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# Does Herding behaviour among traders increase during Covid 19 pandemic?: Evidence from the Cryptocurrency market

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Abstract. Cryptocurrencies are digital currencies and trading these currencies have gained huge momentum in recent years. The sophisticated features, complexities on regulatory framework, and high volatility of Cryptocurrencies would pose trading challenges to new investors and/or investors with limited knowledge. Investors generally are influenced by fund managers, financial analysts or other investors who are considered as well informed and highly knowledgeable peers. Investors mimic their behaviour to perform trading activities and such behaviour is termed as Herding. Covid 19 pandemic triggered severe uncertainties in the cryptocurrencies market and has led to wide fluctuations in prices causing severe volatility and market crashes. This paper aims to examine the herding behaviour in cryptocurrency market during the pre Covid 19 and Covid 19 pandemic period using the Cross-Sectional Standard Deviation (CSSD) approach. The findings of the paper reveal that herding was evident among all the ten crypto-currencies in normal market conditions of the entire sample period but not during market upswing or downswing. However, the herding behaviour was present in the cryptocurrencies Litecoin, Cardano and Dash during the Covid 19 pandemic period in all market conditions.

Keywords: Cryptocurrency, Herding Behavior, CSSD.

## 1 Introduction

Cryptocurrency, a phenomenal financial and technological innovation has become a key investment option for traders in recent years. With the introduction of Bitcoin in the year 2009 and its wide acceptance, an array of other cryptocurrencies was introduced in the market. Cryptocurrencies subsequently launched was tailored to adapt to Bitcoin and other leading cryptocurrencies characteristics while having to demarcation on certain unique characteristics on its own. As of August 5, 2020, top hundred cryptocurrency trading volume was \$83 billion (coinmarketcap.com) which indicate an increased participation and trading activity among the investors. Cryptocurrencies does not have fundamental value and hence their prices do not reflect all the information [1]. Cryptocurrencies also exhibit exceptional returns coupled with high volatility [2]. Being an under-regulated crypto market with lack of transparency in information, naïve traders and investors may venture into this market without realizing the risks associated on their investment. The novel features, ambiguity in information, high volatilities in the cryptocurrency market may cause the investors to rely on the judgments on financial advisors or fund managers or other investing forum. In financial theories, herding behaviour of investors relate to their trading decisions based on the views and actions on others. Lack of confidence, fear or anxiety in the investors may also lead them to mimic the trading behavior and decisions or other investors or fund managers. This behaviour may have several consequences such as price instability, higher volatility, market bubbles or crashes [3].

The financial markets are susceptible to unprecedented calamities, natural disasters, war, and pandemics leading to market crashes and financial crisis. In the case of pandemics/epidemic crisis, the previous occurrences such as the HIV/AIDS, SARS, Ebola and H1N1 which posed a threat to the lives of individuals had impacted the global financial markets and economy [4]. However, the severity in case of the recent Covid 19 pandemic is much higher in the financial markets which has disrupted the global economic activity as a whole causing collapse of several global economies and causing global stock market crashes. Yarovaya et al. [5] has noted that experts opine that Covid 19 may lead to financial crisis and may be predicted as a "black swan event", an event which is unpredictable and has not occurred earlier. Such events may impose challenges on model predictions and calculate risk assessment measures. Hence, investors trading in cryptocurrencies are confronted with uncertainties due to the Covid 19 pandemic which may lead to herd behaviour. The stock market crash and relevant investor uncertainties causes investors to deviate from their rational behaviour and exhibit biases and herding [6].Overexcitement among investors leading to high volume trading causes herding behaviour in extreme volatile conditions [7] and the cryptocurrency prices are driven by herding behaviour [8]. Hence, examination of herding behaviour in cryptocurrency market is important during uncertain market conditions. In particular, when market crashed due to Covid 19 pandemic, herding behavioral characteristics could be a potential contributor on cryptocurrencies price variations and trading volume and its associated liquidity. On this context, this study examines the herding behaviour in the cryptocurrency market prior to Covid 19 pandemic and whether this trend has increased during the pandemic period.

### 2 Literature Review

Several researchers have tried to explore the dynamics of various market crashes particularly in the equity markets. Presence of herding behaviour in stock markets during the crisis period has been investigated in stock markets [3]. Investors tend to herd or mimic other investors during extreme volatile conditions in the markets hoping to make profits [9]. Studies by Lao & Singh [10], Hammami & Boujelbene [11], Jlassi & Naoui [12], Clements et al. [13], Demirer et al. [14] and Bansal [15] have confirmed the herding behaviour during market turbulence or crisis period whereas studies by Ahsan & Sarkar [16] have provided evidence of non-existence of herding behaviour as well.

Given the market severity and volatility during crisis period, investigation on herding behavior of investors becomes vital. Sophisticated features of cryptocurrencies [17] and its extreme volatile nature may cause herding activity among investors particularly during extreme and volatile market conditions. Herding behaviour in cryptocurrency markets were examined during different market conditions. Conrad et al. [18] examined herding behaviour in cryptocurrency market using CSSD, Cross Sectional Absolute Deviation of returns (CSAD) and Markov-Switching model, and found that herding existed in extreme market conditions. Silvia et al. [19] studied herding formation using modified CSAD model on select 50 cryptocurrencies based on liquidity and market capitalization. The study revealed that severe herd behaviour was exhibited during extreme periods. Vidal- Thomas et al. [20] examined herding using static, rolling, and logistic regression model and reported that herding activity increased with market uncertainty. Ballis & Drakos [21] employed GARCH models to examine herding behaviour on top five cryptocurrencies, and found herding existed during market up and down periods. Poyser [9] used Markov-Switching approach and reported that herding existed during different market regimes. Jalal et al. [8] confirmed the presence of herding behaviour in the extreme conditions of bullish and high volatility market situations of major cryptocurrencies listed in CCI30 index and sub-major cryptocurrencies and major stock returns listed in Dow-Jones Industrial Average Index, from 2015 to 2018. Junior et al. [22] noted a positive relationship between herding and market stress conditions. The studies on herding behaviour in the cryptocurrency market had established the presence of herding activity among investors during uncertain market conditions.

Covid 19 pandemic has caused uncertainty across the globe leading to falling economies, market crashes, unemployment, and other unexpected uncertainties. Previous pandemics/epidemics including the Spanish flu, SARS, HINI, HIV/AIDS had caused impact on financial markets. But in the case of Covid 19 pandemic, the lockdown restrictions and the halt of several global industrial and economic activities led to a significant impact on the financial markets [23]. Ma et al. [24] and Baker et al. [25] noted severity in economic impact and Eichenbaum et al. [26] on the huge loss in lives, Under such uncertain economic and high volatile conditions in cryptocurrency markets due to the pandemic, the herding behaviour in investors may tend to increase as established by several researchers. Kizysa et.al., [27] have noted that the Government and regulatory restraints imposed to control the transmission of Covid 19 within and across countries can ease the investor herding behavior in international stock markets. Few studies have examined the herding behaviour in cryptocurrency markets during the Covid 19 pandemic. In case of cryptocurrencies, Yarovaya [6] reported that Covid 19 does not significantly amplify herding in the markets whereas Mnif et al [28] found herding behaviour reduced after Coronovirus outbreak. Most of the studies on cryptocurrency market have tried to capture the herding behaviour in different market conditions. The limited evidences of Yarovaya [6] and Mnif et al. [28] have mixed indication on herding behaviour during Covid - 19 pandemic. Hence this study aims to justify a potential

research gap by examining the herding behaviour during the pre-Covid 19 and Covid 19 pandemic period.

### 3 Methodology

This study aims to examine the herding behaviour in top ten cryptocurrencies. The ten cryptocurrencies used for this study are Bitcoin, Ripple, Ethereum, Bitcoin cash, EOS, Litecoin, Monera, Cardano, IOTA, and Dash. Crypto10 Index. The market index chosen was BITA Crypto10 (B10) Index, provided by the company BITA, a German-based Fintech company was introduced on 20th September 2018. The Crypto10 Index is calculated in US dollars (USD) and calculated on a daily basis. It represents the performance of the 10 largest cryptocurrencies based on the market capitalization. Daily closing prices of the Index and the ten cryptocurrencies (from BITA crpto-10 Index) are sourced from bitadata.com and coinmarketcap.com are used for the analysis. The sample period considered for this study is from July 29, 2019 to July 28, 2020 comprising of the pre Covid 19 and Covid 19 period. The BITA Crypto 10 Index returns are examined for normality and stationarity for usage in subsequent analysis.

The best possible approach to test herding is to directly observe the investor's actions. But in cryptocurrencies, it is almost impossible because of its privacy and so different proxies are developed to detect herding behavior of the crypto market based on returns' regression rate. Hence this study employs the methodology adopted by Chang et al. [29] an improvement from the original methodology offered by Christie and Huang [30]. Christie and Huang [30] suggested the use of Cross-Sectional Standard Deviation of returns (CSSD) to identify herding behavior in financial markets.

$$CSSD = \sqrt{\{((Bitcoin return - Average of B10 return)2) / N-1\}}$$
(1)

where, Bitcoin return is computed using the formula (Today's closing price – previous day closing price)/ previous day closing price,B10 return is computed using (Today's index value – previous day index value)/ previous day index value, and N is the number of days taken for the study.

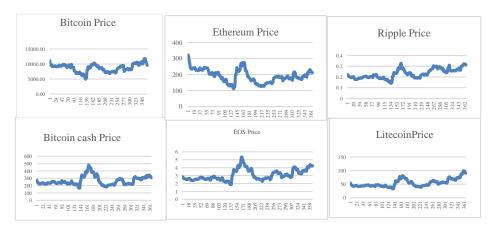
According to Christie and Huang [30] herding can be tested when there are upswings and downswings (under market stress events) by exploiting investors' tendency to overturn their private beliefs in favor of the market consensus. The Capital Asset Pricing Model (CAPM) predicts that the dispersion will increase with the absolute value of the market return since individual assets differ in their sensitivity to the market return. And also, if herding exists, individual returns will not differ greatly from the market results. The CSSD refers to the average proximity of individuals' returns to the mean and will always be equal greater than zero. The value in the lowest bound signifies when all the returns converge while a deviation from the zero represents dispersion. The herding behaviour in the cryptocurrencies are studied using Dummy variable Ordinary Least Square (OLS) regression model as shown in equation 2.

$$Log (CSSDi) = c + dl + du$$
 (2)

where, CSSDi is the CSSD of the log return of the individual cryptocurrency, dl is 1 if market return lies on the lowest side of the distribution and 0 otherwise, du is 1 if market return lies on the upper side of the distribution and 0 otherwise. The residuals of the equation are examined for autocorrelation and heteroskedasticity. The residuals of the Dummy variable regression were verified for presence of autocorrelation using Ljung-Box (L-B) portmanteau test and heteroskedasticity using Lagrange's Multiplier (LM) test for ARCH-effect. Where the presence of ARCH effects in the currency returns GARCH (1,1) regression models was used for the analysis.

## 4 Analysis and Findings

The time series graphs of the ten cryptocurrencies are illustrated in Figure 1 plotted with prices on Y axis and days on X axis. It can be observed that all the cryptocurrencies witnessed a massive fall in their prices during the months December 2019 and March 2020. The fall in December 2019 prices may be attributed to the event when the outbreak of Coronavirus at Wuhan, China was announced. The subsequent major fall in prices during March 2020 may be due to the nationwide lockdown imposed across several global countries to contain the spread of the virus in their respective countries. The global financial markets were forced to stop trading due to the steep fall in prices and the markets moved to bear trend. It may be inferred that in such market stress situations investors uncertainty and panic would have led them exhibit herding behaviour. CSSD series for longer sample periods may not be normally distributed and regularly tend to show excess kurtosis and skewness which are basic with financial parameter [31]. Brooks [32] recommends the usage of natural logarithmic transformations to meet the normality assumption as it can help to make a skewed distribution closer to a normal distribution. The results of the log CSSD value of the cryptocurrencies carried out using ADF test showed that the t-statistic values were lesser than the critical values -2.88 at 5% significance level during both pre-Covid 19 and Covid 19 and were stationary.



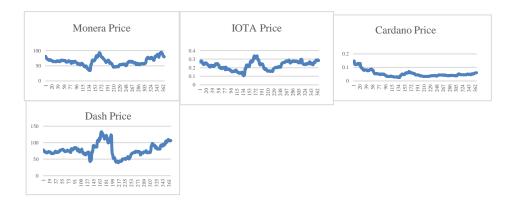


Fig. 1. Time Series Graph of Close Price of select Cryptocurrencies.

#### 4.1 Herding behaviour during pre-Covid 19

The results of the Dummy variable OLS regression model for the ten cryptocurrencies during pre-Covid 19 periods using Equation 3 are provided in Table 1. The residuals of these models were examined for presence of autocorrelation and heteroskedasticity. The residuals of the Ethereum CSSD regression was found to be autocorrelated and hence AR (1) term was added in the model. The residuals of the Bitcoin CSSD and EOS CSSD regression had ARCH effects and hence GARCH (1,1) model was employed. It can be observed from Table 1, the coefficients of dl in the models for the cryptocurrencies Bitcoin (1.1252), Ethereum (1.2068), Ripple (1.1607), Bitcoin cash (1.3006), EOS (1.1954) were positive and significant. According to Christie and Huang [30], a positive and significant coefficient indicates absence of herding behaviour. It can be inferred that during market downswing or when the market returns were negative there was no existence of herding activity. However, for the cryptocurrencies Litecoin (-0.2790), Monera (-0.5218), Cardano (-0.1918), IOTA (-0.4949) and Dash (-0.3103) the coefficients of dl were found to be negative and significant. A statistically significant negative coefficient indicates presence of herding activity in the market downswing period. It can also be inferred that herding activity was not evident for the top five cryptocurrencies during market downswing, whereas the investors trading in the next five cryptocurrencies exhibited herding behaviour during this market condition. The constant term of all the cryptocurrencies which represent the normal market condition were found to be statistically significant and negative for all cryptocurrencies. It can be surmised that during normal market conditions herding activity were present. However, the coefficient dl was found to be statistically insignificant and herding behaviour was not present among investors during market upswing. The residuals were examined for the presence of autocorrelation. The Ljung-Box Q-statistics, LB (36) statistic tests the null hypothesis that autocorrelations up to lag 36 equals zero implying that the residuals and squared residuals are random and independent up to 36 lags. The values of Q (36) of the Ljung-Box Q-statistics for the standardized residuals for the OLS models of the cryptocurrencies Ethereum, Ripple, Bitcoin Cash, Litecoin, Monera,

Cardano, IOTA and DASH were found to be insignificant and hence the residuals were uncorrelated. The values of Q (36) and  $Q^2$ (36) for the models Bitcoin and EOS for the standardized and squared residuals were found to be insignificant and hence the residuals were not serially correlated. The ARCH LM test is a Lagrange multiplier test to assess the significance of ARCH effects or whether the residuals are exhibiting heteroskedasticity. The ARCH LM statistic was found to be insignificant at 5 % level, confirming the removal of heteroskedasticity in the residuals. The ARCH and GARCH terms in variance equation of the models of Bitcoin and EOS were positive and significant at 5% level, suggesting persistence of volatility for longer period when a shock had occurred.

Crypto- currencies	Log Bitcoin CSSD		Log Ethereum CSSD		Log Ripple CSSD		Log Bitcoin- cash CSSD		Log EOS CSSD	
Variable	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Mean Equation										
С	-6.820	0.000	-6.873	0.000	-6.783	0.000	-6.880	0.000	-6.808	0.00
Dl	1.125	0.001	1.207	0.018	1.161	0.001	1.301	0.000	1.195	0.01
Du	-0.113	0.841	0.493	0.115	-0.468	0.157	-0.338	0.351	-0.034	0.88
AR (1)			0.231	0.009						
	Variance Equation									
С	0.817	0.009							0.692	0.011
ArchTerm	0.131	0.166							0.343	0.071
GARCH	-0.17	0.678							-0.337	0.302
Adj R-sq	0.062		0.125		0.079		0.074		0.084	
LB Q (36)	0.115		0.204		0.970		0.288		0.529	
LB Q <sup>2</sup> (36)	0.840								0.610	
LM Arch	0.824		0.845		0.347		0.572		0.432	
Crypto-	Log Litecoin		Log Monera		Log Cardano		Log IOTA		Log Dash	
currencies	CSSD		CSSD		CSSD		CSSD		CSSD	
С	-6.79	0.00	-6.792	0.000	-6.808	0.000	-6.805	0.000	-6.807	0.000
Dl	-0.27	0.000	-0.522	0.000	-0.192	0.00	-0.495	0.000	-0.310	0.000
Du	-0.03	0.503	-0.037	0.417	0.003	0.932	0.023	0.750	0.002	0.960
Adj R-sq	0.193		0.457		0.122		0.231		0.202	
LB Q(36)	0.054		0.996		0.430		0.999		0.705	
LB Q <sup>2</sup> (36)	0.632		0.745		0.882		0.949		0.857	

**Table 1.** Dummy Variable OLS Regression results for herding behaviour on pre-Covid 19

\* Bold indicates significance at 5% level

#### 4.2 Herding behaviour during Covid 19

The presence of herding behaviour during Covid 19 period was examined using Dummy variable OLS regression model and the results are shown in Table 2. The residual for the Bitcoin Cash CSSD and Dash CSSD regressions was found to be autocorrelated. AR(1) and MA(1) terms was added to the model of Bitcoin Cash CSSD and AR(1), AR(2), MA(1) and MA(2) terms were added in the model of Dash CSSD. The residuals for Bitcoin cash CSSD and EOS CSSD and IOTA CSSD had ARCH effects and hence GARCH (1,1) model was used. It can be seen from Table 2, that the coefficient of dl (downswing market) were positive and significant for Bitcoin (1.3349), Ethereum (1.2920), Ripple (1.7878), Bitcoin cash (1.4481), EOS (1.6419). Hence herding behavior was not evident among the investors during market upturn. The coefficient of du (upswing market) were found to be negative and significant for the cryptocurrencies Litecoin (-0.2449), Monera (-0.3705), Cardano (-0.6634), IOTA (-0.3648) and Dash (-0.4589) and the presence of herding activity was found in these cryptocurrencies. The constant term representing the herding behaviour during normal market conditions for all cryptocurrencies were found to be statistically significant and negative and the presence of herding among investors was found. Similar to the pre-Covid 19 period, the coefficients of du were positive and insignificant for Bitcoin (0.4383), Ethereum (0.4110), Ripple (0.4499), Bitcoin cash (0.0347) absence of herding was observed. However, it can be seen that the coefficients of du for the cryptocurrencies Litecoin (-0.0870), Cardano (-0.1958) and Dash (-0.3977) were negative and significant indicating that the herding behavior existed when there was upswing in the market and has negative impact on cryptocurrencies. The cryptocurrencies Monera (-0.0927) and IOTA (-0.0493) coefficients were negative and insignificant and EOS (0.7405) coefficient was positive and significant which implied absence of herd behavior. The residual statistics were verified for the presence of autocorrelation and heteroskedasticity. The insignificant values of LB Q (36) and LB  $Q^2(36)$  showed the absence of autocorrelations in the residuals of the models. The statistic values of the ARCH effect were found to be insignificant and the absence of ARCH effects were statistically confirmed. The previous studies by Gumus et al. [33] found absence of herding behaviour for the cryptocurrencies Bitcoin, Litecoin, Stellar, Monero, Dogecoin and Dash using CCI 30 Index as market proxy whereas Silva et al. [19] detected the presence of herding in 50 cryptocurrencies especially in the market stress conditions. The only study during Covid -19 by Mnif et al. [28] showed that herding decreased during Covid 19. The findings of this study differed by the results of Mnif et al. [28] wherein it was found that similar herding behaviour was found seven cryptocurrencies Bitcoin, Ethereum, Ripple, Bitcoin cash, EOS, Monera and IOTA during pre Covid 19 and Covid 19 periods. However, the investors trading in Litecoin, Cardano, and Dash exhibited herding behaviour during market upswing, downswing, and normal conditions in the Covid 19 period. The fear and uncertainty among the investors trading in these currencies would have led them to imitate the trading behaviour of others anticipating positive returns during the market upswing. It can be presumed that these investors demonstrated excessive herding behaviour due to fear of losing money in the Covid 19 period due to the market

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crashes, economic downturn, and uncertainty across global economies. Studies by Conrad et al. [18], Silvia et al. [19], Vidal- Thomas et al. [20], Junior et al. [22], Jalal et al. [7] also confirmed the presence of herding behaviour during extreme market conditions.

Cryptocur- rencies	Log Bitcoin CSSD		Log Ethereum CSSD		Log Ripple CSSD		Log Bitcoin- cash CSSD		Log EOS CSSD	
Variable	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Mean Equation										
С	-7.006	0.00	-6.930	0.00	-7.040	0.000	-6.968	0.000	-6.892	0.000
Dl	1.335	0.00	1.292	0.00	1.788	0.000	1.448	0.041	1.642	0.000
Du	0.438	0.18	0.411	0.17	0.450	0.241	0.035	0.919	0.741	0.034
AR (1)							0.909	0.000		
MA (1)							-0.823	0.000		
				Varian	ce Equat	ion				
С							0.230	0.362		
Arch Term							-0.024	0.313		
GARCH							0.798	0.001		
Adj R-sq	0.070		0.079		0.090		0.111		0.102	
LB Q (36)		0.42		0.359		0.317		0.226		0.472
LB Q <sup>2</sup> (36)								0.148		
LM Arch		0.42		0.788		0.341		0.800		0.818
Cryptocur- rencies	Log Li CSSD	tecoin	Log M CSSD	onera	Log Ca CSSD	rdano	Log IO CSSD	ТА	Log Da CSSD	sh
Mean Equation										
				Mean	Equation					
С	-6.791	0.00	-6.799	0.00	-6.795	0.000	-6.787	0.000	-6.812	0.000
C Dl	-6.791 -0.245	0.00 0.00	-6.799 -0.371		-		-6.787 -0.365	0.000 0.000	-6.812 -0.459	0.000 0.000
				0.00	-6.795	0.000				
Dl	-0.245	0.00	-0.371	0.00 0.00	-6.795 -0.663	0.000 0.000	-0.365	0.000	-0.459	0.000
Dl Du	-0.245	0.00	-0.371	0.00 0.00	-6.795 -0.663	0.000 0.000	-0.365	0.000	-0.459 -0.398	0.000 0.000
Dl Du AR(1)	-0.245	0.00	-0.371	0.00 0.00	-6.795 -0.663	0.000 0.000	-0.365	0.000	-0.459 -0.398 1.448	0.000 0.000 0.000
Dl Du AR(1) MA(1)	-0.245	0.00	-0.371	0.00 0.00	-6.795 -0.663	0.000 0.000	-0.365	0.000	-0.459 -0.398 1.448 -0.920	0.000 0.000 0.000 0.000
Dl Du AR(1) MA(1) AR(2)	-0.245	0.00	-0.371	0.00 0.00 0.12	-6.795 -0.663	0.000 0.000 0.010	-0.365	0.000	-0.459 -0.398 1.448 -0.920 -1.429	0.000 0.000 0.000 0.000 0.000
Dl Du AR(1) MA(1) AR(2)	-0.245	0.00	-0.371	0.00 0.00 0.12	-6.795 -0.663 -0.196	0.000 0.000 0.010	-0.365	0.000	-0.459 -0.398 1.448 -0.920 -1.429	0.000 0.000 0.000 0.000 0.000
Dl Du AR(1) MA(1) AR(2) MA(2)	-0.245	0.00	-0.371	0.00 0.00 0.12	-6.795 -0.663 -0.196	0.000 0.000 0.010	-0.365 -0.049	0.000 0.238	-0.459 -0.398 1.448 -0.920 -1.429	0.000 0.000 0.000 0.000 0.000
Dl Du AR(1) MA(1) AR(2) MA(2) C	-0.245	0.00	-0.371	0.00 0.00 0.12	-6.795 -0.663 -0.196	0.000 0.000 0.010	-0.365 -0.049 0.001	0.000 0.238 0.005	-0.459 -0.398 1.448 -0.920 -1.429	0.000 0.000 0.000 0.000 0.000
Dl Du AR(1) MA(1) AR(2) MA(2) C Arch term	-0.245	0.00	-0.371	0.00 0.00 0.12	-6.795 -0.663 -0.196	0.000 0.000 0.010	-0.365 -0.049 0.001 0.161	0.000 0.238 0.005 0.000	-0.459 -0.398 1.448 -0.920 -1.429	0.000 0.000 0.000 0.000 0.000
Dl Du AR(1) MA(1) AR(2) MA(2) C Arch term GARCH	-0.245 -0.087	0.00	-0.371 -0.093	0.00 0.00 0.12	-6.795 -0.663 -0.196	0.000 0.000 0.010	-0.365 -0.049 0.001 0.161 0.822	0.000 0.238 0.005 0.000	-0.459 -0.398 1.448 -0.920 -1.429 0.974	0.000 0.000 0.000 0.000 0.000
Dl Du AR(1) MA(1) AR(2) MA(2) C Arch term GARCH Adj R-sq	-0.245 -0.087	0.00 0.04	-0.371 -0.093	0.00 0.00 0.12 Varian	-6.795 -0.663 -0.196	0.000 0.000 0.010	-0.365 -0.049 0.001 0.161 0.822	0.000 0.238 0.005 0.000 0.000	-0.459 -0.398 1.448 -0.920 -1.429 0.974	0.000 0.000 0.000 0.000 0.000 0.000

Table 2. Dummy Variable OLS Regression results for herding behaviour on Covid 19

LM Arch	0.076	0.148	0.860	0.401	0.854		
* Bold indicates significance at 5% level							

#### 5 Discussions and Conclusion

Financial markets react to natural calamities, epidemics political elections, news announcements. The outbreak of Covid 19 pandemic and the rapid transmission of coronavirus across global economies have caused an adverse effect on the global economy and has disrupted the lives of people across the globe. While several epidemics such as the influenza, SARS, Ebola, HINI, HIV/AIDS have posed challenges in terms of lives of people and the economic activity, the impact of Covid 19 pandemic is found to be much severe. The lockdown restrictions imposed by several countries during March 2020 to contain the spread of the virus has brought the economic activity and the lives of people to a standstill which has further aggravated the severity in global economic condition. The impact was reflected in financial markets and the market crash and halt of trading activities of several global financial markets was witnessed during this time. The cryptocurrency market which gained momentum in terms of trading during recent times also experienced the impact of Covid 19 pandemic. The investors tend to herd during situations of uncertainty and extreme volatile conditions. The reasons may be attributed to investor fear or motive to gain profits in volatile conditions. In this context, this study was carried out to examine the presence of herding activity of investors during the pre-Covid 19 and Covid 19 period. The leading ten cryptocurrencies in terms of market capitalization value was chosen and CSSD approach was employed to examine the herding behaviour of investors. The findings of the study revealed that all the ten cryptocurrencies exhibited herding behaviour during normal market conditions during the entire sample period. Herding behaviour was not evident in top five cryptocurrencies Bitcoin, Ethereum, Ripple, Bitcoin cash and EOS under situations of market upswing and downswing during the pre Covid 19 and Covid 19 period. Herding was present during market downswing in the next five cryptocurrencies Litecoin, Monera, Cardano, IOTA, and DASH during the pre Covid 19 and Covid 19 period. It can be inferred from the above findings that the regular pattern of herding existed in the top five cryptocurrencies and Monera and IOTA cryptocurrencies. The highly technological features of the cryptocurrencies, mixed views on regulatory framework may be presumed as reasons to cause investors to herd in normal market conditions. The time series graphs of the cryptocurrencies showed a gradual fall in prices during the six months of pre Covid 19 period which may be due to the fall in global economic activities. Hence investors would have followed the trading pattern of other investors in normal market conditions. They would have tended to avoid risk and hence may not have exhibited herd behaviour during market downswing. Herding was seen in the cryptocurrencies Litecoin, Cardano and Dash during the Covid 19 pandemic period in all market conditions. It can be observed from the time series graphs that two adverse falls in prices of cryptocurrencies occurred during December 2019 and March 2020 when the outbreak of the Corona virus and the lockdown restrictions were announced. The subsequent rise in prices was also observed in the cryptocurrencies. The investors trading in Litecoin,

Cardano, and Dash started to herd in all market conditions during Covid 19 period. It may be reasoned that the investors trading in these cryptocurrencies would have sought to make profits in the extreme volatility in prices. The fear of losing money may also have induced the investors to herd during the Covid 19 pandemic period. The findings would be useful to investors, academicians, and researchers. The study showed the existence and pattern of herding in the cryptocurrencies during extreme market conditions. The novel features of cryptocurrencies would cause less participation in trading of cryptocurrencies and this study shows that herding behaviour is present in all cryptocurrencies in normal market conditions. Investors can make use of this finding for their trading strategies. The research in cryptocurrency is an emerging area in the field of Technology and Finance and the study would be beneficial to academicians in both these areas and gain insights on the functioning of the cryptocurrency market. The findings of this study provide evidence on the presence of an important behavioural bias of investors, herding in the cryptocurrency market particularly during the pandemic crisis situation. There are limited studies on the behaviour of financial markets in pandemic situations and this study would be beneficial to researchers. The realization of profits due to herding in the cryptocurrency market can be taken as a future scope of this study.

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