LIQUIDITY, VOLATILITY, AND HERDING BEHAVIOR: A STUDY OF THE INDONESIA STOCK EXCHANGE DURING THE COVID-19 PANDEMIC

Zuwan Nisfu Nahar
Faculty of Economics and Business, Satya Wacana Christian University, Indonesia
Email: zu.nisfu@gmail.com

Robiyanto
Faculty of Economics and Business, Satya Wacana Christian University, Indonesia
Email: robiyanto@staff.uksw.edu (corresponding author)

Abstract

This research aims to determine liquidity and volatility conditions and differences in herding behavior during the pre-pandemic, early pandemic, and the new normal period of the COVID-19 pandemic in Indonesia. This research examines the microstructure and proves herding behavior on the Indonesian Stock Exchange (IDX). This research will also look at liquidity and volatility to see market sentiment because investor behavior can be reflected in liquidity and volatility. The population used in this research is the IDX-80 index, with 48 companies as the sample. This study uses CSAD to test herding behavior because it is not sensitive to outliers. This research found that the highest market liquidity and volatility occurred during the early pandemic, and the highest herding behavior occurred during the new normal period. The market response to each event can also determine the direction of stock movements, so investors can take advantage of this period to collect shares and sell them again when prices rise. This research offers a summary of the Indonesian capital market during significant events, which can assist investors in developing investment plans that consider the course of events. Practically, this study offers actionable insights for investors by explaining how market conditions during different phases of the pandemic influence investment strategies.

Keywords: Herding; Microstructure; Liquidity; Volatility; Pandemic; Indonesia Stock Exchange

JEL Classification: G10, G11, G40

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INTRODUCTION

According to Fama's (1970) efficient market hypothesis, stock market prices represent all information and the company's intrinsic value. However, empirical findings often find that markets are inefficient. Therefore, it is necessary to research financial behavior to answer this problem (Stavroyiannis & Babalos, 2020). Some research on financial behavior that is often brought up is herding. Such as the studies that explain the herding phenomenon in developed and developing nations by Chang et al. (2022), Economou et al. (2015), Mobarek et al. (2014a), Muharram et al. (2021). This research shows that herding is a function of factors and market conditions (Guney et al., 2016).

So far, herding is the most popular explanation for deviations between stock prices and the company's intrinsic value in the efficient market hypothesis (Stavroyiannis & Babalos, 2020). Herding behavior arises from the attitude of investors who follow other investors in making decisions (Arjoon et al., 2020). According to Muharam et al. (2021), emotional factors play a big role in someone making investment decisions. When a crisis strikes, investors frequently herd others because they are more likely to be sensitive and fear losing money (Chang et al., 2020; Galariotis et al., 2015). Galariotis et al. (2015) also stated that herding behavior deepened during the financial crisis because investment decisions were driven by panic, not rational thinking based on fundamentals.

Several academics have studied research on herding during times of crisis. Chang et al. (2022) discovered that investors sold shares out of fear during the COVID-19 crisis in 2020 and the severe acute respiratory syndrome (SARS) crisis in 2013. Apart from that, the subprime mortgage crisis in 2008 also had an impact on countries in Europe, such as Portugal, Ireland, Italy, Germany, Greece, and Spain. The crisis raised concerns among regulators, policymakers, and investors, giving rise to herding behavior during market volatility. Similar findings were also found in African countries (Guney et al., 2017; Mobarek et al., 2014).

In Southeast Asia, research on herding during times of crisis was conducted by Vo & Phan (2019), who found herding behavior in Vietnam. In addition, herding behavior was discovered in Indonesia during the COVID-19 pandemic. On the other hand, no study has examined the variations in herding behavior in pre-pandemic, early pandemic, and the new normal COVID-19 crisis, particularly concerning the Indonesian Stock Exchange. This needs to be done because herding behavior can also occur before a crisis, as found by Muharam et al. (2021), which shows the existence of herding behavior in Malaysia and the Philippines from 2008 to 2014. Herding behavior during the early crisis and the new normal periods may also differ. This may occur because government policies for handling crises can impact risk levels. Herding behavior is dynamic and always develops over time due to investor behavior. Ferreruela and Mallor (2021) observed that herding behavior subsided during a crisis and resumed at a reduced intensity.

According to data from KSEI (2022), the number of stock market investors in Indonesia increased by 103.6% in 2020. With a 53.47% rise, this gain is significant compared to 2019. The IDX is a topic of interest for research because of the tremendous growth in the number of investors that happened in the year of the COVID-19 pandemic in the IDX. This growth is primarily due to the millennial and Generation Z generations, who are still relatively new to the capital market. The IDX authority also implemented several changes to the stock exchange, such as limiting the lower auto reject (ARB) to 7% and removing broker codes and investor domiciles when the market is running. ARB limit adjustments create an asymmetrical relationship between risk and reward, boosting investor confidence. Hence, investors especially new investors willing to take risk by buying stock without sufficient knowledge.

Conversely, the information available to investors is progressively reduced as broker codes and investor domiciles are removed while the market is open. According to field observations, inexperienced investors follow the transactions of more seasoned investors due to a lack of knowledge and growing self-confidence, which exacerbates market sentiment and uncertainty. This condition also worsened by the spawning of social media about stock investment managed by several unethical individual known as *pom-pomers* who could give misleading information and may lead to herding behavior around the Covid-19 pandemic period. The existence of sentiment and uncertainty

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makes intentional herding behavior interesting to research.

Several previous studies used dummy variables to measure investor actions and market sentiment. However, according to Arjoon et al. (2020), using dummy variables can mask valuable information about actual market behavior at the micro level. Therefore, this research will also look at liquidity and volatility to see market sentiment because investor behavior can be reflected in liquidity and volatility (Tian et al., 2015).

This research aims to determine liquidity and volatility conditions and differences in herding behavior during the pre-pandemic, early pandemic, and the new normal period of the COVID-19 pandemic in Indonesia. Hopefully, this research will provide further light on the herding behavior in the Indonesian capital market, particularly evident when considering the events before, early, and following the COVID-19 pandemic. Additionally, this research offers a summary of the Indonesian capital market during significant events, which can assist investors in developing investment plans that consider the course of events. This research can also be used as a basis for regulators in formulating policies.

LITERATURE REVIEW

Behavioral Finance

In contrast to traditional financial theory, behavioral finance assumes that investors act irrationally. In behavior-based finance, financial decision-making can be based on a person's psychology. This psychology is caused by risk factors, sociology, and uncertainty (Ricciardi & Simon, 2000; Shefrin, 2000). Furthermore, divides behavior-based finance into two types, namely macro and micro. Macro behavior-based finance explains anomalies from the efficient market hypothesis, while micro behavior-based finance explains biases that occur in individuals. Psychological research suggests various biases in decision-making, one of which is finance-related decisions. Herding behavior is one type of bias that can exist (Muharam et al., 2021). According to Demirer and Zhang (2019) and Setiyono et al. (2013), there is currently a growing amount of study interest in this topic due to investors' propensity to mimic the activities of other investors.

Microstructure

Investor behavior in responding to market sentiment can be reflected through microstructure, namely liquidity and volatility (Tian et al., 2015). Liquidity relates to how easily an instrument is traded, while volatility relates to the tendency of price movements. Liquid markets allow investors to transact large amounts quickly without causing significant price changes. Research conducted by Debata et al. (2018) found that liquidity is related to investor sentiment and irrationality, such as overconfidence caused by information asymmetry and misinterpretation of information. When volatility is high, information quality deteriorates, and noise increases, leading to biased trading decisions by investors (Arjoon, 2016).

Market microstructure can be changed by imposed regulations, during Covid-19 pandemic, the IDX change several market regulations, one of them are the changes in intraday limitation of stock changes with 7% limit for stock depreciation. This regulation could affect market volatility in the IDX. So, it is important to split the time period.

Herding Behavior

Herding is the action of investors who follow other investors rather than trust their signals and information (Arjoon et al., 2020; Demirer & Zhang, 2019). Herding is often associated with behavioral correlations between individuals (Ulzii et al., 2018). When herding occurs, investor behavior follows market consensus (Vo & Phan, 2019). Furthermore, Spyrou (2013) stated that three alternatives cause herding behavior. Investors may exhibit herding behavior in response to new information. Analysts can sometimes engage in herding to preserve their reputation in times of market turbulence. Apart from that, institutional investors also carry out herding to maintain the performance of their portfolios.

Gavriilidis et al. (2013) divide herding into two types: intentional and spurious. Intentional herding is a situation that occurs when investors follow the behavior of other investors due to information asymmetry, which results in stock prices not reflecting fundamental values. Meanwhile, spurious herding is a situation where investors have similar perceptions and information, which results in similar decision-making.

During pandemic, because majority of the society were working at home and tend to doing their activity by using online tools or instruments, so online stock investment becomes a fad and this become more flourishing by the spawning of investment related social media, a lot of phenomena happened, and encourage anyone with inadequate financial literacy to do stock trading by using some news posted in social media. Most of them tend to fear of missing out (FOMO). This makes massive intentional herding especially if boosted by prominent internet figures.

Hypothesis Development

Microstructure

Microstructure has an important role in the price formation process. This is because microstructure reflects investor behavior in making decisions when responding to events that occur (Easley et al., 1996). According to Tian et al. (2015), one microstructure form, namely liquidity and volatility, can reflect investor behavior in responding to market sentiment. Market liquidity and volatility can originate from factors such as macroeconomics, stock exchange trading rules, investor protection rules, information environment, and company characteristics (Debata et al., 2018). Liquidity and volatility are higher when a lot of sentiment is going on. This can occur due to a lot of noise in the market and irrational investor behavior (Moshirian et al., 2017). This explanation clarifies that significant market occurrences can increase volatility and liquidity.

Before the COVID-19 pandemic crisis, there were two major events that investors focused on, especially in Indonesia. In 2019, Indonesia faced trade wars and general elections. Aslam (2019) asserts that the trade war between the US and China is a major issue that affects other nations. The trade war resulted in weakening world economic growth. In addition to its economic circumstances, Indonesia has regular general elections every five years. Political uncertainty causes investors to reduce their portfolios from the capital market and switch to safer instruments (Agarwal et al., 2022). Unfavorable macroeconomic conditions and reduced investor participation have decreased stock exchange liquidity and volatility.

Based on research conducted by Suardi et al. (2022), it was found that there was an increase in liquidity during the pandemic. Increased liquidity also causes market volatility to increase. At the start of the pandemic, share prices experienced a significant decline because of fear and anxiety that lead the uncertainty. Investor sell their stock and do flight for safety. A lot of sell-off happened in this period. However, this decline only lasted two weeks and rose again the following week.

This price reversal was caused by the large amount of cash flowing into the capital market because the real sector was seen as less attractive at the start of the pandemic. This is also confirmed by Foley et al. (2022), which revealed an increase in transactions during the pandemic. These transactions created liquidity and volatility during the early pandemic (Alaoui Mdaghri et al., 2021; Ding et al., 2021). Additionally, following the implementation of the new normal era, the real sector started to strengthen, which led to a dip in

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capital market transactions and a reduction in volatility and liquidity. Based on this discussion, a hypothesis can be formulated as follows:

H_{1a}: Market liquidity was higher at the start of the pandemic

H_{1b}: Market volatility was higher at the start of the pandemic.

Herding Behavior

Herding behavior is often found in stock markets in developing countries. This is due to the incomplete disclosure of information in developing countries and the large role of macroeconomics in decision-making, causing investors to follow market consensus (Chang et al., 1997). However, research conducted by Muharam et al. (2021) found no herding behavior in Indonesia's capital market. Herding behavior in Indonesia only occurs when the market is bullish.

In 2019, the capital market in Indonesia was in a bearish situation until the beginning of the pandemic, so there was no herding behavior during that period. The reversal in the direction of price movements occurred in the second week after the announcement of the pandemic entering Indonesia. Therefore, herding behavior tends to occur during the early pandemic. Mentality increased during a crisis due to investors' irrational, panic-driven actions. Research conducted by Chang et al. (2020) also found that investors experienced panic during the severe acute respiratory syndrome (SARS) crisis in 2013 and the Covid-19 crisis in 2020.

Furthermore, Ferrouhi (2021) found a relationship between liquidity, volatility, and herding behavior. Arjoon (2016) believes that the quality of information becomes increasingly reduced when market volatility is high. As a result, investors become hesitant to react to newly acquired information, which leads to intentional herding (Litimi et al., 2016). The higher the liquidity and volatility, the more obvious the herding behavior will be (Economou et al., 2015; Vo & Phan, 2019). During the new normal period, market liquidity and volatility tend to decrease because the real sector is improving, and transactions on the stock exchange tend to decrease. Therefore, herding behavior during the new normal period also decreased along with decreasing liquidity and market volatility. Based on this discussion, a hypothesis can be formulated as follows:

$H_{2:}$ Herding behavior was higher during the early pandemic.

RESEARCH METHODS

Research Design

This explanatory research aims to explain the herding behavior in Indonesia during the pre-pandemic, early pandemic, and the new normal period of the COVID-19 pandemic in Indonesia. Therefore, a quantitative approach is used in this research to prove the existence of herding behavior in Indonesia. The data used in this research are market returns, stock returns, and trading volume obtained through secondary data, with the stock population included in the IDX-80 index. This index was chosen as a population, considering that the IDX-80 index contains liquid companies and consists of companies with good financial performance. Apart from that, the movement of the IDX-80 index is often in line with the composite stock price index (JCI), so it is considered to represent shares on the Indonesia Stock Exchange.

Purposive sampling was used in this research. The criteria for shares included in this research is a company that has never been suspended from the Indonesia Stock Exchange during the research year. A company suspended from the Indonesia Stock Exchange means it cannot be traded for a certain period, so the shares become illiquid during that time. Another criterion used is that the company never left the IDX-80 index during the research period. This criterion was created to eliminate shares unsuitable for inclusion in the sample because they were considered illiquid within a certain time frame when they left the index. This research used liquid shares to avoid shares that are only liquid at certain times due to rumors or trading manipulation so that market mechanisms do not cause price movements. Besides that, illiquid shares are also difficult for investors to transact on a large scale.

This research period employed an event study approach, which is divided into pre-pandemic, early pandemic, and the new normal period. The early pandemic period was a period with high anxiety and uncertainty which lead to higher market volatility due to sell-off in this period, while new normal period calmer compared this period.

Generally, the period used to determine the window estimate is one year before the event or 200-255 trading days (Robiyanto & Yunitaria, 2022). Therefore, this research used 245 trading days, or one year before the pandemic was declared to have entered Indonesia as the pre-pandemic period. The early period of the pandemic was taken based on the announcement of the pandemic entering Indonesia, namely on March 2, 2020, until the implementation of the new normal period on June 1, 2020. Furthermore, the new normal period starts from June 2, 2020, to December 30, 2022, coinciding with the last day of implementing restrictions on community activities in Indonesia (Kemenkes, 2022). Also, this study limits the period of observations to avoid the confounding effect.

Operational Variables

Market Return

Market return is the return on all shares in a particular market. In this research, the market return used is the IDX-80 return index. Market returns can be obtained from the following equation:

$$R_{m,t} = \frac{P_{m,t} - P_{m,t-1}}{P_{m,t-1}} \quad \text{.................................(1)}$$

Where $R_{m,t}$ is the market return in period t, $P_{m,t}$ is the market portfolio price in period t, $P_{m,t-1}$ is the market portfolio price in period t-1.

Cross-Sectional Absolut Deviation (CSAD)

Cross-Sectional Absolute Deviation is the dispersion or level of distribution of stock returns, which can be obtained through the following equation:

$$CSAD_t = \frac{1}{n}\sum_{i=1}^{n}\left|R_{i.t} - R_{m,t}\right| \quad \text{.................(2)}$$

Where n is the number of research samples, $R_{i,t}$ is the return of stock i in period t, and $R_{m,t}$ is the market return in period t.

Analysis Techniques

Market liquidity measurement uses the illiquidity measurement introduced by Amihud (2002) and developed by Karolyi et al. (2012) as follows:

$$Liq_{i,t} = -log\left(1 + \left(\frac{|R_{i,t}|}{P_{i,t}VO_{i,t}}\right)\right) \text{..............(3)}$$

$$Liq_{i,t} = \frac{1}{N}\sum_{i=1}^{N} Liq_{i,t} \quad \text{............................(4)}$$

Market volatility can be obtained using the T-GARCH (1,1) approach. From this approach, the average of the sample can be taken to determine market volatility $\sigma^2{}_{m,t}$ (Arjoon et al., 2020). The T-GARCH (1,1) approach can be obtained through the following equation:

$$\sigma^2{}_{i,t} = \varphi_{i,0} + \left(\varphi_{i,1} + \eta_{i,1}d_{i,t-1}\right) + \varepsilon^2{}_{i,t-1} + \delta_{i.1}\sigma^2{}_{i,t} \quad \text{................................(5)}$$

Furthermore, before testing herding behavior, a classic assumption test is first carried out, which includes a normality test, multicollinearity test, heteroscedasticity test, and autocorrelation. This study uses CSAD to test herding behavior because it is not sensitive to outliers. Herding behavior occurs if a non-linear

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relationship exists between CSAD and squared market returns. Suppose the level of dispersion of stock returns does not increase higher than the squared market return. In that case, investors behave irrationally because the dispersion of stock returns is concentrated, and investors are more likely to follow market consensus. Therefore, the regression test will be used to test herding behavior with the following mathematical equation:

$$CSAD_t = \gamma_0 + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R^2{}_{m,t} + \varepsilon_t ..(6)$$

RESULTS AND DISCUSSION

Results

Descriptive Statistics

This research consists of three periods: pre-pandemic, early pandemic, and the new normal period. The number of samples used in this research was 49 companies, which are summarized in The Table 1. The table shows that before the pandemic occurred, Indonesia's average stock market return fell by 0.061%, and during the early pandemic, it fell by 0.23%. The average market return increased by 3.09% during the new normal period. This is because economic conditions improved during that period, accompanied by an increase in the number of new investors and increased trading volume.

There were variations in the standard deviation in the pre-pandemic, early-pandemic, and new normal periods. Respectively, the standard deviation for each period is 1%, 3.77%, and 0.9%. Standard deviation can be used as a tool to calculate market risk. A higher standard deviation means higher risk because of greater volatility (Muharam et al., 2021).

Based on Table 1, the difference between the average CSAD value and the CSAD standard deviation can also be calculated. Respectively, the difference between the average CSAD value and the CSAD standard deviation is 1.3%, 2%, and -1.2%. The difference between the average CSAD value and the higher CSAD standard deviation indicates that the market has unusual cross-sectional variations. In this study, the highest difference occurred at the pandemic's beginning. This could be caused by unexpected news, namely the Covid-19 pandemic.

Stationary Test

Before measuring the microstructure, Augmented Dicky Fuller was used for a stationary test at levels 1 and 2. The Table 2 is a stationary test of the market before the pandemic, early pandemic, and the new normal period. Based on Table 2, it can be seen that all the data used meets the augmented Dicky Fuller test, with a significance level of 1%. Therefore, the data can be declared to meet the stationary test and does not show a unit root. So, liquidity and volatility testing can continue without a special analysis first.

Table 1. Descriptive Statistics

	Pre-Pandemic		**Early Pandemic**		**New Normal Period**	
	$CSAD_t$	R_{mt}	$CSAD_t$	R_{mt}	$CSAD_t$	R_{mt}
Mean	0.01745832	-0.00061	0.04227	-0.0023	0.00069	0.03095945
Median	0.01645009	0.00017	0.03650	0.00104	0.00053	0.02959566
SD	0.00467423	0.01001	0.02246	0.03769	0.01232	0.00901104
Kurtosis	0.83940138	0.20892	5.73951	2.22891	2.31484	4.19891201
Skewness	0.93814595	-0.1618	1.98577	0.55073	-0.1707	1.38817209
Minimum	0.00782665	-0.0319	0.01431	-0.0846	-0.0591	0.01172656
Maximum	0.03174153	0.02419	0.13991	0.13645	0.04708	0.0875936
N	245	245	58	58	474	474

Source: IDX, Google Finance, and investing.com were analyzed.

Table 2. Stationary Test

Stationary	Pre-Pandemic	Early Pandemic	New Normal Period
Level 0	-13.69860***	-6.697995***	-18.83372***
Level 1	-10.58558***	-10.68063***	-15.16329***
Level 2	-12.14662***	-6.437097***	-13.49549***

Source: IDX, Google Finance, and investing.com were analyzed.
***Significance at α=1%

Market Liquidity Measurement

Market liquidity measurements were carried out three times, namely pre-pandemic, early pandemic, and during the new normal period. This measurement is based on the illiquidity measurement listed in equations 3 and 4. The Table 3 is the results of measuring market liquidity during the pre-pandemic period, early pandemic, and the new normal period.

Based on Table 3, it can be seen that the level of market liquidity at the early pandemic increased from 0.00091 to 0.00159. After entering the new normal period, the liquidity level decreased again to 0.0001. Therefore, the market liquidity level was smaller before the pandemic and the new normal period than during the early pandemic. This shows that market liquidity during the early pandemic was the highest compared to other periods, which means the hypothesis was accepted.

Market Volatility Measurement

Market volatility was measured three times, namely pre-pandemic, early pandemic, and during the new normal period. This measurement uses the T-GARCH (1,1) approach listed in Equation 5. The Table 4 is the results of T-GARCH (1,1) measurements during the pre-pandemic period, the beginning of the pandemic, and the new normal period.

Based on Table 4, it can be seen that the period was volatile before the pandemic at a 5% level and a coefficient value of 0.127111. This value shows that the market is 0.127 times more volatile in response to negative news than positive news. Apart from that, volatility also occurred in the early period of the pandemic and the new normal period at a 1% level with coefficient values of 0.208867 and 0.178036, respectively. This shows that the market was also 0.209 times more volatile during the early pandemic and 0.178 times more volatile during the new normal period in response to negative news. It can also be seen that from these three periods, market volatility during the early pandemic was greater than before the pandemic and the new normal period, which means the hypothesis was accepted.

Classical Assumption Test

Before testing the herding behavior on the Indonesia Stock Exchange, a classic assumption test is first carried out, including normality, multicollinearity, heteroscedasticity, and autocorrelation tests. The classical assumption test was carried out three times according to each period. The Table 5 is the results of the normality test using the Jaque-Bera method.

Data distribution can be normal if it has a probability value of more than alpha 0.05 (Susanto & Robiyanto, 2020). Based on Table 5, all probability values in each market period are more than 0.05, so the data meets the normality test, which means the residual values are normally distributed. Therefore, further testing can be carried out, namely the multicollinearity test. The results of the multicollinearity test by looking at the Centered Variance Inflation Factors (VIF) values can be seen in Table 6.

Table 3. Liquidity Measurement

Period	*Illiquidity*
Pre-pandemic	0.00091
Early Pandemic	0.00159
New Normal Period	0.00001

Source: IDX, Google Finance, and investing.com were analyzed.

Table 4. Volatility Test (T-GARCH (1,1))

Period	Coefficient
Pre-pandemic	0.127111**
Early Pandemic	0.208867***
New Normal Period	0.178036***

Source: IDX, Google Finance, and investing.com were analyzed.
**Significance at α=5%
***Significance at α=1%

Table 5. Normality Test

Period	Probability
Pre-pandemic	0.606526
Early Pandemic	0.705682
New Normal Period	0.165451

Source: IDX, Google Finance, and investing.com were analyzed.

According to Susanto & Robiyanto (2020), data does not experience multicollinearity problems if the VIF value is less than 10. Table 6 shows that all variables in each period have a VIF value of less than 10, so it can be concluded that there is not a high correlation between the independent variables. Next, a heteroscedasticity test was carried out using the Breusch-Pagan-Godfrey method. The results of the heteroscedasticity test for each market period can be seen in Table 7.

Data can be declared to have passed the heteroscedasticity test if it has a Chi-square probability value greater than alpha 0.05 (Susanto & Robiyanto, 2020). Based on Table 7, it can be seen that each period has a Chi-square probability value of more than alpha 0.05, so it can be concluded that the data does not have heteroscedasticity problems. Next, a multicollinearity test was carried out using the Breusch-Godfrey Serial Correlation LM Test. The Tabel 7 the results of the autocorrelation test in the three market periods.

Data can not experience autocorrelation problems if it has a Chi-square probability value of more than alpha 0.05 (Susanto & Robiyanto, 2020). Table 8 shows that all market periods have a Chi-square probability value of more than 0.05, so there is no autocorrelation problem or correlation between the residual data for period t_0 and the previous period.

Regression Test

Based on the classical assumption test, it can be concluded that the data used in this research fulfills all the requirements in the classical assumption test so that it can be continued to the next stage, namely testing herding behavior using the regression method. The regression test results from the three market periods can be seen in Table 9.

Table 6. Heteroscedasticity (Breusch-Pagan-Godfrey)

Period	Prob. Chi-Square
Pre- Pandemic	0.6825
Early Pandemic	0.0863
New Normal Period	0.4481

Source: IDX, Google Finance, and investing.com were analyzed.

Table 7. Autocorrelation Test (Breusch-Godfrey Serial Correlation LM Test)

Period	Prob. Chi-Square
Pre-Pandemic	0.3569
Early Pandemic	0.7795
New Normal Period	0.3002

Source: IDX, Google Finance, and investing.com were analyzed.

Table 8. Multicollinearity Test

Variable	VIF		
	Pre-Pandemic	Early Pandemic	New Normal Period
C	NA	NA	NA
$\|R_{m,t}\|$	7.597291	5.871543	1.427030
R^2_{mt}	7.597291	5.871543	1.427030

Source: IDX, Google Finance, and investing.com were analyzed.

Table 9. Regression Test

Variable	Pre-Pandemic	Early Pandemic	New Normal Period
C	0.013858**	0.029071**	0.029990**
	(31.36964)	(7.304899)	(39.37954)
$\lvert R_{m,t} \rvert$	0.371764**	0.0300674	-0.061868
	(4.139202)	(1.521506)	(-0.552854)
R^2_{mt}	0.766873*	-3.551181*	-10.878709**
	(2.076386)	-(1.982054)	-(3.679370)

Source: IDX, Google Finance, and investing.com were analyzed.
Numbers in parenthesis are t-values
*Significance at α=5%
**Significance at α=1%

According to Chang et al. (1997), herding behavior is characterized by a relationship between the CSAD variable and the y2 coefficient, or in this case, the squared market return coefficient is negative. Table 9 shows that the CSAD variables and squared market returns are correlated at a 5% level in the pre-pandemic and early-pandemic periods. During the new normal period, CSAD and squared market returns were also proven to be related with a 1% level.

However, the period before the pandemic had a positive squared market return coefficient, so herding behavior was not detected. Herding behavior emerged in the early period of the pandemic and the new normal period, as evidenced by the negative squared market return coefficient. Apart from that, the coefficient value during the new normal period was greater than during the initial period of the pandemic. Hence, herding behavior was higher during the new normal period. According to this hypothesis, the data did not demonstrate that herding behavior was more prevalent in the early stages of the pandemic.

Discussion

Market Liquidity

This research found that the level of liquidity during the early pandemic was higher than in the pre-pandemic period and the new normal period. Suardi et al. (2022) also stated that there was an increase in liquidity during the pandemic. The decline in share prices due to selling and reduced transaction volume on the Indonesian Stock Exchange during the early pandemic only lasted two weeks and returned to stability the following week. The capital market became a relatively stable sector during the pandemic due to the government's and regulators' involvement in supporting the financial sector (Alaoui Mdaghri et al., 2021).

As stated by Guney et al. (2016), at the beginning of the crisis, there was concern among policymakers and investors, triggering a sell-off that lowered stock prices. However, the panic soon subsided with stable buying and selling transactions. These transactions created liquidity at the pandemic's start (Alaoui Mdaghri et al., 2021). Similar findings were also put forward by Chung & Chuwonganant (2023) who found an increase in liquidity on the New York Stock Exchange (NYSE) after previously decreasing. Ding et al. (2021) found that the impact of the pandemic was lighter on companies with stronger financials in the annual reporting period before 2020, thereby creating liquidity. Considering that this research uses the IDX-80 index which consists of stocks with good financial conditions, the negative impacts received due to the pandemic are also lighter. Apart from that, the IDX-80 index also contains shares that are index movers in the IDX Composite. Therefore, the shares sampled in this research can represent all shares on the Indonesian Stock Exchange.

Market liquidity during the early pandemic could be the highest because the sell-off and share decline only occurred for two weeks. Not only in Indonesia, the fall in share prices accompanied by price reversals also occurred in the S&P 500 index in the United States. This results in high market volatility. This volatility is caused by uncertainty and potential losses due to the pandemic. Even though the highest market liquidity and volatility occurred at the pandemic's beginning, the highest herding behavior occurred during the new normal period. This is because the stock exchange implemented numerous new policies during the new normal period, including closing broker codes and investor domiciles.

Several studies have also been conducted on the impact of the pandemic on capital markets. When the pandemic occurred, transactions on the global market increased (Foley et al., 2022). Baig et al. (2021) also found that the increase in cases and deaths due to Covid-19 positively affected liquidity. In addition, based on (KSEI, 2022), the increase in the number of investors in 2020 is dominated by generation-z or retail investors. According to Ozik et al. (2021) retail investors can mitigate liquidity decline.

Market Volatility

The fall in share prices, followed by price reversals at the start of the pandemic in Indonesia, resulted in extreme volatility. The same happens to companies in the United States S&P 500 index (Mazur et al., 2021). The volatility at the start of the pandemic was like a repeat of the Great Depression of 1930 and the global financial crisis of 2008 (Sharif et al., 2020). According to Zhang et al. (2020), the main source of volatility is uncertainty and potential losses due to the pandemic.

Social media also stimulates trading activity, which causes extreme price movements (Broadstock & Zhang, 2019). At the beginning of the pandemic, the government of the Republic of Indonesia implemented social distancing and regional quarantine policies, which increased social media users. Based on field observations, much educational content is circulating, which has caused the younger generation to be interested in the capital market. This is confirmed by KSEI (2022), which records that the increase in new investors is dominated by generation-z. New investors contributing to increasing liquidity can cause greater volatility (Bensaïda, 2017).

Herding Behavior

Herding behavior was detected at the beginning of the pandemic and the new normal period, where there was increased volatility. This is in line with the statement of Ulzii et al. (2018), which states that high volatility results in herding behavior. At the start of the pandemic, herding behavior was caused by investor panic about the crisis. This is based on research by Chang et al. (2020), who found panic and herding behavior during a crisis. However, herding behavior was greater during the new normal period. This is because the stock exchange implemented numerous new policies during the new normal period, including closing broker codes and investor domiciles. According to Gavriilidis et al. (2013), this policy development led to intentional herding. Closing the broker code and investor domicile results in the loss of one piece of information, reducing investors' confidence in responding to other information, which gives rise to intentional herding (Litimi et al., 2016). The herding behavior during the new normal period was caused by institutional investors' lack of information and efforts to maintain their portfolios (Spyrou, 2013). Normally, herding behavior can be happened because individual investors follow institutional investors' action in stock market by looking at their brokers' code, however during the pandemic period, the broker code is removed, so individual investors could not monitor their action until the end of trading hour. But a new phenomenon happened in the new normal period, some prominent internet figures suddenly become stock market influencer known as pom-pomers and give some hints regarding stock to buy and to trade.

Herding behavior occurs when investors put aside their opinions and follow market consensus (Hwang & Salmon, 2004). Based on field observations, new figures appeared on social media who provided stock recommendations at the beginning of the pandemic and the new normal period. It is suspected that this has caused an increase in herding behavior. Broadstock and Zhang (2019) said social media can stimulate extreme stock price movements.

CONCLUSION AND RECOMENDATION

The finding shows that herding behavior was detected during early period of pandemic and in new normal period. However, the herding behavior during the new normal period was not driven by market liquidity and volatility, considering that market liquidity and volatility tended to decrease during the new normal period.

The findings in this research can be used as considerations for investors when making stock transactions, especially on the Indonesia Stock Exchange. Market liquidity and market volatility, which increased at the start of the pandemic, can be used by investors to obtain capital gains in the short term if a similar event occurs at another time. Apart from that, with herding behavior, it can be seen that shares on the Indonesia Stock Exchange are inefficient, so investment decision-making should not only be based on company performance alone. The market response to each event can also determine the direction of stock movements, so investors can take advantage of this period to collect shares and sell them again when prices rise.

Regulators also need to pay attention to the increase in liquidity and volatility at the pandemic's start. Liquidity and volatility are needed in the stock market. However, liquidity and volatility that are too high during times of crisis need to be considered by regulators. It is feared that this high liquidity and volatility will be used to manipulate share prices.

Even though the data used in this study had provenly stationary, the usage of time series data could be analyzed by using more appropriate method other than conventional CSAD. The usage of modified CSAD techniques which incorporated the data characteristics should be considered in future studies. Also, several geopolitical events could become basis for the time frame to explain the existence of herding during those events. However, the event study used must keep the confounding effect as minimal as possible to avoid the bias in the result.

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