Indonesian Covid-19 Pandemic Trends: Sentiment Analysis and Stock Return Connectedness

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Abstract. The study aims to analyze the causality relationship of investor sentiment and stock returns during a pandemic. This research is important because the massive impact of the pandemic in various sectors has caused changes in investors' financial behavior, including an increase in covid 19 keyword searches and vaccines on google trends. The word vaccine was categorized as positive sentiment whereas the word covid 19 pandemic as negative sentiment. All data were obtained from google trend from January 2020 to December 2021. The stock return data from January 2020 to December 2021 were obtained from yahoo finance. This study used vector autoregressive to test the causality relationship of the two variables. There is a causality relationship between investor sentiment and stock returns because most investors are noise traders. Hence, their investment is categorized as a herding behavior where one investor prefers to follow the decisions made by other investors.

Keywords: Sentiment Investor · Stock Return · Google Search

1 Introduction

Extreme sentiment plays an important role in determining changes in market returns [1]. Terrorism [2], domestic and international economic conditions [3], and the COVID-19 pandemic are some circumstances affecting the investor sentiment [4]. The COVID-19 pandemic is considered affecting investor sentiment since the risk hampered the investment realization due to investor concerns about the impact [5]. In particular, the impact of the pandemic on investors' concerns is indicated by the dropping the trading volume [6, 7] and stock prices [4].

Dropping in trading volume by 16.76% after the announcement of Covid 19 in March 2020 occurred in Indonesian stock market [7]. Investor panic over COVID-19's effects has led to uncertainly in the capital markets, heightened volatility, and movement in stock returns [8] and [9], causing investors to take additional precautions while investing their money in the capital market.

The Indonesian people's behavior in reacting to information, which is frequently false, misleading, and malicious information, is what triggers the investor panic [10].

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However, as a result of investors' optimism about the economic recovery, from the end of November 2020 to the beginning of 2021, the Jakarta Composite Index (JCI) started to rise. There is no empirical research on the reasons for strengthening this rising. However, [11] documented that the strengthening of the economy occurred after the announcement of the success of the COVID-19 vaccine in mid-November 2021.

Quantifying investor sentiment is a difficult undertaking, because of its unobservable and diverse behaviors. Conventionally, news, return, trading volume, and advertising expense are some proxies for assessing investor sentiment although there are indirect and have shortcomings [12]. However, in the recent years, google trends search engine become a popular index of investor sentiment [13]. The use of google trends not only facilitates the update of covid 19 information but also the process of monitoring policies and the impact of covid 19 [13]. Googling Investor's Sentiment is measured by forming a constructive index based on the search for information on google search engines conducted by investors [14].

The relationship between google search volume and stock return are mixed. Increasing of internet search volume was followed by increasing the stock return [15] but in the other side [16] stated no relationship and even has negative correlation [17]. However, [18] noted that twitter mood can be used to forecast the stock market by analyzing investor sentiments in Twitter feeds. Furthermore, [19] analyze the connection between financial news and the stock market and discover that information about an asset has a big impact on the stock price and volatility. In this study we used Google Trends as a proxy for investor sentiment and used it for analysis the stock return.

Numerous studies on the impact of investor attitude on stock returns have been conducted in various countries, including Indonesia ([4, 11, 20–23]). However, research that discusses the relationship of causality between the two variables is rarely carried out [24]. Therefore, this study aims to analyses the causality relationship between investor sentiment and stock return.

This research is a development according to [25] by dividing investor sentiment into positive and negative [11]. The numerous keyword searches related to the COVID 19 pandemic that reflect the negative sentiment was successfully developed by [25] whereas a keyword search activity for vaccines that reflect the positive sentiment is developed by [11].

The rest of this paper is organized as follow. The second part describes the literature review and development of research hypotheses. The third part explains the research methods, namely sampling techniques, variable measurement, hypothesis testing, and robustness tests to test the validity of research results. The fourth part discusses the results of the research and discussion. The last section lays out the conclusions and implications of the study.

2 Theoretical Framework

2.1 Theory of Financial Behavior

A systematic method used to comprehend and research behavior is called behaviorism [24]. Implementing behaviorism in economics generate the theory of financial behavior [24]. [1] mentioned that the behavior of making investment decisions and portfolio diversification is irrational because it depends on the behavior and emotions of investors. [13] documented that some of the information including past conditions and returns, current trends and performance of the company affect the investors in making investment. All of this information is available in the financial markets, so [26] called the financial markets as active informants who influence investor sentiment. Optimism/pessimism of investors is often translated in terms of investor sentiment, which is defined by [1] as the tendency of investors to speculate.

Investors have limitations in processing information so it is important to consider the cognitive bias of investors like investors who are too confident, investors who only follow the market, and investors who tend to avoid risk by making decisions that only have an impact on increasing investment returns [27]. Investors with cognitive bias become noise traders in the capital market which led to abnormal stock prices and fluctuations since they do not consider the company's fundamental conditions. Furthermore, herding behavior especially by novice investors who tend to follow the financial market phenomenon to avoid risks and minimize losses become another consideration [26].

2.2 Previous Research

Finding about the relationship between market sentiment and stock returns are mixed. [20] documented that investor sentiment does not influence stock returns. In the other side, [4] and [26] noted that during the pandemic, investor sentiment negatively affected stock returns since investors retracted their stock to avoid greater losses. Another reason is that investors are pessimistic about the condition of the company so that investors sell stock which have an impact on dropping the stock prices.

In contrast to these two studies, [13] showed that there is strong connection between market sentiment and stock return. In addition, [13] stated that during the Covid-19 pandemic, investors actively seek out stock information on a variety of platforms to make decisions. The high volume of search of the stock information indicated the high investor attention to the covid-19 pandemic. The results on the study also show that investors tend to increase trading volumes that finally leads to fluctuations in stock returns. A same result also documented by [28] that investor sentiment positively affects to stock returns.

Most investors released their shares as a result of the deteriorating market conditions, giving investors the chance to receive larger stock returns. This condition is supported by [6] noted that in March 2020 to December 2020 investors showed positive sentiment toward investment activities even though they were in a downtrend/bearish condition. Positive sentiment may be due to the hope of economic recovery and investors' view that investment is an opportunity that a return on investment will be obtained after the bearish condition is missed.

2.3 The Effect of Investor Sentiment on Stock Returns During the Covid-19 Pandemic

Investor sentiment is the expectation of the future of cash flow and investment risk that is not supported by facts [29]. Market sentiment creates a tendency for investors to

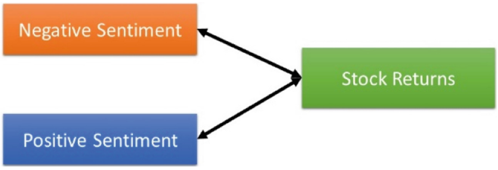

Fig. 1. Model of relationship between investor sentiment and stock return

be optimistic or pessimistic while speculating prices instead of deciding on fundamental factors [30]. The Covid-19 pandemic created a pessimistic among investors toward the company's future [26], causing investors immediately selling their shares. The pessimistic attitude of investors can be seen from the panic of investors in responding to any information about COVID-19 that causes price fluctuations and stock trading [31]. Therefore, the first hypothesis in the study is:

H1a: negative investor sentiment affects stock returns

H1b: positive investor sentiment affects stock returns.

2.4 The Effect of Stock Returns on Positive and Negative Investor Sentiment During the Covid-19 Pandemic

Financial markets are active informants for investors [24] for collecting information about past returns, company financial statements, current stock prices and stock performance [32]. Stock information affects investor sentiment when accepted by noise traders who make transactions according to intuition without analysis of investor sentiment. There for we put forward the second hypothesis as follows:

H2a: stock returns affect investors' negative sentiment

H1b: stock returns affect investors' positive sentiment

The main theory used in this study is the theory of financial behavior to describe the causality relationship between investor sentiment and stock returns. The model in the study is presented in Fig. 1.

3 Research Method

3.1 Data and Variables

Google search data from January 2020 to December 2021 are acquired from Google Trend. We used keyword "vaccines" in google trends developed by [11] for positive sentiment, and the keywords "covid 19 pandemic" developed by [25] for negative sentiment. The stock return data from January 2020 to December 2021 were obtained from the closing price of JCI from yahoo finance. Stock return is measured by reduction in the closing price of the period t minus t − 1, as used by [4] and [7]. Meanwhile, investor sentiment is measured by calculating the Google Search Volume Index (GSVI) on the word "vaccine" for positive sentiment and the "covid 19 pandemic" for negative sentiment. The measurement of variables is presented in Table 1.

The calculation technique of investor sentiment from Google Trend was carried out in several stages as proposed by [24]. The first step is a list of eighty covid-19 pandemic

Table 1. Variable Operationalization of the research

Variables	Definition	Source
Stock Return (SR)	Capital gains that the company gives to investors in exchange for investments investor (Zhao, 2020): $SR = \frac{Pt-Pt1}{Pt}$	Authors Calculation
Pt	JCI Closing Price Period to t	Yahoo Finance
Pt − 1	JCI Closing Price period t − 1	Yahoo Finance
Sentneg (Negative Sentiment)	Covid 19 pandemic keyword search.	Google Trends
Sentpost (Positive Sentiment)	Vaccine keyword search.	Google Trends

keywords developed by [25] for negative sentiment and twenty-four vaccine keywords developed by [11] for positive sentiment. The second step is translating the keywords into Indonesian language. 77 keywords for negative sentiment and 22 keywords for positive sentiment have been generated. The third step is entering these keywords in Google Trends by setting a date from January 2020 to December 2021 with restrictions only in Indonesia. The final step is downloading and tabulating the data.

The following formula was used to calculate the negative and positive sentiment:

$$GSVI = \frac{number\ of\ queries\ for\ each\ keyword}{total\ Google\ search\ queries} \tag{1}$$

The GSVI are used to calculate ΔGSVI to determine the daily change in the search trend. The equation used to calculate the changes is presented in Eq. 2.

$$\Delta GSVIi, t = GSVIi, t - GSVIi, t - 1 \tag{2}$$

3.2 Correlation and Causality

The analysis in this study used the Vector Error Correction Model (VECM) because the data had co-integration, but all changes were integrated at the same level. The step in the testing process is the Augmented Dickey-Fuller (ADF) test on the data before and after differencing to see the data stationarity, determination of optimum lag, co-integration testing, causality testing, and VECM testing.

Testing on data quality consisting of the Stationer Test, Criterion Lag Length, VAR Stability Test, and co-integration test. The Granger Causality Test uses the causality relationship test to see the mutual relationship between variables. In the next stage, VAR/VECM testing is carried out by forecasting investor sentiment on the level of stock returns in the long and short term. The IRF test aims to show the response of a variable to a shock (shock) caused by other endogenous variables. This analysis forecasts long-term effects by showing the time in the future when a shock occurs on the horizontal axis and indicating the magnitude of the response on the vertical axis.

4 Results

4.1 Preliminary Analysis

The average value of each variable is positive, namely 5.049 searches for negative sentiment, 6.792 for positive sentiment, and 0.001 for stock return (Table 1). The results indicated that the average search for the word "covid-19" has increased by five searches per day and vaccines has increased by six searches per day. These results indicate that there is hope for the recovery of COVID-19 through the successful vaccination achieved in mid-November 2020 [11].

In addition, negative sentiment has the highest value volatility with SD 331,552 searches, maximum value 2,300 searches and minimum value −777,000. These results indicate that investors are looking for any information about Covid-19 from the beginning of the COVID-19 pandemic until the pandemic begins to subside [6] (Table 2).

An Augmented Dickey-Fuller (ADF) test was performed on time series data to determine the data stationarity. All data of negative sentiment, positive sentiment, and stock return were categorized as stationer (Table 3).

The optimum lag in this study was two weeks, so the model used in co-integration testing was at lag 2 (Table 4). Optimum lag testing was calculated by using Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and HannanQuin Creation (HQ).

The Covid-19 pandemic is a black swan, unexpected event, that causes panic and investor sentiment [7] that lead to of decision making of investor in the short term [28]. The causal relationship between investor sentiment and stock return in this study (2 weeks) is shorter than the results of [28] which found that investor sentiment affects stock returns within a period of 1 month.

Table 2. Descriptive Statistics of negative sentiment, positive sentiment and stock return

Variables	N	Mean	SD	Min	Max
Negative sentiment	101	5,049	331,522	−777,000	2.300,000
Positive sentiment	101	6,792	115,496	−474,000	504,000
Stock return	101	0,001	0,031	−0,146	0,152706

Table 3. Dicky Fuller Augmented Test

Variables	Degree of Integration	t-statistics	Conclusion
Negative sentiment	I (0)	−2,583	Stationer
Positive sentiment	I (0)	−2,892	Stationer
Stock Return	I (0)	−2.891	Stationer

Table 4. Lag Criteria Test

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−994.9	NA	672926	21.9	22.0[a]	21.9
1	−989.7	9.9	731717	22.0	22.3	22.1
2	−964.7	46.2	51463[a]	21.6[a]	22.2	21.8[a]
3	−958.0	11.8	542646	21.7	22.5	22.0
4	−952.1	10.0	583152	21.7	22.8	22.2
5	−943.9	13.5	595912	21.8	23.1	22.3
6	−942.4	2.3	708712	21.9	23.5	22.6
7	−929.0	20.3[a]	649667	21.8	23.6	22.6
8	−920.8	11.8	671110	21.8	23.9	22.7
9	−916.3	6.2	754739	21.9	24.3	22.9
10	−910.5	7.6	828570	22.0	24.6	23.0

[a] Optimum lag

Table 5. Cointegration Rank Test

Hypothesized No. of CE(s)	Cointegration Rank Test (Trace)			Cointegration Rank test (maximum eigenvalue)		
	Trace Statistics	0.05 critical value	Prob.	Max-Eigen Statistics	0.05 critical value	Prob.
$r = 0$	105,8	29,7	0,0	43,0	21,1	0,0
$r \geq 1$	62,7	15,4	0,0	34,6	14,2	0,0
$r \geq 2$	28,1	3,8	0,0	28,1	3,84	0,0

The co-integration test is used to discover scenarios where two or more non-stationary time series are integrated in such a way that they are unable to diverge from equilibrium over the long term. Three variables have a co-integration relationship when analyzed using a Trace and Maximum Eigen that showed the value greater than the critical value of 0.05 (Table 5). Trace values are 105,816, 62,780, and 28,117 which are greater than critical value 29,797, 15,494, and 3,841 (Table 5). In addition, max-eigenvalues of 43,035, 34,662, and 28,117 are greater than 21,131, 14,264, and 3,841. These results show that the three variables have a long-term direct relationship with one over the other, so they can be analyzed using VECM.

Table 6. Granger Causality Test

Null Hypothesis	F-statistics	Prob.[a]	Granger Status
Negsent does not Granger Sentpost	0,956	0,619	No.
Sentneg does not Granger SR	7,485	0,023	Yes
Sentpost does not Granger Sentneg	0,128	0,937	No.
Sentpos does not Granger SR	0,043	0,978	No.
SR does not Granger Sentneg	15,935	0,000	Yes
SR does not Granger Flashpoint	1,373	0,503	No.

[a] Note: [a] - significant at alpha 0.05

The Granger Causality Test is used to calculate causality relationships between variables. Table 6 results show that the negative sentiment with stock returns is at the level of 0.05 with an optimal lag of 2 variables with a two-way causality relationship. The pandemic cause pessimistic among investors toward the company's future, resulting in investors immediately selling their shares. In accordance with this finding, [26] stated that the impact of the Covid-19 pandemic is an investor's pessimistic feeling toward the company's future. Investors tend to withdraw investments at the beginning of the covid-19 announcement to avoid increasing losses [4]. This influence can be explained by the culture of Indonesia's developing countries which causes Indonesian investors to tend to be more influenced by their sentiment when trading stocks [24]; [4]. In addition, there was an increase in investors during the Covid-19 pandemic [8]. Nonetheless, this increase is an increase in new investors who do not have much experience [24], so they tend to trade under the sentiment. The increase in trading impacts stock prices, affecting the return on shares [24].

Financial markets can provide a variety of useful information for investors, such as past returns, company financial statements, current stock prices, good stock performance, and other available information that can be used as a reference by investors to make decisions [32]. The information provided by the financial markets will affect investor sentiment when received by noise traders.

4.2 IRF Test Results

The IRF analysis showed negative sentiment over the next 20 weeks (Fig. 1). The negative sentiment response to stock returns in the first week is close to 0 but continues to decline to −200 searches in the second week and increases to −100 searches in week six then stabilizes until week twenty. Meanwhile, the response tended to decrease from 400 searches to only 100 in the second week, increase in the fourth week to 150 searches, and stabilize at 150 to the twentieth week. In contrast to the response to stock returns, the response to positive sentiment tends to be stable at 0 at the beginning of the week, increasing in the third week at 50 searches, decreasing in week six at ten searches, and stable until week twenty.

Positive sentiment response to stock returns in the first week is close to 0, increasing until the fourth week with an average of 20 searches in the fourth week, decreasing

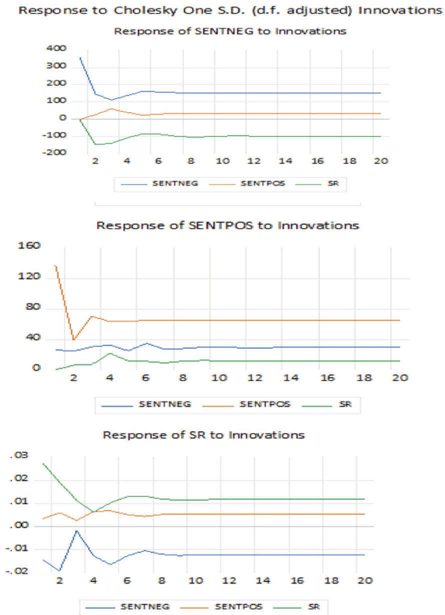

Fig. 2. IRF Analysis

in the fifth week, and continuing to stabilize until week 20 (Fig. 1). Meanwhile, the response tended to decrease from 140 at beginning searches to only 40 in the second week, increase in the third week to 70 searches, and stabilize at 60 to the twentieth week. In contrast to the response to stock returns, the response to negative sentiment tends to be stable at 30 at the beginning of the week, increasing in the seventh week at 35 searches, decreasing in week eight at 30 searches, and stable until week twenty.

The stock return response to negative sentiment in the first week was −0.015%, decreased in the second week to −0.02%, increased until the third week was close to 0%, decreased in the fifth week to −0.015% and continued to stabilize until the 20th week (Fig. 1). Meanwhile, the response tends to decrease from the pandemic's beginning by 0.029% to only 0.005% in the fourth week, experienced an increase in the sixth week to 0.015%, and stabilized until the twentieth week. In contrast to the response to negative sentiment, the response to positive sentiment tends to be stable at 0.005% at the beginning of the week and stable until the twentieth week (Fig. 2).

VDA aims to measure the approximate error variance of variables, which is how big the difference between before and after the shock, both from the variable itself and other variables. The negative sentiment in Table 7 shows that the variable that has the most contribution to negative sentiment is negative sentiment itself, with an average contribution per week of 78.5%, followed by stock returns of 18.9%, and positive sentiment by 2.01% (Table 7).

Table 7. Variance Decomposition Analysis

Periode	S.E.	SENTNEG	SENTPOS	SR
1	359.8128	100.0000	0.000000	0.000000
2	416.2416	87.10355	0.404932	12.49151
3	456.8602	78.29027	2.106929	19.60281
4	490.5430	75.76812	2.499805	21.73207
5	524.0690	75.98080	2.398249	21.62095
6	554.8591	75.86265	2.435236	21.70212
7	584.8831	75.21431	2.511618	22.27407
8	614.2691	74.39522	2.592321	23.01246
9	641.5316	73.76389	2.662083	23.57403
10	667.0837	73.36262	2.712509	23.92487

5 Conclusion

The results showed that negative sentiment affects stock returns due to a large number of trader noise in Indonesia. This trader noise also causes the behavior of imitating the investment activity only of stocks with the highest volatility without considering fundamental analysis. These results contribute to the government's policy-making to filter out any good information, including on social media. The public can obtain that because the herding behavior of investors can affect the capital market as a whole.

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