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Does Herding Behavior Exist in the Cryptocurrency Markets?

Submitted by

Anis Mnif

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Dissertation Supervisor: Dr. Lorán Chollete Signature: ____________________

Committee Member: Dr. Yaseen S. Alhaj Yaseen Signature: Yaseen

Committee Member: Dr. Weijia Peng Signature: Weijia Peng

JACK WELCH COLLEGE OF BUSINESS & TECHNOLOGY

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Abstract

This paper examines herd behavior in the cryptocurrency market using data of the top 15 large cryptocurrencies and the CCi30 Index as a proxy for market return. The idea that investors mimic and follow the behavior of others in the cryptocurrency market rather than conducting their own research has received attention in the finance literature.

The CSAD results in the static model detected herding but given the existence of structural breakdowns and nonlinearities in the data series, we opted to conduct a rolling window analysis. The results indicate strong herding behavior that fluctuates over time. Furthermore, results from the logistic regression reveals that herding develops as uncertainty increases. Our findings are consistent with earlier research on identifying herding behavior in cryptocurrencies. It is an attempt to shed light on portfolio and risk management, trading strategies, and market efficiency.

Keywords: Herd behavior, Crypto Currency Market, Cross-sectional dispersion of returns, Behavioral finance, Rolling window Economic policy uncertainty

JEL classification: C 22, G14, G15, G40

1. Introduction

In the past few years, cryptocurrencies and blockchain technology have emerged as a new concept in the "new economy." The popularity of Bitcoin and other leading cryptocurrencies was credited to using a peer-to-peer network as a safe and encrypted payment method.

The global cryptocurrency market size was valued at USD 826.6 million in 2020 and is projected to grow from USD 910.3 million in 2021 to USD 1,902.5 million in 2028[1].

Even though cryptocurrency trading uses different markets and follows different rules and regulations than traditional stock trading mechanizes, many argue that cryptocurrency trading is still subject to behavioral finance and to the criticisms of financial markets exposed by behavioral finance advocates.

Cryptocurrency transactions are initiated by humans, who naturally find safety in the community and ordinary social life. Such behavior is the essence of the herding mentality and irrational decisions in financial markets.

In behavioral finance, herd mentality refers to the tendency of investors to follow and copy what other investors are doing. Investment decisions are driven mainly by emotion and instinct rather than the investor's independent analysis. An Investor who displays herd instinct often gravitates towards the same or similar investments based almost entirely on the fact that many other investors are buying those securities.

Herd instinct is a mentality distinguished by the absence of individual decision-making or interference, leading people to follow the same behavior as those around them. The fear of losing a profitable investment idea is often the driving force behind this instinct.

Despite the growing investors' and researchers' interest in the cryptocurrency market, there is still a gap in understanding the effects of herding behavior in the cryptocurrency market. The Cryptocurrency market is still characterized by a weak legal framework and a lack of quality information. The study seeks to shed more light on rational and irrational behavior and herding comportment in the cryptocurrency market.

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[1] Fortune Business Insights, Market Research Report, Oct 2021, Crypto Currency Market size. https://www.fortunebusinessinsights.com/industry-reports/cryptocurrency-market-100149

The study adds to our knowledge of financial market efficiency (Fama, 1970) and advances past research that demonstrates various inefficiencies in the cryptocurrencies marketplaces, stemming from its unique characteristics and factors specific to the digital asset space. . As a result, both rational and irrational herding behavior in the cryptocurrency market is highlighted.

Again, we employ cross-sectional standard deviation of stock return rates from the market return rate (CSSD) and the cross-sectional absolute dispersion (CSAD) to detect if this behavior exists. our analysis includes time-varying methods of measuring herding that are robust to possible structural breaks and turbulent periods. We use a new proxy for market return, the CCi30[2] Index, from January 2018 to March 2021 using a larger sample of the 15 well-known cryptocurrencies (market cap).

This paper contributions lies in utilizing a novel dataset that covers a large sample of cryptocurrencies to detect herding behavior in the market. While previous studies have also employed CSSD, CSAD, and dynamic models to examine herding behavior in the cryptocurrency market, this research offers several distinct contributions. Firstly, the dataset includes a comprehensive set of cryptocurrencies, allowing for a more comprehensive analysis of herding dynamics. Secondly, we employ two different measures of herding, capturing the proximity of asset returns to the market consensus, providing a comprehensive assessment of herding behavior. Additionally, we extend the analysis beyond static models and investigate dynamic herding patterns using different subsamples and rolling window regressions. By incorporating these novel elements, our research aims to enhance the understanding of herding behavior in the cryptocurrency market and contribute to the existing literature in a unique and insightful manner."

By emphasizing the novel dataset, the inclusion of comprehensive measures of herding, and the extension of the analysis to dynamic models and different subsamples, this clarifies the paper's specific contribution and distinguishes it from existing studies in the literature review.
The paper is organized into five sections, Section1. Introduction, Section 2. Summary of the relevant literature review. The third section presents the methodology and data used for empirical

[2] The CCi30 is a rules-based index designed to objectively measure the overall growth, daily and long-term movement of the blockchain sector. It does so by tracking the 30 largest cryptocurrencies by market capitalization, excluding stablecoins. It serves as a tool for passive investors to participate in this asset class, and as an industry benchmark for investment managers.

analysis. Sections 4., indicates the findings of the analysis. Finally, the Conclusion section closes this paper.

2. Literature Review

Herding behavior in finance dates several centuries back; it often led to markets and asset bubbles. This type of behavior provides significant evidence of the undesirable impact humans can cause when they abandon their rational thinking and a herd mentality sets in.

The 17th century case, the "Tulip Mania", (Mackay, 2021; Sornette, 2003), was the first asset bubble in recorded history. People saw their neighbors getting rich and sold their homes and land to invest in flowers. This herding behavior allegedly caused the world's first known asset bubble.

Moreover, like most bubbles, it eventually burst. Tulip prices tumbled, greed turned to fear, and speculators began panic selling. The sheer absurdity of the existing situation (herding behavior) is a testimony to the fact that markets are not self-correcting, not at least in the short run.

Since then, investigating herding behavior in different types of financial markets[3] (Stock, Commodity, Cryptocurrency, etc.) has become a growing topic for researchers in behavioral finance literature.

Herd behavior is shared among all types of investors and often generates high market volatility, leading to instability Spyrou, (2013). Herding behavior is instigated by the irrationality of the investors, responding to a piece of new important information, inferring information from previous investors' actions, and protecting their reputation.

Cipriani, M., & Guarino, A. (2014) introduced a model of informational herding that can be estimated with financial transaction data. They estimated the model using data on a NYSE stock (Ashland Inc.) during 1995. They concluded that herding led to significant informational inefficiencies in the market, averaging 4 percent of the asset's expected value.

Devenow & Welch, (1996) focused on the investor's psychology and addressed herding behavior in relation to the investor's thinking and behavior pattern, where trading behavior is predisposed by the investor's personality.

Christie and Huang, (1995) were the pioneer in using the Cross-Sectional Standard Deviation as the primary variable to explain herd behavior in the US equity market.

Their finding recommends that during periods of significant price movements, investors tend to suppress their own predictions about asset prices and blindly follow the trading behavior of their

[3] Spyrou (2013) provides a comprehensive review of the recent herding literature summarizing theory and empirical results of more than two decades.

peers when making investment decisions. Therefore, individual asset returns will not diverge substantially from the overall market return, leading to a smaller-than-normal CSSD.

Later, Chang et al., (2000) criticized the technique developed by Christie and Huang in 1995 and adopted a new method to measure herding behavior called the Cross-Sectional Absolute Deviation of returns, to test the presence of herding in five major markets (US, Hong-Kong, Japan, Taiwan, and South Korea). The results of this study showed mixed evidence of herding. They reported no existence of herding behavior in the US and Hong Kong markets and the existence of herding in Japan, Taiwan, and South Korea.

Hwang and Salmon, (2004) developed an alternative measurement of herding behavior based on the cross-sectional dispersion of assets' sensitivity to market factors. Since their model focuses on the herding behavior originated from the cross-sectional variation of betas instead of returns, it is free from the influence of idiosyncratic components. Furthermore, their methodology was based on state-space models allowing for the control of changes in firm fundamentals and the existence of herding behavior not only during periods of extreme movements, but also during normal market conditions.

In studies of European equity markets, Caporale et al. (2008) also use the CSAD approach and the non-linear regression of Chang et al. (2000) in order to test for herd behavior in extreme market conditions in the Athens Stock Exchange. Their results (on daily, weekly and monthly data) suggest herd behavior that is more pronounced over daily time intervals.

Chiang and Zheng, (2010) investigated herding effects by utilizing a modified version of CSAD in 18 global markets from 1998 to 2009. According to their research, herd behavior was found in Asian markets and developed markets except for the United States. On the other hand, herd behavior was found in Latin markets and the United States market during crisis periods. Herd behavior was also investigated by Do˘gukanlı and Ergün, (2011) in Borsa Istanbul, but no evidence of herding was found.

In addition, Economou et al. (2011) utilized the same methodological approach to test for herding behavior in the Portuguese, Italian, Spanish and Greek market. Daily data between 1998 and 2008 was used to examine whether the return dispersion in one market is affected by the return dispersion in the rest of the markets. Their findings suggest that herding became more intense during the financial crisis of 2007-2008.

Caparrelli et al., (2004) used the CSAD approach as well to evaluate herding effects in the Italian Stock Exchange; they find that herding is present in extreme market conditions, a result consistent with Christie and Huang (1995).

Following the same approach, Henker et al. (2006) examined market wide and industry sector herding with intraday data on Australian equities and found evidence that is inconsistent with intraday herding.

More recently, Arjoon and Bhatnagar (2017) used a time-varying parameter approach and proved that herding is not a static feature in the context of frontier stock markets. Instead, this behavior changes throughout the sample period and fluctuates between herding in the crisis period and anti-herding during regular periods when the investor has better access to information.

Bitcoin, the leading cryptocurrency coin, entered the market at a time when blockchain networks started to gain attention (Nakamoto, 2008), the idea of decentralized currencies (without banks/government regulations) has come to the attention of investors, companies and academics. Initially, researchers have started to discuss the factors and components of cryptocurrencies and how they are linked with the present financial system (Cheah & Fry, 2015; Katsiampa, 2017).

Poyser, O. (2018) used an empirical herding model based on Chang, Cheng, and Khorana (2000) methodology and expanded the model both under asymmetric and symmetric conditions and the existence of different herding regimes by employing the Markov-Switching approach. He concluded that investors frequently deviated from the rational asset pricing benchmark and followed the consensus in market-stress situations.

Cryptocurrencies are considered relatively new financial instrument, therefore studies related to herding behavior in the cryptocurrencies market is limited. Vidal-Tomás, Ibáñez, and Farinós (2019) investigated the herding behavior in the cryptocurrency market using the cross-sectional deviations of returns and cross-sectional absolute deviation of returns approaches. No evidence of herd behavior was detected.

Pele and Mazurencu (2019) investigate the herd behavior in Bitcoin by using Metcalfe's law. King and Koutmos (2020) investigated the forces that drive cryptocurrency prices by testing to what extent herding behavior is present in cryptocurrency markets. Based on the models of Merton (1980), Shiller (1984), and Sentana and Wadhwani (1992).

A few studies focus on the cryptocurrency market, especially over COVID-19. Ballis and Drakos (2020) investigate herding behavior in six major cryptocurrencies during 2015–2018. The CSAD model results indicate herding among investors in the top sector of the cryptocurrency market that becomes stronger during the up market.

Chang, et al. (2000) methodology was based on static model analysis of the market, proven to be unreliable during evidence of nonlinearity. Stavroyiannis and Babalos, (2017) proposed a time-varying approach, based on a rolling window to study the time-varying nature of herding .

Bouri et al. (2019b) also employed the CSAD static model, and the rolling windows approach to examine herding in 14 cryptocurrencies from 2013 to 2018. Their results from the CSAD model reveal no evidence of herding, while the rolling windows approach shows a significant herding behavior.

3. Methodology and Data

3.1. Methodology

In this paper, we opted to use the macro approach of detecting herd behavior in the cryptocurrency market. We first employ the Christie and Huang (1995) Cross Sectional Standard Deviation method, we then use (Chang, et al. 2000) methodology to detect herding behavior based on the static model. We also apply dynamic models, using time-varying methods of measuring herding that are robust to possible structural breaks and turbulent periods.

i. Cross Sectional Standard Deviation - Static models of herding

Christie and Huang (1995) proposed a metric that measures investor herding toward the market consensus. They argue that during periods of extreme market movements investors are most likely to suppress their own beliefs and follow the market consensus.

In this case, returns will not deviate too far from the market return and thus return dispersions should be relatively low; when stocks sensitivity toward the market is different rational asset pricing suggests that dispersions will increase. Their approach starts with the estimation of cross-sectional standard deviation as a metric of herd behavior.

In order to measure the herding intensity, we calculate the daily return of each coin using the following equation:

$$\boldsymbol{R_{c,t} = ln\ \frac{P_{c,t}}{P_{c,t-1}}} \quad \textbf{(1)}$$

$R_{c,t}$: Daily return of Coin ***c*** at time ***t***

As a first step to detect herding behavior in cryptocurrency market, we use the CSSD calculated as:

$$\boldsymbol{CSSD_t = \sqrt{\frac{\sum_{c=1}^{n}(R_{c,t} - R_{m,t})^2}{N-1}}} \quad \textbf{(2)}$$

$R_{c,t}$: is the observed cryptocurrency coin return of the firm c at time t.
$R_{m,t}$: is the market return, in our case we used the CCi30 index.
N : is the number of cryptocurrencies for the selected period.
$CSSD_t$: The Cross-Sectional Standard Deviation of the returns in the aggregated portfolio at time t.

Christie and Huang (1995) Cross-Sectional Standard Deviation of returns captures the particular asset return closeness to the realized average. By using the cross-sectional standard deviation of returns, we can capture the level of dispersion or similarity in the returns of different assets within the data period. Lower cross-sectional standard deviation indicates a higher level of herding behavior, as it suggests a greater degree of similarity or convergence in investor actions. ***The intuition – Interpretation for Eq. (2):*** *if the cross-sectional standard deviation decreases when the markets move up or down significantly it would mean that when there is notable volatility, investors forget about what these coins are individually and just treat them according to the overall market signal or opinions of key influences of the trading industry or the investment industry. So, relating the CSSD to the movement of the market can detect herding potentially or can prove that there is no herding, and the market is behaving rationally.*

We then employ the following regression in order to examine whether the dispersion of returns is significantly lower during periods of extreme market movements.

$$\boldsymbol{CSSD_t = \alpha + \beta_1 D_t^{Down} + \beta_2 D_t^{UP} + \varepsilon_t} \quad \textbf{(3)}$$

Christie and Huang (1995) proposed the regression of the CSSD on dummy variables that signal the right tail and the left tail of the market return distribution.

The CSSD of returns is regressed against a constant and the two dummy variables that are D^{UP} and D^{Down} in order to capture differences in investor behavior in extreme up or down versus relatively normal markets.

> **D^{UP} = 1**, if the market return on day t lies in the extreme 5% upper tail of the distribution and zero otherwise.
> **D^{Down} = 1**, if the market return on day t lies in the 5% lower tail of the same distribution and zero otherwise.
> **The α coefficient** represents the average distribution of the sample apart from the regions corresponding to the two dummy variables.

The use of D^{UP} and D^{Down} allows the identification of differences in investor behavior under extreme market conditions (+ and -). Based on this model**, herd behavior is present with statistically significant negative values for β_1 and β_2**, but if the 2 coefficients are positive, we can then reason that the market behaves rationally with CSSD increasing with market volatility.

Although the cross-sectional standard deviation of returns is an intuitive measure for capturing herding, there have been some criticisms of the CSSD model. As argued by Chiang, Nelling (2008), CSSD has some important shortcomings. The measure is sensitive to outliers and the herding is analyzed under the condition of extreme market movements only, disregarding the herding behavior that might happen in other situations.

ii. Cross Sectional Absolut Deviation - Static models of herding

As such, the CSAD model developed by (Chang et al. 2000), (defined in Eq. (4) below) is a more widely used methodology for detecting herding.

$$CSAD_t = \frac{1}{N}\sum \left|R_{c,t} - \overline{R}_{m,t}\right| \qquad \textbf{(4)}$$

where $R_{c,\,t}$ denotes the returns of an asset C at time t; $R_{m,\,t}$ represents the cross-sectional returns average of the asset market portfolio at time t, and N gives the count of asset returns in the portfolio.

To allow for a possible non-linear relationship between $R_{m,t}$ and CSAD $_{m,t}$ under periods of market stress, we apply the standard model of Chang et al. (2000):

$$\boldsymbol{CSAD = \alpha + \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t} \qquad \textbf{(5)}$$

Where: $|\mathbf{R}_{m,t}|$ is the absolute weighted market return at time t and $(\mathbf{R}_{m,t})^2$ is the squared market return at time t.

They also hint to the following intuition: “if market participants tend to follow aggregate market behavior and ignore their own priors during periods of large average price movements, then the linear and increasing relation between dispersion and market return will no longer hold. Instead, the relation can become non-linearly increasing or even decreasing”.

The presence of herding is tested through the following hypotheses:

H_0: In the absence of herding effects, we expect in the Eq. (5) that β_1>0 and β_2=0.
H_1. If herding exists, we expect β_2<0.
H_2. If anti-herding exists, we expect β_2>0.

A statistically significant negative coefficient will be a good indication that herding is likely occurring, and a significant positive suggests a presence of adverse herding.
Chang et al. argue that this model is much more powerful, and it allows you to detect herding with much greater precision.

iii. Rolling window - Dynamic models of herding

Since herding may display a time-varying dynamic, we use the Bai and Perron (2003) multiple breakpoint to detect structural breaks in the CSAD series. This analysis will identify periods of significant shifts or changes in herding behavior.
The proposed structural 1 to M breaks allow for a comparative analysis of herding behavior across multiple periods. By estimating the CSAD and examining its changes between different sub-periods, we can assess whether there are variations in herding behavior across regimes or over time (Jan 2018 - March 2021).
To further investigate the dynamic nature of the herding behavior in the cryptocurrency market, we implement a time-varying approach based on a rolling window of n observations and a step of one observation. If the model's parameters are constant over the whole sample, the estimates over rolling windows should not differ much; otherwise, the rolling estimates should represent

this instability. The size of the rolling window is proportional to the system's timeframes (reaction times). There is no hard and fast rule for determining the optimal size of the rolling window, and there is a trade-off between having a long enough window to estimate the metrics and a small enough window to infer a trend.

We re-regress Eq. (5) with rolling windows. If β_2 stayed constant throughout a rolling window, it suggested that the link between the square term of the market portfolio return and CSAD was stable; otherwise, our technique captured the time-varying aspect of herding.

3.2. The Data

The data used for this research is daily data for the top 15 cryptocurrency coins based on their market cap from Jan 1, 2018 until March 15, 2021 (with 1168 observations).

Daily data for the same period was collected for the cryptocurrencies (CCi30) Index. This index is rule based and is delineated to gauge the size and movement of the cryptocurrency market. The index tracks the 30 largest cryptocurrencies by market capitalization and was first introduced on Jan. 1st, 2015 and it is the industry standard for cryptocurrencies.

The data is converted into their return form as shown in equation 1. However, to facilitate a comparison of the coefficients of the linear term, absolute values are used for up-versus the down-market as shown in equation 5.

We initially considered the top 100 cryptocurrencies, then we filtered the 15 most liquid coins (Bitcoin, Ethereum, Binance Coin, Tether, Cardano, XRP, Theta, Litecoin, Chainlink, Bitcoin Cash, Stellar, Monero, EOS, Neo, Huobi) representing 64.42% of the market value using a three-stage criterion: (i) currencies with market cap above USD 100 million; (ii) markets with trading volumes above the third-quartile volume; and (iii) those with more than 24 months of active trading and reliable data.

Preliminary tests are applied to check for normality with the Jarque-Bera test, Ovtest: Ramsey RESET test using powers of the fitted values of CSAD, hettest: Breusch-Pagan / Cook-Weisberg test for heteroskedasticity and dwstat Durbin-Watson.

The list of the of 15 crypt coins used in the sample is reflected in Table 3-1 and it is ranked by market-cap. A full list of the 30 cryptocurrencies used in the (CCi30) Index is represented in Table 3-2

Table 3-1 List of 15 coins used in the sample, ranked by market-cap

Name	Symbol	Market cap rank
Bitcoin	BTC	1
Ethereum	ETH	2
Binance Coin	BNB	3
Tether	USDT	4
Cardano	ADA	5
XRP	XRP	6
THETA	THETA	7
Litecoin	LTC	8
Chainlink	LINK	9
Bitcoin Cash	BCH	10
Stellar	XLM	11
Monero	XMR	12
EOS	EOS	13
Neo	NEO	14
Huobi Token	HT	15

Table 3-2. Cryptocurrencies represented in the CCi30

# Market-cap	Coin Symbol	# Market-cap	Coin Symbol
1	BTC	16	LINK
2	ETH	17	XMR
3	BNB	18	OKB
4	XRP	19	UNI
5	ADA	20	XLM
6	DOGE	21	ETC
7	TRX	22	BCH
8	SOL	23	TON
9	MATIC	24	LDO
10	LTC	25	FIL
11	DOT	26	HBAR
12	AVAX	27	CRO
13	SHIB	28	APT
14	LEO	29	VET
15	ATOM	30	NEAR

Table 3-3. Descriptive Stat - Cryptocurrencies Daily Returns

	Mean	Median	Min.	Max.	Std. Dev	Skew	Kurtosis
BTC_DR	0.12%	0.15%	-49.73%	17.74%	4.14%	-1.54	19.75
ETH_DR	0.07%	0.09%	-58.96%	23.02%	5.32%	-1.35	14.49
BNB_DR	0.29%	0.15%	-58.12%	53.06%	6.21%	0.33	18.42
USDT_DR	0.00%	0.00%	-2.16%	2.62%	0.33%	0.36	16.07
ADA_DR	0.03%	0.00%	-53.72%	34.88%	6.33%	-0.16	6.77
XRP_DR	-0.14%	0.02%	-54.39%	41.11%	5.93%	-0.4	15.78
LTC_DR	-0.01%	-0.09%	-48.63%	28.83%	5.36%	-0.45	8.21
THETA_DR	0.31%	0.05%	-63.55%	71.78%	8.08%	0.56	12.32
LINK_DR	0.31%	0.09%	-115.13%	60.90%	8.44%	-1.89	37.56
BCH_DR	-0.13%	-0.16%	-60.30%	38.00%	6.72%	-0.49	11.39
XLM_DR	-0.02%	-0.10%	-42.75%	55.34%	6.22%	1.04	12.95
XMR_DR	-0.04%	0.06%	-51.58%	23.66%	5.33%	-0.95	9.83
EOS_DR	-0.06%	-0.03%	-50.88%	34.89%	6.39%	-0.3	8.12
NEO_DR	-0.06%	0.00%	-51.15%	34.50%	6.25%	-0.72	9.27
HT_DR	0.21%	-0.08%	-54.35%	47.35%	5.58%	-0.12	18.78
CCi30_DR	0.01%	0.27%	-48.45%	17.03%	4.54%	-1.5	13.1

Table 3-3, is the summary of the descriptive statics for the 15 cryptocurrencies and the market daily returns. Individual daily returns of the data from Jan 1, 2018 to March 15, 2021 is also plotted on Figure 1. The average daily return of most of the coins is positive, indicating that on average most the coins experienced gains, while few coins reflect a negative daily average. It's important to note that these negative daily averages are mainly due to extreme outliers, due to major shocks in the cryptocurrency market. The standard deviation results clearly reflect the volatility of the daily returns. The high standard deviation indicates greater variability in the returns, suggesting higher risk or volatility associated with the cryptocurrency coins in particular and the cryptocurrency market in general.

The 2 largest coins, Bitcoin and Ethereum, have a negative skewness, which suggests a longer or fatter tail on the left side, indicating more negative returns.

All 15 coins reflected positive kurtosis, a more peaked distribution with fat tails, this validates the nature of the cryptocurrency market, suggesting a higher likelihood of extreme returns and the presence of outliers. Minimum and Maximum provide another insight into the wide range of returns the coins experienced during the reported period Bitcoin with a min of negative return of almost 50% and a high of 18%, Ethereum's min return of negative 59% and a highest return of 23%.

The high Kurtosis values are in line with what is commonly observed other results from finance and risk analysis, the high kurtosis values indicate a higher risk in the cryptocurrency market and reflects the extreme events during the observed time period. It implies that the distribution has a higher probability of observing extreme positive or negative outcomes.

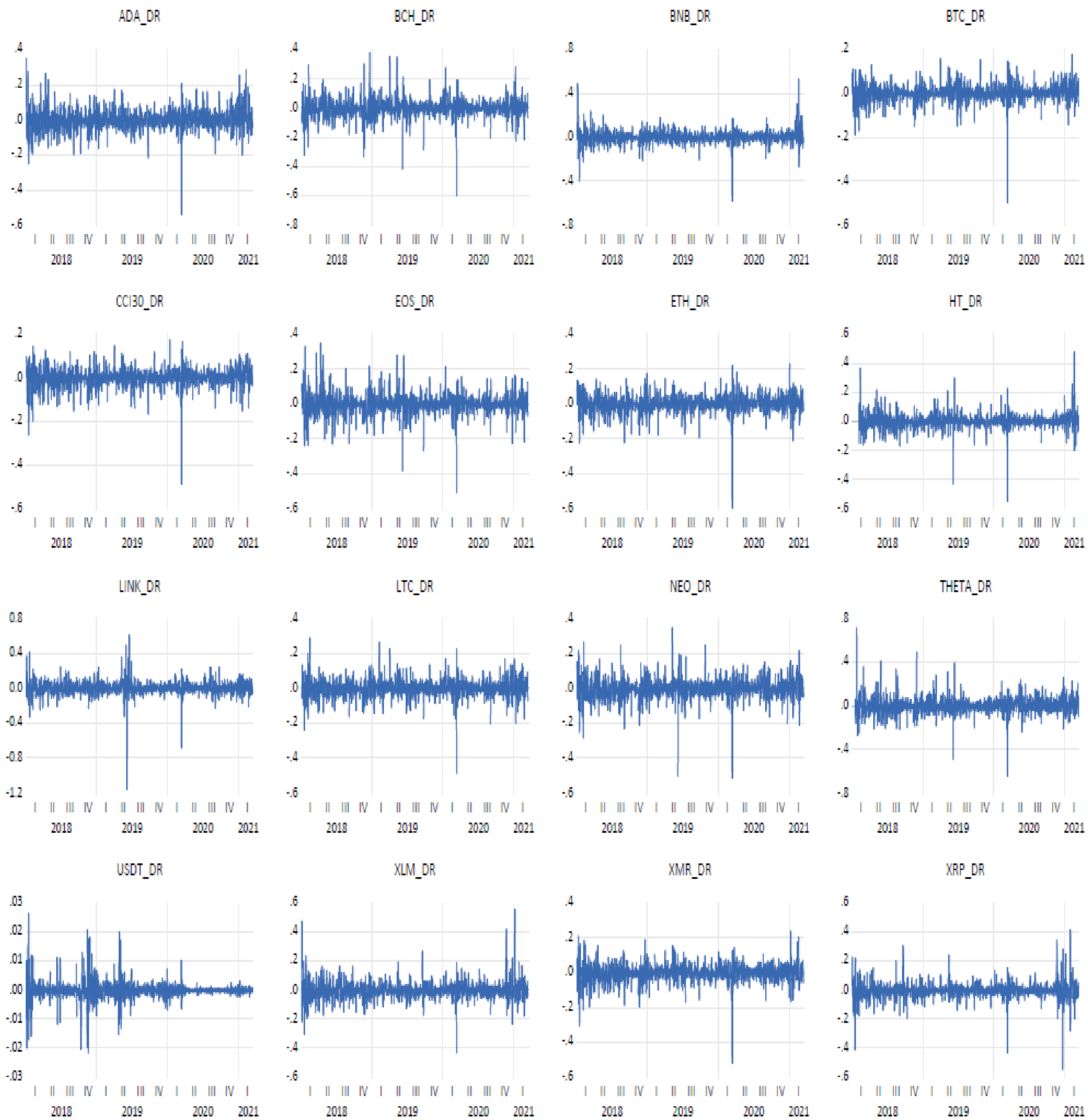

Figure 1. Daily returns of the 15 coins and the market return, Jan 1, 2018 – March 15, 2021

Table 3-4 shows the descriptive statistics for the market return (R_{mt}), CSSD, and CSAD for the whole sample period, and Figures 2, 3 and 4 plot the three variables respectively over the period of analysis.

During the sample period the cryptocurrencies the market daily returns ranged from -48.45% to 17.03%. The CSAD and CSSD exhibited a positive skewness which indicates a longer right tail. All series showed excessive kurtosis, which means that their distributions are leptokurtic.

Table 3-4. Descriptive statistics: R_{mt}, CSSD, and CSAD

	CSSD	***CSAD***	***Market Return***
Mean	0.0366	0.0251	0.0001
Standard Error	0.0008	0.0005	0.0013
Median	0.0298	0.0210	0.0027
Standard Deviation	0.0268	0.0164	0.0454
Sample Variance	0.0007	0.0003	0.0021
Kurtosis	43.1324	34.0601	13.1004
Skewness	4.5476	3.9127	-1.4959
Minimum	0.0069	0.0053	-0.4845
Maximum	0.4214	0.2470	0.1703
Count	1169	1169	1169
Confidence Level (95.0%)	0.0015	0.0009	0.0026

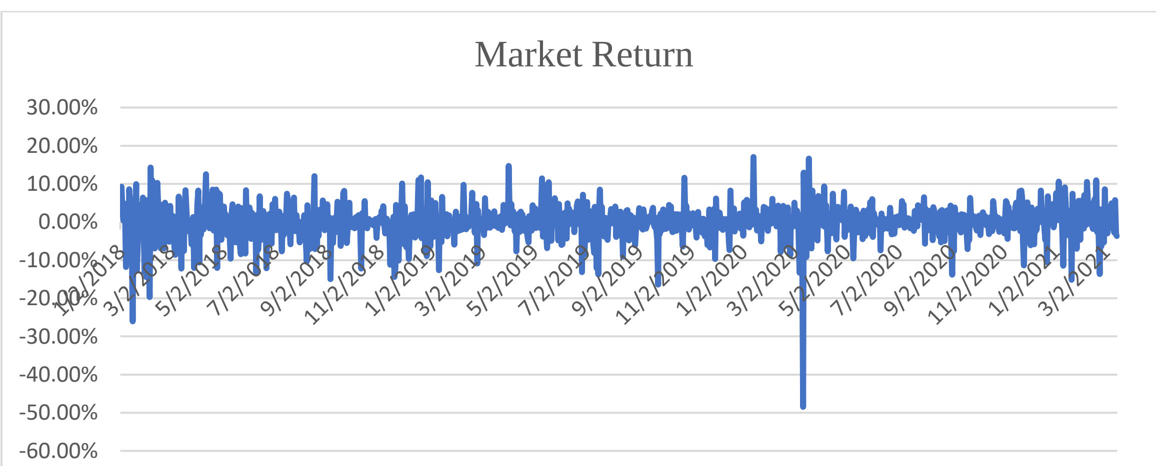

Figure 2. Daily market returns (Rmt), 01/01/2018 -03/15/2021

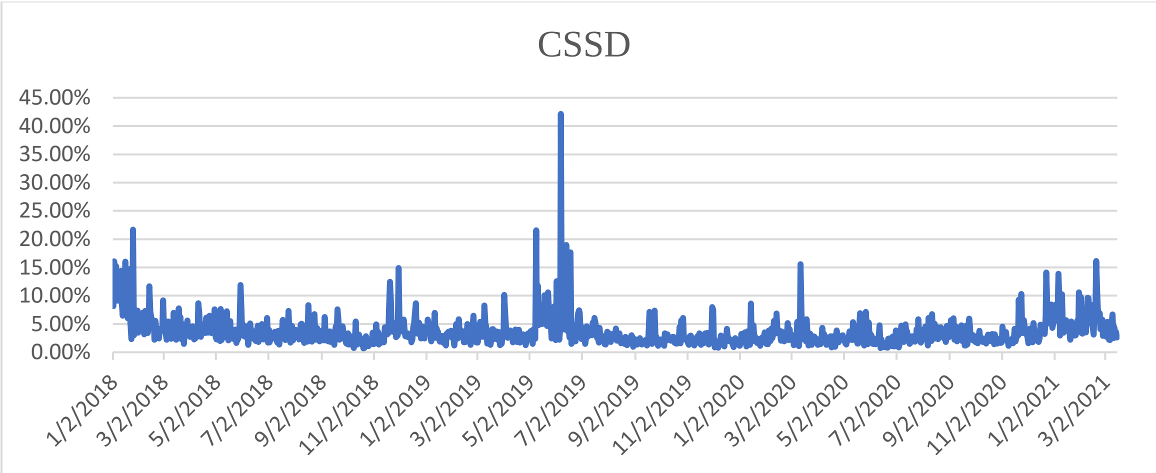

Figure 3. CSSD plots, 01/01/2018 - 03/15/2021

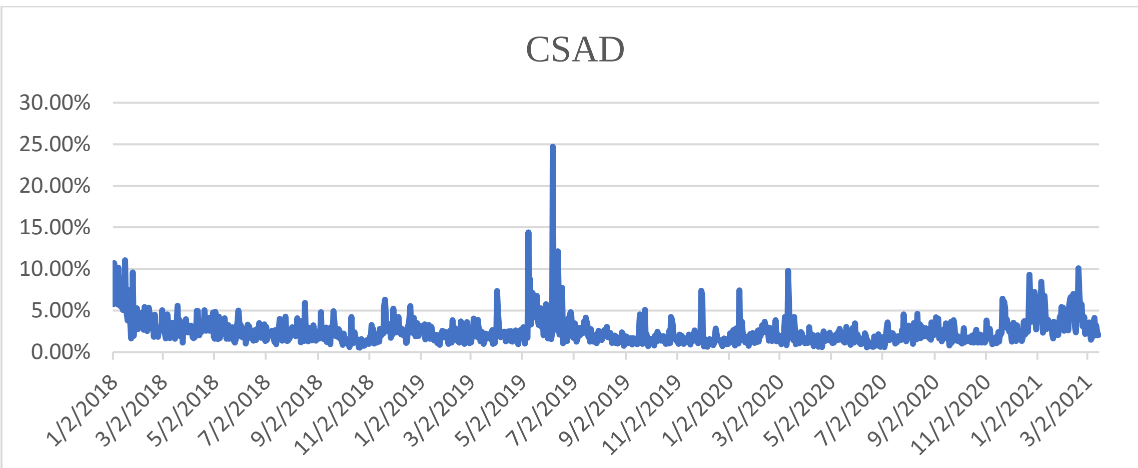

Figure 4. CSAD plots, 01/01/2018 - 03/15/2021

Figures 2, 3 and 4, reflects plotted data for observations of daily market returns (R_{mt}), Cross-sectional standard deviation of returns (CSSD) and for Cross-sectional absolute deviation of returns (CSAD) respectively from, 01/01/2018 - 03/15/2021,

4. Results and discussion

i. Static models of herding

4.1 CSSD Regression Results

The regression results for Eq. (3) are shown in Table 4-1, and the CSSD approach's findings indicated that there was no indication of herding, with both sets of coefficients being positive. Regarding the application of the CSSD model to detect herding, this is in line with the findings of (Ren & Lucey, 2022) and (Vidal-Tomas, Ibanez, & Farinos, 2019). The positive β1 coefficient show that dispersion rises in both dataset's lower tails, while the positive β2 coefficient show the similar phenomenon in both dataset's upper tails.

The (β_1) coefficient indicates the change in the amount of return dispersion given that cryptocurrency return is in the lowest 5% return, which is mentioned as lower market stress. On the other hand, the (β_2) coefficient shows the change in the amount of return dispersion given that cryptocurrency return is in the highest 5% return, which is also mentioned as upper market stress. The lowest and highest 5% refer to the extreme price movement days that lie in the upper and lower tails of the market return distribution. If these 2 coefficients on the dummy variables are negative and significant, we can already detect herding going on, but if they are positive, we can then reason that the market behaves rationally. According to Table 4-1, β_1 coefficient is not negative, but statistically significant, therefore there is no evidence of herd behavior in the cryptocurrency market based on the Christie and Huang (1995) CSSD method.

Table 4-1. CSSD Regression Results

CSSD	Coef	Std. Err	t	p>|t|	{95% Conf. Interval}	
D_t^{Down} ($\boldsymbol{\beta_1}$)	0.0502799	0.00402	12.51	0.000	0.0423926	0.0581673
D_t^{UP}($\boldsymbol{\beta_2}$)	0.0473257	0.003954	11.97	0.000	0.0395685	0.0550829
α _cons	0.0444163	0.000903	49.19	0.000	0.0426447	0.0461879

Table 4-1 reports the results for Equation (3). The results show that the coefficient β 1 is positive and statistically significant. Also, the coefficient β 2 is positive and statistically significant which indicates the presence of anti-herding. It is worth noting that the explanatory power of the model, measured by the adjusted R^2, reported in Table A. 4 is in line with what was reported in other studies (i.e., Vidal-Tomas, Ibanez, & Farinos, 2019).

4.2. CSAD Eq. (5) Regression Result

A positive and statistically significant β_1 coefficient shows that CSAD returns on cryptocurrencies is an increasing function of absolute value of markets returns. Herding is assumed to be absent if $\beta_1 > 0$ and $\beta_2 = 0$. On the contrary, if herding is present, $\beta_2 < 0$. Based on the findings of Table 4.2, that reports the estimated coefficients of the CSAD model Equation (5), β_2 is negative and statistically significant which means that with the CSAD method herding is present in the cryptocurrency market.

In contrast to the CSSD findings, the results of the CSAD approach with the static model detected herding.

Given the discrepancies between the CSAD and CSSD results, it is possible that the lack of herding when employing the CSSD approach contributes to the declining adoption of CSSD among academics in favor of the CSAD model and its variants.

Table 4-2. CSAD Regression Results

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.01664	0.00063	26.42213	0.00000
Absolute Market Return (β_1)	0.29181	0.01935	15.08121	0.00000
Squared Market Return (β_2)	**-0.23374**	0.08122	-2.87791	0.00408

Table 4-2, reflects a negative β2 coefficient on the squared market return, which indicates that herding behavior may be more pronounced during extreme market conditions. When market returns are highly positive or highly negative (in magnitude), investors may exhibit stronger herding tendencies. This could be due to heightened uncertainty and fear in extreme market situations, leading investors to imitate others' actions rather than making independent decisions. The β2 coefficient is statistically significant (with a low p-value) suggests that the non-linear relationship between squared market returns and herding behavior is unlikely to be due to chance.

ii. Dynamic models of herding

4.3. Structural Breaks

The static model in Eq. (5) generally leads to misleading conclusions regarding herd, as parameters are assumed to be constant overtime (Balcilar et al., 2013). To verify this, tests of Bai and Perron (2003) are applied to Eq. (5), to detect 1 to M structural breaks, allowing for heterogeneous error distributions across the breaks; five breaks are detected (see Table B1

Appendix B). Furthermore, the nonlinearity test of Dechert, and Scheinkman (1996), also known as the BDS test, is applied to the residuals of the static model in Eq. (5).

We use it to examine the presence of nonlinear dependencies or patterns in our data.

- Null hypothesis (H_0): assumes linearity in the data, meaning there are no significant nonlinear dependencies or patterns present.
- Alternative hypothesis (H_1): suggests the presence of nonlinear dependencies or patterns in the data.

The BDS test results (see Table B2, Appendix B) show strong evidence of nonlinearity. The structural breaks and nonlinearities confirm the unreliability of the static model.

As a next step, the use of time-varying approach, introduced by Stavroyiannis and Babalos (2017) is particularly useful. The time-varying approach allows for capturing these dynamic patterns by estimating the CSAD statistic in rolling windows. This helps to uncover changes in herding behavior and identify periods of heightened or diminished herding.

4.4. Rolling Windows Results

The time-varying approach is used to detect herding episodes by identifying periods when the CSAD statistic exceeds a certain threshold or exhibits significant deviations from the average behavior. This provides insights into the occurrence and duration of herding episodes.

The time-varying approach applied based on a rolling window of 160 observations[4], which essentially covers the number of data points for the year 2018. The size of the window was determined based on the structural breaks results, since the earliest break date was obtained at the 176th observation, i.e., 06/25/2018.

Fig. 5 depicts the rolling t-statistics of β_2 of Equation (5) and shows short periods of anti-herding at the early (01/01/2018-01/16/2018), middle (11/06/2018-11/20/2018), (09/22/2019-10/04/2019) and end (07/25/2020-08/22/2020) of the sample period.

However, unlike the full-sample estimation using the static model, significant herding is seen between early April thru mid-March 2019 and from early April to mid-June 2019, and then again in March and April 2020. These results are in line with the findings of Bouri et al. (2019b), Ballis and Drakos (2020) and Kallinterakis, & Wang, (2019), who document the existence of significant herding in this market.

4

To allow for a deeper understanding of the stability and generalizability of the findings, we also used smaller window size of 100 observations, to assess whether the observed herding dynamics hold consistently across different time frames. Comparing the results obtained from different window sizes (160 vs. 100) provided insights into the following aspects:

- The herding patterns observed in the original window size persist in the smaller window (100 observation). This indicates that there are consistent herding dynamics across different time frames.
- There was no sensitivity to structural breaks. The presence of structural breaks did not affect the herding dynamics differently in smaller window size, the findings remain consistent.
- The robustness of statistical significance and coefficient estimates for herding indicators under different window sizes (160 and 100) held consistently

Evidence of herding is expected in the cryptocurrency market due to its: i). high complexity and information asymmetry characteristics, ii)., high levels of uncertainty, iii.) limited liquidity and market depth, and iv). lack of quality information.
Evidence of herding implies that the trading decisions of crypto traders are not made in isolation. investor sentiment and excitement can drive herding behavior as individuals rush to participate in what appears to be a lucrative opportunity. The fear of missing out on significant returns can amplify the tendency to herd.

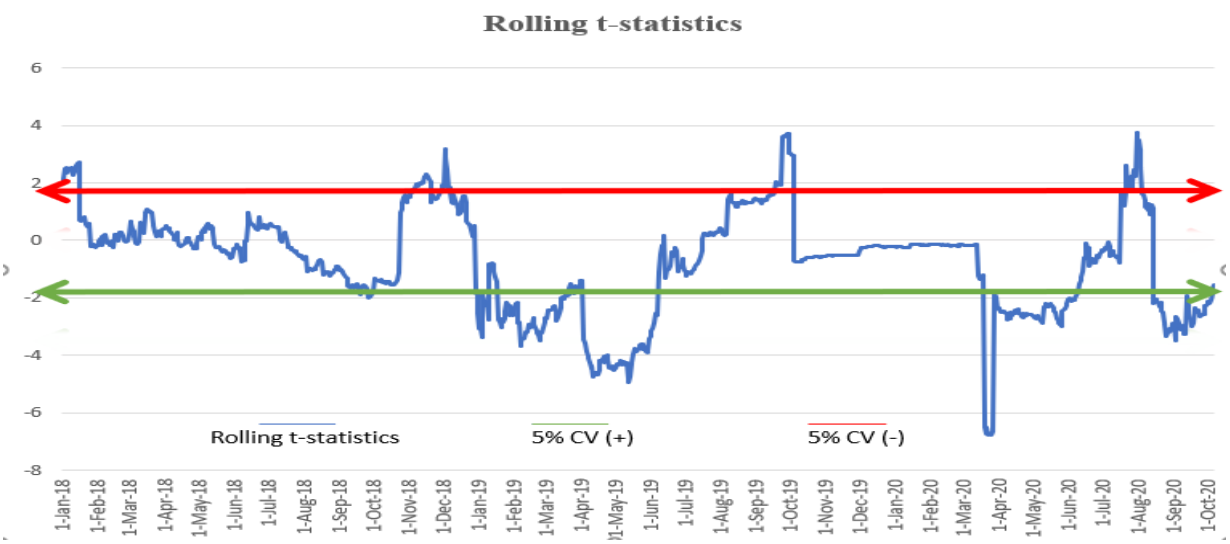

Figure 5. Rolling t-statistic based on a rolling-window (160 observations) estimation of the static model. Note: 5% critical value (CV) (+) stands for 1.96, while 5%CV (−) is equal to −1.96.

According to Demirer and Kutan (2006), this conclusion explains a portion of the high levels of market volatility. Second, herding follows a dynamic pattern, which is not surprising given that investor behavior, including herding, can alter over time (Gbka and Wohar, 2013).

4.5. Probit Model Regression

To help explain this findings "significant herding over certain period", we follow Balcilar and Demirer (2015) approach, relating herding to uncertainty.

Herding behavior in financial markets is often defined as the tendency of investors to follow the actions of others, resulting in a clustering of buy or sell decisions. This behavior can be represented as a binary variable, where a value of 1 indicates herding and a value of 0 indicates no herding. The Probit model is well-suited for analyzing binary outcomes as it models the probability of an event occurring.

We define a dummy variable, which takes a value of 1 during periods of statistically significant herding (i.e., for months when the rolling t-statistic on $\beta_2 < -1.96$) and zero otherwise, and then, we use a Probit model to relate this dummy with the news-based **economic policy uncertainty** (EPU) index of the US, as developed by Baker et al. (2016).

Check the significance level (usually denoted by p-values) of the coefficients associated with the EPU index and other variables. A low p-value (typically below 0.05) indicates that the coefficient is statistically significant and provides reliable evidence of its impact on the outcome variable.

Table 4-3 reflects the Probit model's results, with a positive coefficient for the EPU index. Which suggests that higher levels of economic policy uncertainty are associated with an increased likelihood of herding behavior. The positive coefficient for the EPU index indicates that an increase in the EPU index is associated with a higher probability of the binary outcome represented by the dependent variable. Specifically, for a one-unit increase in the EPU index, the odds of the event (success or presence) represented by the dependent variable being 1 increase by the exponentiation of the coefficient. The McFadden R-squared is a measure of the goodness-of-fit of the Probit model. It assesses how well the model fits the data compared to a null model with no independent variables. The McFadden R-squared is 0.111. The Schwarz Criterion, also known as the Bayesian Information Criterion (BIC), is a statistical criterion used to compare different models in the context of maximum likelihood estimation. It is a measure of model complexity and goodness-of-fit, and it takes into account both the likelihood function and the number of parameters in the model.

Table 4-3. Estimates of the Probit model.

Variable	Coefficient
EPU	0.003440
C	-1.239243
McFadden R-squared	0.111155
S.D. dependent var	0.438927
Akaike info criterion	1.022931
Schwarz criterion	1.032662
Hannan-Quinn criter.	1.026628
Restr. deviance	1159.014
LR statistic	128.8303
Prob (LR statistic)	0.000000

5. Conclusion

The study updates earlier theories on the herding mentality-driven inefficiencies of cryptocurrency markets and extends our understanding of financial market efficiency (Fama, 1970) We use the static models and dynamic models approaches to investigate herding behavior in the cryptocurrency market, Christie and Huang (1995) Cross-Sectional Standard Deviation, the Cross-Sectional Absolute Deviation measure of Chang et al. (2000) and the rolling window approach introduce by Stavroyiannis and Babalos (2017). We demonstrate that the cryptocurrency market exhibits herding behavior that appears to change over time.
These findings are in line with the findings of the previous literature regarding the herding behavior in cryptocurrencies.

It is important to note that while herding behavior is expected in the cryptocurrency market, it is not exclusive to this market. Herding can be observed in various financial markets, driven by similar psychological and behavioral factors. Understanding herding behavior in the cryptocurrency market can help identify potential risks, market inefficiencies, and opportunities for both investors and market regulators. Tougher market laws that discourage herding behavior and encourage market efficiency are required.

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Appendices

Appendix A

Table A 1. Cryptocurrencies by Market Cap

Name	Symbol	Market Cap
Bitcoin	BTC	$1,044,446,559,059.05
Ethereum	ETH	$194,913,443,083.05
Binance Coin	BNB	$41,598,879,255.91
Tether	USDT	$40,500,517,196.83
Cardano	ADA	$38,054,391,213.00
XRP	XRP	$25,006,533,341.53
THETA	THETA	$12,938,681,239.76
Litecoin	LTC	$12,351,098,573.27
Chainlink	LINK	$11,106,204,678.96
Bitcoin Cash	BCH	$9,364,900,285.31
Stellar	XLM	$9,060,062,003.41
Monero	XMR	$4,181,967,798.14
EOS	EOS	$3,926,080,377.41
Neo	NEO	$3,162,981,775.72
Huobi Token	HT	$2,476,476,396.65

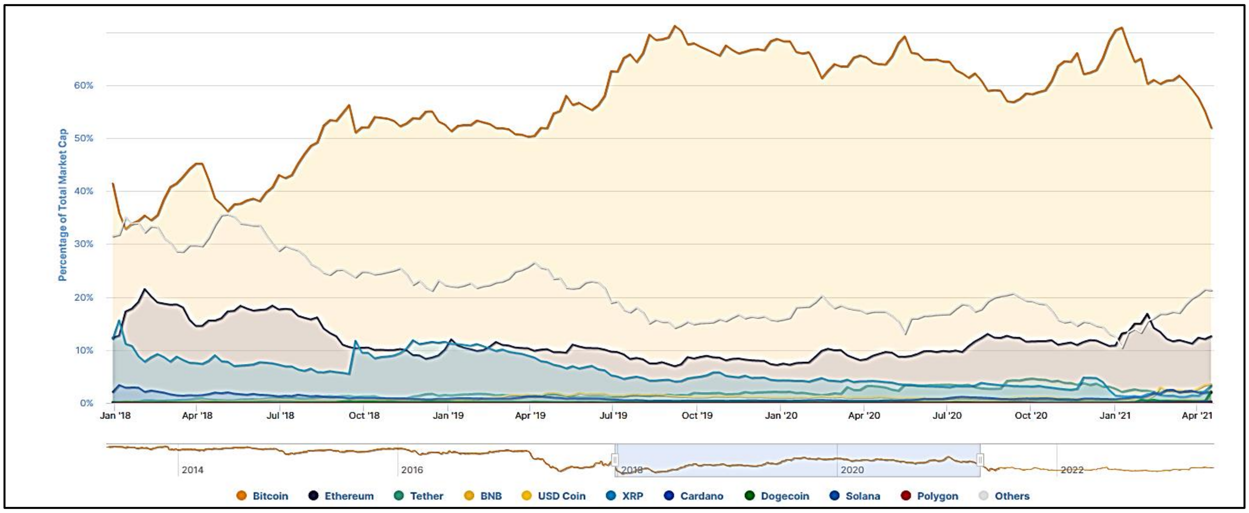

Figure 6. Historical price charts of BTC, XRP, Gold, S&P500, and EUI

Figure 6. shows the individual proportions of the largest crypto-assets relative to the total market capitalization of all assets. It is a four-line charts (one per each return) are labeled on the right-hand side of the chart window.

Descriptive Statistics Results

Table A 2. Unit- Root Test Result - daily returns

UNIT ROOT TEST at Level

	With Constant		With Const & T*		Without Const & T*	
	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
BTC_DR	-36.9612	0	-37.2317	0	-36.9462	0
ETH_DR	-23.3002	0	-23.5506	0	-23.3067	0
BNB_DR	-22.9228	0	-22.9944	0	-22.8613	0
USDT_DR	-22.6666	0	-22.6562	0	-22.6766	0
ADA_DR	-23.5123	0	-36.5229	0	-23.5233	0
XRP_DR	-33.8908	0	-33.9752	0	-33.8845	0
LTC_DR	-36.0835	0	-36.2253	0	-36.0986	0
THETA_DR	-36.9049	0	-37.0829	0	-36.8597	0
LINK_DR	-36.103	0	-36.1307	0	-36.0646	0
BCH_DR	-35.5935	0	-35.6809	0	-35.593	0
XLM_DR	-35.2707	0	-35.3942	0	-35.285	0
XMR_DR	-38.0363	0	-38.1882	0	-38.0496	0
EOS_DR	-37.1552	0	-37.1455	0	-37.1675	0
NEO_DR	-36.3924	0	-36.5146	0	-36.403	0
HT_DR	-22.7411	0	-22.7441	0	-22.6999	0

UNIT ROOT TEST at First Difference

	With Constant		With Const & T		Without Const & T	
	t-Statistic	Prob.	t-Statistic	Prob.	t-Statistic	Prob.
d(BTC_DR)	-17.3876	0	-17.3794	0	-17.3952	0
d(ETH_DR)	-16.065	0	-16.054	0	-16.0721	0
d(BNB_DR)	-17.4938	0	-17.4836	0	-17.501	0
d(USDT_DR)	-15.1604	0	-15.153	0	-15.1674	0
d(ADA_DR)	-16.1197	0	-16.1173	0	-16.1266	0
d(XRP_DR)	-17.8118	0	-17.8046	0	-17.8196	0
d(LTC_DR)	-16.5485	0	-16.5396	0	-16.5546	0
d(THETA_DR)	-18.4365	0	-18.4252	0	-18.4446	0
d(LINK_DR)	-17.4595	0	-17.4509	0	-17.4672	0
d(BCH_DR)	-18.4806	0	-18.4725	0	-18.4887	0
d(XLM_DR)	-15.9112	0	-15.9059	0	-15.9181	0
d(XMR_DR)	-15.9108	0	-15.9023	0	-15.9178	0
d(EOS_DR)	-17.6858	0	-17.6838	0	-17.6919	0
d(NEO_DR)	-17.5167	0	-17.5139	0	-17.5229	0
d(HT_DR)	-16.3508	0	-16.3456	0	-16.3562	0

OLS Regression Results

Table A 3. Regression Results CCi30 over 15 coins

Dependent Variable: CCi30_DR Method: Least Squares				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
BTC_DR	0.306677	0.012984	23.61931	0.0000
BNB_DR	0.064192	0.006841	9.382757	0.0000
BCH_DR	0.022395	0.006344	3.530224	0.0004
ADA_DR	0.086085	0.008002	10.75744	0.0000
ETH_DR	0.167524	0.012021	13.93633	0.0000
HT_DR	-0.001718	0.006377	-0.269444	0.7876
NEO_DR	0.043049	0.007699	5.591358	0.0000
XRP_DR	0.085294	0.006985	12.21086	0.0000
XMR_DR	0.050870	0.008593	5.920048	0.0000
XLM_DR	0.053726	0.007673	7.001648	0.0000
USDT_DR	-0.063409	0.088486	-0.716601	0.4738
THETA_DR	0.008207	0.004074	2.014550	0.0442
LTC_DR	0.091853	0.010223	8.985119	0.0000
LINK_DR	-0.001272	0.004131	-0.307815	0.7583
C	-0.000259	0.000253	-1.026886	0.3047
R-squared	0.963428	Mean dependent var		0.000582
Adjusted R-squared	0.962971	S.D. dependent var		0.043826
S.E. of regression	0.008433	Akaike info criterion		-6.700111
Sum squared resid	0.079656	Schwarz criterion		-6.633578
Log likelihood	3817.313	Hannan-Quinn criter.		-6.674980
F-statistic	2107.463	Durbin-Watson stat		2.397661
Prob(F-statistic)	0.000000			

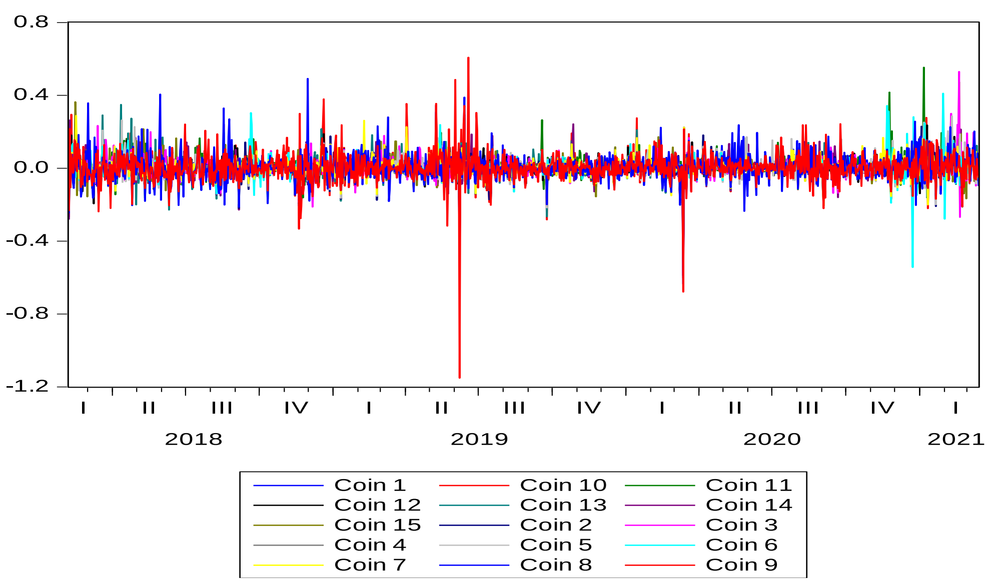

Figure 7. Time Series Plot of Coins Daily Returns

$Eq. (3)\ \ CSSD_t = \alpha + \beta_1 Dt^{Down} + \beta_2 Dt^{UP} + \varepsilon_t$

Table A 4. CSSD Eq. (3) Regression Results

Source	SS	DF	MS
Model	0.24500338	2	0.12250169
Residual	1.0011437	1,165	0.000859351
Total	1.24614708	1,167	0.001067821

CSSD	Coef	Std. Err	t	p>|t|	{95% Conf. Interval}	
Dt^{Down} (β_1)	0.0502799	0.00402	12.51	0.000	0.0423926	0.0581673
Dt^{UP}(β_2)	0.0473257	0.003954	11.97	0.000	0.0395685	0.0550829
α _cons	0.0444163	0.000903	49.19	0.000	0.0426447	0.0461879

Number of Obs	1168
F (2,1165)	142.55
Prob>F	0.0000
R-Squared	0.1966
Adj R-Squared	0.1952
RootMSE	0.02931

Table A 5. Detailed CSAD Regression Result

Source	SS	DF	MS
Model	0.203441693	2	0.101720847
Residual	0.192501979	1,165	0.000165238
Total	0.395943673	1,167	0.000339283

CSAD	Coef	Std. Err	t	p>|t|	{95% Conf. Interval}	
β_1 $(\lvert R_{m,t}\rvert)$	0.4315116	0.032965	13.09	0.000	0.3668335	0.4961898
β_2 $(R_{m,t}^2)$	0.0644368	0.266805	0.24	0.809	-0.4590356	0.5879091
α _cons	0.0165527	0.000686	24.13	0.000	0.0152068	0.0178987

Number of Obs	1168
F (2,1165)	615.60
Prob>F	0.0000
R-Squared	0.5138
Adj R-Squared	0.5130
RootMSE	0.01285

$$CSAD_t = \alpha_0 + \alpha_1.CSAD_{t-1} + \alpha_2.MR_t + \alpha_3.\left|MR_t\right| + \alpha_4.(MR_t^2) + \alpha_5.time + \alpha_6 tsq + \varepsilon_t$$

Table A 6. Preliminary Timeseries Analysis

Source	SS	DF	MS
Model	0.219890248	6	0.036648375
Residual	0.175720163	1,158	0.000151745
Total	0.395610411	1,164	0.00339871

CSAD	Coef	Std. Err	t	p>|t|	{95% Conf. Interval}	
$CSAD_{t-1}$	0.1635494	0.020511	7.97	0.000	0.1233065	0.2037923
MR_t	0.0326003	0.0087253	3.74	0.000	0.154812	0.0497195
$\left\|MR_t\right\|$	0.3787761	0.0322429	11.75	0.000	0.3155149	0.4420372
(MR_t^2)	0.3639349	0.2603185	1.40	0.162	-0.1468138	0.8746836
$time$	-0.000015	4.45E-06	-3.36	0.001	-0.0000237	-6.25E-06
tsq	1.10E-08	3.37E-09	2.96	0.003	3.70E-09	1.83E-08
α_0_cons	0.0164662	0.0014614	11.27	0.000	0.0135989	0.0193334

Number of Obs	1165
F (2,1165)	241.51
Prob>F	0.0000
R-Squared	0.5558
Adj R-Squared	0.5535
RootMSE	0.01232

	$CASD$	$CSAD_{t-1}$	MR_t	(MR_t^2)	$\left\|MR_t\right\|$
$CASD$	1.000				
$CSAD_{t-1}$	0.379	1.000			
MR_t	0.0028	0.0586	1.0000		
(MR_t^2)	0.8069	0.1958	-0.1875	1.0000	
$\left\|MR_t\right\|$	0.8616	0.2253	-0.1230	0.9220	1.0000

Dickey-Fuller test for unit root Number of obs = 1165

	Test Statistic	Interpolated Dicky-Fuller: 1% Critical Value	5% Critical Value	10% Critical Value
Z (t)	-24.582	-3.430	-2.860	-2.570

ovtest Ramsey RESET test using powers of the fitted values of csad:

Ho: model has no omitted variables

F (3, 1096) = 1.82

Prob > F = **0.3530 fail to reject the null**

hettest Breusch-Pagan / Cook-Weisberg test for heteroskedasticity: H o: Constant variance

Variables: fitted values of csad

chi2(1) = 3.03

Prob > chi2 = **0.0915 fail to reject the null**

Number of gaps in sample: 47: Durbin-Watson d-statistic (6, 1105) = 1.852164

Appendix B

Table B 1. Bai and Perron (2003) tests of multiple structural breaks in Eq. (5) - static model

		Scaled	Weighted	Critical Value
Breaks	F-statistic	F-statistic	F-statistic	5% level
1	65.03816	65.03816	65.03816	8.58
2	60.27321	60.27321	71.62662	7.22
3	52.82682	52.82682	76.04935	5.96
4	45.10482	45.10482	77.55498	4.99
5	36.64244	36.64244	80.40719	3.91
UD Max statistic		65.03816	5% UD Max critical value	8.88
WD Max statistic		80.40719	5% WD Max critical value	9.91
Estimated break dates:				
1: 06/25/2018				
2: 07/18/2019, 08/07/2019				
3: 06/25/2018, 07/18/2019, 08/07/2019				
4: 06/25/2018, 01/24/2019, 07/18/2019, 08/07/2019				
5: 06/25/2018, 01/24/2019, 07/18/2019, 08/07/2019, 09/20/2020				
Sequential F-statistic determined breaks:			5	
Significant F-statistic largest breaks:			5	
UD Max determined breaks:			1	
WD Max determined breaks:			5	

Table B 2. BDS test on residuals of Eq. (5) (static model).

Dimension (m)	z-Statistic	Prob.
2	16.54121 ***	0.0000
3	18.29208 ***	0.0000
4	19.63585 ***	0.0000
5	20.91361 ***	0.0000
6	22.51439 ***	0.0000

*Note: m stands for the number of (embedded) dimension which embed the time series into m-dimensional vectors, by taking each m successive points in the series; The BDS z-statistic tests for the null of i.i.d. residuals; *** represent rejection of the null at the 1% level of significance.*