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An Examination of Herding Behaviour in the Cryptomarket

by

Hira Fatima Jan

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I want to dedicate this thesis to my parents, respected teachers and friends for their love, support and care.

CERTIFICATE OF APPROVAL

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Abstract

Virtual currencies have developed as one of the novel financial instruments of current era. Investors who do not wish to use their savings in the money markets, capital markets or markets of precious metals choose crypto currency as a diverse kind of investment. It is not un-common to observe herding behavior in cryptocurrencies. This study examines herding in different conditions of cryptocurrency market. It further explores the effect of macroeconomic fundamentals upon herd formation in this exciting market of digital currencies. The study also captures the effect of COVID-19 pandemic upon herding instincts of Crypto traders and investors. This study employs two different methods proposed by Christie and Huang (1995) and Chang et al. (2000) to measure herd behavior. The daily data for 10 Cryptocurrencies is taken from 1st January 2017 to 18th April 2021. These cryptocurrencies have highest market capitalization. The analysis of daily returns reveals presence of herding in crypto market. However conflicting results are seen about non linearity of herding. When this behavior is examined in Bullish and bearish market, herding is confirmed in Bull market period as well as bear market period. The herding is higher in bullish period in comparison to bearish period. There exists agreement on the effect of macroeconomic factors upon herding by both methods where it shows that World Equity market have insignificant impact on herding behavior of traders. Oil market Index and Interest rate does not influence the herding by cryptotraders. The results also indicate the insignificant impact of COVID-19 on herding behavior of cryptotraders. These findings provide useful insights linked to portfolio and risk management, trading strategies and market inefficiency. This study regarding herding in crypto market is also of great importance to build an understanding of dynamics in prices of cryptocurrencies.

Keywords: Herding Behavior, Cryptocurrency Market, CSSD, CSAD, Macroeconomic Factors, COVID-19 Impact

Contents

List of Tables

Abbreviations

ARCH	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving Average
CAPM	Capital Asset Pricing Model
CCI 30	Commodity Channel Index 30
CCE	Central Europe and South Eastern Europe
COVID-19	Corona Virus Disease of 2019
CRIX	Cryptocurrency Index
CSAD	Cross-Sectional Absolute Deviation
CSSD	Cross-Sectional Standard Deviation
FMH	Fractal Markets Hypothesis
FX	Foreign Exchange
G20	Group of Twenty
GAARCH	Generalized Autoregressive Conditional Heteroscedasticity
GCC	Gulf Cooperation Council
GLS	Generalized Least Squares
GMV	Gross Merchandise Volume
IMF	International Monetary Fund
IR	Interest rate Indexe
Mt.Gox	Magic: The Gathering Online Exchange
MVIS	Micro Vision, Inc. Common Stock
OI	Oil market Index
OLS	Ordinary Least Square
QRR	Quantile-on-Quantile Regression

SARS-COV-2	Severe acute respiratory syndrome coronavirus 2
TV-MS	Time Varying Markov-Switching
USA	United States of America
USD	United States Dollar
VCRIX	Volatility Index for Cryptocurrencies
VIX	Chicago Board Options Exchanges COBE Volatility Index
WHO	World Health Organization
WI	World Equity Market Index

Chapter 1

Introduction

The concept of herding was embedded in zoology at first as compared to psychology, sociology, economics and finance. It is an act where by individual animals are brought together into a group and are moved as a group from one place to another. Animals are directed by the herder. However investors are directed in speculative markets by the information instead of the herder.

The influence of personality factors of an investor on trading are obvious. A neurotic investor will passively follow the significant market trends. Instead of focusing on the available information they pay attention to uncertain conditions, also imitating other investors of the market which creates a sheep flock trend. The psychological herding argument is strengthened by neuro economics perception of herding because individuals overlook a rational response by following other individuals. (Devenow & Welch, 1996). Moreover, reputation factor is one of the sentimental factors that influence herding behavior. Benchmark is set by the fund manager for related market managers who then follows these investment pattern which is rationally valid according to managers but not socially and rationally accurate.

Satoshi Nakamoto launched crypto revolution in 2008 along with a new and disruptive technology known as blockchain technology. Though, the technology is not the only great bombshell, a new class of assets is introduced in the market, called cryptocurrencies. As the consciousness of decentralized currencies attracted not only investors and companies but also are of great concern for governments as well as academics (Extance 2015). Bitcoin experienced exponential growth till December 2017, roused the formation of new coins having dissimilar functionalities (payment methods, cloud services, smart contracts, lending, insurance, data storage and many others), and according to the Coinmarketcap Website different cryptocurrencies over 9000 are registered (2021). This new asset class is now increasingly attracting the attention of academicians and practitioners.

According to World Economic Forum (2016), Blockchain technology has been center of attraction for all over the world starting from the year of its inception. It has substantial influence to transform radically the financial ecosystem. As a new disruptive information technology, blockchain emerged that assists many users to carry out their financial transactions without any intermediating party. A secure way of storing data is provided by Distributed ledgers permitted by blockchain technology, making it largely unalterable. This technology stores information of a transactions in a decentralized method. Blockchain technology can be applied in several capacities such as facilitating such methods in which payments are made in distant regions of the world, attaining financial instruments, collateralized asset management, legal reporting actions to warranty adherence to connected rules and regulations, and casting of votes in annual meetings of shareholders of the companies without physical presence.

At the beginning blockchain is developed for the payment system. With its recognition by enterprises as a payment system, the frequency of consumer oriented transactions increased in the recent years (Bouri, 2018). In the recent times Bitcoin users have found other benefits for diverse purposes. As far as investment perspective is concerned crypto currency has a lot of potentials to offer. Legality factor associated are still widely focused on and are debatable as the market is still developing.

Even bankers and economists could not have anticipated that cryptocurrencies would exist in our lives by the internet era which originated just 20 years ago. In many countries, process of scheming the regulatory structure of domestic cryptocurrency markets is still continued. In some of emerging countries there is ban on crypto trading while developed economies are moving oppositely by recognizing Bitcoin as legal tender. Big firms like Facebook have entered the market of cryptocurrencies with Libra. So regulators are concerned for losing control on the global payment system. Domestic regulators should also consider the effects of the changes in foreign regulations. The application of modified theories of finance helps to understand the behavior of cryptocurrencies. Cryptocurrencies are widely traded and considered as a new investment tool, more than a payment instrument.

It is addressed in the research accompanied by news agency based in the USA, Wall Street Journal that cryptocurrencies can be employed in informal transactions by money launderers. It is indicated that these are credited as an instrument to launder the money that makes cryptocurrencies likely to transfer the money to different countries. The government lack supervision of crypto currencies thus making it probable to transmit the illicit money. For this reason there is ban on use of cryptocurrencies in many countries.

1.1 Theoretical Background

The two contradictory finance theories classical finance theory and behavior finance theory determined the link between behavior finance factors and returns. According to classical finance theory behavior finance factors have no influence on prices because the demand is neutralized by arbitragers transactions, which reduces the influence of emotional investors. Contrarily the theory of behavior finance states that behavioral factors influence asset prices. (Almansour, 2017).

According to the concept of Efficient markets Hypothesis proposed by Fama, 1970, all available information is reflected by the prices. It is the market where huge numbers of profit maximizers are competing rationally in the availability of important current information. Thus in proficient market the real prices of securities will be a worthy estimate of their intrinsic values at any point of time. So it can be said that according to efficient market hypothesis financial markets react on the new information arrival. But this efficient market hypothesis is not always true because the supposition that investors perform rational analysis of the oppo-

-rtunity hence rationally value investments by estimating net present values of cash flows to be generated in future, properly discounted for risk is not backed by the evidence, which indicate relatively that investors decisions are altered by: herd instinct, a propensity to churn their portfolios, a trend to react under or over reaction to news (Sheifer, 2000; Barber and Odean, 2000), distorted judgments around the reasons of profits and losses occurred previously.

The literature proposes two major justifications for herding; intentional herding and unintentional herding behavior. Intentional herding is caused when investors intentionally follow the crowd. These traders think that others have beneficial information so they mostly ignore the private information of their own. On the other hand unintentional herding occurs by identical reactions to information publicly available and signals (Bikhchandani and Sharma, 2001). It is important to distinguish the reasons of herding behavior for the purposes of making regulations and for noticing the effect of herding leading towards market inefficiency and financial bubbles. Intentional herding plays critical role in destabilizing stock prices resultantly impairing financial markets to function appropriately. If the interrelated trading is not determined by central values even unintentional herding leads to inefficient markets. (Scharfstein and Stein (1990) and Hirshleifer and Teoh (2003)).

Unintentional herding can arise by such institutions which are paying attention to stocks with unique features such as highly liquid stocks or also when they depend on same source of information that leads these institutions to alike conclusions concerning individual stocks (Hirshleifer et al. (1994)). Sometimes professionals form a uniform group where all members possess similar education and professional qualifications resultantly construe informational signals similarly. A noticeable example is the similar reaction of financial institutions towards a common risk measures. While the herding driven by sentiments is intentional herding. Investors imitate other investors in the market results in simultaneous purchasing or selling of the similar stocks regardless of past beliefs.

In view of the inflationary issues, Corbet et al. (2018) indicate that these digital assets undergo excessive destabilization under the episodes of extreme volatility because of several undesirable characteristics, connected with cryptocurrency, recognized as the trilemma of cryptocurrency: the potential for inherent bubbles, cybercrimes and regulatory issues. Behavior anomalies such as a herd effect exists in the digital market (Bouri et al., 2018; Vidal-Toms et al., 2018). Among investors herding behavior is observed due to higher unpredictability and short run trends in financial markets, being studied by many (Lakonishok et al., 1992; Christie and Huang, 1995; Chang et al., 2000; Hwang and Salmon, 2004). Since the cryptocurrency market is in development phase therefore this market is considered immature. It lacks market depth and it is less transparent.

Furthermore, there exists uncertainty among investors and crypto traders. Decision-making is characterized by dispersion of information. There exists no unanimity on how to value a cryptocurrency unlike equities. There is wide range of opinions of practitioners, many view cryptocurrencies as deceitful and some consider them as future of the currency. This leads to the controversy where financial analysts are reluctant to recommend cryptocurrencies and to determine factors to rate them. Furthermore, the average individual investors of cryptocurrency markets are young and have no prior experience so they have to rely on chat forums online and media for the decision-making process of investment thus they are influences greatly. Greedy investors fear about losing the good opportunities drive the prices of cryptocurrencies to an unjustifiable level.

It is also observed that speculation of Bitcoin and other large cryptocurrencies results in high volatility in crypto markets which inevitably leads to herding. (Baur et al., 2018). However, crypto traders are insensitive towards negative shocks and are not triggered by it to start selling in the market of cryptocurrencies.

Herding involves the aptitude to perceive the actions of others or it sometimes results due to the coordination of a price movement (Devenow and Welch, 1996). Herding is present in the cryptocurrency market because internet, networks and social media simply permit the distribution of information and promoting ideas of people effortlessly. Remarkably, it is quite easy to look into the movements of giant cryptocurrency holders, called whales by the use of cryptocurrency whale watching applications and also different websites that allow users to access the trading actions of whales. Additionally, it is suggested that sharing of such information is legal because cryptocurrencies are not considered as securities.

Commodity and Financial markets all over the world have stumbled due to the worldwide outbreak of COVID-19, commonly famous as SARS-COV-2. The confirmed number of cases and deaths has extended to an alarming situation. The hunt for safe assets in such an ambiguous and terrible market condition is a natural longing by the investors mostly. Several studies have proposed digital currencies as one of the numerous kinds of such safe assets. Everywhere all traditional financial assets appeared to lose value easily, a lot of investors were observing carefully the behavior of such virtual currencies, during this tense period.

Recently Investors have focused their attentions to these digital assets because of the huge returns delivered since the inception just a decade ago. The demand of these assets and extraordinary profits provided by this has appealed the attention of the scholars also. COVID-19 has triggered high level of turbulence in not only global financial markets but also in the crypto markets. This has severe impact on investment behavior of individual; however, limited studies have explored the impact of COVID-19 on herding behavior in Crypto markets .Therefore, this research also examines herding behavior in Cryptomarkets during the COVID-19 pandemic to understand the investment behavior in Cryptomarkets under immense conditions.

1.2 Gap Analysis

Crypto currencies are an emerging investment tool that has attracted the investors across the globe. As cryptocurrencies are seen as the new tool of investment worldwide so investors are interested to gain insights on each and every aspect of the digital currency. The limited information and high price fluctuation provide the possibility of existence of herding in these markets which is supported by Bouri (2018). Therefore, there is need to examine presence of herding in various market conditions.

Few study has been conducted on the topic of herding in crypto market but little focus has been given macro-economic factors that affect the herding behavior in cryptocurrencies so there is a need to find the herding behavior in cryptocurrencies and its macroeconomic determinant. Additionally, this study investigates herding behavior in Crypto markets during the COVID-19 pandemic to understand the investment behavior in crypto market under these conditions.

1.3 Problem Statement

History dictates that herding affect movements in the market very intensely. Herding is more often explored in financial markets yet not much studied in the crypto market that many individual investors are concerned about this controversial market. Mostly cryptocurrencies are volatile and exhibit unexpected returns in the absence of justification. The crypto market is known for weak legal framework and availability of quality information is too low for investors to make the best investment decisions, as a result investors have to rely on the limited information available to them and being inexperienced they are prone to such risks that they are unaware of. They are influenced by the market and ignore the rational decisions leading to herding in the time of uncertainty and extreme conditions of the market. As the interest of investors is more towards investment in cryptocurrencies worldwide so it is important to investigate whether this cryptomarket exists in isolation or global macro-economic variables are integrated with it. COVID-19 pandemic has created uncertain situation for investors about investing in cryptomarket. This research will give an insight that how herding is affected by COVID-19 especially in the market of cryptocurrencies.

1.4 Research Questions

On the basis of the research gap, following questions are raised:

Research Question 1

Do herding behavior exist in Cryptocurrencies?

Research Question 2

Do extreme market conditions have impact on herding behavior in the Crypto market?

Research Question 3

Do bullish and bearish condition have impact on herding behavior in the Crypto market?

Research Question 4

Do herding behavior follows a nonlinear pattern?

Research Question 5

Does herding behavior in crypto market is different during COVID-19 period?

Research Question 6

Do Interest rate variation affect the herding behavior among cryptocurrencies?

Research Question 7

Does equity market variation affect the herding behavior among cryptocurrencies?

Research Question 8

Does oil market variation affect the herding behavior among cryptocurrencies?

1.5 Objectives of the Study

This study has the following Research Objectives:

Research Objective 1

To identify the presence of herding in cryptocurrencies.

Research Objective 2

To analyze herding behavior in cryptocurrencies in various market conditions.

Research Objective 3

To examine the non-linearity in herd formation.

Research Objective 4

To explore impact of COVID-19 on herding in Crypto market.

Research Objective 5

To examine the role of selected global macro-economic factors influencing herding in cryptocurrencies.

1.6 Significance of the Study

Due to the instability in financial markets investors are in search of different investment platforms. The cryptocurrency market has created new investment opportunities for investors. Therefore, investors across the globe are focusing their attention to invest in cryptocurrency market. Immense consideration is given to cryptocurrency market in media and academia worldwide as its price showed fluctuations.

Investors often differed from rational decisions and follow the market trends to which they are exposed when conditions are uncertain. So the study of herding behavior in cryptocurrencies is vital for many reasons. The foremost purpose of this research is to impart a role in the ongoing discussion of investment in cryptocurrency market by evaluating herding behavior from perspective of behavioral finance.

Herding can cause extreme volatility in the returns of assets so it is important for investors because herding damages the market ability to represent essential information creating hurdles in market efficiency. Markets are dependent on views and attitudes constructed socially and crypto market is not an exception. It is important to identify and analyze herding behavior in the cryptocurrencies as it can leads to speculative bubbles because crypto-investors have little access to information and consequently have to rely on others for investments decisions.

To study the herding in crypto market is also of great importance to build an understanding of distortions in prices of cryptocurrencies. The issues that highlight the importance of this study based on literature review are: the effect of herding in cryptocurrencies, impact of Covid-19 on herding behavior in cryptomarket and detection of global factors that affect herding by investors in the cryptocurrencies market and in turn how diversely the effects of herding are expanding to economic fronts.

1.7 Contribution of the Study

This study contributes to the limited work done to explore herding in cryptocurrency market previously in a way that it not only adds up to the herd formation observed in cryptocurrencies but also explains the behavior in various market conditions. Contributing to the knowledge of dynamism found in cryptocurrency market, it enhances investors information resulting in making informed decisions to serve their purpose. The implication of the outcomes can help hit and run crypto investors to be progressively organized to remain in the crypto market and improve their capabilities to set on the best available choices.

This study also provides information on the link between crypto market and loan market, equity market, and oil market through exploring the causal relationship between the markets. This may be an added advantage in resource allocation. Besides, the results of this work may inspire financial specialists to understand that traditional finance theory is sufficient to explain the behavior of the crypto market investors. This study is also helpful in terms of investors and the decision makers who will be able to make informed investment decisions in the stressful situations such as COVID-19 pandemic situation.

1.8 Plan of the Study

An outline of this study is as follows. Chapter 1 includes Introduction, Theoretical Background, Gap Analysis, Problem Statement, Research questions, Objectives of the study and its significance. Section 2 briefly summarizes the vast literature of past researches on herding in financial market and herding behavior in cryptocurrencies along with Hypothesis formulation. Chapter 3 entails Econometric model of the research and data chosen. Chapter 4 discusses about Data Analysis along with results and their interpretation. Study is concluded in Chapter 5 where conclusion, recommendations, limitations and future directions for researches are presented.

Chapter 2

Literature Review

Cryptocurrencies such as Bitcoin, were built on the blockchain technology headed the evolution of new asset class. Cryptocurrencies have now turned out to be an investment choice which is considered more of a fashion. Portfolio investors are paying close attention to this class of assets as the correlation between conventional assets and cryptocurrencies are very low. (Bouri et al., 2017; Corbet et al., 2018).

It has been a matter of great debate for the academicians and practitioner to discover how investors trading pattern affect the price mechanism. It is a firm belief of academicians that price formation is explained by the Efficient market hypothesis proposed by Fama (1970). The returns expected in crypto market exhibit high volatility pointing towards speculative market. Intrinsic dynamic forces that may be unrelated to conventional factors has shifted the attention of researchers to look back into the Efficient Market Hypothesis. Different models have been suggested by West (1998) that may have impact on the stock prices includes fads, psychological and sociological mechanisms. Further during financial crises Kindleberger (1996) highlight the importance of such factors. These behavioral factors include Herding. The mass errors due to herding are responsible for Crashes and bubble formation as viewed by Kindleberger (1996) and Galbraith (1993).

Imitation is the second name of herding in capital markets. As per Banerjee (1992) definition of herding, it is the act of copying others decisions despite their own sources suggests differently. This results in price deviations from base and intensifying returns volatility. All of these together causes the destabilization of financial markets, making the financial system more fragile. Furthermore worsening the situation in the form of the crises. These behavioral effects are connected to stock price movements and impact the risk and return and thus effects the asset pricing models (Tan et al., 2008).

Javaira and Hassan in 2015 examined investors herding behavior in Pakistani Stock market. To test the herd formation they collected daily and monthly data of stocks for duration of 2002-2007 and employed two methodologies Christie and Huang (1995) and Chang et al. (2000). In 1995 Christie and Huang embraced a technique by empirical examination of herding in equity returns. While in 2000 Chang et al. improved their model into a new means by adding another regression parameter for identification of herding behavior in stock returns .These methods are used frequently to investigate herding in different markets.

The results of herding obtained are mix .While common observation is that herding is more among emerging markets as compared with developed markets. Christie and Huang (1995) discovered that herding was not evident in USA .Chang et al. (2000), explored about herd formation by investors in foreign markets and also worked on different markets like USA, Hong Kong, Japan, South Korea and Taiwan and stated that herding is evident in developing countries while herding is not reported for the developed countries because in developed countries investors have availability of better information and they employ superior analytical tools. On the other hand investors in emerging markets lack reliable information and it leads to herd formation.

The analysis done provides no evidence of herding for daily and monthly return because during extreme price movements the empirical results show the dispersion of, equity return increases instead of decreasing. It provides evidence against herd behavior. The results obtained are consistent with results of Christie and Huang (1995) and favors the assumption of the rational asset pricing model as markets are efficient by showing the during extreme market conditions. Likewise the results using the model of Chang et al. (2000) also supported the results of the former. Non linearity is also examined and the coefficient results were significant and no herding was found in stock market of Pakistan. The absence of herding in bullish or bearish trends in Pakistani market was also reported.

Filip et al. (2015) studies the herding behavior of investors at industry levels in emerging markets. Including stock markets majorly from Central Europe and South Eastern Europe. Industry level analysis is conducted including banks, energy and pharmaceutical because the behavior of investors is highly uniform at group level. As a result the likelihood is increased to detect herding at group level. The time period of study lied from January 2008 till December 2010. There are two central directions in the examination of the herding behavior in stock markets.

The first measurement is to examine the propensity of groups of investors or individuals to herd with further market members while trading an asset at the same time. The second path denotes the herding behavior in an extensive direction, the joint behavior of all the investors alongside the market trend. The literature have also mentioned two statistical methods proposed by Christie and Huang (1995) and Hwang and Salmon (2001). This research tests herding behavior using the CSAD methodology (Chang et. al, 2000). The results provide indication of presence of herding behavior at sector level by investors for all the CEE capital markets, except Poland. The hypothesis that herding is more noticeable at the group level because investors take related trading decisions. Moreover, during the periods of market decline the herding is observed.

Underlying Factors have potential impact upon the behavior of investors and traders especially in emerging markets. Because investors in these countries have few diversification options available to them in domestic markets so they are quite sensitive towards global shocks .Mehmet et al. (2017) explore oil market speculation impact on herding behavior of investors in context of emerging markets. Their work focus oil-rich Gulf Cooperation Council (GCC) countries stock markets because such markets offer productive ground for study of how oil market dynamics are linked to investor actions in stock markets. The herding model used for this study is Markov switching time varying parameter (MS-TVP).

The results express a positive correlation among speculative actions of the oil mar-

-ket participants with anti-herding behavior of major exporters stock market. It further argue that the speculation signals coming from oil market are perceived as positive sign by traders so they expect to create higher profits in their local markets by not following the crowd. It is also observed that the pattern is demonstrated in the time of low volatility in the market while during high volatility a significant herd formation have taken place. In light of these findings it is suggested that policy makers who are worried of stock stability in the markets must observe energy market speculation to monitor effect of volatility into their markets.

Lagarde, (2017)the managing director of the IMF indicate that while digital currencies have certain risks but they have the potential in long run to be used by central. She stress that cryptocurrencies should not be undermined. Instead of blocking them, central banks should notice how to use this technology more efficiently in more cost-effective way. Cryptocurrencies can be employed instead of adopting currency of another country by the Countries with weak institutions and an unsound currency .Recognizing cryptocurrencies as a feasible alternative, this approach is called as dollarization 2.0.

Leclair (2018) focus on market herding in cryptocurrencies. Contrary to other forms of herding, it is a kind of herding with respect to the market consensus and can be estimated straight away with price data. The study argue that herding could concurrently be the outcome of the ambiguity of value of cryptocurrencies as financial assets and described the risky volatility in the market. Several investors possess restrained degrees of technical & fundamental knowledge of this topic so they possibly rely on others to make and modify their opinions leading to herd formation in the market. The initial technique of Christie and Huang (1995) is applied followed by the seminal work of Hwang and Salmon (2004). CAPM framework is applied as structural framework. The return of each asset is regressed on a market portfolio. Market index represents the market consensus.

Questionably there are no major shocks on the acceptance of cryptocurrencies into the existent economy that can rationalize asset movements. The blockchain technology being fundamental discovery in cryptography, increase in prices can be described by a rational bubble factor driven by beliefs of investors for future adoption. However, very high increase or decrease in prices cannot be explained by a rational bubble and this theory cannot justify the weak connection among cryptocurrencies as financial assets and their anticipated function in the real economy. It may be debated that due to extreme volatile nature of cryptocurrencies, it may be detrimental to adopt blockchain into the real economy. The use of this digital currency for transaction purpose caused uncertainty about the value expected by the recipient against the worth contracted by the sender.

Current volatility can also be viewed in connection with a massive deflationary environment, for incentivized investors who prefer to hold cryptocurrencies instead of using it for transactions. Consequently speculation of cryptocurrencies clashed with other anticipated purpose. Also it has been proposed by few major actors in the industry that some of these currencies should be tied to a stable currency such as the US dollar. It can also be planned to upkeep moderate inflation instead of dangerous deflation.

These virtual currencies did not fit into traditional asset pricing models. These do not pay dividends unlike many investment assets further not administered by formal institutions. Manifestly a pronounced situation of informational uncertainty is created which can affect prices in financial markets as well.

The results show major evidence of high persistence in herding. Investors in cryptocurrency market herd more in down market trends. It indicate sign of overconfidence in positive time periods on the other hand throughout low market period investors doubted their own information. The positive impact is noted of introduction of futures upon herding behavior. Overall Shocks has positive influence upon herding so concluded that when faced with new information. Market participants without any rational decision blindly follow others in market.

With an increase in inefficiency and rising levels of financial fragility caused by herding can also trigger financial crisis during period of market instabilities. Cakan et al. (2018) examine the relationship between oil market speculation and herding by investors of stock markets. Data of Firm level of three major energy importing and exporting countries is used that included Russia, Brazil, and Turkey. Oil is a widely traded commodity so the variations of time in the level of investor herding is compared to speculation in the oil market as oil is considered a feedstock because it affects cost of productions. Crude oil experienced tremendous trading volume, of which a major proportion is associated with speculation.

Results show that higher speculation in oil market was linked to higher level of herding. So it is suggested that policymakers must watch out for the measures of commodity market speculation along with other variables for measuring speculation as it could provide important insights on investor behavior in emerging stock markets. For Investors increase in speculation in oil markets is an indication of increased insecurity about the trend of global demand and they herd following market during the period of uncertainty.

In financial markets herding behavior is more commonly empirically studied while it is less explored in the market of cryptocurrency. The discussion about herding in crypto market began by Bouri et al. (2018). They worked on the sample of fourteen Cryptocurrencies leading at that time; for a fixed period from 2013 to 2018 to examine the herding. The study select the point of reference as market-capitalization weighted (cap-weighted) portfolio. In static approach the study find no evidence of herding by employing the methodology of cross-sectional absolute standard deviations (CSAD) of Chang et al. (2000). The study conclude that herding of cryptocurrencies varies with time and crypto traders follow the footsteps of other investors are exposed to high risk. The presence of herd investing advocates that portfolio diversification is insufficient so those investors who are holding only cryptocurrencies are exposed to further risk. On the other hand investments will not be profitable if herding prevails for substantial time.

More rational players as well as analysts may join crypto trading because of the addition of institutional investors. This may reduce speculation. Stronger evidence of herding is predictable as the cryptocurrency market is new and is in the phase of expansion as it experiences price volatility. Investors lack of quality information. Crypto traders are only expecting positive outcomes extremely. The decisions taken by investors here are not considered in isolation implying herding. Rather the investors may overlook characteristics of individual cryptocurrencies and take part in herd formation on the basis of performance of the cryptocurrency market.

They may have strong beliefs that prices will never go down. These herding indicate inefficiencies of relative market. The study contribute in the greatest debate going on about investments in the cryptocurrency market from a behavioral finance perspective in general and to analyze herding behavior in specific.

Vidal-Toms and Farins (2018) extend the same employing an alternative return dispersion measure for a large cross-section of asymmetric herding using sample of Sixty Five Cryptocurrencies for the period 2015 to 2017. In order to do herding analysis a market portfolio is required that show the behavior of cryptocurrencies as compared to the market consensus. It is important to analyze herding in the market as its presence is a sign of inefficient market where asset pricing models cannot be applied properly. Interestingly it is seen that herding is perceptible when market is getting down rather than up markets. So when prices are falling investors follow the market trends.

This study not only examine cross-sectional absolute standard deviations (CSAD) but also worked on Christie and Huang (1995) suggested CSAD approach. By using the cross-sectional standard deviation of returns (CSSD), following Chiang and Zheng (2010), the sample is divided into two phases of up and downturn to account for asymmetric herding. The results are consistent with findings of Bouri et al., (2018) as the herding is not evident in CSAD and CSSD in standard form. While herding is obvious during bearish market trends when tested for asymmetric herding using CSAD. It is further observed that the smallest digital currencies are also herding with the largest cryptocurrencies.

The literature on financial markets biases serve as a starting point to recognize crypto-markets. Poyser et al. (2018) explore price determination of cryptocurrencies from perspective of behavioral finance suggesting these are driven by herding using model of Chang, Cheng, and Khorana (2000) under both asymmetric and symmetric conditions. Markov-Switching approach is also employed to test the presence of different herding regimes.

Under the extreme conditions of price movements, it seems difficult to line up a future where cryptocurrencies tend to bring economic change. Economists face complications to build an understanding of the stock market crashes for many years. In financial economics the theoretical foundations are built on the assumption of efficiency of markets. However the results of many studies are contrary to foundations of efficient markets. The systematic deviations are exposed by behavioral economics that individuals are following cognitive biases instead of rational decision making that further leads to anomalies and market fragility.

Behavioral finance advocate that cryptocurrency markets are similar to financial markets to a great extent. It further aims to provide reasons for investors actions in the market.so the researchers hypothesize that in behavioral finance investors cognitive biases contribute to explain volatility in cryptocurrencies market prices. The revision of empirical studies along with theoretical evidences show investors actions are not associated with rationality. So the same can be considered for crypto- market problem. As crypto traders have inadequate information sources along with limited prior knowledge so they rely on collective decision making process leading to herd formation triggering speculative bubbles in the market.

To some level it is anticipated that Blockchain is challenging to recognize even for information technology enthusiasts. Particularly in cryptocurrency markets as articulated before, any revelation inducing a new economy will be alluring people to gain profits, as it is accompanied by a perception of foolproof investment with low probability of loss. The extreme price boom of Bitcoin in 2013 lead the genesis of mass hysteria which provided the opportunity to speculators to play with the information. Once Again high prices of Bitcoin in 2017 attracted public attention that increased the unanimity between economists that it is tough to reconcile high volatility with a the store of value function that currency should exhibit. These increase in prices attracted huge group of investors with a desire to cultivate high profits without ignoring the potential and mechanism of how these cryptocurrencies work although mindful of the opportunity cost of missing out is comparatively high.

Enthusiasm is also promoted by media and news thus further upsurges price, with a self-fulfilling prophecy. These situations favors the argument that cryptocurrencies reveal characteristics of a speculative bubble. But it is difficult to predict when it is going to occur. To differentiate between the fundamental and non-fundamental (spurious) herding and to find out its impact on market efficiency in cryptocurrency market, Chamil W et al. (2019) examine that the investor herding brings correlations in cryptocurrency returns with the help of methodologies of Chang et al. (2000) and Galariotis et al. (2015) for period 3/30/2015 to 5/24/2019.

Initially the results show that CSAD measure can be described by GSCI oil and gold index return. No relationship is found between CSAD and other variables (return on CCi30, US equity risk premium, and US/Euro exchange rate return). These findings are aligned with the interpretations of Baur and Lucey (2010) because the returns of cryptocurrency are un correlated with the return on stocks and exchange rates. As opposed to the efficient market concept by Fama (1965) this kind of herding can cause pseudo-efficient conditions as cryptocurrency lack intrinsic value.

Under normal market circumstances the herding regression reflected stronger tendency to herd on spurious information that describes CSAD of returns. This is an evidence about the speculative nature of cryptocurrency that causes price changes and supporting that returns of cryptocurrency could not be anticipated on the foundation of major economic information and main macroeconomic announcements. In cryptocurrency market herding upon non-fundamental information is more evident when market is moving upward. While herding is not evident on fundamental information under normal or other market conditions (e.g., bullish, crisis, high volatility) when market is not showing upward trend.

Likewise da Gama Silva et al. (2019) investigate herding and contagion phenomenon by using daily data of 50 most liquid as well as capitalized currencies. The period of study is March 2015 till November 2018 in cryptocurrency market by employing Hwang and Salmons (2004) model in addition to cross-sectional absolute deviation (CSAD) and cross-sectional standard deviation (CSSD). Those currencies are selected based on criteria of liquidity and market capitalization .Due to short term trends and excessive volatility, herding is exhibited by investors as a popular behavioral explanation. Contagion is being studied since 1990 and World Bank defined contagion as a shock process transferred to countries in relation to co-market movements which increases the correlation between different economies.

The results of CSSD test and Hwang and Salmons (2004) model indicate presence of herding behavior in cryptocurrencies. The study reveals that negative information in the cryptocurrency market is interrelated with herding behavior as cryptocurrency investors in cryptomarket are affected by negative news than by positive news, indicating risk aversion towards loss .With the help of modified FR test the results of contagion effect showed presence of the Bitcoin contagion in other digital currencies as well except few currencies.

Today, cryptocurrencies are studied as a kind of alternate currency and a subcategory of digital currencies. Cryptocurrencies signify as a medium of exchange based on cryptography. A paradigm shift in the ownership, money creation and transaction processes are introduced by the manner cryptocurrencies are designed and used. Third parties are not required to address issues of trust in comparison to traditional fiat currencies. The decentralized nature of cryptocurrencies permitted trust issues to be resolved by specialized algorithms. Even though cryptocurrencies trading have an inherent feature that decentralized electronic platforms are involved in it. However the real time information of all cryptocurrencies is accessible to all parties involved with quite ease building a digital global investment community. The availability of information in real time can cause herding consistent trading decisions.

Ballis and Drakos (2019) investigate the existence of herding behavior in rapidly emerging cryptocurrency market. Six major cryptocurrencies are selected based on criteria of market capitalization, market volume, availability of data and trading in listed platforms of cryptocurrencies. These included Bitcoin, Dash, Ethereum, Litecoin, Monero and Ripple. The time period of the study is over 3 years daily prices. Christie and Huang (1995) submit metric to observe the distribution of beliefs through assets, by using the cross-sectional standard deviation (CSSD) method. Chang et al. (2000) propose the cross-sectional absolute deviation (CSAD). Both CSSD and CSAD methodology are employed and results indicate the presence of herding. By means of the cross-sectional absolute deviation model, this research disclose a statistically significant negative coefficient specifying the existence of herding in the market. The study conclude that crypto investors of upper sectors take irrational investing decisions. Resultantly, the cryptocurrencies move in a hike without true reflection of their fundamentals.

Technological developments affect every edge of the economy. Financial system are reshaped by those improvements and explorations. As recently created innovations Cryptocurrencies acquire considerable attention of investors. Gm et al. (2019) intend to ascertain and evaluate the herding behavior of the cryptocurrency market participants. CCI 30 Index as well as cryptocurrencies of such index are analyzed for historical periods from the January 1, 2015 till December 31, 2018. Their study contribute to the literature of cryptocurrency market by seeing herding of a greater sample and by the use of first generated cryptocurrency index having the lengthiest time period. Christie and Huang (1995) methodology is employed to test herding behavior. The results are in line with findings of Bouri et al. (2018) as no herding is found. Haryanto et al. (2019) also use two dispersion based CSSD and CSAD methodologies to examine herding behavior in Bitcoin market. The study uses an extensive data set of approximately 21.2 million individual trade records of about 127k unique trader IDs acquired from Mt.Gox from Apr 1, 2011 to Nov 30, 2013.

Though CSSD test results do not show any herding, while CSAD methodology by using different market conditions show that presence of herding is aligned through market movement (in the market of bullish trend a positive market return rises herding, whereas in the bearish market a negative market return intensifies herding). Findings reveal that a low trading volume increases herding behavior, which are in contradiction from the outcomes of the work on the stock market (Demirer and Kutan, 2006). Besides, herding becomes weaker and less consistent when measured against weekly interval data.

Kaiser and Stckl (2019) examine herding involving all coins accessible at each point in time. They add to the literature on herding in cryptocurrencies by considering Bitcoin as transfer currency and incorporate beta herding. Their finding are in contrast to the findings of Vidal-Toms et al. (2019) as strong evidence of herding are provided by them. The study argue the contrasting results are due to the selection bias of previous studies because their sample consisted of only few cryptocurrencies so they employ entire cross section of cryptocurrencies available. The introduction of beta herding concept further provide robustness for results.

A further precise view of dispersion of investors beliefs is added by the concept of Bitcoin as a transfer currency as it is empirically shown that herding measures involved in crypto market. Additional insight are provided on herding between cryptocurrencies by using a standardized measure of beta herding which is suggested by Hwang and Salmon (2009). The measure of beta herding is mainly based on the idea that rolling betas of herding cryptocurrencies must be greatly close to one (the beta of the reference currency) and hence the standard deviation of cross section decreases with the level of herding.

The irrational investors individually chase for high returns are prone to information available to them without any root cause. This causes volatility higher in the market returns and may cause shocks as well. If we are more interested in knowing about a transfer currency concept than a relevant alternative measure to consider is beta herding. Beta herding increases when outlook of market seems positive and herding usually takes place significantly when market is low based on Hwang and Salmon (2009) technique yielding significant insights for of the crypto market.

The digital currencies have appealed significant attention by every kind of market participants. This phenomenon of herding in the marketplaces of digital currencies is also explored by Kyriazis et al. (2019). The study contribute in developing understanding of rational and irrational behavior upon herding phenomena in financial markets, a comparative examination of herding across markets along with an empirical estimation of herding. Study is conducted by using data of a reasonable number of cryptocurrencies and comparison between bullish market and bearish market periods is estimated. The interested reader are enabled to have a compass while investing in digital currencies and investments. Findings of empirical investigation indicate presence of herding behaviour in cryptocurrency markets in the bullish period whereas herding was not evident in the bearish market.

Kallinterakis and Wang (2019) contribute to this stream of research by examining herding in the cryptocurrency market. The research focused on how performance, volatility, volume and size as determinants of cryptocurrency herding. The study provide insight about the role played by cryptocurrencies smaller in size in the herding dynamics of assets. The study tries to figure out the link between performance, volatility and volume of cryptocurrencies against their price movements and peer-to-peer interactions. The study also investigate which market dynamics are associated with herding.

Daily data of price indices, market capitalization and volume of the top 296 cryptocurrencies are taken from coinmarketcap website for period of 27-12-2013 till 10-07-2018. Hinged on the measure suggested by Chang et al. (2000) empirical design is built, which evaluates the relationship among dispersion of cross-sectional returns and absolute market returns. Results report that strong herding is evident by investors of cryptocurrencies. The test of variability of herding with respect to market performance, volatility and cryptocurrency trading volume denoted that herding show asymmetric properties. On days when cryptocurrency market performed positively strong herding appears. Further herding is evident during both high and low volatility days. Herding behavior is substantial through all three sub-periods of price evolution of Bitcoins.

The cryptocurrencies are anticipated to function external to national regulations, but their estimations and dimensions respond significantly to news of regulatory actions. Cankaya et al. (2019) examine the relationship between cryptocurrencies volatile returns and the impacts of different news types on nominated cryptocurrencies. The news used as dummy variables is quantified. 22 categories are formed by using clustering analysis. Categories are then ordered into six groups. Autoregressive conditionally heteroscedastic (ARCH) models are applied by addition of the news groups to ARMA models. This study was based on news analysis and on price of cryptocurrencies from January 1, 2014 to January 18, 2018. The news data included the declarations, announcements, rules and guidelines for cryptocurrencies. It is inferred that in spite of the free and unrestricted structure of cryptocurrencies, news regarding regulations or potential activities and every other news have a definite level of consequence on cryptocurrency market valuations.

Stavroyiannis and Babalos (2019) provide new insights on cryptocurrencies herd-

-ing behavior. Their sample include daily closing prices of eight cryptocurrencies i.e. Bitcoin, Ethereum, Ripple, Litecoin, Dash, Monero and Stellar. The time period covered by study is from 9th August 2015 till 18th Feb 2018 with total 925 observations. The findings of the study using the standard testing procedure of ordinary least squares direct towards the presence of herding behavior in the crypto market. These evidence of herding are also corroborated by quantile regression method that accounted for the asymmetric behavior of returns of cryptocurrencies. Conversely, when a more robust time-varying regression model is employed to detect the herding effect, results reveal no herding is there.

Keller & Scholz (2019) studies Bitcoin exchange trading and examine factors that have impact on the behavior of different types of cryptocurrencies investor. Three key issues are addressed. Firstly, different types of investors who are trading cryptocurrencies and how do they differ? Second important aspect is analyzed about indicators which are influencing the trading actions of these investor types. Lastly it is observed the types of investors which drive the exchange rate of cryptocurrencies.

Recently, cryptocurrency exchanges have grabbed attention of researchers who are fascinated by determinants that impact this virtual currency market in terms of price, market volatility, and volume of transactions. These factors fall into three broader categories of Indicators of the macro financial market condition, reflecting fundamentals of cryptocurrency along with technological features and market sentiments of cryptocurrency which worked as a proxy of market attractiveness. Market bids in terms of offers and orders are considered proxy of behavior. It is assumed that actual market bids made by investors give, a more exact measure of investors behavior than the exchange rate.

The findings of the study recognize ten different types of trading investors. Six of them are offering Bitcoins and remaining four types of traders are ordering Bitcoins. Investors are influenced specially by macro-financial indicators when placing offers like the USD index or the oil prices .However while placing orders investors decisions is influenced by mood of the market, macro-financial and technical indicators. Nakagawa et al. (2020) investigate the relationship between expected returns on cryptocurrencies and macroeconomic fundamentals by employing a dynamic factor model of Stock & Watson (2002) and Ludvigson & Ng (2007), and summarize that the common factors are linked strongly to the cryptocurrency expected returns at a quarterly frequency although it is not observed by using a few macroeconomic indicators such as inflation and money supply. Philippas et al. (2020) also report that investors herding is related to cryptocurrency returns.

Cryptocurrencies have caught attention in the past few years. Raimundo Junior et al. (2020), analyze with statistical tools linked to behavioral finances to measure the presence of herding phenomenon and its amplitude concerned with these assets in the cryptocurrency market. The study tests two hypotheses. Firstly herding is present in the cryptocurrency market and secondly, during market stress the level of herding is increased. The study argue that these hypotheses are also endorsed by study of Hwang and Salmon (2004) in the stock market. It covers the concept of beta herding into the cryptocurrency market along with specific control variables of market index, market volatility, and the volatility index.

The methodology used is founded on the theory of beta herding, which measures the cross-sectional deviation of betas, herding causes the bit to deviate from its true bit (medium long-term beta) through the state-space model. Daily closing prices of the 80 largest cryptocurrencies from website of CoinMarketCap are collected. The period of study is from July 2015 till March 2020. For the market return, CRIX and for the volatility index VCRIX is used.

The results reveal that independent of the market conditions, significant movement and determination are seen by herding toward the market which is expressed by market return and the volatility index. A strong correlation is found among market stress and herding parameters shown by high volatile days. Relationship amid herding and market stress is also analyzed using parameters of market volatility and the volatility index. A strong correlation among herding parameters and market stress suggest herding is higher in this observed economic scenario.

Caferra (2020) investigate the link among news-driven attitudes and the convergence of investors behavior in the market of cryptocurrencies. The central idea is that media opinions might outline humors of investors, further influencing price expectation. This study check the possibility to identify uniformities in prices of cryptocurrencies in periods with no extreme events. For this purpose, data is obtained starting from the time after the surge and the peak of the 2017 bubble. The behavior of cryptocurrencies is also excluded during COVID-19, as both of these times ponder specific and extreme events. Daily observations are collected from 01/01/2018 till 01/01/2020, for a sample of 13 cryptocurrencies.

Based on methodologies of Christie and Huang (1995) and Chiang and Zheng (2010), both Cross Sectional Standard Deviation (CSSD) and Cross Sectional Absolute Deviation (CSAD) of returns of cryptocurrencies are used to build different model specifications. Results of mean-variance returns relation suggest no evidence of herding. However dispersion is decreased in days where media spread wave of optimism.

Amirat & Alwafi (2020) explore the creation of behavioral-based patterns in markets of cryptocurrency. The cross-sectional absolute deviation method of Chang et al. (2000) is used to notice herding for a sample of 20 cryptocurrencies which create the MVIS large cap digital index. The period of study is from 1 January 2015 to 31 January 2019. Bloomberg consumer comfort index was used to explain the presence of herding behavior by the rise in comfort level. The results advocate anti herding behavior for the period of the study and through three diverse sub-groups. Rolling window analysis favor herding behavior in several periods particularly from 2016 till the beginning of 2017. Logistic regression is applied to enlighten herding behavior built on the Bloomberg consumer comfort index, inflation rates, and prices of crude oil. An inverse relationship is seen among the index and herding behavior.

From the behavioral outlook of cryptocurrencies there is a new key characteristic that cause major data flows that reveal investors preferences. Gurdgiev and Loughlin (2020) figure out price changing aspects of cryptocurrencies are affected by the interaction among social aspects behind decisions made by investors and freely available data. The absence of hard financial basics in evaluation, joined with active participation by investors on media forums make the cryptocurrencies market a chief targets for behavioral and sentiment analysis.

The Fractal Markets Hypothesis (FMH) of Peters and Peters, 1994, offer indirect behavioral connection between choice made by investors for liquidity supply and demand and pricing of the assets with respect to market. From these point of view, behavioral analysis opened a favorable avenue for exhibiting prices of cryptocurrencies, potentially permit to detect herding and such other aspects of the investors decision. This provide information on likely investment decisions by the actual and prospective investors and comprises an empirical estimation of public sentiments regarding assets prone to risk and particularly about the crypto assets. These further capture the effects of behavioral choices on price and returns dynamics in cryptocurrencies.

Investor sentiment identification methods is applied to find the behavioral information behind investors valuations of the crypto assets upon top ten cryptocurrencies based on market capitalization. The time period of study lied January 1, 2017 till April 2, 2019. Following behavioral factors are observed. VIX Markets Fear Index is used as reflection of the common opinion of the investors to traditional risky assets.US Equity Market Uncertainty index reflect deeper uncertainty feeling of investors about the traditional risky assets. Views conveyed by the Bitcointalk.org forum participants are used as a measure of positive and negative sentiments of investors concerned with cryptocurrencies.

Bull and bear period trends in financial markets are estimated by the CBOE Put/Call ratio. This ratio specified investor views about liquidity situations in the financial markets. To detect short-term price-sentiment relationships a generalized least squares (GLS) panel model with robust standard errors is applied. Results show that investor sentiment are linked significantly to the price direction of cryptocurrencies and during uncertain situations these currencies can be deployed as a hedge against the equities. However, cryptocurrencies are not an appropriate safe haven contrary to stock markets during times of fear. The prices of cryptocurrencies grow when there is positivity in investors. This indicate herding biases among crypto traders. However an asymmetric impact prevailed on cryptocurrencies prices during bullish and bearish financial markets.

Nabeel-Ud-Din et al. (2020) examine effect of herding in market asymmetries, in-

-ter-dependency and intra-dependency cases. The study use daily returns of major and sub major cryptocurrencies listed in CCI30 index and returns of major stocks listed in Dow-Jones Industrial Average Index. The time period of study is from 2015 till 2018 while using daily data and the technique of quantile regression. The herding is tested under market asymmetries, the relation between major and sub major cryptocurrencies is also analyzed and the effect of equity market on cryptocurrencies was examined.

A market portfolio is formed by using a specific group of securities to test herding. .Results reveal that herding exits in high volatile period in cryptocurrencies and this herding primarily due to market activity and not because of market movement. Because of major cryptocurrencies in low volatility periods the effect of interdependency exist in sub-major cryptocurrencies as investors prepare to hedge against weak securities as they want to take minimal risk. Conversely, this effect of interdependency by major equity stocks in major cryptocurrencies is not observed it may be the results of regulations in equity market and the Dow-Jones competence to rectify any irregularity that occurs.

Herding is connected with the weak regulation of crypto market. This market is extremely speculative and volatile so any anomaly gives rise to volatility. During COVID-19 pandemic the investors must focus their attention to the prevailing trends in the market and related information as the volatility in market has increased so its difficult to decide and investors are mostly selling their securities causing turbulence in the market. It is a general belief that Market activity is the cause of herding in cryptocurrencies creating bullish trends in market because the trading volume increases to aggressive investment from investor (Bikhcandani & Sharma, 2000).

Mostly the studies of herding only focus on CSSD and CSAD methodology and only fewer studies helped to investigate the effect of different volatility regimes. Alp et al. (2020) examine the presence of herding behavior under uncertainty in cryptocurrency. For overall sample as well as sub periods they employ methods of cross-sectional absolute deviation (CSAD) of returns, ordinary least squares (OLS), generalized autoregressive conditional heteroscedasticity (GARCH) meth-

-ods and Time-Varying Markov-Switching (TV-MS) models.

A theory of Akerlof (1978) is based on asymmetric information and adverse selection is a more realistic view of market mechanism. Instead of rational choices, the effect of uncertainty is considered in the markets, Akerlof (1978) add to the theory of decision making. The results of TV-MS model suggest anti herding behavior for overall sample of the market.

Mostly the literature is about small group of cryptocurrencies, some have studied the properties of cryptocurrencies while few have considered the properties with respect to other markets ignoring the internal dynamics of crypto market as a whole. Cryptocurrency markets are subject to high volatility as investor sentiments can influence major and sudden price shifts. Thompson et al. (2020) investigate psychological factors involved in the investment decisions in cryptocurrency. It analyzes the impact on cryptocurrency investment imposed by factors of Perceived Behavioral Control, Subjective Norm, Subjective Knowledge, Discounting Own Information and Imitating others. Additionally, the research sought to comprehend the extent to which these attitudes impact the investor behavior in cryptocurrency market.

Attitude toward cryptocurrency investment is defined as the consideration of the contributors view towards cryptocurrency investment. The view of the opinions by social circle of an individual on cryptocurrency investment is considered as Subjective Norm. Perceived Behavioural Control is precisely defined as an individual perception to be capable to manage their actions with respect to cryptocurrency investment. Subjective Knowledge is named as the opinion of an individual about knowledge of cryptocurrency market and investment. Imitating Others are deemed as the readiness to follow decision making of other individuals. Discount Own Information is taken in context of the willful disregard by an individual of the own information, in agreement of the knowledge of a group. Results show that attitudes to invest in cryptocurrency were a solid predictor of real investment behaviour. This study besides establish that these attitudes en route for cryptocurrency investment are impacted positively by Subjective Norms, Perceived Behavioural Control, and Imitating Others. Those human factors which effect in-

-vestments in cryptocurrency and markets still need more investigation.

As Compared to the existing studies, Vidal-Tomas in 2020 contribute to the existing cryptocurrency literature by inspecting market transitions using 69 long lived cryptocurrencies with the help a network approach. The analysis focus on the examination of the evolutionary system of cryptocurrency when challenged with the COVID-19 pandemic. It is witnessed very interestingly that the cryptocurrency market is considerably affected during period from 12 March 2020 to 1 April 2020 by COVID-19. And after some time the market recovers progressively to its initial state. It is shocking to witness that the effect of COVID-19 vanished completely after July.

This study provide relevant information to investors by underlining the transition phase of this digital market as a system throughout the pandemic. It also highlighted the time periods during which the market is highly or less affected by COVID-19 as the transitions of market can be related to few of the findings that exists in the literature such as diversification, efficiency and herding. Alternatively it can be said that the results perceived by scholars may possibly be connected and compared with the market level in which the cryptocurrency market is analyzed. Because of the in efficient measure by European Central Bank (ECB) in response to COVID-19, On 12 March 2020 all the financial markets faced a negative shock which is declared officially a pandemic by the WHO on 11 March 2020. For future research they refer that dynamic methods to be used instead of static methodologies to further analyze the effect of COVID-19 pandemic.

Drod et al. (2020) include the peculiar time of the Covid-19 pandemic in their study by focusing attention to this event and probed its effect on the structure and dynamics of the cryptocurrency market. The study concentrate on dynamical properties and structural characteristics of the cryptocurrency market. The Empirical data signifying the exchange rates of 129 cryptocurrencies including BTC traded on the Binance platform is analyzed. The exchange rate returns are multifractal during the considered interval, with discontinuous signatures of bifractality that can be linked with the utmost volatile phases of the market dynamics like a bull market commencement in April 2019 and the Covid-19 upsurge in March 20-

20.

Cryptocurrency market have attracted unrestrained interest primarily due to its price growth and higher returns prospects. The study by Omane-Adjepong et al. (2021) examine herd trading within the utmost liquid cryptocurrency markets comparative to traditional financial markets of 10 developing economies in the G20. Based on three-stage criterion of market capitalization, trading volume and active trading data of more than two years, eight most liquid markets are filtered which included Bitcoin, Ethereum, Ripple, Litecoin, Dash, Ethereum Classic, NEO, and Zcash . Stocks and bilateral currencies of emerging markets within the G20 are also considered. The span of all variables are from 29.10.2016 to 07.06.2019, obtained in US dollars. Cross-sectional absolute deviation (CSAD) approach of Chang et al. (2000) are employed to measure return of dispersion with OLS and quantile-based regression in time varying samples along with rolling-window analysis.

The results highlight that in the emerging stock and cryptocurrency markets more pronounced herd trading is seen especially under the GMV, signaled rational decisions made by investors .In Fx market herding behavior was not evident so the model of rational asset-pricing model can best describe the extreme variations in prices at the tail distribution and the behavioral features of the cryptocurrency market are comparatively qualitatively less distinguished from that of the stocks.

These findings can also be interpreted in a behavioral perspective that herding not only result in increased risk for investors but also render markets as incompetent so benefits of diversifications become low. Because traders give up their own strategies to follow other participants or market performance. This fuel up speculation that can end up in market ambiguity and instability.

In a recent research paper by King & Koutmos (2021) estimate feedback trading approach upon nine major cryptocurrencies, to determine herding and its direction in cryptocurrency markets in reaction to lagged returns. They work on forces that drive prices of crypto assets. The digital currencies include in sample are Bitcoin, Ethereum, XRP, Bitcoin cash, EOS, Litecoin, Stellar, Cardano and IOTA based on highest market capitalization. Daily closing prices and trade volumes (in USD) of these currencies are used. The results reveal heterogeneity in cryptocurrency herding and feedback effects. Further suggest that cryptocurrency markets may be segmented, in spite of the seemed co movements. So herding exist in cryptocurrency markets and also drive price dynamics.

In the pandemic situation that world is currently facing the paper currency is being well-thought-out as a source of dissemination of contagious viruses as it moves between different hands .The necessity for a contactless payment system and paper money replacement is never felt more before now. Influence of COVID-19 is investigated in cryptocurrencies market by Iqbal et al. (2021) by assessing the increase in confirmed cases of COVID-19 worldwide daily (pandemic intensity) influence the cryptocurrency market daily returns. On the basis of market capitalization the daily prices of ten top currencies are analyzed. The daily returns are calculated manually and transformed into the logarithmic values. . The sample period comprises of daily observations from January 1, 2020 till June 15, 2020. To increase the robustness of results the figure of daily number of deaths caused by this virus are used as an alternate proxy for the pandemic intensity to increase the robustness of our results.

QQR (Quantile-on-Quantile Regression) technique is used. This technique already been employed effectively to test the asymmetric nexus between the variables of interest in various studies connected to economics and finance (Bouri et al., 2017). The quantile regression is an effective methodology as it reflects the variations in effects of COVID19 at different points of the Crypto distribution. Results reveal that the relationship between the COVID-19 and the cryptocurrencies returns at different quintiles of both variables is not symmetric and fluctuated in magnitude and direction.

Yarovaya et al. (2021) conduct analysis on herding behavior in cryptocurrency market during the period of the COVID-19 pandemic. The four most traded markets of cryptocurrency are selected (USD, EUR, JPY and KRW). A mix of quantitative methods was applied to hourly prices .The timeline of the study is from January 1, 2019 to March 13, 2020. The researchers observe the black swan effect on herd formation in cryptocurrency market and conclude that herding is not amplified by COVID-19 in cryptocurrency markets. Herding is contingent upon upward and downward market trends but is not affected by COVID-19. These findings are of great significance for cryptocurrency investors, traders and regulators to improve understanding regarding financial impact of pandemic on cryptocurrency markets.

It is of great importance to explore that how Crypto markets act as safe haven in the times of economic uncertainty. The main focus is to study crypto market under the hypothesis that crypto-investors have restricted access to process information and have weaker knowledge so they rely on others sources to valuate cryptocurrencies, which can unchain unexpected results. Based on the studies already conducted this research contributes to the existing research on herding behavior in cryptocurrencies on a broader level which is limited in these studies using updated data from coinmarketcap website because it is crucial for fair representation of crypto market. In addition, the impact of extreme conditions such as COVID-19 will be analyzed upon herding behavior in cryptomarket because the whole world is shocked by the effects of COVID-19 and it is still trying to cope up. Because the cryptocurrencies are a center of attraction for investors nowadays worldwide so analyzing how global factors impact herding of cryptocurrencies will serve the purpose of guidance for crypto traders and new investors for decision making process, who have inadequate knowledge. For this purpose, methodology of Christie and Huang (1995), Chang et al. (2000) is employed.

2.1 Hypothesis of the Study

The following hypotheses are formulated:

H1: There is a significant herding in the cryptocurrency market.

H2: Herding is non-linear in nature.

H3: Herding is higher during bullish trends in the cryptocurrency market.

H4: Herding is higher during bearish trends in the cryptocurrency market.

H5: Interest rate have impact on herding cryptocurrency.

H6: Equity market effect herding in crypto traders.

H7: Oil market index influence herding in crypto market.

H8: Herding is higher in COVID-19 period in the cryptocurrency market.

Chapter 3

Research Methodology and Data Description

3.1 Population and Sample of the Study

The population of the study is all Cryptocurrencies. The sample period is from 01-01-2017 to 18-04-2021 using 10 Cryptocurrencies. For comparability, I have used market capitalization and date of initiation therefore those cryptocurrencies are chosen in the sample whose data is available from 1st January 2017 as well as these cryptocurrencies are highest in market capitalization above $4.5 Billion.

These include Bitcoin (BTC), Ethereum (ETH), XRP (XRP), Tether (USDT), Dogecoin (DOGE), Litecoin (LTC), Stellar (XLM), Neo (NEO), Monero (XMR) and Ethereum Classic (ETC). Cryptocurrencies Data for this study is obtained from website of COINMARKETCAP (https://coinmarketcap.com).

World index (Morgan Stanely) is used as a proxy of international equity markets. Oil prices (WTI) are used as a proxy of commodity market and interest rate (U.S.) is used a proxy of bond market. As on March 11, 2020 The World Health Organization (WHO) declared the novel coronavirus (COVID-19) outbreak a global pandemic so for Covid-19 Dummy using the data from 11th march and onward is 1 and for remaining period is taken as 0. The effect of these macroeconomic variables and COVID-19 is observe.

3.2 Econometric Model

It is an investigation of presence of herding in Crypto market by using methodology of Christie and Huang (1995), Chang et al. (2000) and Gleason et al. (2004). The main focus of these methodologies is to examine cross-sectional correlation dispersion in cryptocurrencies in reaction of market situations especially during COVID-19. Few empirical researches have reported presence of herding behavior in crypto traders and investors in crypto market due to information asymmetry.

The proposed methods measure cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) between returns of crypto market. Christie and Huang (1995) have employed cross-sectional standard deviation (CSSD) as a measure of the average proximity of asset returns (individual) to the realized market average, to test the herding behavior whereas CSAD is used by Chang et al. (2000) to study the relationship among total market returns and level of equity returns dispersion in specification of non-linear regression.

Gleason et al. (2004) have used both CSAD and CSSD to observe herding in various market situations. Both CSSD and CSAD are used as CSSD measure takes square root of the values so that positive and negative values may not offset while CSAD methodology takes absolute values to remove this offsetting affect.

The return for each cryptocurrency is calculated as:

$$R_{i,t} = ln[\frac{P_t}{P_{t-1}}] * 100 \tag{3.1}$$

Where,

$R_{i,t}$ = observed price returns of cryptocurrency 'i' at time "t"

P_t and P_{t-1} are the closing prices of the individual cryptocurrencies at time 't' and 't-1',

Whereas cross-sectional average cryptocurrency of N price returns ($R_{m,t}$) is calculated by taking average of all individual cryptocurrencies price returns at time 't':

$$R_{m,t} = \frac{\sum R_{i,t}}{N} \tag{3.2}$$

Where $R_{i,t}$ is the observed price return of cryptocurrency i at time t , and N is number of cryptocurrencies included in the sample. For the detection of herding Christie and Huang (1995) measured average proximity of the realized market returns to individual asset returns by using CSSD, as follows:

$$CSSD_t = \sqrt{\sum_{i=1}^{N} (R_{i,t} - R_{m,t})2/(N-1)} \tag{3.3}$$

Where,

N is number of cryptocurrencies in the portfolio,

$R_{i,t}$ = observed price returns of crytocurrency 'i' at time 't'

$R_{m,t}$ = the cross-sectional average cryptocurrency of N price returns in the portfolio at time 't'.

When there is stress in the market herding predictions contradicts from the traditional model of asset pricing regarding CSSD returns. Because change in individual securities to market returns causes an increased dispersion.

However, herding can cause low dispersion during the time of large movements by the market. The same is now applied to crypto market to test the herding by using empirical design of Christie and Huang (1995):

$$CSSD_t = \alpha + \beta_1^U C_t^U + \beta_2^L C_t^L + \varepsilon_t \tag{3.4}$$

Where,

C_t^U = 1 when return on the aggregate market portfolio for the time period t lies in the extreme upper tail of the returns distribution, and 0 otherwise.

C_t^L = 1 when return on the aggregate market portfolio for time period t lies in the extreme lower tail of the returns distribution, and 0 otherwise.

If β_1 and β_2 coefficients are negative and significant this is an indication of herd formation by participants in the market. On the contrary, if β_1 and β_2 are significantly positive predicts rational asset pricing model.

$$CSSD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{3.5}$$

If the non-linear coefficient γ_2 is negatively significant it indicates the existence of herding otherwise if γ_2 is statistically positive, it shows no evidence of herding. Another methodology to identify herding was proposed by Chang et al. (2000). They argue that Christie and Huang (1995) model needs to define market stress. They employ CSAD instead of CSSD as follows:

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |R_{i,t} - R_{m,t}| \tag{3.6}$$

The behavior of herding Extreme conditions is compared by using the follow equation:

$$CSAD_t = \alpha + \beta_1^U C_t^U + \beta_2^L C_t^L + \varepsilon_t \tag{3.7}$$

Where,

$C_t^U = 1$ when return on the aggregate market portfolio for the time period t lies in the extreme upper tail of the returns distribution, and 0 otherwise.

$C_t^L = 1$ when return on the aggregate market portfolio for time period t lies in the extreme lower tail of the returns distribution, and 0 otherwise.

This method is proposed by Chang et al. (2000) on general quadratic relationship between $CSAD_t$ and $R_{m,t}$ is based on non-linear relationship:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{3.8}$$

If the non-linear coefficient γ_2 is negatively significant it indicates the existence of herding otherwise if γ_2 is statistically positive, it shows no evidence of herding. Gleason et al. (2004) argue that under stress situation in the market this non-linear component is evident for CSSD if herding is there. Gleason et al. (2004) comprehensively test two models by substituting the dependent variables in Equations. It is a matter of common observation that when market is going towards decline the dispersion rate is higher as compared to market returns on aggregate. So, to investigate about asymmetry in bearish and bullish market trends herding regression is analyzed for both negative and positive market returns separately. It can be expressed as:

For CSSD:

$$CSSD_t^{BULL} = \alpha + \gamma_1^{BULL} + |R_{m,t}^{BULL}| + \gamma_2^{BULL}(R_{m,t}^{BULL})^2 + \varepsilon_t \tag{3.9}$$

when $R_{m,t}$ >0

Where,

$CSSD_t^{BULL}$ is the value of CSSD at time t because of inclining market returns.

$R_{m,t}^{BULL}$ is equally weighted portfolio return of bullish market trends during time t.

$(R_{m,t}^{BULL})^2$ is square of equally weighted portfolio return to check non linearity of returns when market is moving upward (inclined).

$$CSSD_t^{BEAR} = \alpha + \gamma_1^{BEAR} + |R_{m,t}^{BEAR}| + \gamma_2^{BEAR}(R_{m,t}^{BEAR})^2 + \varepsilon_t \tag{3.10}$$

when $R_{m,t}$ <0

Where,

$CSSD_t^{BEAR}$ is value of CSSD at time t because of declining market returns.

$R_{m,t}^{BEAR}$ is equally weighted portfolio return of the bearish market trends during time t.

$(R_{m,t}^{BEAR})^2$ is square of equally weighted portfolio return to check non linearity of returns when market is moving downward (declined).

For CSAD:

$$CSAD_t^{BULL} = \alpha + \gamma_1^{BULL} + |R_{m,t}^{BULL}| + \gamma_2^{BULL}(R_{m,t}^{BULL})^2 + \varepsilon_t \tag{3.11}$$

when $R_{m,t}$ >0

Where,

$CSAD_t^{BULL}$ is the value of CSAD at time t because of inclining market returns.

$R_{m,t}^{BULL}$ is equally weighted portfolio return of bullish market trends during time t.

$(R_{m,t}^{BULL})^2$ is square of equally weighted portfolio return to check non linearity of returns when market is moving upward (inclined).

$$CSAD_t^{BEAR} = \alpha + \gamma_1^{BEAR} + |R_{m,t}^{BEAR}| + \gamma_2^{BEAR}(R_{m,t}^{BEAR})^2 + \varepsilon_t \tag{3.12}$$

when $R_{m,t}$ <0

Where,

$CSAD_t^{BEAR}$ is value of CSAD at time t because of declining market returns.

$R_{m,t}^{BEAR}$ is equally weighted portfolio return of the bearish market trends during time t.

$(R_{m,t}^{BEAR})^2$ is square of equally weighted portfolio return to check non linearity of returns when market is moving downward (declined).

Macroeconomic factors that drive herding in cryptocurrency market have not been discussed much in detail in past studies. Therefore, the impact of three macroeconomic factors such as Interest rate (U.S. Interest rate), Equity market (World Index) and Commodity market (Oil Market Index) is examined on herd formation in crypto market. The factors are chosen as representative of loan market, equity market and commodity market that have great impact on prices of financial assets as well. Any change in interest rate effect worth of the financial assets because the value of an asset is assessed by discounting future cash flows at the required rate of return by investor. The non-linearity is examined by adding $R_{m,t}^2$. If $R_{m,t}$ turns out to be statistically insignificant and $R_{m,t}^2$ becomes insignificant and non-linear in the presence of three macroeconomic factors then changes in $CSSD_t$ and $CSAD_t$ are expected to be due to these fundamentals rather than herding. These macroeconomic fundamentals are taken into account for as interest rate, oil prices and world index have impact on financial markets worldwide so now this is to be explore for cryptocurrency market as well. Therefore, these macroeconomic variables take into consideration the effect of macroeconomic information while determining the level of herding through $CSSD_t$ and $CSAD_t$.

$$CSSD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \delta_1(IR_t) + \delta_2(WI_t) + \delta_3(OI_t) + \varepsilon_t \tag{3.13}$$

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \delta_1(IR_t) + \delta_2(WI_t) + \delta_3(OI_t) + \varepsilon_t \tag{3.14}$$

Earlier studies have disclosed that crisis period have more noticeable herding (Bikhchandani and Sharma 2000; Bowe and Domuta 2004; Hwang and Salmon 2004; Philippas et al., 2013; Yao et al., 2014; Bekiros et al., 2017). So, to capture the COVID-19 impact on herding in crypto market, a dummy variable of COVID-19 DC_t is introduced that takes the value of 1 during COVID-19 crises or otherwise 0.

$$CSSD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 DC_t + \varepsilon_t \tag{3.15}$$

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \gamma_3 DC_t + \varepsilon_t \tag{3.16}$$

Where $\gamma_3 DC_t$ is a cross dummy that captures the non-linearity of returns during COVID-19 period (from March 11, 2020 till April 18,2021).

Chapter 4

Results and Discussions

This chapter provides the results of herding analysis of Cryptocurrency market regarding non linearity and during different market conditions through various tests.

4.1 Descriptive Statistics

Descriptive Statistics tells about the statistical behavior of the data used in the study. Mainly includes three elements i.e. Location, measure of central tendency and measure of dispersion of the data. Mean and median represents Measure of central tendency of data. Kurtosis and skewness shows location of data under observation.

While Standard deviation throws light on the average risk per day which is measure of dispersion of the data. Firstly Descriptive Statistics of sample of 10 Cryptocurrencies is observed to describe main features of the collected data. Secondly Descriptive Statistics of Herding measures used (CSSD & CSAD) along with Macroeconmic variables of Interest rate, Oil Market and World equity market index are observed.

Table 4.1 shows the mean, maximum and minimum returns per day along with Skewness and Kurtosis of major Cryptocurrencies under study. These statistics of Bitcoin (BTC) shows that average return of BTC is 0.2571% per day. The

Table 4.1: Descriptive Statistics for Sample Cryptocurrencies

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
BTC	0.0026	0.2251	-0.4647	0.0426	-0.8096	14.8862
ETH	0.0036	0.2901	-0.5507	0.0566	-0.4128	12.1524
XRP	0.0034	1.0275	-0.6164	0.0768	2.1789	35.1630
USDT	0.0000	0.0572	-0.0492	0.0067	0.1907	16.4387
DOGE	0.0046	1.5162	-0.5149	0.0832	4.8501	81.7435
LTC	0.0026	0.5104	-0.4490	0.0606	0.6193	12.8738
XLM	0.0034	0.7232	-0.4100	0.0790	1.9033	19.4838
NEO	0.0043	0.8012	-0.4668	0.0790	1.3415	18.4802
XMR	0.0020	0.4303	-0.4942	0.0591	-0.0436	10.3514
ETC	0.0021	0.4577	-0.5078	0.0649	-0.0887	11.7519

maximum return earned in a day is 22.51% and maximum loss incurred is 46.47% in a day. The value of average risk of Bitcoin is is 4.26% per day. Skewness value is negative for BTC indicating the negative returns are higher in some days. The kurtosis shows data is peaked so BTC exhibit leptokurtic behavior in market.

Statistics shows Ethereum (ETH) average return per day is 0.3579%. Maximum returns in a day is 29% while maximum loss is 55.07%. Average risk per day is 5.66%. Data is negatively skewed showing the negative returns are greater in some days. The Kurtosis value is greater than 3 for all the Cryptocurrencies confirming data is leptokurtic peaked in nature.

The average return for XRP (XRP) is 0.34%. Maximum return is 102.74% per day and maximum loss is 61.64%. The average risk is 7.67% per day. The data is positively skewed which shows that positive returns are greater in some days for XRP. Tether (USDT) average return is 6.87E-17%. Maximum return is 5.71% per day and maximum loss for USDT is 4.92%. The average risk is 0.66% per day. The data is positively skewed which shows that positive returns are more in some days for USDT.

The average return for Dogecoin (DOGE) is 0.4623% per day. Maximum return in a day is 151.62% and maximum loss is 51.49% per day. The average risk is 8.32% per day. The data is positively skewed which shows that there are more positive returns in some days for DOGE.

Litecoin (LTC) average returns per day is 0.2617%. Maximum returns per day are 51.03% and maximum loss is 44.9% in a day. Average risk is 6.06% in a day. The data is positively skewed which shows that there are more positive returns in some days for LTC.

The average return for Stellar (XLM) is 0.3439%. Maximum return is 72.31% per day and maximum loss is 41%. The average risk is 7.99% per day. The data is positively skewed which shows that positive returns are greater in some days for XLM. The average return for Neo (NEO) is 0.4289%. Maximum return in a day is 80.11% and maximum loss is 46.68% per day. The average risk is 7.89% per day. The data is positively skewed which shows that there are more positive returns in some days for NEO.

The average return for Monero (XMR) is 0.2%. Maximum return is 43.03% per day and maximum loss is 49.42%. The average risk is 5.91% per day. Data is negatively skewed showing the negative returns are greater in some days for XMR. The results of Ethereum Classic (ETC) shows average returns of 0.2088% per day. Maximum returns per day are 45.77% and maximum loss is 50.78% in a day. Average risk is 6.48% in a day. Data is negatively skewed showing the negative returns are higher in some days.

Table 4.2 represents the mean, maximum and minimum returns per day along with Skewness and Kurtosis of Herding measures used CSSD, CSAD along with the three macroeconomic variables of Interest rate, Oil Market and World equity market index.

The statistical results of herding (CSSD) shows average herding of 208.61 per day. Maximum herding per day is 210.48 and minimum herding is 206.73 in a day. Average variation is 108 in a day. Data is negatively skewed showing the negative returns are higher in some days. The Kurtosis value is less than 3 is consider platykurtic. It means distribution creates fewer and less extreme outliers than do-

TABLE 4.2: Descriptive Statistics for Herding measures CSSD & CSAD along with Macroeconomic Factors

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
CSSD	208.6138	210.4852	206.7317	1.0852	-0.0056	1.7979
CSAD	20.8614	21.0485	20.6731	0.1085	-0.0056	1.7979
IR	0.0000	0.0614	-0.0600	0.0054	-0.2530	8.2070
OI	0.0002	0.0806	-0.5043	0.0155	-22.2307	4.9420
WI	0.0005	0.3196	-0.2822	0.0291	0.0378	7.2145

-es the normal distribution.

The statistical results of herding (CSAD) shows average herding of 20.86 per day. Maximum herding per day are 21.04% and minimum herding is 20.67% in a day. Average variation is 18 in a day. Data is negatively skewed showing the negative returns are higher in some days. The Kurtosis value is less than 3 is consider platykurtic. It means distribution creates fewer and less extreme outliers than does the normal distribution.

The statistical results of interest rate (IR) shows average interest rate of 0.003% per day. Maximum interest rate per day are 6.14% and minimum interest rate is -5.9% in a day. Average risk is 0.54% in a day. Data is negatively skewed showing the minimum interest rate are higher in some days. The Kurtosis value is greater than 3 confirming data is leptokurtic peaked in nature.

The statistical results of oil market index (OI) shows average returns of 0.015% per day. Maximum returns 8.05% per day are and maximum loss is 50.4% in a day. Average risk is 1.55% in a day. The data is positively skewed which shows that there are more positive returns in some days. Data is negatively skewed showing the minimum returns are higher in some days. The Kurtosis value is greater than 3 confirming data is leptokurtic peaked in nature.

The statistical results of world index (WI) shows average returns of 0.53% per day. Maximum returns per day are 31.96% and minimum return is -28.22% in a day. Average risk 2.91% in a day. Data is positively skewed showing the positive returns is higher in some days. The Kurtosis value is greater than 3 confirming data is leptokurtic peaked in nature.

4.2 Impact of Extreme Market Conditions on Herding in Cryptocurrencies Market

Table 4.3 represents the results for impact of extreme market conditions on herding behavior using CSSD measure of Christie and Huang (1995):

TABLE 4.3: Impact of extreme market conditions on Herding Behavior measured through CSSD

CSSD	***Coefficients***	***S.E***	***t Stat***	***P-value***	**F stat**	**Fi Sig**	**Adj r**
Intercept	0.0219	0.0005	42.7053	7.78E-265	317.7905	0.0000	0.2879
Lower tail	0.0232	0.0022	10.4150	1.32E-24			
Upper tail	0.0523	0.0022	23.4791	1.11E-104			

The Beta Coefficients of upper and lower tails are significant at α =0.05. The Coefficients p-value indicates that herding is higher at extremes. The coefficient of upper tail is 0.0523 greater than lower tail 0.0232 indicating that at right tail herding is higher in comparison to left tail. This reveals that herding is higher during bullish periods using CSSD measure of Christie and Huang (1995). F value is significant showing model is correctly specified. The explanatory power of model is 28% which looks good. Robustness of results is examined using CSAD measure proposed by Chang et al. (2000).

Table 4.4 represents the results for impact of extreme market conditions on herding behavior using CSAD measure proposed by Chang et al. (2000). The Beta Coefficients of upper and lower tails are significant at α =0.05. The Coefficients p-value indicates that herding is higher at extremes in cryptocurrency market. The

Table 4.4: Impact of extreme market conditions on Herding Behavior measured through CSAD

CSAD	***Coefficients***	***S.E***	***t Stat***	***P-value***	**F stat**	**Fi Sig**	**Adj r**
Intercept	0.0306	0.0007	39.8560	2.26E-240	282.4596	0.0000	0.2642
Lower tail	0.0313	0.0033	9.3917	2.01E-20			
Upper tail	0.0743	0.0033	22.3013	6.79E-96			

coefficient of upper tail is 0.0743 greater than lower tail 0.0313 indicating that at right tail herding is higher in comparison to left tail. This reveals that herding is higher during bullish periods. F value is significant showing correct specification of model with the explanatory power of model is 26% indicating model is good for studies.

So, from results of Table 4.3 and Table 4.4 above it is concluded that Null Hypothesis is rejected alternatively Hypothesis 1 i.e., **H1:** There is a significant herding in the cryptocurrency market is accepted, Hypothesis 3 i.e., **H3:** Herding is higher during bullish trends in the cryptocurrency market and Hypothesis 4 i.e., **H4:** Herding is higher during bearish trends in the cryptocurrency market are accepted.

4.3 Non-Linearity in Herding in Crypto Currencies Market

Non-linearity in herding in cryptocurrencies market is examine by using both the approaches of CSSD and CSAD. Table 4.5 represents the results of non-linearity on herding behavior in Cryptocurrencies market using CSSD measure of Christie and Huang (1995).

This table shows the results for presence of herding in Crypto market. The results for CSSD indicates coefficients of quadratic term is insignificant showing that

Table 4.5: Non-linearity in Herding Measured by CSSD

CSSD	*Coefficients*	*S.E*	*t Stat*	*P-value*	F stat	Fi Sig	Adj r
Intercept	0.0176	0.0011	16.1187	3.39E-54	388.6924	0.0000	0.3310
abs(rm)	0.6063	0.0375	16.1493	2.22E-54			
$\boldsymbol{rm^2}$	-0.0925	0.2011	-0.4597	0.645787			

non linearity doesnt exist. The rm^2 is negative but insignificant further means herding is linear. F stats is significant which shows model is correctly specified. The explanatory power of model is 33%. The robustness of results is also tested by CSAD measure of herding.

Table 4.6 shows the results of non-linearity on herding behavior in Cryptocurrencies market using CSAD measure proposed by Chang et al. (2000):

Table 4.6: Non-linearity in Herding Measured by CSAD

CSAD	*Coefficients*	*S.E*	*t Stat*	*P-value*	F stat	Fi Sig	Adj r
Intercept	0.0121	0.0007	16.7668	3.72E-58	448.9794	0.0000	0.3638
abs(rm)	0.4633	0.0249	18.6331	3.83E-70			
$\boldsymbol{rm^2}$	-0.2783	0.1332	-2.0893	0.0368			

Above table indicates that quadratic term is significant which is evidence of presence of nonlinear herding is. The rm^2 is negative and significant further means herding is non-linear in cryptocurrency market. F-stats is significant which shows model is correctly specified. The explanatory power of model is 36%.

The above table shows mix results. Herding is linear in nature for CSSD approach whereas Herding is non-linear for CSAD approach. These results provide that possibility of non-linearity cannot be completely ruled out. Table 4.5 and Table 4.6 suggests that null hypothesis is accepted and Hypothesis 2 i.e., **H2:** Herding is non-linear in nature is rejected for CSSD approach but using CSAD Approach herding is nonlinear so H2 is accepted and null hypothesis is rejected. These conflicting results needs further investigation so herding in bullish and bearish periods have been examined too.

4.4 Non-Linearity in Herding During Bullish Period in Cryptocurrencies Market

Non-linearity in herding during Bullish period in cryptocurrencies market is examine by using both the approaches of CSSD and CSAD. Table 4.7 presents the results of non-linearity in herding behavior in Bullish market period of Cryptocurrencies using CSSD measure of Christie and Huang (1995):

TABLE 4.7: Non-linearity in Herding in Bullish Market using CSSD

CSSD	**Coefficients**	**S.E**	**t Stat**	**P-value**	**F stat**	**Fi Sig**	**Adj r**
Intercept	0.0286	0.0009	33.103	1.35E-182	445.7418	6.12E-154	0.3621
ABS BULLR	0.0573	0.0553	1.0353	3.01E-01			
$\boldsymbol{BULLR^2}$	6.5106	0.5056	12.8767	3.88E-36			

First non-linearity in herding in bullish market is analyzed by using CSSD Approach. The results shows P value is significant for quadratic term means herding is present in nonlinear fashion in bullish market. F stats is significant which shows model is correctly specified. The explanatory power of model is 36%.

Table 4.8 exhibits the results of non-linearity in herding behavior in Bullish market period of Cryptocurrencies using CSAD measure proposed by Chang et al. (2000):

TABLE 4.8: Non-linearity in Herding in Bullish Market using CSAD

CSAD	Coefficients	S.E	t Stat	P-value	F stat	Fi Sig	Adj r
Intercept	0.0203	0.0006	34.8565	1.70E-197	464.0229	5.84E-159	0.3715
ABS BULLR	0.0832	0.0373	2.23	0.0259			
$\boldsymbol{BULLR^2}$	4.1137	0.3409	12.068	3.96E-32			

Secondly non linearity in herding in bullish market is examined by using CSAD. The results shows P value is significant for quadratic term means herding is present in nonlinear fashion in bullish market. F stats is significant which shows model is correctly specified. The explanatory power of model is 37%. So herding is non-linear during bullish period in cryptocurrency market.

Table 4.7 and Table 4.8 shows that null hypothesis is rejected and alternatively H3 (H3: Herding is higher during bullish trends in the cryptocurrency market) is accepted as Herding is non-linear in Bullish market. In next step non linearity in herding is checked in bearish market using CSSD and CSAD measure of herding. This is helpful in testing robustness of results.

4.5 Non-Linearity in Herding During Bearish Period in Cryptocurrencies Market

Non-linearity in herding during Bearish period in cryptocurrencies market is examine by using both the approaches of CSSD and CSAD. Table 4.9 shows the results of non-linearity in herding behavior in Bearish market period of Cryptocurrencies using CSSD measure of Christie and Huang (1995):

TABLE 4.9: Non-linearity in Herding in Bearish Market using CSSD

CSSD	Coefficients	S.E	t Stat	P-value	F stat	Fi Sig	Adj r
Intercept	0.0247	0.0006	37.8083	8.95E-223	33.3947	6.33E-15	0.0397
ABS BEARR	0.0170	0.0323	0.5267	0.5984			
$\boldsymbol{BEARR^2}$	0.7596	0.1676	4.532	6.28E-06			

At first non-linearity in herding in bearish period is analyzed for cryptocurrency market using CSSD Approach. The results shows P value is significant for quadratic term means herding is present in nonlinear fashion in bearish market. F stats is significant which shows model is correctly specified. The explanatory power of model is 39% which is considered best.

Table 4.10 exhibits the results of non-linearity in herding behavior in Bearish period of Cryptocurrencies market using CSAD measure proposed by Chang et al. (2000):

TABLE 4.10: Non-linearity in Herding in Bearish Market using CSAD

CSAD	Coefficients	S.E	t Stat	P-value	F stat	Fi Sig	Adj r
Intercept	0.0348	0.0009	36.2517	2.01E-209	33.26535	7.11E-15	0.0395
ABS BEARR	-0.0204	0.0476	-0.4287	0.6681			
$\boldsymbol{BEARR^2}$	1.3044	0.2468	5.2852	1.43E-07			

Secondly non linearity in herding in bearish market is also examined by using CSAD. The results shows P value is significant for quadratic term means herding is present in nonlinear fashion in cryptocurrency market. The f-stats are significant indication of correct specification of model with an explanatory power of 39%.

Table 4.9 and Table 4.10 results confirms that null hypothesis is rejected and Hypothesis 4 (H4: Herding is higher during bearish trends in the cryptocurrency market) is accepted. The results confirms investors behavior in cryptocurrency market is not rational and enthusiasm and reactions of market drive the decision-making tendency of investors.

They tend to make buying decisions when they observe that market is showing a minor or major increase and when the market is going down as a result it produces panic between investors so they try to sell their assets. These findings are consistent with the results of study of Nabeel-Ud-Din et al. (2020).

4.6 Impact of Macroeconomic Variables on Herding in Cryptocurrencies Market

Impact of Macroeconomic Variables on herding behavior in Cryptocurrencies market is tested using both the approaches of CSSD and CSAD. Table 4.11 shows the results of Impact of Macroeconomic Variables on herding behavior in Cryptocurrencies market using CSSD measure of Christie and Huang (1995):

In the below table the coefficient of quadratic term is significant indicating non linearity does exist. Further p value of World Index (WI) is insignificant means there is no impact of WI on herding. Its coefficient value is negative but insignificant. The coefficient of Oil Market index (OI) is negative and insignificant showing that it does not affect herding in Cryptomarket. Third macroeconomic factor Interest rate (IR) is positive but insignificant which indicate that IR has no impact on herding in crypto market. The F-stats is significant indicates that model is correctly specified with an explanatory power of 1.29%.

Table 4.12 shows the results of Impact of Macroeconomic Variables on herding

Table 4.11: Impact of Macroeconomic Variables on Herding using CSSD

CSSD	Coefficients	S.E	t Stat	P-value	F stat	Fi Sig	Adj r
Intercept	208.7384	0.0375	5569.2544	0.0000	5.0783	0.0001	0.0129
abs(rm)	-3.5087	0.8464	-4.1454	0.0000			
$\boldsymbol{rm^2}$	-8.6557	4.5355	-1.9084	0.0565			
W.I	0.5385	0.9876	0.5452	0.5857			
O.I	-1.5826	1.9196	-0.8245	0.4098			
I.R	2.6900	5.4333	0.4951	0.6206			

behavior in Cryptocurrencies market using CSAD measure proposed by Chang et al. (2000):

Table 4.12: Impact of Macroeconomic Variables on Herding using CSAD

CSAD	Coefficients	S.E	t Stat	P-value	F stat	Fi Sig	Adj r
Intercept	20.8738	0.0037	5569.2544	0.0000	5.0783	0.0001	0.0129
abs(rm)	-0.3509	0.0846	-4.1454	0.0000			
$\boldsymbol{rm^2}$	-0.8656	0.4535	-1.9084	0.0565			
WI	0.0538	0.0988	0.5452	0.5857			
OI	-0.1583	0.1920	-0.8245	0.4098			
IR	0.2690	0.5433	0.4951	0.6206			

To further check the impact of macroeconomics factors CSAD approach is used. The coefficient of quadratic term is significant indicating that non linearity does exist. Further p value of World Equity Market Index (WI) is insignificant means there is no impact of WI on herding.

Its coefficient value is positive but insignificant. So we may say herding in cryptocurrency market have no impact by equity market although both markets share common features, but the dynamics of both markets are quite different as equity market is extremely regulated in comparison of crypto market. These results are aligned with results of the study of Nabeel-Ud-Din et al. (2020).

The coefficient of Oil Market index (OI) is negative and insignificant showing that it does not effects herding in Cryptomarket. Third macroeconomic factor Interest rate (IR) is positive but insignificant which indicate that IR has no positive impact on herding crypto market. The f-stats are significant showing model is correctly specified with an explanatory power of 1.29%.

From Table 4.11 and Table 4.12 concludes that Equity Market Index (WI), Oil Market index (OI) and Interest rate have no impact on herding of Therefore Hypothesis 5, 6 and Hypothesis 7 are rejected using both the approaches.

4.7 Impact of Covid-19 On Herding in Cryptocurrencies Market

Impact of COVID-19 on herding behavior in Cryptocurrencies market is checked using both the approaches of CSSD and CSAD. Table 4.13 shows the results of non-linearity in herding behavior of Cryptocurrencies market during COVID-19 period using CSSD measure of Christie and Huang (1995):

Coefficients of quadratic term is insignificant showing that non linearity does not exist and further p value of COVID-19 is also insignificant means herding during COVID-19 period is not different from rest of the period. The F-stats is significant indicating model is correctly specified with an explanatory power of 33%.

Table 4.14 shows the results of non-linearity in herding behavior of Cryptocurre-

TABLE 4.13: Non Linearity in Herding during COVID-19 period using CSSD

CSAD	Coefficients	S.E	t Stat	P-value	F stat	Fi Sig	Adj r
Intercept	0.0181	0.0012	15.3114	0.0000	259.5375	0.0000	0.3311
abs(rm)	0.6043	0.0376	16.0765	0.0000			
$\boldsymbol{rm^2}$	-0.0839	0.2013	-0.4170	0.6767			
COVD	-0.0017	0.0016	-1.0734	0.2833			

ncies market during COVID-19 period using CSAD measure proposed by Chang et al. (2000):

TABLE 4.14: Non Linearity in Herding during COVID-19 period using CSAD

CSAD	Coefficients	S.E	t Stat	P-value	F stat	Fi Sig	Adj r
Intercept	0.0127	0.0008	16.1766	0.0000	300.7291	0.0000	0.3646
abs(rm)	0.4612	0.0249	18.5350	0.0000			
$\boldsymbol{rm^2}$	-0.2691	0.1332	-2.0201	0.0435			
COVD	-0.0018	0.0011	-1.7468	0.0809			

Coefficients of quadratic term is significant showing that non linearity does exist and further p value of COVID-19 is insignificant means herding during COVID-19 period is not different from rest of the period using technique of CSAD. The F-stats is significant indicating model is correctly specified with an explanatory power of 36%. Table 4.13 and Table 4.14 confirm that herding is not different in COVID-19 period so null hypothesis is accepted and Hypothesis 8 i.e., H8: Herding is higher in COVID-19 period in the cryptocurrency market is rejected.

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

This study examines the presence of herding behavior in Cryptocurrency market. The analysis of daily returns reveals presence of herding in Cryptomarket. The empirical results shows that in periods of extreme price movements, the return dispersions also increases creating evidence of herding behavior by investors. These results are inconsistent with those acknowledged by Christie and Huang (1995) and are against the assumption of the rational asset pricing model which is an indication of the inefficient crypto markets in extreme market movements. Likewise, results founded by Chang et al. (2000) model also confirm herding during extreme market conditions. These favors the Gleason et al. (2004) argument that measure of dispersion employed is relevant as returns of cryptomarket reveal same behavior for alternate proxies.

The likelihood of non-linearity of relationship is explored by Christie and Huang (1995) technique. The results for CSSD indicates coefficients of quadratic term is insignificant showing that non linearity doesnt exist meaning herding is linear. It is also checked by Chang et al. (2000) model and quadratic term is found significantly positively measure of dispersion .According to Chang et al. (2000), existence of significantly negative non-linear coefficient endorse the presence of herding activities, or else a statistically positive specifies no evidence of herding. Consequently, it may be rightly said that herding is observed in Cryptocurrency market with this technique. The results are conflicting.

Herding is examined in Bullish and Bearish market trends by using both techniques. Results show presence of herding in bullish market by both of the two methods. So it is confirmed that herding exists in Bullish cryptomarket. Results are obtained for bearish market where Christie and Huang (1995) method reveals presence of herding in bearish trends and Chang et al. (2000) model also confirms herding during bearish trend.

The effect of macroeconomic factors is also explored it is observed that World Index have insignificant role on herding behavior of traders. Oil market Index and Interest rate does not impact the decision making process of cryptotraders. In the last the effect of COVID-19 is detected on herding instincts of market participants. The result reveals insignificant impact of COVID-19 on nonlinear herding behavior of cryptotraders when all two measures are used.

5.2 Recommendations and Future Research

This study reveals that herding is present in cryptocurrency market by techniques of Christie and Huang (1995) and Chang et al. (2000) it implies that crypto trades copies the decisions of other investors. It has implications on portfolio and risk management decisions. Evidence of herd formation advocates insufficiency in portfolio diversification so the investors are exposed to additional risk who have investment in cryptocurrencies only.

Conversely if herd formation prevails for significant duration investments cannot make profits. Such an implication should be reflected in future research. The presence of herding behavior is an indication of market inefficiencies regarding policy makers. Systematic risk is more likely to occur which could risk market stability, causes a critical concern for policy-makers.

- Herding behavior is present in markets of cryptocurrencies that determines their price dynamics. So prices cannot be reason on economic variables that can explain the returns of traditional assets. So portfolio managers in such conditions of herding have to let go the superior information they possess and "go with the flow" in order to lessen deviations from the benchmark.

- Presence of Herding in Cryptocurrencies market causes uncertain situation so traders and investors are prone to risk. So the risk managers must consider this risk and incorporate it while making investment decisions.

- Change in Interest rate causes uncertainty so investors and crypto traders follow herd behavior so herding increases in the market.

- Oil prices and Herding exhibit inverse relation so when oil prices increases investors watch it as a positive outcome and herding decreases while on the other hand decrease in oil prices is consider as negative news so uncertainty gives birth to herd formation.

Study is limited to Cryptocurrency market and with few macroeconomic fundamentals. So other markets can also be incorporated in this study for future research and for a comparable results with other better techniques. Avenues for future examination of digital currencies could embrace estimations through alternate methodologies.

Moreover, a greater spectrum of digital forms of money could be covered in investigations. It would be very exciting to have empirical research concentrating on the nexus concerning herding levels in cryptocurrency markets against herding intensity in alternative markets .Research could also be conducted on alternate weighting schemes of digital currencies in portfolios under different market conditions and in different countries.

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