

The Impact of Investor Sentiment on Value and Growth Stocks Return

1st Suchi Gamella Putri* ^a

2nd Tafdil Husni ^a

3rd Rida Rahim ^a  <https://orcid.org/0000-0001-7493-9860>

^a Faculty of Economics and Business, Universitas Andalas

Abstract

The aim of this research is to investigate the impact of investor sentiment on value and stocks return. Two investor sentiment indicators, volatility index VIX and sentiment index are used as independent variables. Technical proxies (relative strength index, psychological line index, trading volumes and adjusted turnover rate) are used to construct sentiment index using principal component analysis. The dependent variable is value and growth stocks return formed based on the book to market ratio. Three Fama-French factors are used as control variables to isolate the impact of investor sentiment from systematic risk and fundamental factors. We use companies listed on Kompas 100 index over the sample period February 2017-January 2023. The sampling technique was carried out by purposive sampling and obtained 45 companies as the research samples. The empirical analysis employs multiple regression analysis using 1.385 daily time series computed by Microsoft Excel and Stata 13. The regression results indicate that volatility index VIX has a negative significant effect on value and growth stocks return. Sentiment index has a positive and significant effect on value stocks return but does not have a significant effect on growth stocks return. Investor sentiment has a greater effect on value stocks than growth stocks.

Keywords: Investor Sentiment, Stocks Return, Volatility Index VIX, Sentiment Index

*Correspondence: 1920522059_suchi@student.unand.ac.id

1. Introduction

Investment in the Indonesian capital market always increases every year. Statistical data in table 1.1 based on the Financial Services Authority shows that capital market activity grew positively from year to year despite being faced with the Covid-19 pandemic situation in 2019-2021. The performance of the Stock Price Index (JCI) reached a level of 6,850.62 at the close of the end of 2022, an increase compared to previous years. This was the highest trading close in six years. Trading activities of the Indonesia Stock Exchange in the last six years have also increased. This is reflected in the average trading frequency at the end of 2022 at 1.04 million times per day and the highest record at the end of 2021 which grew 91 percent to 1.31 million times per day at the end of 2021 compared to the previous year. This makes the trading liquidity of the Indonesia Stock Exchange higher than other exchanges in the Southeast Asian region (KSEI, 2021)

The number of investors in the Indonesian Capital Market increased by 2.75 million *Single Investor Identification*(SID) at the end of 2022 to 10.24 million. A drastic increase occurred in 2021, which was 93 percent reaching 7.49 million *Single Investor Identification*(SID) which was previously only 3.88 million SID in 2020. The increase has been nearly ninefold over the past six years from 1.12 million investors in 2017. In addition, stock investors also rose to 5.5 million SID in 2022. The increase occurred up to eight times compared to 2017 which was only 638 thousand SID. Based on an article on the Kontan website, observers assess changes in community behavior with increasing public awareness to invest (Putriadita, 2021).

Table 1 JCI Statistical Data, Average Trading Frequency/Day, Capital Market and Stock Investors for 2017 – 2022

Year	Jakarta Composite Index (JCI)	Average Trading Frequency/Day	Capital Market Investor (SID)	Stock Investor (SID)
2022	6.850,62	1.046.352	10.242.207	5.507.555
2021	6.581,48	1.317.470	7.489.337	3.451.513
2020	5.979,07	688.050	3.880.753	1.695.268
2019	6.299,54	500.139	2.484.354	1.104.610
2018	6.194,50	389.972	1.619.372	852.240
2017	6.355,65	315.034	1.122.668	628.491

Source: OJK, data reprocessed

Investing in the capital market based on the financial function has the aim of obtaining profits for parties who allocate their funds in accordance with the type of investment chosen (Agustin, 2019). Investors who are well informed and diligent in planning investments will achieve good financial goals (H. K. Baker & Puttonen, 2019). Investors need to analyze more information to synchronize with stock returns (Hou et al., 2020).



In the concept of efficient markets, the available information plays an important role and naturally influences the functions of pricing, allocation and performance measurement in the investment process (Schoenmaker & Schramade, 2019). There are three forms of the efficient market hypothesis: weak, semi-strong, and strong, all of which assert that prices reflect available information (Bodie et al., 2018). So investors cannot beat the market systematically because information is available to everyone (Schoenmaker & Schramade, 2019). This theory assumes investors think rationally and always make the right investment decisions so that they affect asset prices and are aligned with the market (Sharma & Kumar, 2019).

In reality, not all investors think rationally. Some research in Indonesia such as Agustin (2019) tested the theory of the efficient market hypothesis of the Indonesian Sharia Stock Index (ISSI) in 2017-2019 and declared ISSI inefficient in weak form. Inefficiency is caused by Indonesian stock price movements influenced by the dominance of individual or retail investors in trading activities. Where individual investors often exhibit irrational behavior resulting in inefficient market conditions. Malini (2019) tested the market efficient weak form on the LQ 45 Index in 2013-2018 and stated the LQ 45 Index was not entirely efficient because it found anomalies whereby investors could secure abnormal returns on any given day (*Monday effect*). LQ 45 investors tend to form patterns of behavior *wait and see* to certain news and events that will affect stock prices so that these anomalies occur. Rahim et al. (2021) declaring Indonesia's stock market inefficient in half-strong form, there are abnormal returns due to the presence of *panic selling* due to fear of pandemic uncertainty. This means that efficient market theory does not capture the entire investment dynamics and irrationality of investors (Sundaram, 2020).

Financial behavioral theory explains the existence of bias in decision making resulting in anomalies and speculation in the stock market (Sharma & Kumar, 2019). Behavioral financial theory suggests that irrationality has important implications for markets, which can be overvalued or undervalued for long periods of time (Schoenmaker & Schramade, 2019). One of the irrational factors investors have in financial behavior is emotion. Investors form beliefs in investment decisions by engaging sentiments represented by emotions of excitement, greed, hope, and fear (Aggarwal, 2022). Sentiment related to emotions, both optimistic and pessimistic can influence investment decisions and have an impact on asset prices (Reis & Pinho, 2020b).

Investor sentiment in developing countries will be mixed compared to developed countries. Unique interpersonal culture, regulatory framework on information disclosure, volatile and volatile companies, and a greater number of retail investors than institutional investors are some of the main reasons behind sentiment bias trading in emerging market financials (Chung et al., 2017).

Investor sentiment analysis helps us understand investors' tendency to invest in certain financial instruments or products (Sundaram, 2020). The majority of investors are frequent making mistakes due to sentiment factors, even the smallest mistake leads to deviations in market prices (Aggarwal, 2022). Investors as market participants tend to be biased and emotional in making decisions and this behavior plays an influential role in asset prices (Sharma & Kumar, 2019). In theory, negative sentiment will push a stock price below its fundamental value, resulting in a small average return (Smales, 2017b). High investor sentiment causes the stock market to rise (*bullish*) and can create trading noise (*noise trading*) (López-Cabarcos et al., 2020). This implies that investor sentiment has a role to play in the dynamics of asset returns (K. Kim et al., 2019). Based on this statement, a research gap was found on the effect of investor sentiment on stock returns.

Given that the character of sentiment cannot be observed, only proxies are available, testing is needed to assess its ability to assess stock returns (Aggarwal, 2022). Sentiment can be measured based on market-based data, survey data, and computational techniques-based sentiment analysis, and other measures to represent sentiment and to forecast market movements (Reis & Pinho, 2020a).

The volatility index (VIX) is a market-based sentiment that represents investor fears (Aggarwal, 2022). In the beginning, volatility indices were designed to express a view of the expected future volatility of the stock market (Liao et al., 2021). If the VIX is higher, the greater the fear in the market and it happens because investors choose options *Put* to avoid higher risk, so that market volatility increases (Smales, 2017a). However, in its development, the VIX index has a wider range of applications, especially as an indicator of sentiment towards stock returns. Smales (2017b) stated the VIX sentiment measure was superior in terms of providing an explanation for market returns. Reis and Pinho (2020b) states the VIX as a prospective sentiment variable featuring strong causality and predictability effects for stock returns. Liao et al. (2021) states that the VIX affects stock prices thus advising investors to observe the movement of the VIX index in order to profit from stock returns. To see its effect on the Indonesian stock market, this study chose the volatility index as a proxy for investor sentiment.

Many previous studies have used market-based sentiment proxies in forming sentiment indices to examine issues of investor sentiment and stock returns (B. Kim & Suh, 2021). The sentiment index is a comprehensive measurement formed from several market proxies using analysis of key components. One approach that is quite popular among academics is the Baker and Wugler Sentiment Index (*BW Index*), by utilizing popular market ratios and macro variables as proxies and simplified in the form of sentiment indices (Aggarwal, 2022). Seok et al. (2019)

Stated market sentiment information and data are often insufficient for emerging markets. Furthermore, the size of a broad market may not precisely capture the sentiments, motives, expectations and beliefs of investors investing in a company. For this reason, a sentiment index is created that is measured based on technical proxies, such as: *relative strength index (RSI)*, *psychological line index (PLI)*, *logarithm of trading volume (LTV)* and *adjusted turnover rate (ATR)* so it can be used as a meaningful indicator for developing countries (C. Yang & Zhou, 2015; H. Yang et al., 2017). This sentiment index is built from easily accessible data (Seok et al., 2019). The advantage of this sentiment index is that it uses data with high intervals (daily), data is easy to obtain considering emerging market data often suffers from insufficient data problems, and can capture the trading behavior and expectations of speculative traders (H. Yang et al., 2017). This index is then used by academics from emerging markets to see how it affects stock returns, such as: China (C. Yang & Zhou, 2015) Korean (K. Kim et al., 2019; Seok et al., 2019; H. Yang et al., 2017), and Thailand (Rodjuhntong, 2020). Seeing that this sentiment index can represent the confidence of Indonesian investors as a developing country, this study uses a sentiment index based on technical analysis as an indicator of investor sentiment to see its effect on stock returns in Indonesia.

Research conducts portfolio formation based on stock valuations (*growth* and *value stocks*) To see the difference in the influence of investor sentiment on the stock returns of both portfolios. Research using ratio values *Book to Market* to distinguish the two portfolios. *Growth stocks* Classified as a company that has a value ratio *Book to Market* the low, while *Value stocks* is the opposite, namely a company that has a value ratio *Book to Market* the high (Fama & French, 1998). Although empirical research generally states that *Value stocks* on average has a higher return compared to *Growth stocks*, but investors have a tendency to over-behave patterns toward information and technology, so they bid too high for stocks *Growth stocks* that causes *Overpriced* While stock price *Value stocks* fell well below its value based on fundamentals (Gagliolo & Cardullo, 2020). *Value stocks* It generally has a history of poor performance and when investors project past growth into the future, favorable sentiment is created for *Growth stocks*. Investors are more interested in investing in growth stocks than stocks that have weak past performance. This phenomenon is also used by *Fund Manager* who prefer well-performing stocks to make their portfolios attractive to potential investors. Due to arbitration limitations, patterns *mispricing* This happens over a long period of time (Chan & Lakonishok, 2004).

From a psychological perspective, investing in both value and growth stocks is influenced by investor sentiment bias (Byun et al., 2015). Yang and Zhou (2015) Different states of influence are generated by investor sentiment on each different portfolio based on stock valuations. Forming a portfolio based on company value and size is a great way to determine the effect of sentiment on assets (Smales, 2017b). Ding et al., (2019) indicates that investor misperceptions can affect asset prices *Cross-sectional*. Seok et al. (2019) states the effect of investor sentiment becomes stronger when explaining price dynamics *Value stock* and *growth stock*. Wang et al. (2021) Stated investor sentiment has an impact on returns on the size and valuation of different stocks in developed and emerging markets.

2. Literature Review

Efficient Market Hypothesis Theory

By Bodie et al. (2018) The efficient market hypothesis is that stock prices already reflect all available information. This concept helps in understanding the pricing mechanism taking place in the market.

There are three forms of efficient market hypotheses based on: Bodie et al. (2018), among others:

- a. *Weak form*; i.e. stock prices already reflect all the information that can be obtained by examining market trading data such as past price history or trading volume. This hypothesis states investors cannot predict future market performance from past stock data.
- b. *Semistrong form*; states that all publicly available information regarding the company's prospects must already be reflected in the share price. Such information includes, in addition to past prices, fundamental data on the company's product lines, management quality, balance sheet composition, patents held, revenue forecasts, and accounting practices.
- c. *Strong form*; that the stock price reflects all information relevant to the company, even including information that is only available to company insiders (information that is not published).

Behavioral Financial Theory

Behavioral finance combines psychological, behavioral and cognitive theories with conventional economics and finance to explain inefficient markets (H. K. Baker & Nofsinger, 2010). The assumption of financial behavior is that the information structure and characteristics of market participants systematically influence individual

investment decisions as well as market outcomes, whereby the human brain often processes information using shortcuts and emotions resulting in financial decisions that seem irrational, routinely violates the concept of risk aversion, and makes predictable errors in their forecasts. The impact of these financial decisions has consequences for capital market efficiency, personal wealth, and company performance.

By Bodie et al. (2018) Conventional theory assumes that investors are rational, whereas behavioral financial theory assumes that investors are irrational. Irrationality results in investors not always processing information correctly so they often make inconsistent decisions that lead to errors in future returns.

López-Cabarcos et al. (2020) Behavioral financial theory began to develop and be applied to finance to explain market anomalies that efficient market theory failed to explain. This theory considers that investors are not always rational and explains the behavior of investors making decisions from a psychological and sociological perspective. When investors make decisions, their sentiments and state of mind influence those decisions.

Investor Sentiment

M. Baker and Wurgler (2006) It defines investor sentiment in two parts, first in terms of propensity to speculate and second, in terms of investor optimism/pessimism about future stock market activity. Bodie et al. (2018) defines sentiment as a general level of optimism among investors. Reis and Pinho (2020b) Expressing sentiment relates to an investor's emotions, beliefs, distrust, level of optimism or pessimism that are capable of influencing investment decisions. Sentiment comes from ongoing opinions or ideas that reflect feelings about a particular situation. Sentiment can give an idea of the ongoing state of the economy.

Investor Sentiment Measurement

According to Aggarwal (2022) Investor sentiment can be measured by various sentiment indicators. Academics try to develop proxies for sentiment assessment, whereas practitioners focus more on using different sentiment proxies to obtain more favorable guidelines for use in the market. In general, investor sentiment measurement can be divided into three subgroups, namely: Measurement based on market data, survey data, and sentiment analysis based on computational data.

Proxies with a market data approach interpret sentiment as exogenous. Market data is indirectly considered a measure of sentiment. This indicator reveals investors' enthusiasm for trading and the opportunities they see in the market. Examples of measurements based on market data such as: stock price, trading volume, volatility, and comprehensive measurement of sentiment indices. The approach with survey data allows direct measurement of sentiment, for example the consumer confidence index. The survey approach can separate the sentiment of small and large investors because types of investors have different opinions regarding the state of the economy. However, this approach has challenges in capturing sentiment, such as the repression of survey participants who may be doubtful and sample rates that do not necessarily explain actual market behavior. Measurement with computational data is an indirect gauge of investor sentiment. This sentiment analysis collects text data from various media such as blogs, journals, and social media, then processed with computational techniques to become sentiment indicators. The limitations of this approach are the subjectivity and possible measurement errors due to the techniques and sources used.

Volatility Index (VIX)

The most well-known measure of volatility is *Chicago Board Options Exchange Volatility Index* (CBOE VIX). The VIX index is a volatility index consisting of options rather than stocks, with the price of each option reflecting the market's expectation of future volatility (Cboe, 2022).

By Smales (2022), The VIX index is calculated using a price range *mid-quote* from options *Call and Put* on the S&P500 Index. The calculation yields a measure of the expected volatility of 30 days in the United States stock market. The VIX quoted in percentage points then translates to S&P500 Index movement expectations over the next 30-day period then divided by a year. For example, if the VIX is 20, the S&P500 is expected to have a range of $\pm 5.77\%$ (or $20\sqrt{12/12}$) in the next 30 days.

Investor Sentiment Index

By H. Yang et al. (2017), the sentiment index is an index formed based on the incorporation of sentiment proxies using the analysis of the main components initiated by Baker & Wurgler (2006). Key component analysis is particularly useful because it summarizes the information contained in big data tables into indexes that can be analyzed more easily and provide more efficient explanations for time series data (Phan et al., 2023). Sentiment proxies Formed based on technical indicators, namely: *relative strength index (RSI)*, *psychological line index (PLI)*, *logarithm of trading volume (LTV)* and *adjusted turnover rate (ATR)*:

- *Relative strength index (RSI)*, developed by J. Welles Wilder Jr., represents the relative strength of rising and falling pressure on stock prices by indicating whether the stock is *Oversold* or *Overbought* (Seok et al., 2019).
- *Psychological line index (PLI)*, reflects short-term price reversals and investors' psychological stability by calculating the amount of stock price movement (Seok et al., 2019). For a stock, when the indicator is above 50, buyers control the market and general sentiment towards the stock is expected to improve. Similarly, when it is below 50, sellers of the stock are dominant in the market and overall sentiment is considered to be declining. If it moves along the 50 zone, it indicates the balance between buyers and sellers causing the market *Sideways* (Phuong, 2020).
- *Logarithm of trading volume (LTV)*. Trading volume, or more generally liquidity, reflects investor expectations and prospects for a stock and can be seen as a proxy of investor sentiment (Seok et al., 2019).
- *Adjusted turnover rate (ATR)*. Level *turnover* reflects liquidity and can be used to distinguish between optimistic and pessimistic sentiment (Seok et al., 2019).

Stock Portfolio Return

In theory, the meaning of stock returns or *return* Investing in risky assets must always have positive rewards to encourage risk-averse investors (Bodie et al., 2018). According to Tandelilin (2017), *return* Become the motivation of investors to invest and in return to bear the risks of investing.

The use of portfolios as a benchmark for performance evaluation has been documented by Fama and French (Bodie et al., 2018). Fama and French (1992) in Bodie et al. (2018) states that company size and ratio *Book to Market* can predict stock returns. Ratio *Book to Market* A high B/M is an indication that a company's value is driven by existing assets, not by future growth prospects. This is referred to as *Value Firm*. Instead *Growth Firm* has a ratio *Book to Market* which is low and is a type of company whose market value comes mostly from broad growth. Fama and French also found that historically *Value Firm* has a higher return than *growth firm*.

Following the Fama-French classification, portfolio *Value stocks* formed from companies that are ranked in the top 30% of the ratio *Book to Market* (B/M), and companies ranked in the bottom 30% as *Growth stocks* (Smales, 2017b).

3. Research Methods

The essence of research design is a plan based on research questions, a guide to selecting sources and types of information, a framework for determining relationships among research variables and an outline of procedures for each research activity (Cooper & Schindler, 2014). This research design is a quantitative method using an experimental approach that is commonly used to establish causal relationships (Sekaran & Bougie, 2016). Experimental design is appropriate when one wants to discover whether a particular variable produces an influence on another variable (*causal explanatory*). Experiments provide the strongest support for causation hypotheses (Cooper & Schindler, 2014).

In this study, the research population is issuers listed on the Kompas 100 Index on the Indonesia Stock Exchange. The data type is *time series* data taken from daily data for the period February 1, 2017 to January 31, 2023.

In the official website of the Kompas 100 index, selected stocks included have high liquidity, large market capitalization value, fundamentals and good performance. The stocks included in the Kompas 100 are estimated to represent around 70-80% of the total market capitalization value of all stocks listed on the IDX. Thus, it is expected that investors can see the tendency in the direction of the index movement by observing the movement of the Kompas 100 index.

The sample in this study was selected from the population using *the nonprobability sampling* method, that is, the elements in the population do not have an inherent probability in those selected as sample subjects (Sekaran & Bougie, 2016). This study used purposive sampling as a sampling method. This process is limited to certain criteria that can provide the desired information, and in accordance with the determination of the researcher (Sekaran & Bougie, 2016).

This study used quantitative tests. Microsoft Office Excel and Stata 13 are used for data processing and hypothesis testing. Processing and calculation of data for dependent variables, independent variables, and control

variables using Microsoft Office Excel. While processing data in the form of *time series* data to test hypotheses using the Stata 13 application. The data analysis techniques in this study are as follows:

The data used include *variable returns*, volatility indices, sentiment indices, market risk premiums, *small minus big* and *high minus low*, all of which use a ratio scale. Data is collected based on documentation of historical data on stock prices and annual financial statements of the companies studied. Descriptive statistics which are an overview and summary of statistics for each variable will be presented in *mean*, standard deviation, maximum and minimum.

Hypothesis testing was conducted to determine the effect of volatility index and sentiment index on different returns: *return from selected growth and value stock portfolios* from Kompas 100. The test forms that can be used are significant tests (t-test), simultaneous tests (F-test), and determinant coefficients (R-squared).

a. Significant Test (*t-test*)

The t test is known as the partial test which is a type of statistical test used to determine the effect of the independent variable on the dependent variable individually. This test can be done by comparing t count with t table or by looking at the significance column on each t count.

Test criteria can be determined as follows:

- H_0 is accepted if $t \text{ count} < t \text{ table}$
- H_0 is rejected if $t \text{ count} > t \text{ table}$

With the significance value t calculate by the criteria:

- H_0 is received if the probability value t is calculated > 0.05
- H_0 is rejected if the probability value t is calculated < 0.05

b. Simultaneous Test (Statistical Test F)

The F test is used to determine the effect of independent variables together (simultaneously) on the dependent variable. F test testing is done by comparing F count with F table.

Test criteria can be determined as follows:

- H_0 is accepted if $F \text{ counts} < F \text{ table}$
- H_0 is rejected if $F \text{ counts} > F \text{ table}$

With the significance value of F-stat with the criteria:

- H_0 is accepted if the sign value. $F\text{-stat} > \alpha$ ($\alpha = 0.05$)
- H_0 is rejected if the sign value. $F\text{-stat} < \alpha$ ($\alpha = 0.05$)

c. Coefficient of Determination (*R-Squared*)

The coefficient of determination or R-squared is an important measure in regression because it can inform whether or not the regression model is estimated or used to measure how much influence the independent variable has on the dependent variable. The coefficient of determination is basically to measure the correctness of the regression model. The measure of the coefficient of determination is between zero and one. If the value of the *R square* is close to one then the regression model is said to be good, meaning that the ability of the independent variable provides almost all the information needed to estimate or predict the dependent variable. And vice versa, if the *R square* is close to zero, the regression model is said to be less good because the influence of the independent variable will be smaller on the dependent variable.

4. Results and Discussion

Description of the object of study

This study uses issuers listed on the Indonesia Kompas 100 Index to analyze the effect of the volatility index and sentiment index as independent variables on stock returns as dependent variables, which are formed based on *portfolios of value stocks* and *growth stocks*. Data from 45 issuers that met the research sample criteria were

used to form a sentiment index (with RSI, PLI, LTV, and ATR indicators) and control variables. The list of issuers each year in forming a portfolio of *value stocks* and *growth stocks* is presented in table 4.1. The study used data for the period February 1, 2017 to January 31, 2023 and obtained 1,385 daily data by deleting 121 days of asynchronous and problematic data.

Table 2. List of Issuers for Each Portfolio

Year	Value Stocks		Growth Stocks	
2017	CTRA	INCO	UNVR	ICBP
	LPKR	INDY	HMSP	TLKM
	PTPP	WIKA	LPPF	BBCA
	BSDE	TINS	TBIG	GGRM
	AALI	ELSA	SCMA	AKRA
	ADRO	ANTM	KLBF	INTP
	LSIP	MEDC	ACES	PWON
	INCO	PTPP	HMSP	KLBF
2018	BBTN	TINS	UNVR	TBIG
	LSIP	LPKR	LPPF	BBCA
	BSDE	ELSA	CPIN	TLKM
	WIKA	ADRO	SCMA	GGRM
	MNCN	MEDC	ACES	PTBA
	ANTM	INDY	ICBP	INTP
	BBNI	BBTN	UNVR	CPIN
	LSIP	BSDE	BRPT	KLBF
2019	TINS	PTPP	HMSP	BBCA
	ANTM	EDC	LPPF	SCMA
	WIKA	ELSA	TBIG	TLKM
	ITMG	LPKR	ACES	INTP
	ADRO	INDY	ICBP	BBRI
	WIKA	LSIP	UNVR	BBCA
	AALI	INDY	SCMA	TBIG
	MNCN	BBTN	HMSP	KLBF
2020	CTRA	ADRO	LPPF	ICBP
	PTPP	BSDE	ACES	TLKM
	BBNI	LPKR	BRPT	BBRI
	EDC	ELSA	CPIN	ANTM
	CTRA	MEDC	LPPF	HMSP
	BBNI	WIKA	UNVR	SCMA
	GGRM	INDY	TBIG	TLKM
	AALI	BSDE	BBCA	BRPT
2021	BBTN	PTPP	ACES	ICBP
	LSIP	ELSA	CPIN	ANTM
	MNCN	LPKR	KLBF	INTP
	SMGR	MNCN	LPPF	ICBP
	JSMR	BSDE	UNVR	TLKM
	CTRA	WIKA	TBIG	BRPT
	INDY	ELSA	KLBF	AKRA
	AALI	BBTN	BBCA	BBRI
2022	LSIP	PTPP	CPIN	SCMA
	GGRM	LPKR	HMSP	BMRI
	JSMR	BSDE	LPPF	ICBP
	ADRO	BBTN	UNVR	BRPT
	CTRA	ELSA	KLBF	TLKM
	GGRM	MNCN	BBCA	AKRA
	AALI	WIKA	TBIG	BBRI
	INDY	PTPP	HMSP	ANTM
2023	LSIP	LPKR	CPIN	SCMA

Shaping the Sentiment Index

The sentiment index is formed based on the technical indicators RSI, PLI, LTV, and ATR based on the main analysis components and linear regression analysis controlled the market risk premium. The residual value of the regression result is a sentiment index which is then used as an independent variable. Based on table 3, the correlation between sentiment index indicators is positive. RSI and PLI show a stronger correlation compared to other sentiment indicators. In other words, the higher the RSI value, the overbought market conditions that make the stock trend *bullish*. The value of PLI also rose and caused general sentiment towards stocks to increase.

Table 3. Correlation Matrix Between Sentiment Index Indicators

	RSI	PLI	LTV	ATR
RSI	1,0000			
PLI	0,7164	1,0000		
LTV	0,2833	0,1928	1,0000	
ATR	0,2385	0,2257	0,1419	1,0000

Table 4 shows 1,385 observational data for each indicator. RSI, PLI, and LTV have symmetrical distributions. This can be seen from the mean and median values that are close to the same, while the ATR data is distributed asymmetrically, as seen from the average value that is lower than the median. This indicates that the distribution of ATR data is skewed towards lower values. RSI and PLI have high standard deviation values indicating high volatility. This can also be seen from the minimum and maximum values of RSI and PLI which differ very much. Thus, there are days that have low sentiment and *oversold* market conditions make stock trends *bearish* and there are days that sentiment is very high that cause market conditions *to be overbought* and stock trends to be *bullish*.

Table 4 Descriptive Statistics of Sentiment Index Indicators

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
RSI	1.385	50,85642	50,27076	15,76176	10,12365	92,55256
PLI	1.385	50,32491	50	13,82634	16,66667	83,33334
LTV	1.385	21,22096	21,17043	0,375938	20,32084	22,93473
ATR	1.385	0,0001383	0,0007943	0,001511	-0,0071142	0,004427

Table 5. KMO Test and First Component of Main Component Analysis

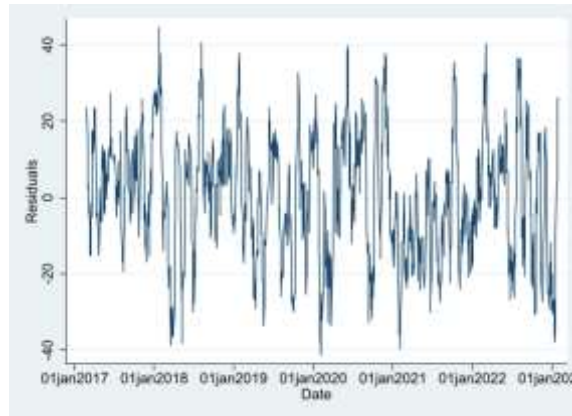
Variable	KMO	Comp1 (F)
RSI	0,5528	0,6271
PLI	0,5544	0,6058
LTV	0,7405	0,3499
ATR	0,8521	0,3426
<i>Overall</i>	0,5842	

Furthermore, principal component analysis (PCA test) is used to simplify the sentiment indicator component. The overall Keyser-Meyer-Olkin test (KMO test) result is 0.5842 which can be seen in table 5. The overall KMO test value is greater than 0.5. This suggests major component analysis is feasible for the sample. The first component (F) (table 4.4) of the principal component analysis is used to obtain the *parsimonious value of* the sentiment index (S) with equation 16:

$$S_t = 0,6271RSI_t + 0,6058PLI_t + 0,3499LTV_t + 0,3426ATR_t \quad (16)$$

Linear regression is performed to remove market risk from the sentiment index and produce equation 17. Residual (obtained from the regression is the value of the sentiment index (IS). ε_t)

$$S_t = 84,92688 + 334,604RMRF_t + \varepsilon_t \quad (17)$$



Picture 1. Daily Sentiment Index Chart Illustration

The sentiment index is plotted to a graph based on daily data as per figure 1. The chart illustration shows that there is sentiment variation. There are times when sentiment goes too high and falls too steeply. This needs to be considered so as not to cause problems in future tests.

Hypothesis Testing

Hypothesis testing is carried out by significant test (*t-test*), simultaneous test (*F-test*) and coefficient of determination (*R-squared*), which are as follows:

Significant Test (*t-test*)

The significant test aims to determine the effect of the independent variable on the dependent variable individually. The test results can be seen in table 4.7. In the *value stock* portfolio, the VIX variable produces a calculated *t* value of -10.93 with a probability (significant) value of 0.00. The probability value of the VIX variable is less than alpha 0.001, hence H_0 is rejected. So it can be concluded that the volatility index has a significant effect on the return of *value stocks* with a confidence level of 99.9 percent. The IS variable yields a calculated *t* value of 1.99 with a probability value of 0.047. The probability value (significant) of the IS variable is smaller than alpha 0.05, hence H_0 is rejected. So it can be concluded that the sentiment index has a significant effect on the return of *value stocks* with a confidence level of 95 percent.

In *growth stocks*, the VIX variable produces a calculated *t*-value of -8.36 with a probability (significant) value of 0.00. The probability value of the VIX variable is less than alpha 0.001, hence H_0 is rejected. So it can be concluded that the volatility index has a significant effect on the return of *growth stocks* with a confidence level of 99.9 percent. The IS variable produces a calculated *t* value of 0.64 with a probability value of 0.520. The probability (significant) value of the variable IS greater than alpha 0.05, hence H_0 is accepted. So it can be concluded that the sentiment index does not have a significant effect on the return of *growth stocks*.

Simultaneous Test (*F-test*)

The simultaneous test aims to determine the effect of the independent variable on the dependent variable simultaneously. The test results can be seen in table 4.7. In the *value stocks* portfolio, a statistical *F* value of 744.2 is obtained with a probability value of 0.00. The statistical *F* probability value is less than 0.001, hence H_0 is rejected. So it can be concluded that together the independent variables of the volatility index and sentiment index and control variables have a significant effect on the return of *value stocks* with a confidence level of 99.9 percent. In the *growth stocks* portfolio, a statistical *F* value of 253.9 is obtained with a probability value of 0.00. The statistical *F* probability value is less than 0.001, hence H_0 is rejected. The conclusion is that the independent variable and the control variable together have a significant effect on the return of *growth stocks* with a confidence level of 99.9 percent.

Coefficient of Determination (*R-squared*)

The coefficient of determination is useful for measuring the correctness of regression models in explaining their dependent variables. The regression model is said to be good when the *R-squared* value is close to the value of one. In the *value stocks* portfolio model, the *R-squared* value is 0.782 which means the model can explain 78.2 percent of the variation in return *value stocks* is the contribution of the independent variable and the control variable. In the *growth stocks* portfolio model, the *R-squared* value of 0.592 which the model means can explain 59.2 percent of the variation in return of *growth stocks* is the contribution of the independent variable and the

control variable. Both regression models have a fairly good effect in providing information to estimate the value of the dependent variable.

Discussion

Based on the results of classical assumption test analysis, descriptive statistics and hypothesis tests, the discussion of the effect of volatility indices and sentiment indices on stock returns *value stocks* and *growth stocks* is as follows:

The Effect of Volatility Indices on Stock Returns

The research divides stocks into two portfolios, namely *value stocks* and *growth stocks* based on the *book-to-market ratio*. The test partially states that the volatility index variable has a negative coefficient and a probability value (significant) smaller than alpha. Thus the first hypothesis (H1a and H1b) can be accepted, that volatility indices have a negative and significant effect on the return on *value stocks* and *growth stocks*.

These results are in line with previous research. Smales (2017a) states a significant relationship between investor fear and stock returns. Lee (2019) and Shu and Chang (2019) state that the VIX is important information and has power in explaining stock returns. The VIX indicator is significantly representative of market behavior based on investor sentiment. This is because the VIX is formed based on the purchase of stock options (*put* or *call*). When the VIX value is high, it means that investors prefer to buy *put* options rather than *call options*, which indicates that investors' fears are getting bigger. This causes stock movements to tend to be *bearish*, resulting in low stock returns. Vice versa, when the VIX value is low it indicates high investor sentiment. Call options have a larger trading volume than *put* options. This causes stock movements to tend to be *bullish* resulting in high stock returns (Reis and Pinho, 2020b).

The Effect of the Sentiment Index on Stock Returns

The results of sentiment index testing have different impacts on the return of *value stocks* and *growth stocks*. The H2a hypothesis states that the sentiment index has a negative and significant effect on the return on *value stocks*. The test partially states that the sentiment index variable has a positive coefficient and a probability value (significant) smaller than alpha, then the hypothesis is rejected. Thus, the sentiment index has a positive and significant effect on the return of *value stocks*. The H2b hypothesis states that the sentiment index has a negative and significant effect on the return of *growth stocks*. The test partially states that the sentiment index variable has a positive coefficient and a probability value (significant) greater than alpha, then the hypothesis is rejected. Thus, the sentiment index has a positive but not significant effect on the return of *growth stocks*.

This result is in line with Yang, Ryu and Ryu's (2017) research which states significant positive sentiment indicates high sentiment will be followed by high returns. Vice versa, low sentiment will be followed by low returns. The significantly different returns between the two portfolios come from the Indonesian stock market not being entirely efficient. In an inefficient market, arbitrageurs are unable to balance the market immediately from *noisy traders* resulting in depressed trades for longer as sentiment persists longer. As a result, stock returns continue to increase or decrease for a certain period of time (Seok, Ryu and Ryu, 2019).

Test the Different Effects of Investor Sentiment on Stock Returns

The difference in the influence of investor sentiment from the two portfolios is seen from the value of the coefficient and significant value. The VIX sentiment coefficient is -0.000318 with t calculated at -10.93, where the probability value of 0.0 is significant alpha value of 0.1% for portfolio *value stocks*. In *growth stocks*, the VIX sentiment coefficient is -0.000309 with t calculated at -8.36 where the probability value of 0.0 is significant or less than the alpha value of 0.1%. Although the VIX has the same significant effect on the 99.9% confidence level on the returns of both portfolios, the value of the VIX coefficient of portfolio *value stocks* is slightly superior to the value of the VIX coefficient of *growth stocks*. The sentiment index has a more significant influence on the return of a *value stocks* portfolio than a *growth stocks portfolio*. This can be seen from the value of the coefficient in the portfolio *value stocks* value 0.0000247 with t count 1.99 where the probability value of 0.047 is significant or smaller than alpha 5%. While in *growth stocks portfolios*, the value of the coefficient is 0.64 with t calculated 0.64 where the probability value of 0.52 is insignificant or greater than alpha 5%. Based on these results, the hypothesis (H3) is acceptable, then investor sentiment has a significantly greater influence on the return of *value stocks* compared to *growth stocks*.

These results are consistent with previous studies, Yang, Ryu and Ryu (2017) and Seok, Ryu and Ryu (2019) which found that the influence of investor sentiment becomes stronger when explaining the price dynamics of *value stocks* than *growth stocks*. Investor sentiment has a greater effect on small stocks, low valuations, high *book-to-market* ratios, high volatility, stocks that are widely traded by individual investors. They argue the cause of the discrepancy is due to investors' preference for company size and stock price. Institutional investors are considered more rational, experienced and better informed than individual investors who have biased behavior.

Institutional investors who are less affected by investor sentiment and biased behavior, prefer large-sized stocks and more glamorous stocks such as *growth stocks* because these stocks are easier to arbitrage. While stocks that are difficult to arbitrage such as *value stocks* are more susceptible to sentiment.

5. Conclusion

Conclusion

Based on the results of research and discussion in the previous chapter, conclusions can be drawn:

1. Volatility indices have a negative and significant effect on the return on *value stocks* and *growth stocks*. The volatility index significantly represents the sentiment from the side of investors' fears. Effective volatility indices are used to enhance the benefits of portfolio diversification.
2. The sentiment index has a positive and significant effect on the return of *value stocks* but does not affect *growth stocks*. This happened because the Indonesian stock market was not entirely efficient. Arbitrators are unable to balance the market immediately from *noisy traders*, resulting in depressed trades longer because sentiment lasts longer and affects stock returns on portfolio *value stocks*.
3. Investor sentiment has a significantly greater influence on the return on *value stocks* compared to *growth stocks*. Sentiment is more influential on stocks that are difficult to arbitrage such as *value stocks*.

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