period. Furthermore, CSAD shows significant variation during the COVID-19 ranging from 0.004 to 0.558 with a standard deviation of 0.045. Similarly, GSV varies in the range of 0.212 to 0.868 with a standard deviation of 0.132. For stylized facts, we report the JB (Jarque-Bera) test for normality test and ADF (Augmented Dickey-Fuller) test to investigate the stationarity. The results indicate that CSAD and GSV are positively skewed and non-normally distributed. The ADF test statistic shows that all the given series are stationary.

Table 2: Descriptive Statistics

	Whole-sample		Pre-COVID-19		COVID-19 period	
	CSAD	GSV	CSAD	GSV	CSAD	GSV
Mean	0.035	0.421	0.035	0.417	0.037	0.448
Median	0.025	0. 42	0.025	0.418	0.025	0.426
Minimum	0.0008	0.10	0.001	0.100	0.004	0.212
Maximum	0.558	0.922	0.305	0.922	0.558	0.868
Std dev	0.0349	0.0135	0.033	0.136	0.045	0.132
Skewness	4.022	0.255	2.486	0.161	6.550	0.851
Kurtosis	36.238	0.297	9.798	0.192	64.372	0.449
Jarque-Bera	110526.9	28.009	8106	9.416	54701	39.839
ADF	-10.369 **	-6.413 **	-5.876 **	-5.114 **	-6.607 **	-6.607 **

This table reports the descriptive statistics of the herding effect and investor attention. CSAD stands for Cross-Sectional Absolute Deviation; GSV stands for Google search volume. ADF test for the Augmented Dickey-Fuller test. Columns 2nd and 3rd demonstrate the results for the whole sample period. Columns 4-7 presents the results for the pre-COVID-19 (from August 7, 2015, to January 14, 2020) and COVID-19 period (from January 15, 2020, to November 23, 2020). ** denotes significance at 1% level.

2.4 Vector autoregression (VAR) model

To analyze the relationship between herding effects and investor attention, we consider the following Vector autoregression (VAR) models:

$$(CSAD_t) = \alpha_0 + \sum_{f=1}^{T} \beta_f(\,CSAD_{t-f}) + \sum_{r=1}^{T} \beta_r(\,GSV_{t-r}) + e_t \tag{4}$$

$$(GSV_t) = \alpha_0 + \sum_{f=1}^{T} \beta_f(\,CSAD_{t-f}) + \sum_{r=1}^{T} \beta_r(\,GSV_{t-r}) + e_t \tag{5}$$

where $CSAD_t$ is the herding statistic in cryptocurrencies at time *t*; GSV_t is the investor attention at time *t* and e_t is the error term. *T* represents the lag length. We use Schwarz Information Criterion (SIC) to obtain the optimal lag lengths.

3. Empirical Results

Table 3 reports the results of equation (3). We can see that the values of β_1 and β_2 are positive and significant for the whole sample and the COVID-19 period. This infers that there is anti-herding behaviour in the cryptocurrency market. These results are in line with Coskun et al. (2020), which shows evidence of anti-herding in the cryptocurrency market. This anti-herding behaviour can be attributed to the increased presence of informed traders in the cryptocurrency market preceding the occurrence of uncertain events (Feng et al., 2018; Yarovaya et al., 2021). We report the vector autoregression estimates for investor attention and herding in Table 4. The 2nd and 3rd columns report the results for the whole sample period. The results for CSAD as the dependent variables show that investor attention has a one-day lagged positive effect on CSAD and that there is no effect for the second and third lag of investor attention. The results indicate that the anti-herding effect increases in the short run with increased investor attention. From our findings, it appears that increased investor attention can eventually increase the price efficiency in the cryptocurrency market as investors are able to process more cryptocurrency specific information on their own, which can alleviate herding effects. These findings add to the literature of information discovery aspect of investor attention (Vlastakis and Markellos, 2012)

Table 3: Results of CSAD on Market Return

	Whole sample		Pre-Covid		Covid period	
Parameter	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
α_0	0.018 **	0.0017	0.016 **	0.001	0.018 **	0.0025
β_1	0.612 **	0.060	0.785 **	0.079	0.724 **	0.069
β_2	0.993 *	0.410	-0.690	0.824	1.093 **	0.149
Adj. R^2	0.453		0.412		0.600	

This table shows the results of equation (2). The sample period of the analysis is from August 7, 2015, to November 23, 2020, with 1936 observations. Columns 2nd and 3rd demonstrate the results for the whole sample period. Columns 4-7 presents the results for the pre-Covid (from August 7, 2015, to January 14, 2020) and Covid period (from January 15, 2020, to November 23, 2020). ** denotes significance at 1% level.

Table 4: Results of the VAR model

	Whole sample		Pre-COVID-19		COVID-19 period	
	CSAD	**GSV**	**CSAD**	**GSV**	**CSAD**	**GSV**
Constant	0.015 ** (0.001)	0.019 ** (0.006)	0.014 ** (0.001)	0.022 ** (0.008)	0.015 ** (0.005)	0.015 (0.011)
CSAD (-1)	0.486 ** (0.079)	0.174 (0.149)	0.417 ** (0.034)	0.172 (0.185)	0.743 ** (0.229)	0.290 (0.229)
CSAD (-2)	−0.086 * (0.048)	−0.480 ** (0.160)	0.000 (0.035)	−0.446 * (0.191)	−0.423 * (0.183)	−0.634 * (0.258)
CSAD (-3)	0.183 ** (0.031)	−0.242 (0.154)	0.173 ** (0.032)	−0.354 * (0.176)	0.291 ** (0.108)	0.048 (0.197)
GSV (-1)	0.018 ** (0.004)	−0.348 ** (0.034)	0.017 ** (0.004)	−0.340 ** (0.037)	0.026 ** (0.010)	−0.425 ** (0.058)
GSV (-2)	0.001 (0.004)	−0.231 ** (0.029)	0.004 (0.004)	−0.225 * (0.032)	−0.013 (0.012)	−0.287 ** (0.051)
GSV (-3)	−0.000 (0.004)	−0.119 ** (0.021)	−0.002 (0.003)	−0.113 ** (0.023)	0.031 * (0.014)	−0.171 ** (0.054)
Adj. R^2	0.276	0.125	0.250	0.110	0.40	0.170

This table presents the VAR model results with herding effect (CSAD) and investor attention (GSV) as a dependent variable. The standard errors are reported in parentheses. We use Schwarz Information Criterion (SIC) to obtain the optimal lag lengths. Columns 2nd and 3rd demonstrate the results for the whole sample period. Columns 4-7 presents the results for the pre-COVID-19 (from August 7, 2015, to January 14, 2020) and COVID-19 period (from January 15, 2020, to November 23, 2020). ** and * denotes significance at 1% level and 5% level, respectively.

To investigate the impact of investor attention on herding during the COVID-19 pandemic, we divide our sample into two periods. The pre-COVID-19 period from August 7, 2015, to January 14, 2020, and the COVID-19 period from January 15, 2020, to November 23, 2020. The COVID-19 period is chosen from January 15, 2020, as the first confirmed case of COVID-19 was detected outside China on January 14, 2020, based on WHO Disease Outbreak News. Results are shown in Columns 4-7 of Table 4. The results indicate a positive effect of investor attention on anti-herding in both regimes; however, the difference in the magnitude of the coefficients indicates that the impact is more prevalent in the COVID-19 period. Also, there is a three-day lagged positive effect of investor attention on CSAD during the COVID-19 period. The strong relation during the COVID-19 period is not an unexpected result as investors paid more attention to cryptocurrencies during the ongoing pandemic (Chen et al., 2020). Our results are in line with the findings of Yarovaya et al. (2021), which claims that herding in the cryptocurrency market decreased during the COVID-19 pandemic.

3.1 Additional Analysis

There is a possibility that during the COVID-19 period, the herding is influenced directly by the spread of coronavirus. We, therefore, perform an additional analysis using "coronavirus" as a search keyword. We obtain a daily Google search volume index of the keyword "coronavirus" from Google trends globally from January 15, 2020, to November 23, 2020. Table 5 reports the results of the VAR model for the herding effect and investor attention. The estimated coefficients show that investor attention on "coronavirus" is positively related to the anti-herding in cryptocurrencies in the short run, indicating a temporal effect that balanced out in two days.

Table 5: "Coronavirus" search volume and herding effect in cryptocurrencies.

	Constant	CSAD (-1)	CSAD (-2)	CSAD (-3)	GSV (-1)	GSV (-2)	GSV (-3)	*Adj. R^2*
CSAD	0.013 **	0.581 **	−0.296 *	0.115	0.383 *	-0.366	0.0269	0.458
	(0.004)	(0.144)	(0.124)	(0.093)	(0.188)	(0.205)	(0.099)	
GSV	0.002	-0.197 *	0.284 **	−0.042	1.154 **	−0.142	−0.030	0.977
	(0.002)	(0.837)	(0.086)	(0.050)	(0.113)	(0.114)	(0.1031)	

This table shows the VAR results of the herding effect (CSAD) and investor attention (GSV), where GSV is the Google search volume of the "coronavirus" keyword at the global level. The standard errors are reported in parentheses. The sample period is from January 15, 2020, to November 23, 2020. ** and * denotes significance at 1% level and 5% level, respectively.

Furthermore, we run quantile regression to model the herding effect as a function of various quantiles of investor attention. We provide the results in Table 6. According to the results, all the coefficients are positive and significant at a 1% level. However, the greatest effect is observed for the 95th% and 90th% quantiles for $GSV_{(t)}$ and 80th% and 90th% quantiles for $GSV_{(t-1)}$. The results indicate that an increase in GSV will lead to an increase in CSAD. We also report the test of differences in coefficient across the quantiles (Q1, Q4, Q6, A9, and Q11). The evidence shows significant differences in the coefficients, indicating heterogeneity in the relationship between investor attention and CSAD across different quantiles.

Table 6: Quantile regression results

Regression results			Differences of coefficients across quantiles		
Quantiles	**GSV**	**GSV (-1)**	**Quantiles**	**GSV**	**GSV (-1)**
Q1 (0.05)	0.01 **	0.005 **	Q1-Q4	-0.018 **	-0.014 **
Q2 (0.10)	0.012 **	0.007 **	Q1-Q6	-0.034 **	-0.027 **
Q3 (0.20)	0.02 **	0.017 **	Q1-Q9	-0.057 **	-0.058 **
Q4 (0.30)	0.028 **	0.019 **	Q1-Q11	-0.064 **	-0.055 *
Q5 (0.40)	0.033 **	0.023 **	Q4-Q6	-0.016 **	-0.013 *
Q6 (0.50)	0.044 **	0.032 **	Q4-Q9	-0.039 **	-0.044 **
Q7 (0.60)	0.051 **	0.042 **	Q4-Q11	-0.046	-0.041
Q8 (0.70)	0.055 **	0.051 **	Q6-Q9	-0.023 *	-0.031 **
Q9 (0.80)	0.067 **	0.063 **	Q6-Q11	-0.030	-0.028
Q10 (0.90)	0.083 **	0.064 **	Q9-Q11	-0.007	0.003
Q11 (0.95)	0.074 **	0.060 **			

This table presents quantile regression results with the herding effect (CSAD) as a dependent variable for the whole sample period (August 7, 2015, to November 23, 2020). The regression equation is $CSAD_{(\delta)t} = \alpha_{(\delta)0} + \lambda_{(\delta)}GSV_{(t)}$ and $CSAD_{(\delta)t} = \alpha_{(\delta)0} + \lambda_{(\delta)}GSV_{(t-1)}$. δ represents different quantiles. Columns five and six show the differences of coefficients across quantiles (0.05,0.30,0.50,0.80, and 0.95). ** and * denotes significance at 1% level and 5% level, respectively.

4. Conclusion

This study explores the relationship between investor attention and herding behaviour, one of the prominent behavioural characteristics evident among investors. The period of uncertainty confronted in the COVID-19 outbreak opens a scenario to look at this relationship in the cryptocurrency market. Academic literature underlines that where there is low inertia in the information acquisition process, individuals obtain information from various sources and tend to show herd mentality (Bikhchandani et al., 1992; Sgroi, 2002).

Our study is one of the initial attempts to examine the impact of investor attention on herding in cryptocurrencies. We use the Google search volume index as a proxy for investor attention, which acts as a free information source and measures investors' attention propensity. Our study shows important findings on herd mentality in the cryptocurrency market. The overall sample results show a positive effect of investor attention on anti-herding in the cryptocurrency market. According to sub-period analysis, the results indicate a positive effect of investor attention on anti-herding behaviour in both periods. However, the difference in the magnitude of the coefficients suggests that the impact is more prevalent in the COVID-19 period. During the current COVID-19 outbreak, there is a greater exertion of information regarding the market operation stemming from individual investors' greater attention.

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