An Empirical Investigation on the Workings of the Cryptocurrency Market : Focusing on the Fear of Missing Out (FOMO) Effect

By

KIM, Dongwook

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ABSTRACT

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The main objective of this study is to empirically investigate the existence of the herding phenomena in the cryptocurrency market, and if so, explore whether the Fear of Missing Out affect such phenomena. To that end, the data utilized are the cryptocurrency price data, the Economic Policy Index (EPU Index) of the United States, and the Fear and Greed Index (FGI). Thirty-seven cryptocurrencies daily price data cover from January 1st, 2014, to August 31st, 2021. The EPU Index indicates the degree of an uncertain economic policy environment that the investors face. Whereas the FGI is the proxy for the Fear of Missing Out phenomenon in the market. The core methodology is Cross-Sectional Absolute Deviation (CSAD). Based on the structural break detected in the market trend, a 60-days rolling window CSAD regression is applied. The main findings are as follow. First, eight separate periods of herding are observed in the total sample period. Second, uncertain sentiment on economic policy increased the probability of herding occurrence. Third, a higher level of greed that prevails in the cryptocurrency market also increases the likelihood of herding. Fourth, the herding phenomenon did not mean a significantly different level of return on investment, compared to the return under the non-herding period.

Keywords: Cryptocurrency, Speculate, Herding, FOMO

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And I would like to thank my parents, Daegyu Kim and Wonhee Lee. I'm not actually good at expressions, but I always look up to you and love you. I am following the great steps you have made for the family. And want to be the proud son.

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1. Introduction

There is an old saying in Korea that goes: "it hurts when a cousin buys land." It means one may be green with envy seeing their kin making a profit whilst they don't. It may seem a cold feeling, but it happens in the real world. The busting cryptocurrency market is a recent case where we can see this. The considerable, unprecedented returns heard about every day were enough to draw attention of those unaware of cryptocurrency, and even of those recording steady profit in the traditional asset markets. Comparing their portfolio profit with others, more investors knocked on the door of the cryptocurrency market.

Bitcoin, which was once 0.0025 USD in 2010, grew to 10,432 USD in 2020.09.11 and reached 63,179 USD by 2021.04.16, raised sixfold increase in about half a year. However, it fell back to 30,928 USD in 2021.07.20, meaning a drop of half its value in only three months. Despite the bust witnessed, the speculative boom was more convincing to attract investors. Therefore, the total cryptocurrency market's capitalization has reached nearly 2.5 trillion USD as of 2021.10.03[1].

Since the traditional stock market has also grown since 2010 and Big-Tech stocks such as Google and Apple showed outstanding performances, some might consider the cryptocurrency market's boom is not different. However, unlike the traditional stock market, the cryptocurrency market is still a vastly unexplored area. For example, its foundation is vague with no backup asset, utility is not straightforward, and huge volatility is under unprecedented return.

To make things worse, imperfect information is frequently transmitted from mass media. The development of social media and individual information production platforms such as YouTube, which have become a part of life, actively distributes information with low reliability.

[1] According to CoinMarketCap (https://coinmarketcap.com/). Bitcoin market capital is 1,068,745,694,730,060 USD and dominance is 42.3%. converting it to total market makes 2.52658 trillion USD.

It makes investors easily learn the value of the product from the sources. Potential investors are also exposed to this information. It makes the investors unbearable to be engulfed in Fear of Missing Out (FOMO) (Laurent, 2021). FOMO can stimulate a herding situation in the investment markets. In other words, investors would herd on market consensus regardless of the valuation of the assets. Peter DeMarzo, Professor of Finance at the Stanford Graduate School of Business, points out that relative-wealth concerns are a crucial part of the psyche, and it is hard to escape from this (Hicks, 2018). Also, Bobby Lee, CEO of crypto wallet company Ballet, specifically warns that the Bitcoin market's huge return will arise related news, and will lead to a FOMO situation, attracting more investors to join the rally (Park, 2021).

Following this line of argument, the present research aims to find if an uncertain policy environment and FOMO are increasing the possibility of herding to occur. As such, the daily price data of 37 cryptocurrencies were chosen among 100 candidates that cover at least three years of circulation. Furthermore, the Economic Policy Uncertainty index (EPU) and Fear and Greed Index (FGI) are used as causal variables of the herding phenomenon. Regarding the sequential analysis, it is designed as follows. First, well-known cross-sectional standard deviation (CSSD) and cross-sectional absolute deviation (CSAD) regression for the whole sample period are executed. Secondly, two structural break tests are applied to examine if the regression as the entire period is valid. Thirdly, 60-days rolling regression is done to detect the herding period in a precise manner. Fourthly, the probit Model is used to investigate the relationship between EPU, FGI, and herding occurrence. And lastly, a linear regression compares the difference in returns between the herding and non-herding period.

Four results are derived throughout the analysis. First, eight herding periods are found in the total sample period. Second, uncertainty in the economic policy environment makes investors follow a herding behavior on the cryptocurrency market. Third, the phenomenon of fear of missing out increases the possibility of herding. Lastly, herding itself does not produce a significant difference in returns, compared to usual conditions.

The subsequent sections cover contents as follows. In section 2, the background of the study is given. The section addresses brief information on the overall markets of Bitcoin and other cryptocurrencies, their features, concept, and literature review of herding and FOMO. In section 3, based on literature review, data selection (daily return, EPU, FGI) and methodologies are introduced. In section 4, sequentially planned rolling CSAD regression is executed. Finally, the results and suggestions for policy design are provided in the conclusions.

2. Background of study

A. Bitcoin and cryptocurrency

Bitcoin, the dominant cryptocurrency in the market (41.21%[2]), was first defined by Nakamoto (2008). The introduction of Bitcoin would seem to be sudden and accidental. But in fact, it is the result of prolonged willingness to alter the traditional financial system. In a centralized financial system, the central bank has authority for monetary policy, including quantitative easing or tightening. Therefore, it is a credible system in terms of financial stabilization. But going through a severe financial crisis and a countermeasures scheme through monetary policies, dissatisfaction with financial self-determination has been on the rise (Jung, 2019). David Chaum announced the early movement of cryptocurrency in the 1980s (Chaum, 1983). He is a cryptographer and computer scientist who suggested an anonymous transaction system, and based on this idea, "Digicash" was established in 1998, but subsequently failed. In 1993, Eric Hughes announced "Cypherpunk's manifesto" (Hughes, 1993). As the name symbolizes, it aims to resist (punk) from the centralized incumbent financial system with cipher and crypto technology. After that, B-Money by Dai (1998), and Bitgold by Szabo (1998) were

[2] As of 2021.09.22. (https://www.coingecko.com)

developed and launched. But failing during the early stages of adoption, they didn't make a significant footprint due to technology and utility shortage. At the expense of the early trials, Bitcoin was announced in 2008, in the middle of the unprecedented financial crisis. Witnessing the failure of financial institutions and their subsequent bailout, raised a skepticism on traditional money system and functioned as a cornerstone for the emergence of cryptocurrency.

Bitcoin and subsequent coins have advanced in several ways, not limited to their value as exchange medium. Following the success in gaining attention by Bitcoin, Vitalik Buterin was responsible for the birth of the Ethereum platform in 2015. Ethereum used POS (proof of stake) rather than POW (proof of work) for efficiency, and strengthened the contract verification function, which means that Ethereum can make safe contracts without mediators (Jung, 2019).

The recent trend of DeFi, standing for Decentralized Finance, is another example of variation. Unlike the previous cryptocurrencies being unstable in their use, DeFi allows investors to access various financial services. As illustrated in Table 1, each cryptocurrency has a chain and category. Chain refers to the base of the coin, while the category is the DeFi service the coin is providing. Each service varies in operation, but aims to alter the incumbent central financial structure, and the magnitude is constantly growing. Also, the services treated as exclusive for the traditional banking section are adapted to the DeFi (Han & Lee, 2021).

Table 1. *Top-10 DeFi Service Summarize*

Coin	Chain	Category	Locked
Aave	Multichain	Lending	$ 13.30B
Maker	Ethereum	Lending	$ 11.52B
Curve Finance	Multichain	DEXes	$ 11.22B
InstaDApp	Ethereum	Lending	$ 10.38B
Compound	Ethereum	Lending	$ 9.62B
Uniswap	Ethereum	DEXes	$ 5.85B
Convex Finance	Ethereum	Assets	$ 5.74B
yearn. finance	Ethereum	Assets	$ 4.16B
Sushi Swap	Ethereum	DEXes	$ 3.73B
Liquity	Ethereum	Lending	$ 1.94B

Source: defipulse.com

Notes. The rank is based on the data updated as of 2021.09.21

On the Government side, central bank digital currency (CBDC) development has been progressing, while inheriting the core cryptocurrency solutions. As Facebook's Libra was announced, IMF and BIS rapidly advised governments to focus on CBDC (Han, 2019). CBDC is expected to be safeguarded with secure technology and make a step toward a cashless society. As shown in Table 2, CBDC is fiat money with renewed technology. Although it is an upgraded version of the current money system, key solutions adapted from cryptocurrency allow CBDC to cooperate with the action of Anti-Money Laundering (AML), Know Your Customer (KYC), and Combating the Financing of Terrorism (CFT) (Bank for International Settlements et al., 2021).

Table 2. *Comparison of Fiat Money, Cryptocurrency and CBDC*

	Fiat Money	Cryptocurrency	CBDC
Issuer	Central Bank	Market	Central Bank
Decision of Quantity	Central Bank	predetermined	Central Bank
Unit	Unit of Ledger Tender	Individual unit	Unit of Ledger Tender
Exchange Value	Fixed as printed	Determined by supply	Fixed as printed
Embedded Technology	Print	Blockchain	Blockchain +

Source: Han (2019) p.16

To summarize, the value as currency of Bitcoin and other cryptocurrencies seems incomplete. But its derived value as an asset and a technological testbed appears to be hold. And the market needs consistent attention and follow-up because cryptocurrency is still differentiating itself.

B. Features of Cryptocurrency Market

Key features derived from the cryptocurrency market as an asset investment market are summarized in three aspects. First, the identity of cryptocurrency is unclear. Second, the market is highly speculative and volatile. Third, the market is prone to imperfect information.

First, the identity of cryptocurrency is unclear. Although the cryptocurrency started to alter the central monetary system, its features and volatile phenomena show it is closer to an investment asset. Baur and Dimpfl (2018) analyzed Bitcoin transactions and concluded it is more of a speculative investment but not for money purposes. Cheah and Fry (2015) warns the Bitcoin market of its speculative bubble and zero fundamentals. After analyzing the long-term fundamental value of Bitcoin assets, the result has shown it is not significantly different from zero. Baek and Elbeck (2015) also found evidence that the return of Bitcoin is caused not by fundamental economic factors but buyers and sellers' interaction. According to the research, internal factors spread between daily high and low prices impacted Bitcoin's market return, whereas other external economic conditions such as CPI, industrial production, consumption expenditure, stock market return, 10-year treasury, euro exchange rate, and unemployment ratio did not. The vague concepts of a cryptocurrency confuse the regulatory field of countries as well. According to Sonksen (2021), the U.S. treasury treats cryptocurrency as convertible virtual currency. But complex features of cryptocurrency, such as acting as securities, commodities, payment, and else is ensuing confusion among states to deal differently from the federal regulatory body. Looking at a worldwide perspective, some countries like Singapore, Japan, Indonesia, and South Korea monitor the cryptocurrency in legal boundaries, but regulatory schemes and allowing ranges differ. For example, Singapore is taking a hands-off approach and has become one of the most attractive cryptocurrency hubs. South Korea also embraced cryptocurrency into the legal field, but ICO is banned. Furthermore, the regulation frame is unstable. For example, it caused a giant bust of the bitcoin market in January 2018 and April 2021, when the minister of Justice announced strong regulation on the market.

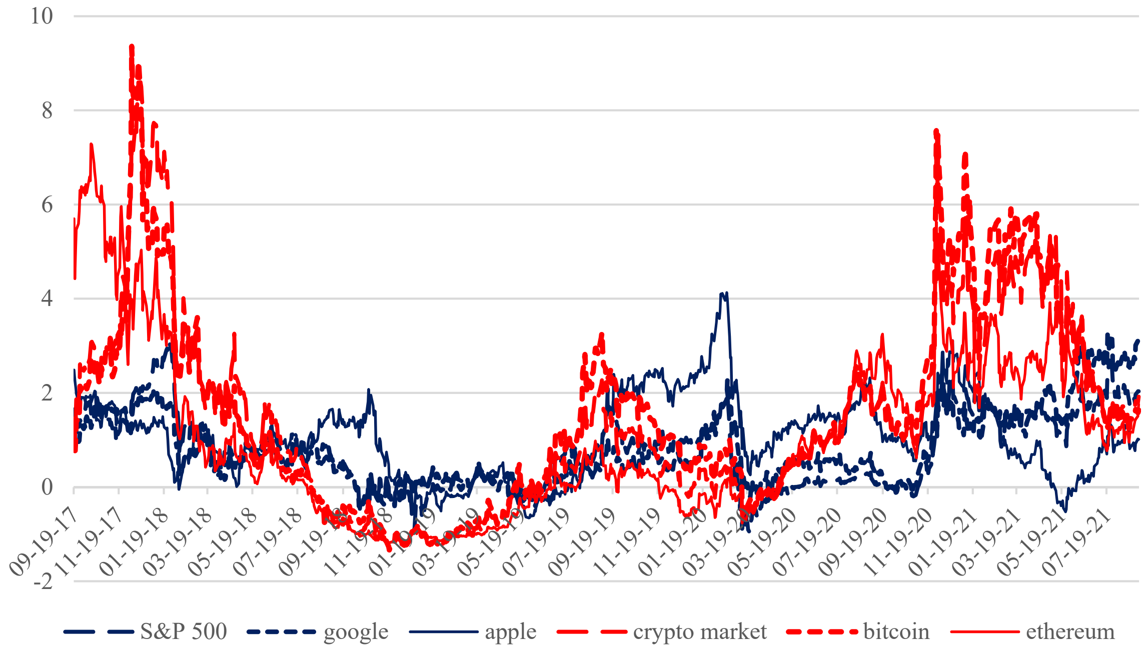
Secondly, the cryptocurrency market shows a cyclical movement with immense volatility. Analyzing the market risk, Sharpe ratio, return, and volatility movement, the cryptocurrency market shows an interesting trend. As illustrated in Table 3, annualized return of the cryptocurrency market is much higher than the stock market. Comparing the overall market return with S&P 500 index and capital weighted cryptocurrency market index, the cryptocurrency market shows about six times higher profit gain annually. Also, the ex-post Sharpe ratio indicating the soundness of investment is higher in the cryptocurrency portfolio (crypto 1.64 > S&P 0.96). In sum, it seems the cryptocurrency market is a more attractive and sound investment market. However, the annual risk shown in the cryptocurrency market is much higher (crypto 87.94% > S&P 23.58%). In other words, speculative boom resulting in an immense gain in the sample period makes ex-post risk-adjusted portfolio evaluation a safe investment. For a closer look, the 180-days rolling Sharpe ratio is illustrated as Figure 1. 180-days Sharpe ratio of the stock market is relatively more stable than cryptocurrency. When the cryptocurrency market's Sharpe ratio rises, it is generally higher than the stock market, indicating better performance with more stability. But in the period where the cryptocurrency market's performance gets worse, from early 2018 to the end of 2018, the portfolio becomes more dangerous than the stock market. Furthermore, such a period is where the cryptocurrency market goes through the bust phase. 180-days return illustrated in Figure 2 also shows an extensive range of short-period return recorded while stock market returns show a relatively stable performance. 180-days volatility of the cryptocurrency market illustrated in Figure 3 shows that the risk of the cryptocurrency market is generally higher than the stock market. To sum up, the cryptocurrency market in the boom period is attractive to investors, with high annual returns dominating the high risk behind it. But in the bust period, high risk embedded in the market comes and collapses the portfolio soundness.

Table 3. *Portfolio Comparison of Stock and Crypto market*

	S&P 500	Google	Apple	Cryptocurrency market	Bitcoin	Ethereum
annualized return	24.66%	51.50%	68.52%	146.52%	155.07%	157.51%
annualized risk[3]	23.58%	32.81%	36.97%	87.94%	86.70%	111.40%
Sharpe ratio[4]	0.96	1.51	1.8	1.64	1.77	1.4
Beta[5]	1	1.07	1.2	1	0.93	1.06
Treynor ratio[6]	0.23	0.46	0.56	1.45	1.64	1.47
Jensen's Alpha	.	0.25	0.39	.	0.18	0.02

Source: reproduced from author using Finance.yahoo and CoinGecko data
Notes. Analyzed sample period is from 2017.01.01 to 2021.08.31. Risk free rate is assumed as 2%.

Figure 1. *180-Days Sharpe ratio Comparison*



Source: reproduced from author using Finance.yahoo and CoinGecko data

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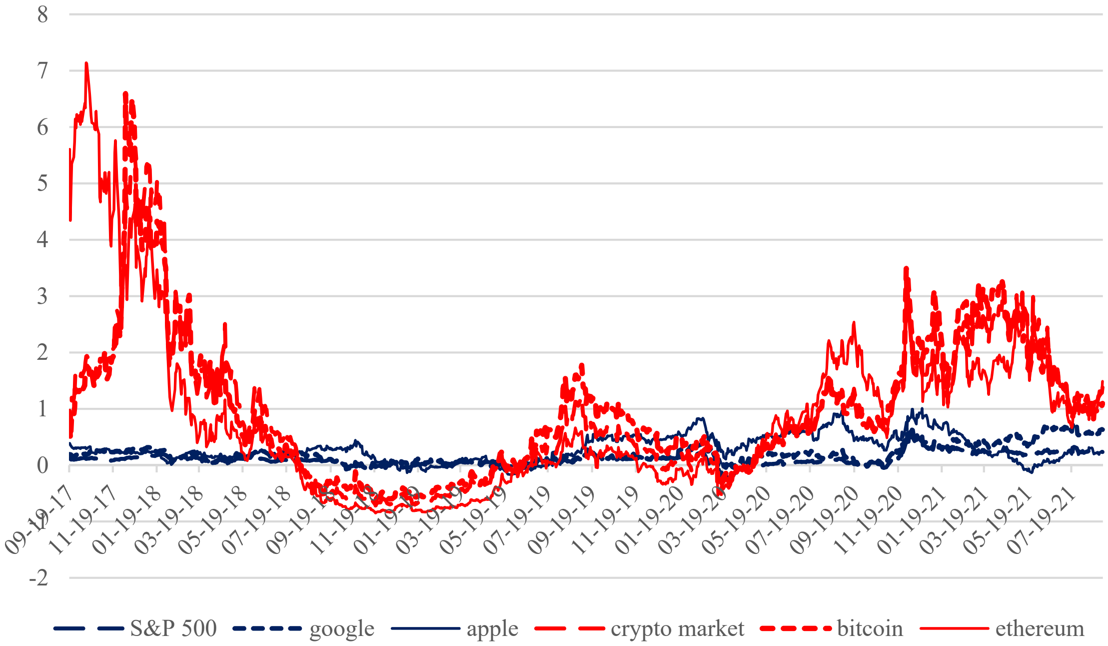
[3] As a measure of volatility, annualized standard deviation of the return is used.

[4] $Sharpe\ ratio = \frac{r_p - r_f}{\sigma_p}$. Whereas $r_p(return\ of\ portfolio)$ is in annualized form, $r_f(risk\ free\ rate)$ is assumed as 2%.

[5] $\beta_p = \frac{Covariance_{p,m}}{Variance_m}$. The p stands for portfolio, m stands for market, which is S&P 500 for stock market and crypto market index for the cryptocurrency market.

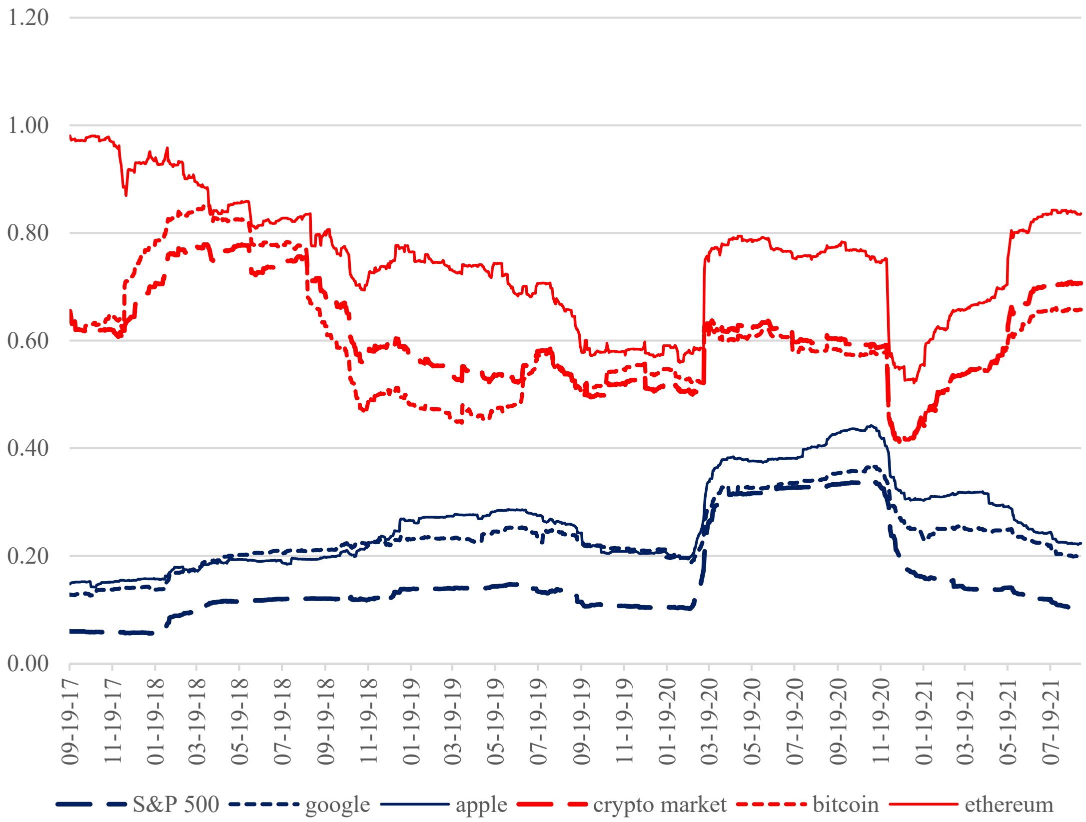
[6] Treynor ratio $(T = \frac{r_p - r_f}{\beta_p})$ and Jensen's Alpha $(\alpha_p = r_s - \{r_f + \beta_p(r_m - r_f)\})$ shows selected sample of stock and the cryptocurrency exceed the performance of overall market performance of stock market and the cryptocurrency market. Which makes sense since Google and Apple are the top leading stocks in the US stock market. Also, Bitcoin and Ethereum are the top leading and dominating item in the cryptocurrency market.

Figure 2. *180-Days Return Comparison*



Source: reproduced from author using Finance.yahoo and CoinGecko data

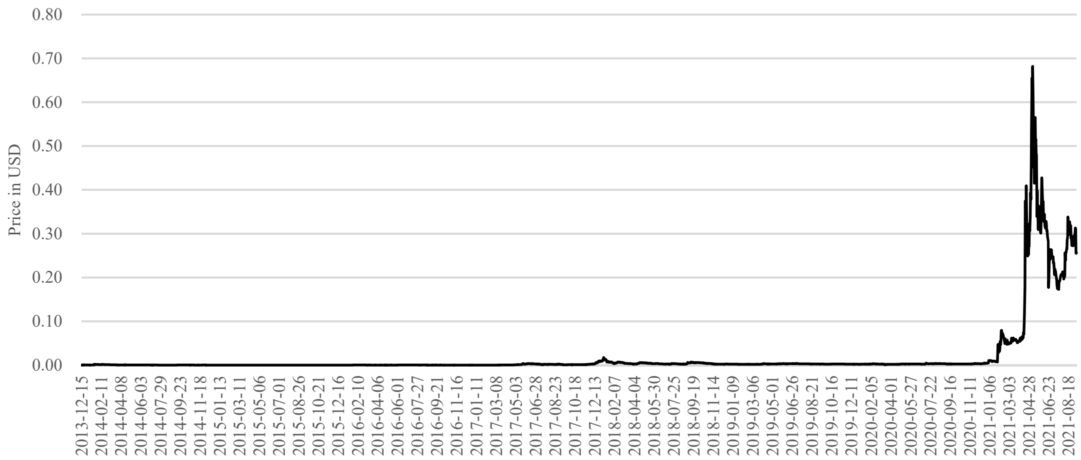
Figure 3. *180-Days Volatility Comparison*



Source: reproduced from author using Finance.yahoo and CoinGecko data

As the last argument, the cryptocurrency market is prone to imperfect information through media and social networks. According to Shiller (2014), speculative booms are easily driven by fad and social epidemics carried through insufficient information sources and news. Lee et al. (2019) also argues the price of Bitcoin is related to trends and attention in media rather than the natural economy, such as supply-demand variables. Evidence is shown in the example of the Dogecoin case. Established in Figure 4, the price of the Dogecoin was 0.0074 USD by 2021.01.28. But as Elon Musk, CEO of Tesla, mentioned the Dogecoin on Twitter, it rose to 0.0473 USD in two days, a 536% rise. And as he constantly mentions the Dogecoin and shows support to such coin, it grew to 0.27 USD by 04.27. Then, he tweeted as "Doge father, SNL, May 8th"[7]. Its ripple effect spread and increased the price to 0.68 USD. But as he stated the Dogecoin is a scam in the SNL show, it fell under 0.5 USD. Furthermore, he keeps mentioning about it, and his tweet and behavior shown in the media resulted in a boom-bust in such coin. Regarding its fragile bubble characteristics, with a low profile of fundamentals and volatility, the cryptocurrency market needs caution and an elaborated pricing scheme for investment.

Figure 4. *Dogecoin price chart*



Source: reproduced from author using CoinGecko data

[7] It is not clear whether he mentioned as prank or based on legit value expected on dogecoin.

C. Herding

Herding is behavior that follows others' actions. In other words, it mimics the group's decisions like a herd of sheep. Herding frequently happens in the financial field. For example, in the dot-com bubble period (1998 to 2001), financial institutions exhibited a strong herding behavior toward the internet related stocks (Singh, 2013). This section shows two representative models of rational herding to understand general herding phenomena in the cryptocurrency market. And introduce various precedent approaches analyzing the herding existence in the cryptocurrency market.

The first is the payoff externality. According to Devenow and Welch (1996), agents are worth gaining further information only if others do so. So, it is more profitable to watch the others acting as it reflects the information they acquire for their own good. In the asset market, this information and investment decision of others is reflected in the price. And since the information in the cryptocurrency market is imperfect relative to the stock market, herding on others' decisions may be the best option under given information.

The second is the information cascade model. Information cascade occurs when individual investors have access to private information. Since the decision reveals to sequential investors, the posterior probability of belief in the actual market state leads toward the same decision. The more superior the information is, the acceleration of the cascade becomes faster. However, the model may lead to a dangerous consequence. First, the initial signal can be wrong but lead the market. Second, as other influential sign reveals that exceed the reliability of the previous one can overturn the situation. Third, even the superior signal can be based on imperfect information (Easley & Kleinberg, 2010). An example of Dogecoin in the previous section shows how fragile the up/down market cascade can be under imperfect information delivered through social media.

Like the herding analysis in the stock or property market, various research is also tried in the cryptocurrency market. Although it is a relatively new market still in the investigation, meaningful approaches give insights into this study. Vidal-Tomás et al. (2018) used CSSD and CSAD methods and tried the various approaches. Using CSSD, no herding was detected in the sample period of 2015 to 2017. But using CSAD, it caught significant herding existence in the down market. Also found, the minor coins are herding to the largest coins (Bitcoin, Ethereum, Ripple, Litecoin, Dash, Stellar). Ballis and Drakos (2020) used daily price data of 5coins (Bitcoin, Litecoin, Monero, Dash, Ethereum) from August 2015 to December 2018. The research adapted CSAD and GARCH method and found herding exists in the sample period and found upmarket appears faster pace of following market consensus than the down market. Bouri et al. (2019) also used the CSAD method and found a structural break is shown in the cryptocurrency market using 14 coins price data of April 2013 to May 2018. Since the existence of structural break, the analysis used rolling window regression and detected four sub-period of herding. Also adapted U.S. Economic Policy Uncertainty Index to see the relationship of herding probability and external economic state and proved relevant. Differently from other studies, Yarovaya et al. (2020) used hourly data with CSAD and quantile/time-varying regression. The research tried to prove if the COVID-19 pandemic boosted the herding tendency. And the resulted in no evidence of amplifying in the cryptocurrency market. Finally, Philippas et al. (2020) tried to find the relationship between signals investors receive and herding in the market. The daily data of 100 coins from January 2016 to May 2018 generated three interesting results. First, the high performance of the stock market associate with reduced herding in the cryptocurrency market. Meaning investors make independent decision schemes on two separate markets. Second is investors herd less on market return when higher volatility in equity is detected. Third, herding on bitcoin is amplified when tweet (proxy of information supply) and Google trend (proxy of information demand) increase unexpectedly. It means the even the mild rumor circulating in media can cause herd behavior on the cryptocurrency market, and it shows the fragility and volatility of such a market.

D. Fear of Missing Out

Fear of missing out, or FOMO in abbreviation, is defined as anxiety being absent in the profitable scene while others might enjoy rewarding experiences (Przybylski et al., 2013). Specifying the term in the cryptocurrency market, it can be referred to as one's fear of missing the opportunity of positive return in the coin market while others benefit already. FOMO is one possible explanation of herd behavior since it is the motivation of collective action. For example, in the consumer behavior study, a high FOMO raises higher brand involvement, leading to the herding phenomenon on such brands (Kang et al., 2020).

FOMO is not only linked to the sociological field but also gives a convincing explanation in speculating bubbles in the financial market. Baur and Dimpfl (2018) have found that the cryptocurrency market shows asymmetric volatility reaction against past asset return, associating the FOMO as a factor. Investors are classified as either informed traders or uninformed traders. Informed traders have private access to fundamental information while the latter don't. However, the uninformed trader is more of a speculative investor injecting liquidity in the market. Using a GARCH model in the literature, the impact of positive shock exceeds the effect of negative shock on volatility, representing the power of noise traders in the market, and asymmetric reaction makes an example of FOMO leading even enabling pump and dump scheme. A similar argument is made by Wang et al. (2021), especially finding asymmetric volatility phenomenon caused by FOMO in Bitcoin rising market. Güller (2021) connects investor sentiment to bitcoin return and volatility. And found bitcoin's main driver is emotions rather than analytical modeling, leaving space for FOMO to interrupt.

Financial experts in the field also point out recent cryptocurrency boom-bust is driven by

FOMO. Shari Greco Reiches, the behavioral finance expert, says recognizing one's acquaintances' success in the market causes rising confidence of winning for own investment (Vega, 2021). Moreover, Twitter, WhatsApp, Youtube, Facebook, and other social network services make more accessible to news of others' wealth. As associates with the low barrier of entrance and real-time price monitoring availability of cryptocurrency boost the phenomenon. Fabrizio Campelli, Deutsche Bank AG's global head of wealth management points especially millennials are afraid of missing out as they are more exposed to the social network, resulting in them exploring non-banking partners for financial support (Stupples, 2018).

To summarize, FOMO is considered as a motivation for herding in general. Moreover, reviewed literature gives evidence that FOMO affects the participation of noise traders and shows how sentimental driven the cryptocurrency market is. But the research of FOMO affecting the possibility of the herding phenomenon is not yet discussed empirically. So, this thesis tries to prove the linkage between herding occurrence possibility and FOMO level in the cryptocurrency market.

3. Data and Methodology

A. Data Selection

i. Cryptocurrency price data

As the material of the analysis, price and market capitalization data of 37 cryptocurrencies are used. The range of data covers from 2014.01.01 to 2021.08.31. The data is gained from CoinGecko (https://www.coingecko.com/), a well-known cryptocurrency data aggregator founded in 2014. CoinGecko is one of the largest cryptocurrency portal websites that scraps more than 6000 crypto assets from over 400 exchanges worldwide. It is also a credible source frequently cited across various major information publishers such as Forbes, The Wall Street Journal, CNBC, and else.

Initial coin selection started from the top 100 coins based on the market capitalization as of 2021.08.31. And period was from 2013.04.28. However, not all coin assets cover the entire period of targeted analysis. And in the early data sample did not have a stable price and capitalization data. So, for the research, 63 coins are trimmed, keeping 37 coins that cover at least 1200 days (about 3-years) and sliced the period as 2014.01.01 to 2021.08.31, which contains at least four major coins (Bitcoin, Ripple, Litecoin, Dogecoin) traded in the market. Summary statics of selected coin assets are described as Table 4.

ii. U.S. Economic Policy Uncertainty Index (EPU index)

Two indices are used for the probit model, verifying the effect of uncertainty and anxiety on the economy. The first index is U.S. Economic Policy Uncertainty Index (EPU) (fred.stlouisfed.org, 2021). The index is used in the previous study of connecting herding behavior to economic uncertainty recognized by investors by Bouri et al. (2019). U.S. EPU is tracked by Baker, Bloom & Davis (2016). It measures the policy-related economic uncertainty. It uses news covered in ten major newspapers[8], tax code expiration dates, and economic forecaster disagreement. Combining the three components, the higher score shows overall uncertainty of the daily economic status of the United States. There is another index representing the worldwide range uncertainty. But it is not available for daily mode. So, using daily U.S. EPU is the best option overall.

iii. Fear and Greed Index (FGI)

Crypto Fear & Greed Index (https://alternative.me/) is used as a proxy of FOMO. Fear & Greed Index (FGI) was developed by Gregor Krambs and Victor Tobies of alternateive.me.

[8] USA Today, The Mianmi Herald, The Chicago Tribune, The Washington Post, The Los Angeles Times, The Boston Globe, The San Francisco Chronicle, The Dallas Morning News, The Houston Chronicle and the Wall Street Journal (https://www.policyuncertainty.com/us_monthly.html)

Like Volatility Index (VIX) reflects the fear on the stock market, FGI also works in the same logic. It is calculated daily based on six scoring components. Items to be concerned are volatility (25%), market momentum/volume (25%), social media[9] (15%), surveys (15%), dominance (10%) and trends[10] (10%). Analyzed data is converted into a score scale of 100, while a higher score represents the coin market is in greed, and close to zero means fear is prevalent. The measure is originally developed to save investors from fear of missing out and prevent overreaction. In other words, a high score indicates investors should be aware of FOMO and take a halt for rational investment. Güller (2021) also claims FGI as good proxy of investor sentiment. Although it is not perfect measure of FOMO in the cryptocurrency market, mixture of conventional and unconventional data and the intend of the index meaningful. Therefore, the score measured can be considered as a proxy of rising FOMO. As the index is available from 2018.02.01, the following probit model uses such period data, checking if the greediness of the market driving FOMO elevates the probability of herd behavior.

B. Methodology

The analysis takes the sequential examination to test the hypothesis of herding existence and find the factor affecting herding.

First, cross-sectional standard deviation test ($CSSD$) and the cross-sectional absolute deviation test ($CSAD$) are used in the sample of the total period. $CSSD$, which is equation (1-1), approach is implemented in the study of investment behavior by Christie and Huang (1995). It utilizes the cross-sectional deviation of market return as a proxy of individual investment asset return on average (Chang et al., 2000). If the market participants follow their own information set and calculation for investment, the dispersion of $CSSD$ will show high value.

[9] Twitter is used, counting post and hashtag, also speed of interaction between tweets (https://alternative.me/crypto/fear-and-greed-index/)
[10] Change of Google trend search volume is used (https://alternative.me/crypto/fear-and-greed-index/).

In other words, lower dispersion indicates that investors following the market consensus but own investment model, which means the herding. Christie and Hwang test $CSSD$ in two conditions of the market. As described in the equation (1-2), D_U (dummy variable indicating 5% extreme up market in date t) and D_L (dummy variable indicating 5% extreme down market in date t) separates the condition of the market into an extreme upmarket and down market. So, the significant negative coefficient of each dummy (β_U, β_L) shows if the herding is shown in each market condition.

$$CSSD_{m,t} = \sqrt{\frac{\sum_1^N (r_{i,t} - r_{m,t})^2}{N-1}} \qquad \text{… equation (1-1)}$$

$$CSSD_{m,t} = \alpha + \beta_U D_{U,t} + \beta_L D_{L,t} + u_t \qquad \text{… equation (1-2)}$$

$CSAD$, which is equation (2-1), method makes different assumptions to $CSSD$ approach. It starts from the hypothesis when investors show market consensus following behavior in the market in the condition of large average price volatility, the increasing linear relation of dispersion and market return will not be linear but non-linear movement will appear (Chang et al., 2000) in the basis of rational assumption of CAPM. Hence, the quadratic term of market return ($r_{m,t}^2$) is used, and if the coefficient (β_2) is significantly negative, herding behavior is expected. In contrast, a significant positive coefficient (β_2) indicates anti-herding movement in the market. Thus, investors mistrust the market consensus and make an investment decision based on their own beliefs.

$$CSAD_{m,t} = \frac{\sum_1^N |r_{i,t} - r_{m,t}|}{N} \qquad \text{… equation (2-1)}$$

$$CSAD_{m,t} = \alpha + \beta_1 |r_{m,t}| + \beta_2 r_{m,t}^2 + u_t \qquad \text{… equation (2-2)}$$

In both equations, the market return ($r_{m,t}$) is calculated as equation (3-1) and. Weight of the coin in time t is based on the capitalization of 37 sampled coins in each day. Recently, indices have been developed by major market analysis portals such as S&P (S&P MegaCapCrypto Index) or Bloomberg (Bloomberg Galaxy Crypto Index) and else. However, these indices cover only weekdays, excluding weekend data. So, it leads to a vast amount of loss in the dataset. As a result, like the precedent studies have used, the weighted average of market return is used as equation (3-1), individual coin return ($r_{i,t}$) follow as equation (3-2). The weight of coin i in time t ($w_{i,t}$) is calculated based on the 37 sampled coins' capitalization of each day. Since not all coins cover the entire sample period, such items are ignored for the day t.

$$r_{m,t} = \sum_{i=1}^{N} w_{i,t} \times r_{i,t} \qquad \text{… equation (3-1)}$$

$$r_{i,t} = (price_t - price_{t-1})/price_{t-1} \qquad \text{… equation (3-2)}$$

Following the methodology, Chiang and Zheng (2010) detected herding evidence in Asian and advanced stock markets through the $CSAD$ approach. And Vidal-Tomás et al. (2018) also verified the existence of the herding phenomenon in the cryptocurrency market from 2015 to 2017 with the $CSAD$ method. Also, the primary analysis reference of this thesis, Bouri et al. (2019), used $CSAD$ analysis with rolling window regression and found the herding phenomenon of the cryptocurrency market in the period of 2016.04.14 to 2018.01.21.

As a second step, the analysis contains the Bai-Perron test (Bai & Perron, 2003) to check if the structural breaks appear in the whole sample period. Applying the econometric model in the entire period, assuming the constant coefficient, easily leads to a hasty conclusion (Balcilar et al., 2013). So, if the structural breaks representing the trend of the cryptocurrency market are detected, the next step of rolling window regression should be executed to detect the herding period. Also, the cumulative sum test is applied as a double check on structural break existence. Each test is available in the STATA 17 program.

Following the structural break test result, the third step is to run a rolling window regression slicing the period of regression into 60 days (as "window"). Rolling window first slice the sample observation into the number of window (60), iterates the equation (2-2) moving the window sequentially. The number of the window must be smaller than the day of the first structural break appears. Since the first breakpoint is detected in the 2018.01.14, 60 as the window is a feasible choice. Furthermore, to precisely cover the boom-bust cycles in the cryptocurrency market, setting 60 days as the presumed cycle is not short.

Finally, the probit model is used to find if the herding is affected by uncertainty and greediness. The study of Bouri et al. (2019) proved economic uncertainty lifts the probability of significant herding behavior using the EPU index. It means following the argument that herding is related to the uncertain prospect (Balcilar & Demirer, 2015), investors of the cryptocurrency market mimic other investors' trade. Since the study covers analysis up to 2018, the following analysis will update the period to 2021.08.31. In addition to the study, FGI is used to verify the main question of the thesis whether the FOMO affects herding behavior in the cryptocurrency market. Probit model, equation (4) takes herding period as binary variable of 1 and 0. And two independent variables are value of EPU Index (x_1) and FGI (x_2). Significantly positive coefficients mean higher the index level increase the probability of herding.

$$P(y = 1) = \Phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2) \qquad \ldots \text{ equation (4)}$$

C. Summary and Trend

i. Summary Statistics

Table 4 provides summary statics of selected sample coins. The order of the table is in the market cap in USD, as of 2021.08.31. Mean return, standard deviation (or risk), minimum return, and maximum return are daily. And beta indicates market return's effect on individual coin's return. All betas among included coins are statistically significant with 1% critical value except Binance coin, which beta is significant with 5% critical value. Since Bitcoin dominates the total cryptocurrency market by 54%, mean return, risk, and beta are not much different from weighted market return. Comparing the risk among the coins, Bitcoin shows a relatively stable return of 0.23%, with the lowest volatility, 3.94%. However, it is in terms of relative comparison, still, it shows considerable volatility. Considering that the data is daily, given high volatilities and return ranges of coins is convincing to say how speculative the market is.

Table 4. *Summary statics of coin return*

	Coin	Obs	Mean	Std. dev.	Min	Max	Beta	Market cap (USD)
1	Bitcoin	2,799	0.23%	3.94%	-35.19%	33.26%	0.927	885,729,263,616
2	Ethereum	2,216	0.53%	6.42%	-53.00%	55.62%	0.931	378,977,091,584
3	Cardano	1,414	0.60%	8.03%	-40.81%	139.21%	1.05	87,653,687,296
4	Binance coin	1,444	2.54%	67.34%	-63.30%	2532.95%	1.155	71,302,037,504
5	XRP	2,800	0.39%	7.50%	-59.88%	141.40%	0.969	51,552,698,368
6	Dogecoin	2,798	0.58%	10.33%	-39.77%	338.90%	1.058	35,462,721,536
7	Bitcoin cash	1,491	0.29%	8.24%	-48.05%	139.82%	1.096	11,902,191,616
8	Chainlink	1,392	0.64%	7.78%	-48.43%	61.40%	1.043	11,293,069,312
9	Litecoin	2,799	0.24%	5.84%	-42.17%	67.14%	1.182	11,187,356,672
10	Ethereum classic	1,865	0.54%	9.21%	-41.43%	265.83%	1.149	8,011,871,744
11	Stellar	2,577	0.67%	12.26%	-65.13%	411.83%	1.217	7,839,292,928
12	Theta network	1,316	0.55%	7.73%	-46.71%	65.69%	1.191	6,566,388,224
13	Tron	1,392	0.59%	8.95%	-42.56%	122.35%	0.964	6,182,969,856
14	Monero	2,658	0.43%	7.43%	-42.91%	123.40%	1.174	5,081,457,152
15	Eos	1,515	0.32%	7.35%	-38.44%	52.58%	0.956	4,674,846,208
16	Neo	1,815	0.68%	10.37%	-57.66%	205.64%	1.105	3,635,871,744
17	Iota	1,540	0.30%	7.21%	-42.95%	50.56%	1.237	2,683,420,416
18	Waves	1,917	0.43%	7.40%	-43.26%	52.75%	0.924	2,672,446,976
19	Decred	2,030	0.51%	7.29%	-40.48%	61.59%	1.005	2,248,572,928
20	Dash	2,753	0.53%	7.93%	-49.26%	114.29%	0.916	2,246,820,352
21	Enjin coin	1,391	0.74%	9.71%	-47.51%	111.96%	0.941	1,956,913,792
22	Synthetix	1,260	0.62%	8.68%	-46.15%	70.29%	1.111	1,918,219,520
23	Holo	1,220	0.59%	8.47%	-44.42%	90.95%	1.158	1,853,512,448
24	Nem	2,345	0.60%	8.49%	-34.13%	159.79%	1.2	1,708,177,920
25	Zcash	1,768	0.19%	9.33%	-83.03%	249.76%	0.939	1,629,488,896
26	Bitcoin gold	1,393	0.25%	8.07%	-42.73%	104.03%	1.174	1,334,414,464
27	Zilliqa	1,298	0.32%	7.22%	-44.57%	41.55%	1.019	1,328,896,256
28	Qtum	1,540	0.31%	7.93%	-45.36%	73.26%	0.959	1,261,217,024
29	Decentraland	1,402	0.70%	9.59%	-47.98%	191.19%	0.955	1,259,745,024
30	Telcoin	1,306	0.75%	11.81%	-63.61%	147.33%	1.019	1,231,176,704
31	Ravencoin	1,260	0.43%	8.04%	-50.17%	75.88%	1.223	1,209,346,688
32	Basic attention token	1,546	0.33%	7.05%	-44.82%	35.16%	1.062	1,181,665,536
33	Horizen	1,540	0.46%	8.48%	-44.11%	158.46%	0.993	1,007,040,512
34	Siacoin	2,198	0.69%	9.46%	-46.69%	81.25%	0.872	946,393,216
35	Iost	1,317	0.38%	10.06%	-47.64%	237.58%	1.038	934,011,712
36	Icon	1,404	0.40%	8.19%	-45.45%	58.84%	1.163	877,561,856
37	Omg network	1,508	0.50%	8.28%	-44.73%	76.62%	0.325	871,282,048
Tot	Sampled Market	2,800	0.22%	4.00%	-36.73%	21.23%	.	1,619,413,139,648

Source: reproduced from author using CoinGecko daily data

Notes. Observations are based on daily price movement. Market cap is in USD, as of 2021.08.31. Beta means the effect of total market movement on individual cryptocurrencies' return. 37 coins are organized as rank of capitalization.

ii. CSSD/CSAD Regression as Full Sample Period

Table 5 and Table 6 each show the result of CSSD regression and CSAD regression in the entire sample period of 2014.01.01 to 2021.08.31. CSSD captures the herding phenomenon in extreme 5% upmarket and down market. The coefficient for both market condition dummies is significantly positive. It means there is enough dispersion in market return in the stressed market and cannot reject the null hypothesis that there is no herding in the extreme market condition. The negative coefficient for squared return presented in CSAD makes a clue that there might be herding in the sample period. But it is not statistically significant with a 0.145 p-value. Likewise, the regression of CSSD cannot reject the null hypothesis of no herding in total sample regression.

Table 5. *CSSD Regression on Full Sample Period*

VARIABLES	5% extreme up market	5% extreme down market	Constant	Obs.	R-squared
CSSD	0.0690***	0.0630***	0.0694***	2,799	0.024
	(0.0111)	(0.0109)	(0.00238)		

Note. Standard errors in parentheses. Significantly negative coefficient means herding is captured. No herding is detected in total period (2014.01.01 to 2021.08.31)
*** p<0.01, ** p<0.05, * p<0.1

Table 6. *CSAD Regression on Full Sample Period*

VARIABLES	Absolute return	Squared return	Constant	Obs.	R-squared
CSAD	0.503***	-0.000253	0.0184***	2,800	0.346
	(0.0241)	(0.145)	(0.000602)		

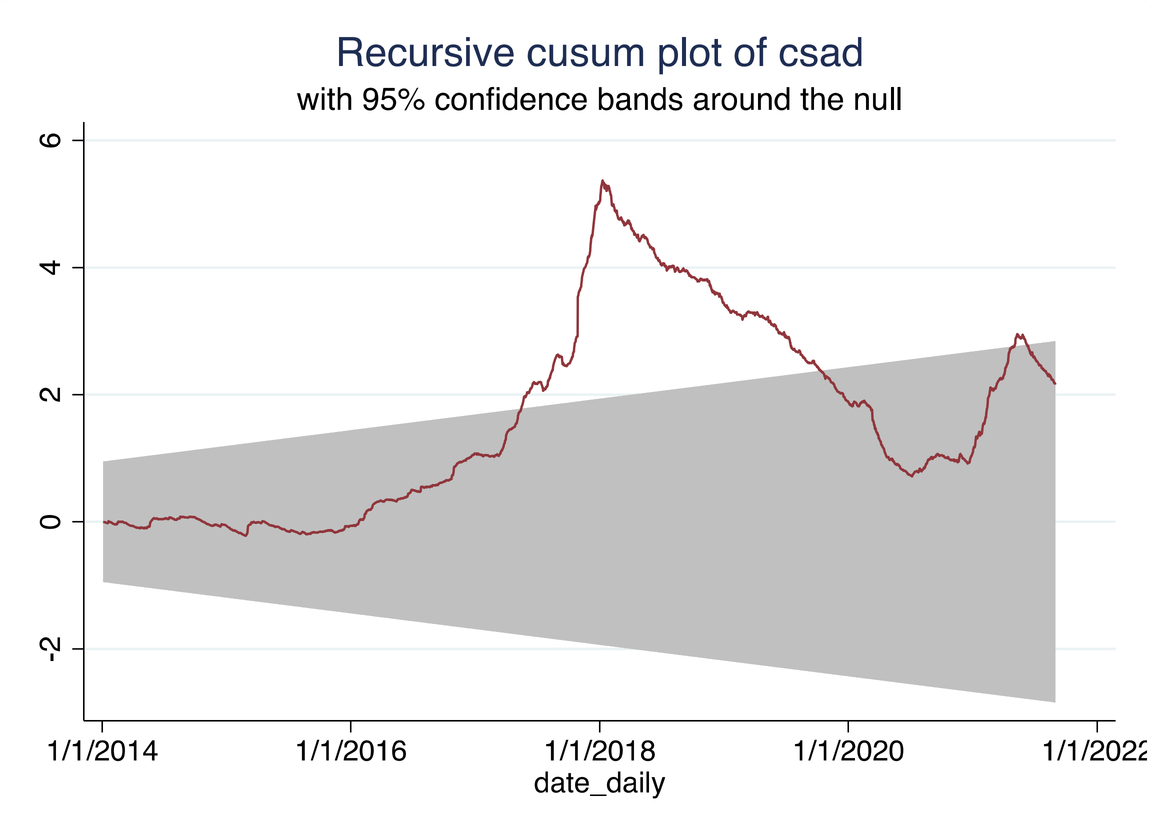
Note. Standard errors in parentheses. Significantly negative coefficient on squared return means herding is captured. No herding is detected in total period (2014.01.01 to 2021.08.31)
*** p<0.01, ** p<0.05, * p<0.1

iii. Structural Break Test

Encountering the result that there is weak evidence of herding in the sample period (CSAD) and no evidence of herding in extreme up/down market. It leads to the doubt that using the full sample period can lead to a hasty conclusion. So, two tests are adapted.

The first is the cumulative sum test. If there is no structural break, the parameter should be stable lying in the 95% boundaries. Figure 5 suggests parameter after around 2017 is breaking upper bound of confidence level and showing unstable movement. Result in Table 7, test static over 1% critical value also gives a clue of rejecting the null hypothesis of no structural break.

Figure 5. *Cumulative Sum Test*



Note. Recursive cusum plot exceeding the 95% confidence band means structural break exists around the period.

Table 7. *Cumulative Sum Test*

Cumulative sum test for parameter stability				
Sample : 2014.01.01 through 2021.08.31				
H0 : No structural break				
Number of obs. : 2,800				
	- Critical value -			
	Test statistic	1% Critical Value	5% Critical Value	10 % Critical Value
UDmax(tau)	2.6214	1.143	0.9479	0.8499

Note. Test statistic over 1% critical value allows rejecting the null hypothesis of no structural break in the period.

For a more thorough check of structural break, Bai-Perron test is used as Table 8. Setting the null hypothesis of no structural breaks against the alternative hypothesis of the existence of one to five structural breaks shows there is a structural break. The test statistic (245.115) exceeding 1% critical value (7.71) makes rejection on the null hypothesis. And the estimated break was detected in 2018.01.14.

Table 8. *Bai and Perron Structural Break Test*

Test for multiple breaks at unknown breakdates				
(Bai & Perron. 1998. Econometrica)				
H0 : no break(s) vs. H1 : 1<= s <= 5 breaks				
	- Critical Values -			
	Test statistic	1% Critical Value	5% Critical Value	10 % Critical Value
UDmax(tau)	245.15	7.71	5.85	5.08
Estimated break points: 2018.01.14				
* evaluated at a level of 0.95				

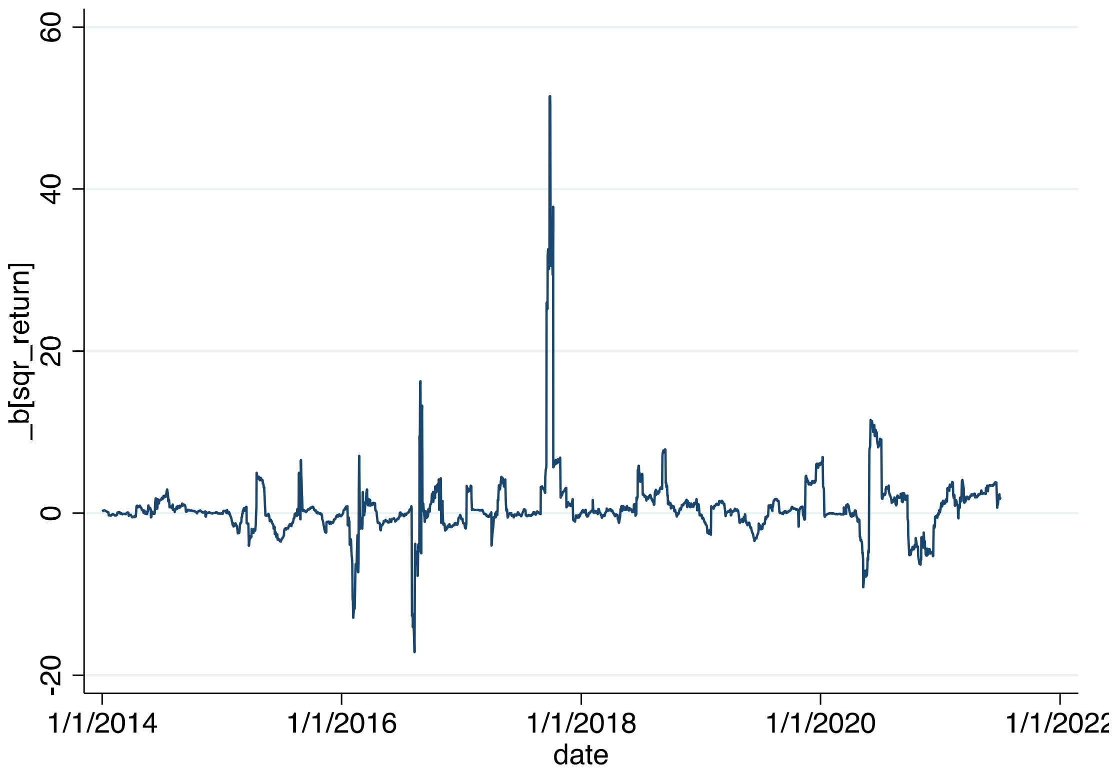
Note. Test statistic over 1% critical value allows rejecting the null hypothesis of no structural break in the period.

4. Empirical Results

A. Rolling regression – 60-days Rolling window

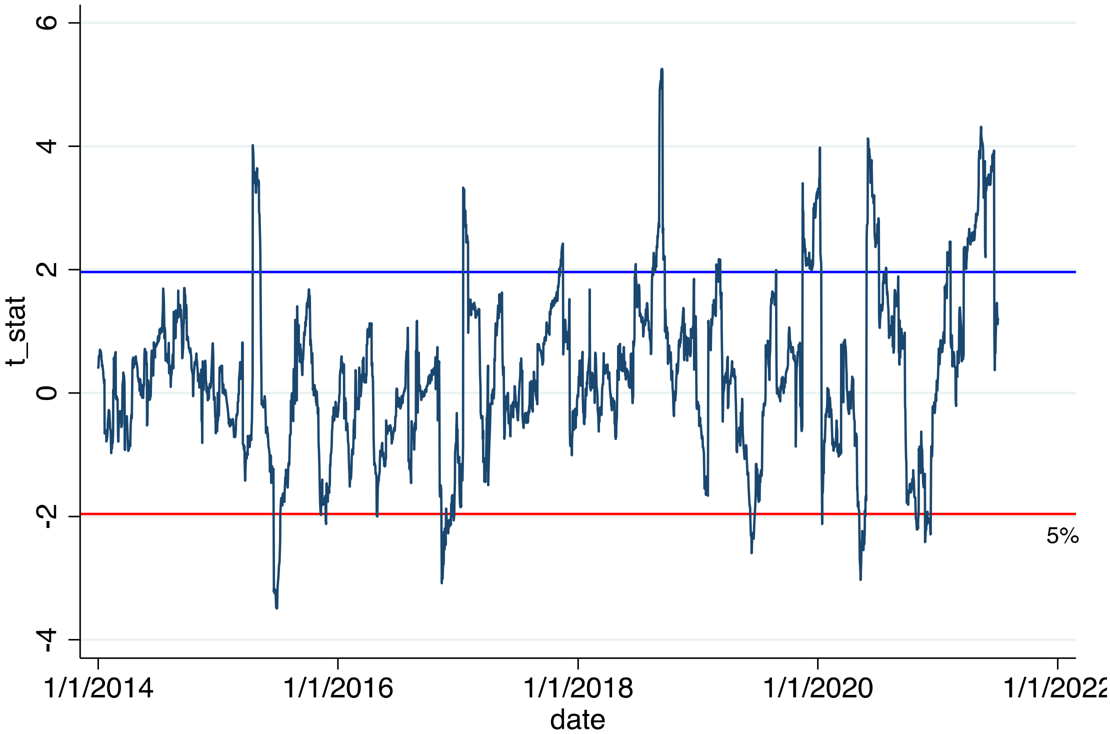
As structural break is detected in the sample period, regression as a whole period is not feasible. Instead, rolling window regression can catch herding by breaking period into a shorter sample period. In this research, the window is set as 60 days regarding the fast fashion of the cryptocurrency market. Rolling regression slice 60 days in a row as one sample and execute the same regression with the same range of date, moving one day every time regressing. As shown in Figure 6, coefficient for squared return on CSAD is moving differently along the time series. In some periods, a negative coefficient also appears. But it is not sure if the coefficient is statistically significant or not. As a solution, Figure 7 is used, motivated by Bouri et al. (2019). The graph is plotted with the t-stat of squared return's coefficient. Suppose the t-stat lies under the line of 5% confidence level (-1.96), statistically significant herding is detected. In contrast, the period where t-stat lies above 1.96 is where anti-herding is detected. This means coin returns diversify in the period.

Figure 6. *180-Days rolling Beta Analysis*



Note. Beta plotted in the graph is the coefficient of squared return. If the beta is significantly negative, it means herding is detected in the period.

Figure 7. *180-Days rolling T-stat Analysis*



Note. t-stat plotted under 5% CV indicates significantly negative herding beta is shown in the period.

By that, eight periods of herding were detected. Which is 2015.06.20 to 2015.09.07, 2015.11.16 to 2016.01.24, 2016.04.29 to 2016.06.28, 2016.11.12 to 2017.02.17, 2019.06.11 to 2019.08.21, 2020.01.14 to 2020.03.13, 2020.05.08 to 2020.07.23 and 2020.10.26 to 2021.02.07. A close look into the detected period is illustrated as Table 9. In each period, the beta of squared return shows significantly negative with a 95% confidence level.

Table 9. *Detected Herding Period*

Period	VARIABLES	absolute return	squared return	constant	Obs.	R-squared
2015.06.20~2015.09.07	CSAD	1.030***	-2.397**	0.00436***	80	0.917
		(0.0824)	(0.996)	(0.00102)		
2015.11.16~2016.01.24	CSAD	0.924***	-1.180**	0.00917***	70	0.944
		(0.0643)	(0.585)	(0.00106)		
2016.04.29~2016.06.28	CSAD	1.031***	-2.106**	0.00937***	61	0.920
		(0.108)	(1.042)	(0.00143)		
2016.11.12~2017.02.17	CSAD	0.848***	-1.276**	0.0109***	98	0.915
		(0.0644)	(0.593)	(0.000876)		
2019.06.11~2019.08.21	CSAD	0.459***	-2.553**	0.0198***	72	0.226
		(0.141)	(1.232)	(0.00290)		
2020.01.14~2020.03.13	CSAD	0.288***	-0.478**	0.0228***	60	0.318
		(0.0770)	(0.225)	(0.00219)		
2020.05.08~2020.07.23	CSAD	0.495***	-4.353**	0.0177***	77	0.264
		(0.133)	(1.913)	(0.00156)		
2020.10.26~2021.02.07	CSAD	0.684***	-4.151**	0.0269***	105	0.156
		(0.200)	(1.871)	(0.00413)		

Note. Standard errors in parentheses. Eight sub-periods show statistically significant coefficient of squared return in 95% confidence level.

*** p<0.01, ** p<0.05, * p<0.1

B. Probit Model – EPU Index & FGI on Herding Probability

Crucial question delivered sequentially to period detection of herding is what makes cryptocurrency investors herd on market consensus. To answer the question, the probit model using EPU and FGI on herding is used. The binary variables of 1 and 0 are used for herding and non-herding periods each and independent variables are score of EPU and FGI as illustrated in the equation (4).

Applying probit model as Table 10, Coefficient of FGI and EPU both show statistically significant relation to herding occurrence. First, It makes the same line of argument as Bouri et al. (2019), that the EPU raises the probability of herding. This can be interpreted that as higher economic policy uncertainty is given to investors, they consider the cryptocurrency market as a safer asset (Bouri et al., 2017). Secondly, FGI also raises the probability of herding. FGI gets higher as greed sentiment among cryptocurrency market investors rises. As the index was initially invented as a warning for investors who can dive into the intensive market because of the feeling FOMO, the index level can be a feasible proxy of prevailing FOMO. In this term, when the FOMO spread in the cryptocurrency market, it is more likely the herding can occur.

To check the goodness of fit of the estimated model, the Hosmer-Lemeshow test is used. As Table 10 shows, the p-value of the Hosmer-Lemeshow test is 0.6941, which indicates the estimation model is designed adequately.

Table 10. *Probit Analysis*

VARIABLES	FGI	EPU index	Constant	Obs.
Herding dummy	0.0238***	0.00254***	-2.349***	1,305
	(0.00186)	(0.000300)	(0.124)	
Log likelihood = -595.05167				
Pearson Chi2(1301) = 1274.63				
Hosmer-Lemeshow P-value = 0.6941				

Note. Standard errors in parentheses. FGI and EPU index both shows statistically significant positive coefficient. As FGI and EPU index rises, probability of herding increases. Due to FGI's data coverage, 1305 observations are used (2018.02.01 to 2021.08.31)
*** p<0.01, ** p<0.05, * p<0.1

However, the limitation remains since FGI is only available from 2018.02.01. Therefore, only 1305 observations out of 2800 days of the total sample are used. As half of the observations are lost, reliability may be weakened. Therefore, consistent updates of the study should be followed.

C. Comparison of Herding on Average Market Return

Before concluding the analysis, an additional question is raised: Does herding make a difference in average market return in such period. However, the existence of herding didn't make a significant difference in the average return in the market as shown in Table11. First, the total period market return is categorized as an up/down market based on its daily return. Then dummy variable indicating herding existence is generated. By that, regression in Table 11 generates herding's effect on each up/down market. However, as shown in both tables, both coefficients are statistically insignificant. This means herding makes no difference in average market return.

Table 11. *Comparison of Average Return Under Herding Occurrence*

VARIABLES	Herding (Up market)	Herding (Down market)	Constant	Obs.	R-squared
Market return	-0.00161		0.0261***	1,542	0.001
	(0.00168)		(0.000818)		
Market return		0.00212	-0.0271***	1,258	0.001
		(0.00227)	(0.00104)		

Note. Standard errors in parentheses. Herding days are total 631 days. 365 days are in upmarket, 266 days are in down market. As beta for both up/down herding dummy is insignificant, can't reject null hypothesis that return under herding and non-herding condition has no difference.
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusion and Policy Suggestions

The analysis was designed to figure if the likelihood of herding increases when the uncertain economic policy environment and fear of missing out are given to investors. Therefore, CSSD/CSAD in the whole sample period, structural break test, rolling window regression, probit model, and simple dummy regression are executed in order. As a result, there was no statistically significant outcome in CSSD/CSAD regression as a whole period due to the structural break in the market. However, eight periods showed herding existence through 60-

days rolling CSAD regression with a 95% confidence level. Furthermore, using the periods as dummy dependent variable and EPU and FGI as the independent variable, the probit model shows a higher level in both indexes increase the possibility of the herding phenomenon. However, herding occurrence did not have a statistically significant effect on the level of return.

Four findings are generated through the analysis. First, eight periods of herding are detected through CSAD regression: namely, 2015.06.20 to 2015.09.07, 2015.11.16 to 2016.01.24, 2016.04.29 to 2016.06.28, 2016.11.12 to 2017.02.17, 2019.06.11 to 2019.08.21, 2020.01.14 to 2020.03.13, 2020.05.08 to 2020.07.23 and 2020.10.26 to 2021.02.07. 631 days out of 2800 days show herding and 365 days were in the positive return days, and 266 days were in the negative return market. Second, uncertainty in economic policy makes investors in the cryptocurrency market to herd, considering such market as the individual safe alternate. Third, internally in the cryptocurrency market, the rise of fear of missing out makes investors more likely to herd on market consensus. Lastly, unlike the expectation that the herding phenomenon tort the average return in the market, it did not show a significant difference whether herding is in the market or not.

Considering the findings, three suggestions are made. First, further studies on cryptocurrencies in depth are needed. Although the market seems speculative and irrational in a look, the market is diversifying its utility. Also, growing market volume and participants make it hard to ignore that the market is now one part kind of asset market. Furthermore, as gen Zs actively participate in the investment market (Locke, 2021), analyzing the nature of the cryptocurrency, market, and follow up on the fast-diversifying cryptocurrency market is essential. Secondly, financial education based on the in-depth study of the cryptocurrency is needed. The analysis shows a herding phenomenon in the cryptocurrency market, and FOMO is proved to be one factor leading such a movement. Herding can be reflected as one of the rational choices in bounded information and time for investors. But negligence in assessing portfolio and following the FOMO with anxiety is a dangerous scheme. Therefore, financial education to deal with this new asset market should be adapted for a stable individual portfolio and overall financial market. Lastly, stable regulation should be organized worldwide. Current regulations, even the definition of the cryptocurrency is applied differently in worldwide aspect. Therefore, it makes investors flight to the niche market. Furthermore, unstable regulation makes prices move in suddenly as policymakers mention the market in either good or bad ways. So, for the stable monetary system, international cooperation for setting proper regulation is needed.

There are limitations to this research. First, only 37 coins are considered due to data availability, and it may detect different herding periods and conclusions if it covers more diverse cryptocurrencies. Second, only the U.S. market is concerned. So other exchange markets such as Ethereum/Bitcoin exchange, Bitcoin/EUR, and else market might show different patterns. Third, the EPU index and FGI's coverage is about three years. As a result, 4 out of 8 periods are dropped in the probit model. The first and second limitations are due to data availability, and last is due to the relatively short history of the cryptocurrency market. So, better access to price data and further update of related study is expected to make the analysis more precise.

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