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Impact of Bias Behavior, Price Volatility, and Market Capitalization on Cryptocurrency Purchase Decisions in Indonesia

Dampak Perilaku Bias, Volatilitas Harga, dan Kapitalisasi Pasar terhadap Keputusan Pembelian Kripto di Indonesia

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ABSTRACT

This study investigates how market capitalization, price volatility, and behavioral biases affect decisions to buy cryptocurrencies. Because of its decentralized structure and extreme volatility, the cryptocurrency market frequently affects investment choices through psychological elements, including loss aversion, overconfidence, and herd mentality. This study uses a quantitative methodology to analyze data from the nine most traded cryptocurrencies using independent t-tests, multiple linear regression, and simple linear regression. According to the study's findings, decisions to buy cryptocurrencies are significantly positively influenced by herd behavior and overconfidence, as shown by high volatility, but not significantly by loss aversion. Furthermore, it has been demonstrated that price volatility significantly affects herd behavior, meaning that investors are influenced to follow the majority lead when prices fluctuate significantly. However, the degree of herd behavior is not affected by market capitalization, suggesting that psychological elements like herd behavior are more impacted by general market conditions than by market capitalization size. These results highlight how crucial it is to comprehend the psychological aspects of cryptocurrency market decision-making, since doing so can offer a better understanding of investor behavior and the workings of this extremely unpredictable market.

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INTRODUCTION

The global rise in cryptocurrency assets in recent years has altered how society engages with the financial system. The public's interest in cryptocurrencies, such as Bitcoin, Ethereum, and many others, has grown because of its decentralized structure, transactional anonymity, and substantial profit potential. The use of cryptocurrency assets has significantly increased in emerging nations, especially in Southeast Asia, according to reports sourced from (Chainalysis, 2023). As one of the biggest marketplaces in the area, Indonesia has demonstrated a good trend in both the number of investors and the volume of cryptocurrency asset trading. According to data from the Commodity Futures Trading Regulatory Agency (Commodity Futures Trading Regulatory Agency (Bappebti), 2023), there were 17.25 million cryptocurrency investors in Indonesia by the end of 2022, a 47% rise from the year before. However, in addition to economic and technological considerations, behavioral biases also play a large role in this adoption, greatly influencing investor decision-making. Investors who are uncertain about the cryptocurrency market are frequently tempted to adopt a herd mentality, in which they imitate the choices of others without doing in-depth research.

One of the special difficulties brought about by the unpredictability of cryptocurrency assets is their high price volatility. For instance, during a single year, the price of cryptocurrency has risen by almost 300%, but has also dropped sharply by up to 80% (CoinMarketCap, 2023). When there is more volatility, emotional reactions and cognitive biases frequently have an impact on purchase decisions, in addition to fundamental analysis. When it comes to purchasing cryptocurrency assets, behavioral biases such as herd behavior (propensity to follow the herd), overconfidence (extreme self-confidence), and loss aversion (propensity to avoid losses) have a significant impact. The necessity for further thorough research on the variables impacting cryptocurrency purchasing decisions in Indonesia, including market capitalization, price volatility, and behavioral biases, is thus highlighted by this observation.

Because cryptocurrency investors frequently behave differently than traditional investors, behavioral bias analysis is crucial when discussing cryptocurrency assets. Cryptocurrency investors are more likely to be exposed to information shared through social media, online forums, and digital communities, which increases their propensity for herd behavior. This is especially true for Millennial and Gen Z investors, who make up the largest group in cryptocurrency transactions. According to prior research, such biases can impact the overall market stability (Shiller, 2019) . Furthermore, despite the significant risk associated with cryptocurrency assets, investors who are confident in their capacity to manage market uncertainty are sometimes seen to exhibit overconfidence. Loss aversion, on the other hand, can make investors hang onto their assets for long periods of time, even when there are obvious symptoms of loss, which eventually reduces the effectiveness of their investment portfolio. The tendency of people to make less-than-rational decisions, frequently influenced by feelings, perceptions, and social factors, is known as behavioral bias. When it comes to investing, these biases can cause investors to make judgments based on inaccurate or insufficient information, leading to significant losses. For instance, investors frequently purchase cryptocurrency assets when prices increase due to the Fear of Missing Out (FOMO) phenomenon, disregarding fundamental analysis or related risks. Furthermore, this bias may be worsened by the cryptocurrency market's excessive price volatility, which may cause investors to act rashly and ignore long-term investing methods.

This phenomenon is also influenced by market capitalization and price volatility. While lower market capitalization makes cryptocurrency assets more vulnerable to price manipulation, a higher level of volatility frequently stimulates herd behavior (Chainalysis, 2023; CoinMarketCap, 2023). Further evidence that psychological variables have a substantial impact on consumer behavior in the context of investing supports the decision to buy cryptocurrency assets. This approach makes it crucial to comprehend how behavioral biases might influence cryptocurrency market investment decisions, particularly for inexperienced investors who might not have the necessary skills or expertise.

To produce thorough insights into investor behavior in quickly developing markets like Indonesia, research on the effects of herd behavior, price volatility, and market capitalization on the decision-making process regarding the purchase of cryptocurrency assets is not only pertinent but also crucial. Investors can improve their risk management skills and use more reason in their financial choices by learning about behavioral biases.

This study employs a quantitative methodology to accomplish this goal by gathering historical data on cryptocurrency transactions in Indonesia over a predetermined time frame. It is anticipated that important trends and connections between the variables under investigation will become apparent as a result of data analysis. This research will not only make scholarly contributions to the fields of investment and consumer behavior, but it can also be a useful resource for market participants and investors who want to make wise choices in the nascent cryptocurrency market.

Behavioral finance integrates psychology and economics to explain how biases influence financial decisions. Contrary to the rational investor model, (Kahneman & Tversky, 1991) highlight biases like overconfidence, loss aversion, and herd behavior. Herd behavior arises when individuals imitate others in uncertain conditions, often fueled by online information (Nareswari et al., 2021). Overconfidence leads to excessive trading and risk-taking (Ahmad & Shah, 2020; Odean & Barber, 2001). Loss aversion causes individuals to avoid realizing losses, affecting portfolio efficiency (Wrońska-Bukalska, 2020).

Investment decisions in cryptocurrencies are distinct due to extreme volatility and digital influence. Sudden price swings often result in panic selling or irrational buying, with social media amplifying biases (Seraj et al., 2022). Young, digitally native investors are particularly vulnerable to misinformation (Khan, 2023; Rijanto, 2024). Studies in Indonesia (Denura & Soekarno, 2023; Nurbarani & Soepriyanto, 2022) find that behavioral traits like overconfidence and loss aversion, shaped by socio-demographic and digital exposure, strongly affect crypto decisions. Despite global interest (Bouri et al., 2019), research on emerging markets like Indonesia remains limited.

This study fills that gap by examining how behavioral biases, price volatility, and market capitalization influence crypto purchasing decisions in Indonesia.

The framework proposes that investor behavior is shaped by a combination of behavioral biases and market conditions.

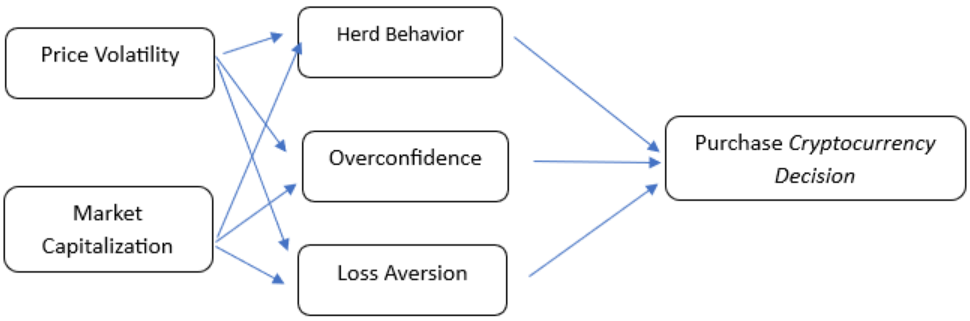

Figure 1. Research Framework

Hypotheses:

1. H1: Herd behavior positively and significantly influences crypto purchases.
2. H2: Overconfidence positively and significantly influences crypto purchases.

3. H3: Loss aversion significantly and negatively influences crypto purchases.
4. H4: Herd behavior has a stronger effect than overconfidence and loss aversion.
5. H5: Price volatility significantly increases herd behavior.
6. H6: Higher market capitalization is associated with lower herd behavior.

METHODS

Design of the Research:

The quantitative methodology of this study attempts to quantify the correlation between the dependent variable (purchase cryptocurrency decision) and independent factors (herd behavior, overconfidence, loss aversion, price volatility, and market capitalization). This strategy was carried out by statistical analysis using an independent t-test, multiple linear regression, and simple linear regression.

Research Information:

Data Type: Secondary data from the CoinMarketCap website were used in this study. As of May 2023, the nine most popular cryptocurrencies held by Indonesian investors are Bitcoin, Ethereum, Dogecoin, Binance, Shiba, Tether, Solana, Cardano, and the USDC.

Unit of Analysis: For each cryptocurrency under study, price swings, trading volume, and market activity were observed using daily data as the unit of analysis. The information gathered spans 529 days, from January 2023 to June 2024.

Research Variables:

Table 1. Research Variables

Variable Type	Variable Name	Operational Indicator	Data Source
Dependent Variable	Purchase decision	Daily transaction frequency	CoinMarketCap
Independent Variable	Herd behavior	Trading volume ratio to average volume (Volume_Avg)	CoinMarketCap
	Overconfidence	Transaction frequency during high volatility	CoinMarketCap
	Loss aversion	Frequency of holding assets when prices drop	CoinMarketCap
	Price volatility	Standard deviation of daily prices	CoinMarketCap
	Market capitalization	Large asset capitalization (high vs low market cap)	CoinMarketCap

Data Analysis Techniques:

Table 2. Data Analysis Techniques

Hypothesis	**Analysis Method**	**Decision Criteria**
H1: Herd behavior → Purchase	Multiple Linear Regression	Coefficient $\beta_1 > 0$ and significant ($p<0.05$)
H2: Overconfidence → Purchase	Multiple Linear Regression	Coefficient $\beta_2 > 0$ and significant ($p<0.05$)
H3: Loss aversion → Purchase	Multiple Linear Regression	Coefficient $\beta_3 < 0$ and significant ($p<0.05$)
H4: Dominance of Herd Behavior	Comparison of Beta Coefficients	The value of the coefficient $\beta_1 > \beta_2, \beta_3$
H5: Volatilitas → Herd Behavior	Simple Linear Regression	Coefficient $\alpha_1 > 0$ and significant ($p<0.05$)
H6: Market cap vs Herd Behavior	Independen t-Test	Significant difference between μ_1 and μ_2

1. Regression Analysis: The purpose of this research is to quantify how behavioral biases and cryptocurrency buying decisions are related. To ascertain the degree to which independent factors influence the dependent variable, a multiple linear regression model is employed (testing hypotheses H1, H2, and H3). The following regression formula was applied:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon$$

   - Y: Cryptocurrency purchase decision (dependent variable).
   - X_1, X_2, X_3: *Herd behavior*, *Overconfidence*, dan *Loss aversion* (independent variables).
   - B: Coefficient of each independent variable.
   - ϵ : Error/residual.

2. Comparison of Standardized Coefficients. This method compares the standardized beta (β) values from multiple linear regression findings to identify the most important independent variable impacting purchasing decisions (H4).
3. Simple Linear Regression. The impact of price volatility on the degree of herd behavior was examined using this technique (H5). The equation applied

$$X_1 = \alpha_0 + \alpha_1 Z + \epsilon$$

   - X_1: Herd behavior
   - Z: Volatilitas harga

4. Independent t-Test. The degree of herd behavior between cryptocurrencies with high and low market capitalization was compared using this test (H6).

Tool for Research Analysis:

1. SPSS was used to perform independent t-tests, simple linear regression, and multiple linear regression analyses.
2. Excel was used for processing and cleaning unprocessed data from CoinMarketCap and other sources.

RESULTS

The purpose of this study is to determine and examine how certain behavioral biases, such as loss aversion, overconfidence (shown by high volatility), and herd behavior, affect decisions to buy cryptocurrencies. The degree to which each of these independent factors can affect decisions to buy or not was examined in this study using multiple linear regression analysis, as indicated by the dependent variable. It is anticipated that the analysis's findings will shed light on the ways in which behavioral biases affect investor behavior in the cryptocurrency market and deepen our understanding of the variables that affect investors' choices in this extremely unpredictable market.

We can perform a number of studies on the generated dataset to learn more about the connection between behavioral bias and cryptocurrency buying decisions. This dataset can explain a number of phenomena, including:

Table 3. Variables Description

Variable	Variable Description
Herd Behavior	This variable quantifies how mass behavior affects decisions to buy cryptocurrencies. The percentage change in trading volume relative to the average is used to compute the Herd Behavior value in this dataset. This demonstrates how closely investors adhere to market trends or the actions of the majority.
High Volatility (Overconfidence)	The significant degree of volatility in cryptocurrencies values is reflected in this variable. Overconfidence behavior, in which investors are convinced that prices will continue to move in the way they have anticipated, is frequently linked to high levels of volatility. High volatility in this dataset is recorded as True or False, and each value is transformed into a numerical value (1 for True and 0 for False).
Loss Aversion	This variable quantifies the degree to which investors typically steer clear of losses. The True or False value in this dataset indicates if investors suffered losses on their investments, and in this context, a price fall indicates loss aversion.
Purchase Decision	This dataset's dependent variable shows whether or not investors choose to purchase cryptocurrencies. When trading volume exceeds the average, this variable is rendered binary (1 for purchasing, 0 for not buying).

Descriptive statistics such as mean, standard deviation, minimum, and maximum for independent and dependent variables can be computed from this dataset. A summary of the data distribution and each variable's variability will be given by this.

Multiple linear regression analysis

The association between the independent factors (High Volatility, Loss Aversion, and Herd Behavior) and the dependent variable (Purchase Decision) can be explained by multiple linear regression analysis findings. The regression findings indicate the variables that significantly influence the choice to buy and the magnitude of that influence.

Table 4. Multiple linear regression result

Variabel	Koefisien Unstandarized (B)	Koefisien Standarized (Beta)	t	Sig.	Confidence Interval for B
(Konstanta)	0.179	-	7.647	0.000	0.133 - 0.225
Herd_Behavior	0.000	0.038	2.153	0.031	0.000 - 0.001
High_Volatility	0.138	0.147	8.409	0.000	0.106 - 0.170
Loss_Aversion	-0.001	-0.001	-0.053	0.957	-0.030 - 0.028

Herd Behavior significantly influences purchasing decisions according to the regression results, which show that the coefficient for Herd_Behavior is 0.000, with a p-value of 0.031, which is less than 0.05. Thus, Hypothesis 1 (H1) was supported. Herd behavior and purchase decisions have a very weak positive link, as indicated by the standard coefficient (beta) of 0.038. This shows that while there is a positive relationship, its impact is minimal.

The coefficient for High_Volatility is 0.138 with a p-value of 0.000, which is less than 0.05, supporting Hypothesis 2 (H2), which holds that overconfidence (expressed by high volatility) influences purchase decisions. This finding suggests that high volatility has a significant impact on purchasing decisions. Therefore, H2 is approved. The likelihood of making a purchase decision increases with volatility, as indicated by the standard coefficient (beta) of 0.147, which shows a moderately positive link between high volatility and purchasing decisions.

The coefficient for Loss_Aversion is -0.001, with a p-value of 0.957, which is considerably higher than 0.05, suggesting that loss aversion has no discernible impact on purchase decisions, contrary to Hypothesis 3 (H3), which claims that it influences such decisions. Therefore, H3 is rejected. Loss aversion has a negligible impact on purchase decisions, as indicated by the standard coefficient (Beta) of -0.001.

Standardized Coefficients

Standardized Beta Coefficient Explanation for Response H4: The standardized coefficients (Beta) for each independent variable are shown in the regression results table you specifically provided:

Table 5. Standardized Coefficients (Beta)

Variabel	Koefisien Standarized (Beta)
Herd_Behavior	0.038
High_Volatility	0.147
Loss_Aversion	-0.001

The standardized coefficients from the multiple linear regression results can be used to test Hypothesis H4, which claims that Herd Behavior has a greater influence on cryptocurrency purchasing decisions than Overconfidence and Loss Aversion. After accounting for the impact of the other variables, the standardized coefficients (Beta) show the relative influence of each independent variable on the dependent variable (buying decision). A larger beta value indicates a greater influence on the decision to buy. Herd Behavior has a beta of 0.038, which indicates a very slight positive influence on purchase decisions, according to the regression results that are shown. With a beta of 0.147, high volatility, which characterizes overconfidence, has a stronger beneficial impact than herd behavior. With a beta of -0.001, loss aversion, on the other hand, has a negligible and adverse impact on buying decisions. As a result, it is evident that High Volatility influences decisions to buy more than Herd Behavior. Furthermore, Loss Aversion has no impact. According to this standard beta value, the regression result does not support the H4 hypothesis that Herd Behavior is more dominant than Overconfidence and Loss Aversion, since Overconfidence (High Volatility) has a greater influence on cryptocurrency purchasing decisions.

Simple Linear Regression

Hypothesis H5 asserts that the degree of herd behavior is significantly impacted by price volatility (High_Volatility). Market uncertainty is frequently linked to price volatility, which may lead investors to follow crowds. As a result, it is critical to examine whether sharp price swings can affect investors' propensity to rely their decisions on what the majority does. We quantify the degree to which price volatility influences herd behavior in the cryptocurrency market using a basic linear regression. The results are as follows:

Table 6. Simple linear regression result

Variabel	Koefisien Unstandarized (B)	Koefisien Standarized (Beta)	t	Sig.
(Konstanta)	91.949	-	132.360	0.000
High_Volatility	23.946	0.325	20.425	0.000

We can test hypothesis H5, which claims that price volatility (High_Volatility) has a considerable impact on the degree of herd behavior, based on the regression findings. According to the table of findings from the simple linear regression, the unstandardized coefficient for High_Volatility is 23.946. This indicates that with the right unit, herd behavior rises by 23.946 for every unit increase in price volatility. A moderately positive correlation between price volatility and herd behavior is indicated by the standardized coefficient (beta) for High_Volatility, which is 0.325. Accordingly, the degree of herd behavior that takes place increases with price volatility. With a p-value of 0.000, which is less than 0.05, and a t-value of 20.425, the High_Volatility coefficient is highly significant in influencing herd behavior. These findings suggest that price volatility significantly affects herd behavior. The findings of this regression support hypothesis H5, which states that price volatility does, in fact, have a major impact on herd behavior.

Independent t-Test

An independent t-test was used to evaluate Hypothesis H6, which claims that cryptocurrencies with large and low market capitalizations exhibit different levels of herd behavior. To determine if the average herd behavior of the two independent groups—that is, low and high market capitalization—differs significantly, an independent t-test is employed. This test is crucial because it enables us to compare the two groups and ascertain whether particular attributes—in this case, market capitalization—have an impact on market behavior and investment choices.

Market_Cap is separated into two groups, low market capitalization and high market capitalization, using the median as a threshold prior to the t-test. In situations when the data distribution may not be normal or contains notable outliers, the median value was selected because it is a more robust metric (resistant to outliers) than the mean. The median created a reasonable border between the two categories for comparison by splitting the data into two equal sections. This is consistent with the suggestions made by a number of several experts, who state that the median is a suitable metric for classifying data when the distribution of the data is not symmetrical or when there are extreme values that may have an impact on the analysis's findings (Hadi & Chatterjee, 2015). To guarantee that the division of market capitalization categories can more properly reflect the data distribution, the median was selected as the category border.

Table 7. Independent t-Test result

Group Statistics

cap_category		N	Mean	Std. Deviation	Std. Error Mean
Herd Behavior	.00	1773	100.3907794	38.39097467	.9117478972
	1.00	1773	100.3225989	31.75613705	.7541770279

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Herd Behavior	Equal variances assumed	31.387	.000	.058	3544	.954	.0681804305	1.183244361	-2.25172820	2.388089065
	Equal variances not assumed			.058	3423.648	.954	.0681804305	1.183244361	-2.25175607	2.388116927

With average values of 100.3907 for low market capitalization and 100.3226 for large market capitalization, the independent t-test results demonstrate that the average herd behavior for the two groups (low and high market capitalization) is extremely similar. The standard deviations of the two groups differed, although the difference was not statistically significant. The t-test for unequal variances was employed since Levene's test results revealed a p-value of 0.000, indicating that the assumption of equal variances was not satisfied. There is no discernible difference in herd behavior across assets with large and low market capitalization according to the t-test results, which display a p-value of 0.954, greater than 0.05. In other words, H6, which claims that the two groups' herd behaviors differ significantly, is rejected.

There is no discernible difference between investors who invest in assets with low and high market capitalizations in terms of their propensity to follow the herd's behavior according to the independent t-test, which shows that market capitalization does not significantly affect herd behavior overall. To handle data distributions that might not be normal and to provide a more equitable category division, the median has been successfully used in category division. This increased the reliability of the test results.

DISCUSSION

With typical market volatility and sharp price fluctuations, cryptocurrency businesses are currently experiencing a high level of uncertainty. The findings of the hypothesis test offer crucial information on how investors behave in this market.

1. Impact of overconfidence (H2) and herd behavior (H1):

Overconfidence and herd mentality appear to be major issues in the cryptocurrency sector. The influence of herd behavior on buying decisions is a reflection of investors' tendency to follow market trends without fully weighing the consequences. Furthermore, despite significant dangers, investors are encouraged to have greater confidence in their choices because of the high volatility of the cryptocurrency market, which strengthens the effect of overconfidence. This is evident from the spike in interest in some cryptocurrencies, such as Ethereum and Bitcoin, driven by investor confidence in the possibility of rapid returns and market trends. In their study, King and Koutmos suggested that herd behavior may have an impact on cryptocurrency price dynamics. They tested the existence of herd behavior in cryptocurrency trading using a herding model, which demonstrates that investors frequently imitate the behavior of others without taking the dangers into account. (King & Koutmos, 2021).

2. Lack of Loss Aversion Influence (H3)

It is interesting to note that the test results indicate that loss aversion has no bearing on decisions about what to buy. This demonstrates that even though the cryptocurrency market is notoriously volatile, many investors are more concerned with the possibility of long-term returns or other psychological factors such as FOMO (fear of missing out) and are not greatly impacted by short-term losses. This finding suggests that cryptocurrency investors are more psychologically resilient to short-term losses. One of the ideas of prospect theory is loss aversion, which describes the tendency of people to experience losses more intensely than comparable gains. There are a number of reasons why loss aversion may not have as much of an impact on cryptocurrency transactions as other factors that drive investment choices. The fact that many cryptocurrency market participants are more concerned with possible short-term gains than potential losses is one of the contributing causes. FOMO (Fear of Missing Out), which makes investors feel compelled to participate in order to avoid missing out on rapid profit chances, is frequently the cause of this phenomena. Friederich's research demonstrates that FOMO can motivate investors to continue investing despite past losses, demonstrating psychological resilience to losses (Friederich, 2023).

3. Dominance of Overconfidence (H4) and Influence of Volatility (H5)

The findings from H4 show that overconfidence is a more important factor in cryptocurrency market investing decisions than herd behavior, which is the leading component. This is consistent with the industry experience that a large number of investors grow overconfident about possible returns without taking current dangers into account. For a variety of reasons pertaining to investor psychology and market dynamics, overconfidence frequently influences investment decision making more than herd mentality or loss aversion. The following justifications lend credence to this assertion.

a. The overconfidence bias may be strengthened by the fact that seasoned investors frequently feel more secure in their choices. According to (Beatrice et al., 2021), confidence levels and investment experience are positively connected, with more seasoned investors typically feeling more confident about their capacity to turn a profit. This implies that investors may become more likely to ignore dangers and concentrate on possible rewards as their level of experience increases.
b. Rapid fluctuations in prices in a market, as volatile as cryptocurrencies, can make investors feel confident. According to (Mao & Wang, 2020), investors that exhibit overconfidence tend to act more in accordance with their personal convictions than with market trends, which might have an impact on trading volume and market volatility. Despite the possibility of losses, investors may feel more secure and willing to take chances when the market trends upward.
c. Investors who are overconfident frequently ignore contradicting evidence in favor of information that confirms their opinions. Kresnawati demonstrates how overconfident investors often deceive themselves by looking for data that supports their conclusions, which can result in illogical investment choices (Kresnawati, 2024). Because investors are more likely to believe information that supports their opinions, overconfidence becomes a dominant factor in decision making.

Even though prices might fluctuate greatly, high price volatility provides a motivating incentive for investors to base their judgements on their personal opinions, which is also described by the acceptance of H5. In financial markets such as the cryptocurrency market, price volatility has a big impact on herd behavior. The following are some explanations for why price volatility fuels investors' growing herd mentality.

a. Uncertainty in the market caused by high price volatility can make investors unsure how to respond to fresh information. According to (Dewan & Dharni, 2022), investors often adopt the behavior of others as a way to lower risk when faced with uncertainty, which increases herd mentality. Following the group's judgements rather than making their own may make investors feel safer when prices are volatile.
b. Investors frequently experience emotional emotions in response to price volatility. Investors may feel euphoria or panic when asset prices move quickly, which might strengthen their propensity to follow the herd. Herd behavior tends to rise at times of high volatility, according to research by Wijaya and Meirisa. This suggests that market emotions can collectively impact investment decisions (Wijaya & Meirisa, 2020).
c. Information is frequently absent or ambiguous in highly volatile markets, which can leave investors unsure of the asset's underlying value. According to (Babar et al., 2016), investors may be influenced to imitate the behaviors of others due to a lack of sufficient information and significant price volatility, which may result in price changes that exceed the fundamental value. Investors are more inclined to follow the crowd when they believe that they lack the knowledge necessary to make the best choice.

In the financial market, price volatility is therefore a key factor in determining herd behavior. Investors may follow the herd due to uncertainty, emotions, and unclear information, which can worsen market swings and start a vicious cycle of behavior.

4. There is No Difference in Herd Behavior Based on Market Capitalization (H6):

The results of the t-test indicate that the degree of herd behavior in the cryptocurrency market is unaffected by market capitalization. This may be the result of the cryptocurrency market's lack of consideration for an asset's market capitalization level while making investment decisions, particularly during periods of extreme volatility. Given that investors are typically more swayed by the general market trend than by the amount of a cryptocurrency's market capitalization, this could also help explain why cryptocurrencies with high and low market capitalizations display comparable degrees of herd behavior.

Extreme volatility is a common occurrence in the cryptocurrency market for both low and big market capitalization assets (like Ethereum and Bitcoin). Yousaf et al.'s research demonstrates that herd behavior can happen at any level of market capitalization, particularly in high-uncertainty scenarios when investors have a propensity to follow market trends regardless of capitalization size. (Yousaf et al., 2021). This suggests that herd behavior is more impacted by general market conditions than by specific asset categories.

Information on cryptocurrencies is frequently readily available and accessible to all investors, irrespective of the size of the market capitalization. According to Komalasari, information asymmetry can affect herd behavior. However, in a market as transparent as a cryptocurrency, investors typically respond to the same information, which lessens the disparities in herd behavior between assets with high and low market capitalization (Komalasari, 2016).

According to research by (Kallinterakis & Wang, 2019), investors in the cryptocurrency market frequently exhibit herd behavior, where their decisions are influenced more by group psychology and emotions than by market capitalization size. Similar herd behavior might result from the same market mood influencing both big and small investors in stormy markets.

Therefore, the factors driving investor behavior in the cryptocurrency market tend to create comparable outcomes in terms of herd behavior, regardless of whether the asset has a large or low market capitalization, notwithstanding disparities in market capitalization size.

CONCLUSION

Several inferences on the impact of behavioral bias, price volatility, and market capitalization on cryptocurrency purchase decisions in Indonesia may be made based on the examination of hypotheses H1 through H6 investigated in this study are the study's findings indicate that herd behavior significantly and favorably influences Indonesians' decisions to buy cryptocurrencies. This suggests that investors frequently follow the herd, particularly in erratic market conditions, where social pressure and uncertainty may persuade them to base their investments on apparent patterns. The study also discovered that decisions to buy cryptocurrencies are positively and significantly affected by overconfidence. Investors frequently make illogical decisions because they are overconfident about their capacity to forecast price fluctuations. This demonstrates that psychological bias has a significant impact on how people invest in the cryptocurrency market.

The test results demonstrate that decisions on what to buy are unaffected by loss aversion. This demonstrates that even though the cryptocurrency market is notoriously volatile, many investors are more concerned with the possibility of long-term gains than short-term losses. This illustrates how psychologically resilient investors are to short-term losses. The study's findings indicate that overconfidence has a greater impact on investment choices than herd mentality. This demonstrates how investors' overconfidence in their own skills frequently controls decision-making, even when they may be influenced by collective activities.

It has been demonstrated that price volatility has a major impact on herd behavior. High price swings create uncertainty, which encourages investors to imitate the moves of others. This can worsen the herd mentality in the cryptocurrency market. And the last is the test results indicate that market capitalization has no discernible impact on the degree of herd behavior. Given that investors are swayed more by the general market trend than by the amount of particular market capitalizations, this suggests that in the context of the cryptocurrency market, assets with high and low market capitalizations can display comparable herd behavior.

This study offers profound insights into Indonesian cryptocurrency market investor behavior. These results suggest that while loss aversion seems to have less of an effect on investing decisions, psychological factors such as herd behavior and overconfidence do. Furthermore, market capitalization size does not distinguish the degree of herd behavior in this market; rather, price volatility is the primary driver of herd behavior. Investors and other stakeholders can use this research as a reference to better understand the dynamics of investment behavior in the always changing cryptocurrency market.

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