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SENTIMENT ANALYSIS THROUGH SEARCH VOLUME INDEX ON BITCOIN VOLATILITY

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Abstract

This study aims to assess the link between investor sentiment, volatility, and Bitcoin return. Connections between the three are extremely intricate and diverse. Increasing search activity on Google Trends may presage a price increase, but it can also indicate heightened speculative sentiment or information saturation, potentially resulting in a price reduction. Volatility, while frequently seen negatively, may have a beneficial impact on Bitcoin's earnings by attracting risk-tolerant investors, stimulating trading activity, and facilitating hedging and arbitrage. However, volatility carries considerable risks, discouraging risk-averse investors, impeding institutional adoption, and impeding the practical use of Bitcoin as a means of exchange. Finally, the influence of SVI on investor mood and the volatility of Bitcoin returns is determined by a number of factors, including market sentiment, legislative changes, and technological advancements. As Bitcoin and its ecosystem continue to evolve, the nature of these interactions may shift.

Keywords **: *Search Volume Index, Volatility, Cryptocurrency, Bitcoin.***

1. INTRODUCTION

Recent study indicates a high correlation between investor sentiment and investment performance. Da et al. (2019) found that investor mood can impact investing decisions that are not only based on factual facts. These findings suggest that investor attitude has a considerable impact on asset prices and capital flows in the financial markets. Macroeconomic issues are not the primary elements that frequently impact the market. Investor sentiment has a crucial influence in determining stock market volatility. According to Brown and Cliff (2004), investor sentiment has the potential to impact stock market volatility. Investor mood is viewed as a characteristic that influences stock price formation, particularly in inefficient markets such as Indonesia. Investor sentiment shows their optimism in future cash flows, which is not necessarily justified by fundamental information (Beer et al., 2013). This phenomenon is also one of the behavioral finance assumptions that can contribute to systematic risk, with noise influencing stock volatility. As a result, investor sentiment will be negative when the market is negative, and positive when the market is positive. Furthermore, research indicates that investor attitude can influence the volatility of financial markets. Li et al. (2021) discovered that investor sentiment can be a major component in causing substantial price changes.

Market volatility is often low during periods of good mood because investors are confident and optimistic. However, negative sentiment may contribute to market volatility since investors are apprehensive and unwilling to make investment decisions. Studies have shown a correlation between asset volatility and the Search Volume Index (SVI), which measures the number of internet searches for that asset. SVI may offer an overview of investor interest and attitude toward an investment asset, which can impact price volatility. Bollen et al. (2011) found a correlation between Internet search activity and total stock market volatility. The study's findings revealed that internet search traffic may be utilized as a key indication of short-term stock market volatility. Also, Preis et al. (2013) looked at the link between stock price volatility and internet search activity. The study's findings indicate that there is a positive relationship between stock price volatility and high SVI. This means that when interest and the internet searches for a stock rise, so does the volatility of its share price. Researchers as well as practitioners have used Google Trends data to investigate the link between online search activity and a variety of economic and financial metrics.

They, for example, utilize the data to better analyze consumer behavior, stock market movements, and macroeconomic patterns. Preis, Moat, and Stanley (2013) investigated the link between Google search traffic and trading activity in the financial markets. Their research findings revealed that variations in search traffic might give insight into future price fluctuations, implying that Google Trends data has great predictive power. The use of Google Trends data as a proxy for search traffic opens new avenues for scholars and practitioners to study and forecast economic and financial trends. The volatility of an asset can influence investor sentiment in a variety of ways. When asset volatility rises, investors become more risk averse and gloomy. This is because bigger price volatility might generate uncertainty and raise the risk of loss. In contrast, during periods of low volatility, investors are more hopeful since asset values are steady and risk is thought to be minimal. Following the previous discussion, this study seeks to investigate the link between investor emotion and the volatility of cryptocurrency assets, particularly Bitcoin. Given the complexity of financial markets and the need to understand the factors that drive investor behavior, research on investor mood utilizing SVI and Bitcoin volatility has become increasingly essential. SVI gives useful insights into public interest and attitude toward a certain asset, whereas Bitcoin volatility represents the magnitude of price swings that might influence investment decisions. Combining these two methodologies can give a more complete picture of how investor attitude about Bitcoin influences its volatility.

2. IMPLEMENTATION METHOD

This study employs a quantitative technique to examine SVI's effect and impact on Bitcoin volatility. The regression study was performed using Google Trends as a measure of SVI and the HAR-RV model created by Corsi (2009) to calculate volatility. The HAR-RV model successfully reflects the long memory pattern of volatility and has a high prediction ability. The linear regression approach is a straightforward and effective way to describe the connection between many variables. The model's simplicity makes it ideal for this research. We utilize secondary data from Bitcoin, namely price and market capitalization values from 2018 to 2022. The CoinMarketCap page (*https://coinmarketcap.com/coins/*) has Bitcoin capitalization price data, whereas the Yahoo Finance page (*https://finance.yahoo.com*) provides daily trading data. Furthermore, for the SVI statistics, data acquired from Google Trends (*https://trends.google.com*) is utilized with the phrase "bitcoin". Since we want to keep the Bitcoin price stable, we convert it to a rate of return. Equation (1) illustrates how to compute the rate of return, with the subscript t representing time. Return that used is a daily return that may be translated to weeks for subsequent searches.

$$r_t = log(price_t) - log(price_{t-1}) \qquad (1)$$

Where r_t is the return of bitcoin in period t, $\log(price_t)$is the logarithmic form of the bitcoin price in period t while $\log(price_{t-1})$ is the logarithmic form of bitcoin price in period t-1. The SVI measurement from Google Trend is to provide information about the keyword "Bitcoin" over a set period. Google Trends data gives normalized rates for search terms. Seasonal recurrence was evaluated in Google's daily trends data but was not detected. Analyzing bitcoin's price and rate of return is the first step in estimating its volatility. We employed the notion of realized volatility to calculate the most exact estimate of Bitcoin volatility. We first utilized high-frequency data to calculate daily Bitcoin returns (at 10-minute intervals). Equation (2) calculates realized volatility with Δ = 10 minutes. While T represents the day, and j represents the day's time interval, so $r_t – j_\Delta = (p_t - j_\Delta) - (p_{t-1} - j_\Delta)$ is the continuous return computed at 10-minute intervals, and p is the logarithm of the Bitcoin price. The weekly realized volatility is determined using a simple 5-day average of daily volatility (see Equation (3). Monthly volatility is derived logically by taking a 22-day average of daily volatility. The aggregation period is denoted by w (weekly) or m (monthly). Because realized volatility has a very atypical distribution, researchers like Liu and

Maheu (2008), Chiriac and Voev (2011), and Dimp and Jank (2016) convert it using logarithms. In our investigation, weekly realized volatility was determined using Equation (4).

$$RV_t^{\prime d} = \sqrt{\sum_{j=0}^{M-1} r_{t-j-\Delta}^2} \tag{2}$$

$$RV_t^{\prime d} = \frac{1}{5}\left(RV_t^{\prime d} + RV_{t-1}^{\prime d} + \cdots + RV_{t-4}^{\prime d}\right) \tag{3}$$

$$RV_t^{w} = log(RV_t^{\prime w}) \tag{4}$$

Google Trends provides information on the search term "Bitcoin". Google trend data shows how popular a given search phrase is among users over time. Over a defined length of time, Google trend data gives normalized rates for certain search phrases. Normalized rate compares recent search volume to highest search volume in that period. Seasonality was investigated using Google's daily trend data, but no seasonal trends were discovered. Checking seasonality in daily trend data entails recognizing recurrent patterns or trends in search traffic over time. Despite extensive investigation, no seasonal trends were discovered in the daily trend data for the search phrase "Bitcoin". This suggests that no consistent patterns in search volume were seen over the time examined. The original Google trend variable (Trend) is then modified using Equation (5).

$$GoogleTrend_t = \frac{Trend_t - \overline{Trend}}{\sigma(Trend)} \tag{5}$$

where t represents the time. The mean and standard deviation are determined over the preceding year, as detailed by Bijl et al. (2016) and Kim et al. (2018). This technique is used to update Google's daily and weekly trend variables. The first regression model was used to evaluate daily and weekly data and determine which variables explain Bitcoin's daily return. Using this regression model, we can investigate the relative impact of those variables on Bitcoin's daily returns and uncover the elements that influence Bitcoin's price movements.

$$Return_t = \alpha + \beta_1 GoogleTrend_t + \beta_2 Volatility_t + \varepsilon_t \tag{6}$$

3. RESULTS AND DISCUSSION

Bitcoin weekly trade price data is utilized to compute Bitcoin returns. Meanwhile, the technique stated before is used to compute trend data from Google searches for the phrase "Bitcoin". While volatility is estimated using Bitcoin's daily trading data to achieve weekly volatility, methodologies such as those employed by Liu and Maheu (2008), Chiriac and Voev (2011), and Dimp and Jank (2012) are implemented. The first statistical test is to identify a link between the two separate time series data sets. The following findings show a cross-correlation between Bitcoin's Weekly Returns, Trend, and Volatility.

Figure 1. Cross-Correlogram Return and Trend

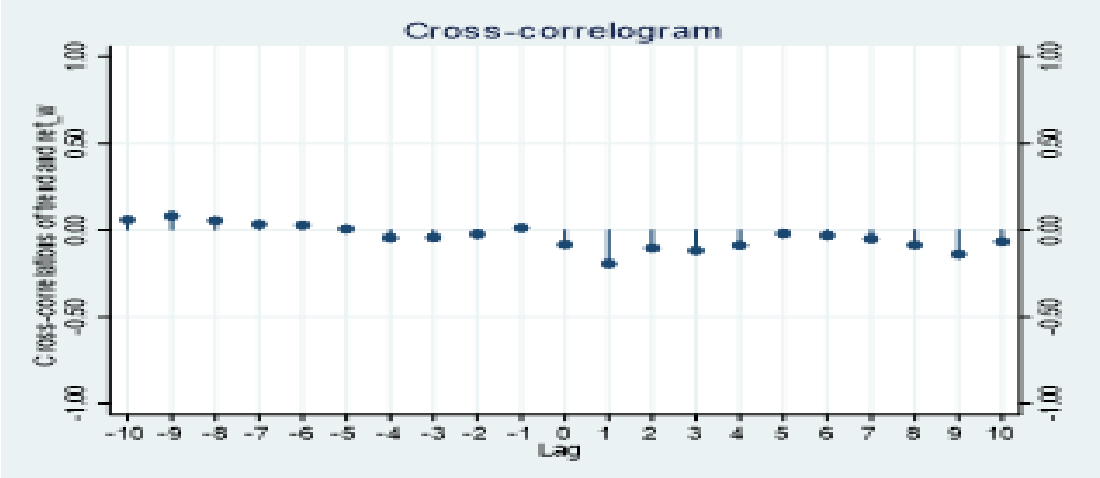
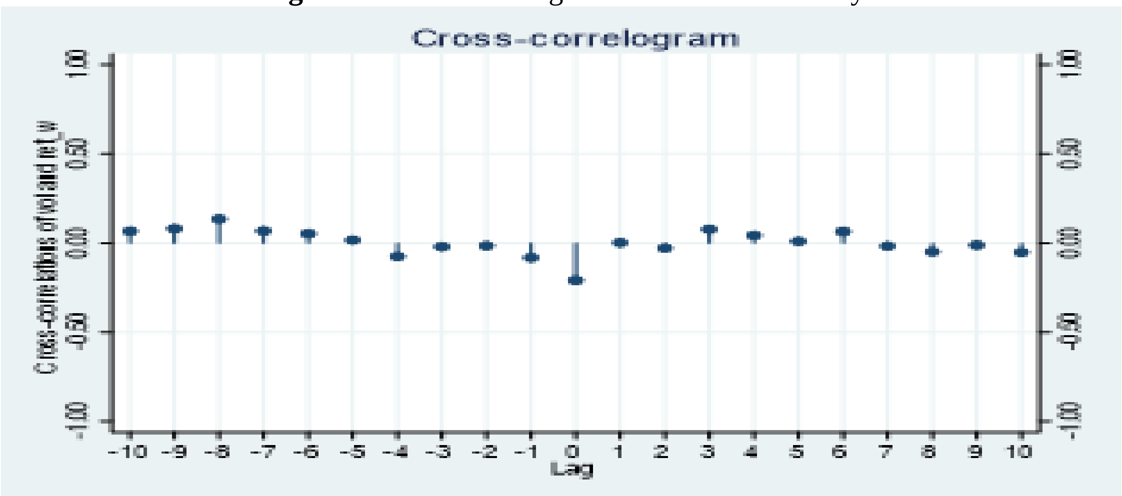


Figure 2. Cross-Correlogram Return and Volatility



According to the results, Cross-Corellogram Lag (0) suggests a negative association between the two time series variables. The cross-correlogram data are presented below in a tabular format for easier interpretation in order to better identify the link.

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Figure 3. Cross-Corellation Return dan Trend Table

LAG	CORR	-1 0 1 [Cross-correlation]
-10	0.0670	
-9	0.0811	
-8	0.1352	
-7	0.0685	
-6	0.0534	
-5	0.0175	
-4	-0.0759	
-3	-0.0202	
-2	-0.0147	
-1	-0.0830	
0	-0.2091	
1	0.0020	
2	-0.0286	
3	0.0768	
4	0.0426	
5	0.0102	
6	0.0652	
7	-0.0165	
8	-0.0490	
9	-0.0112	
10	-0.0521	

LAG	CORR	-1 0 1 [Cross-correlation]
-10	0.0602	
-9	0.0823	
-8	0.0556	
-7	0.0334	
-6	0.0282	
-5	0.0061	
-4	-0.0433	
-3	-0.0412	
-2	-0.0222	
-1	0.0121	
0	-0.0823	
1	-0.1927	
2	-0.1036	
3	-0.1184	
4	-0.0872	
5	-0.0196	
6	-0.0305	
7	-0.0489	
8	-0.0852	
9	-0.1400	
10	-0.0655	

The two tables above demonstrate a negative association at lag (0), indicating that if the trend or the number of searches for the phrase "Bitcoin" increases, Bitcoin's weekly return will plummet. Similarly, if volatility rises, Bitcoin trading will result in a lower weekly return. The table shows a substantial negative link between Return and Volatility. This illustrates how volatility has a significant impact on return. Additionally, stationarity testing is required when evaluating time-series data to determine whether a root unit exists between variables, hence validating the link between the variables in the equation. This Stationer test employs the root unit test or the Dikey-Fuller test. If a time sequence data is not stationary on order zero / level, the stationarity of the data can be explored via the following order, yielding the level of stationarity on the n^{th} order (First Difference, Second Difference, etc.). The results of the Diky-Fuller test are shown below:

Figure 4. Dicky-Fuller Stationer Test Results

```
Augmented Dickey-Fuller test for unit root

Variable: ret_w                          Number of obs  = 254
                                         Number of lags =   5

H0: Random walk without drift, d = 0

                                        Dickey-Fuller
                  Test        -------- critical value ---------
               statistic           1%           5%          10%
----------------------------------------------------------------
 Z(t)             -6.072       -3.460       -2.880       -2.570
----------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000.
```

The test findings show that at the level of data levels in the stationary state, the t-statistic results are -6.072 and the prob z(t) is 0.000. The null hypothesis for this test is that time sequence data is non-stationary. However, the test findings indicate prob Z(t) = 0.000, indicating a substantial rejection of the null hypothesis and acceptance of the alternative hypothesis that the data is stationary. Furthermore, regression was performed using the Ordinary Least Squares (OLS) approach to determine the effect of the independent variable on the dependent variable. The regression results may be seen below:

Figure 5. Regression Results with the Ordinary Least Square Method

Source	SS	df	MS
Model	.000463983	2	.000231991
Residual	.010139455	257	.000039453
Total	.010603437	259	.00004094

Number of obs	=	260
F(2, 257)	=	5.88
Prob > F	=	0.0032
R-squared	=	0.0438
Adj R-squared	=	0.0363
Root MSE	=	.00628

ret_w	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
trend	-.0000382	.0004199	-0.09	0.928	-.000865	.0007887
vol	-.1513514	.0480024	-3.15	0.002	-.2458796	-.0568233
_cons	.0022648	.0008011	2.83	0.005	.0006871	.0038424

The regression findings reveal that there is no substantial effect of the Search Volume Index, as evaluated by the trend, on bitcoin's weekly return. The t-statistic result of -0.09 with prob = 0.928 > 0.05 demonstrates that SVI has no effect on Bitcoin Return. This is possible given that the trend data utilized was Indonesian regional data with a relatively broad term, "Bitcoin". The statistical t value of -3.15 with prob = 0.002 < 0.05 shows a significant link between Bitcoin volatility and return. The regression coefficient of -0.1513 suggests a negative association, implying that increasing volatility will result in a fall in Bitcoin returns. This refers to Bitcoin assets that are deemed high risk, thus if volatility increases, so will the risk that investors must bear. Augmented Dicky Fuller (ADF) testing was utilized to confirm that data models that are not individually stationary but can be linear combinations of two or more time series data are all stationary. This test is also known as the Cointegration Test with Residual Series. If stationary results are obtained while using this residual value, the regression can be stated as a unified regression.

Figure 6. Cointegration Test Results

Augmented Dickey-Fuller test for unit root

Variable: e

Number of obs = 249
Number of lags = 10

H0: Random walk without drift, d = 0

	Test statistic	Dickey-Fuller critical value 1%	5%	10%
Z(t)	-3.459	-3.460	-2.880	-2.570

MacKinnon approximate *p*-value for Z(t) = 0.0091.

The ADF test on the residual value above yields a t-statistic value of -3.459 < -2.880, indicating a 95% residual confidence level in stationary or cointegrated situations. This describes how regression models with time series data may be used to estimate model assumptions in research. The F test results indicate values of 0.0032 < 0.05, indicating that the model meets the requirement of goodness of fit and rejects null hypotheses while admitting alternative hypotheses. All independent factors utilized in this study had a substantial influence on the dependent variable. This demonstrates that both trend and volatility influence Bitcoin's return. Furthermore, the

Portmanteau Test was employed to determine that the study's model did not exhibit any signs of heteroscedasticity. The test findings revealed that the time sequence data still followed white noise, indicating that there were no signs of heteroscedasticity (for lag-40, Prob > Chi2 = 0.5704 and lag-10, Prob > Chi2 = 0.1728, both more than 0.05). The findings are presented in the table below:

Figure 7. Portmanteau Test (lag-40)

```
Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    37.7861
 Prob > chi2(40)           =     0.5704
```

Figure 8. Portmanteau Test (lag-10)

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Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    14.0043
 Prob > chi2(10)           =     0.1728
```

Autocorrelation tests also need to be performed regarding assessing time series data. The

Durbin-Watson Test, Durbin's Alternative Test, and Breusch-Godfrey Test were utilized for autocorrelation analysis. The test findings demonstrated that there were no autocorrelation difficulties with the time series data utilized in the study (Durbin-Watson = 1.821, Durbin's Alternative 0.2144 > 0.05, Breusch-Godfrey 0.2122 > 0.05).

Figure 7. Autocorrelation Test

Durbin-Watson d-statistic(3, 260) = 1.821615

Durbin's alternative test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	1.543	1	0.2144

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	1.556	1	0.2122

From the results of statistical tests, it can be explained that the model used is valid to be tested and the model can be used to predict. The study's findings using OLS regression reveal that search patterns from Google patterns have no meaningful effect on Bitcoin returns from 2018 to 2022. The regression findings reveal that there is no substantial effect of the Search Volume Index, as evaluated by the trend, on bitcoin's weekly return. The T-Statistic score of -0.09 with prob = 0.928 > 0.05 implies that SVI has no affect on Bitcoin Return. This is possible given that the trend data utilized was Indonesian regional data with a relatively broad term, "Bitcoin". Other studies discovered a negative association, implying that increasing internet search activity for Bitcoin may be linked to subsequent price drops. For example, Cheah and Chu (2015) noticed that the rise in Google Trends searches for Bitcoin was followed by a period of decreasing volatility and lower prices. The negative impact of the Google Trends search volume index on Bitcoin returns can be attributed to a variety of reasons, including Herding Behavior. The rise in search activity may be due to herding tendency among investors, in which people follow the activities of others without performing sufficient investigation. This collective mindset can result in overbought market circumstances and subsequent price corrections. A surge in Google Trends searches might indicate information saturation, making it harder for investors to separate important insights from excessive information. This can lead to confusion and illogical decisions, perhaps lowering costs. A rise in search traffic might suggest that investors are becoming more speculative, either due to media hype or fear of missing out (FOMO). Such speculative activity can result in unsustainable price bubbles that inevitably burst.

Volatility testing of Bitcoin returns produced favorable findings. The statistical results show that there is a substantial association between Bitcoin volatility and return. The regression coefficient is negative, indicating that a rise in volatility will result in a fall in Bitcoin returns. This refers to Bitcoin assets that are deemed to be high risk, therefore as volatility increases, so will the risk that investors must bear. Volatility accentuates the risks connected with Bitcoin investments, discouraging risk-averse investors and making it more difficult to determine the cryptocurrency's genuine worth. Volatility prevents institutional investors, like as hedge funds and pension funds, from adopting Bitcoin in large numbers (Bouri & Gupta, 2016). Sudden price swings might cause panic selling among investors, resulting in further price drops and market instability (Yousef & Kwak, 2017; Chu & Zhang, 2017). More importantly, volatility can raise transaction costs and complicate liquidity difficulties, making it harder for investors to buy or leave holdings quickly. Furthermore, Bitcoin's volatile value makes it unsuitable as a means of trade.

4. CONCLUSION

This study aims to determine the link between Investor Sentiment as defined by the Search Volume Index, volatility, and Bitcoin Returns. The link between the three is complicated and diverse. While an increase in search traffic on Google Trends may presage a price gain, it can also indicate an increase in speculative attitude or information saturation, potentially leading to price decreases. Volatility, while sometimes seen negatively, might benefit Bitcoin's profitability by attracting risk-tolerant investors, driving trading activity, and allowing hedging and arbitrage. However, volatility creates considerable dangers, discouraging risk-averse investors, impeding institutional adoption, and limiting Bitcoin's practical utility as a means of exchange. Finally, the influence of investor mood via SVI and volatility on Bitcoin returns is determined by several factors, including market sentiment, changes in regulations, and technological breakthroughs. As Bitcoin and its ecosystem grow, the mechanics of this connection may shift. Further investigation is needed to properly understand how these variables interact and what they mean for Bitcoin's long-term trajectory. The following study may leverage SVI by using considerably more particular terms, resulting in much more targeted trend measurements. In addition, future studies can define volatility assessments more accurately based on daily, weekly, and monthly measurement findings, capturing the core of volatility. Furthermore, future studies can incorporate other factors linked to market performance, industry, and macroeconomics to better understand complicated interactions.

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