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Interaction between Stock Return and Retail Investor Sentiment on the Indonesia Stock Market

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Abstract:
This study investigated the relationship between retail investor sentiment and stock return in Indonesian markets. The examination was based on the firm size characteristics of the big, middle, and small stock indexes obtained from Morgan Stanley Capital Indonesia (MSCI). The study assessed the monthly statistics of the Indonesia Stock Exchange (IDX) on returns on the MSCI index and stock trading volume between January 2015 and January 2021 to analyze the influence of retail investor sentiment. Retail investor sentiment as an object of research has criteria, namely stock trading volume activity carried out by individual investors registered on the IDX. We find that retail investors' irrational sentiments should have a larger impact on all stock market return indexes than their rational sentiments and retail investors' irrational sentiments had the largest impact on the middle stock return index. We also document that the all-stock returns index is significantly and negatively impacted by investor sentiment. Unlike prior research, which placed all of the blame for the negative stock market sentiment on the irrational actions of investors, the new data lends credence to the thesis that underlying economic fundamentals drive stock market returns. Since both rational and irrational emotions affect stock returns, investors can enhance their portfolio performance by considering both. This research adds to the growing literature on behavioral finance regarding the impact of retail investor sentiment on the performance of all stock indices based on firm size characteristics and adds to the understanding of the impact of retail investor sentiment on stock returns, particularly in Indonesia as a representative of an emerging market.

Keywords: retail investor sentiment, Indonesia Stock Exchange, stock returns, error correction model, vector error correction model.

印尼股市股票回报与散户投资者情绪的相互作用

摘要：
本研究调查了印度尼西亚市场散户投资者情绪与股票回报之间的关系。该检查基于从摩根士丹利资本印度尼西亚(摩根士丹利资本国际)获得的大、中、小股票指数的公司规模特征。该研究评估了印度尼西亚证券交易所（IDX）2015 年 1 月至 2021 年 1 月期间摩根士丹利资本国际指数回报率和股票交易量的月度统计数据，以分析散户投资者情绪的影响。作为研究对象的零售投资者情绪有标准，即在 IDX 上注册的个人投资者进行的股票交易量活动。我们发现散户投资者的非理性情绪对所有股票市场回报指数的影响应该大于他们的理性情绪，散户投资者的非理性情绪对中等股票回报指数的影响最大。我们还记录了全股票回报指数受到投资者情绪的显着负面影响。与之前的研究将负面股市情绪全部归咎于投资者的非理性行为不同，新数据证实了潜在经济基本面推动股市回报的论点。由于理性和非理性情绪都会影响股票回报，因此投资者可以通过同时考虑两者来提高投资组合的表现。这项研究增加了关于散户投资者情绪对基于公司规模特征的所有股票指数表现的影响的行为金融学文献，并增加了对散户投资者情绪对股票回报影响的理解，特别是在印度尼西亚作为 新兴市场的代表。

关键词：零售投资者情绪，印度尼西亚证券交易所，股票收益，误差修正模型，向量误差修正模型。

1. Introduction

The potential relationship between investor conduct and stock performance has recently been the subject of increased discussion. Given the challenges that conventional finance theory has had to address, a new school of thought has evolved in the form of behavioral finance. In a nutshell, the core tenet of behavioral finance is that certain monetary phenomena can be better known by considering scenarios where certain participants are not reasonable. In particular, it investigates situations where one or both principles supporting people's rationality are disregarded, as proposed by Barberis and Thaler (2003).

Shefrin and Statman (1994) designed a framework that engages noise and information traders in a two-way dialog regarding behavioral capital asset pricing. The study showed how certain cognitive errors affect noise traders' impact on demand. According to the findings, noise traders' attitudes are a second driver besides information, making the market inefficient.

This study used the noise trader technique as an alternative to the efficient market hypothesis due to two main premises. First, investors' irrational views and sentiments unsupported by fundamental news impact the demand for hazardous assets. Second, Shleifer and Summers (1990) defined arbitrage as trading by reasonable investors not subject to any presumption, implying possible danger. Uygur and Tas (2012) examined the language of contemporary behavioral finance. According to the study, limits to arbitrage reflect the high risks and costs linked to wagering against sentimental investors.

Black (1986) is the first to examine investor emotions, noise trading, and their impact on the financial markets. According to Black, "noise" allows for trade in financial markets but also makes them flawed. Black compares noise and information in his simplified version of the financial markets and says that investors and traders may occasionally rely on noise in the absence of reliable information. After establishing that noise trading should play an influential role in the securities demands, Trueman (1988) elaborates on why investors would logically engage in such activity.

De Long et al. (1990), based on Black's (1986) work, proposed a model, in which noise traders, working together, can affect the equilibrium price of a stock. According to their methodology, systematic risk is introduced and priced whenever investor mood causes a price to deviate from its underlying value. According to De Long et al. (1990), the allure of engaging in arbitrage is dampened by the danger introduced by the unpredictability of investor views.

A portfolio allocation model by noise traders was designed by De Long et al. (1990). The study proved that noise traders outperform rational investors in the extended run. Noise traders succeed in the extended run despite conspicuous consumption and high risk-taking levels. The study showed that the evidence against noise traders' long-term viability is less solid, countering the usual belief. A model was provided by Campbell and Kyle (1993), which developed Black's (1986) ideas where the interplay between noise and information traders influences stock prices. This signifies that noisy traders could impact stock costs because utility-maximizing investors are risk-averse.

Shleifer and Summers (1990) presented an option for the efficient demand paradigm. The study examined the importance of investor emotion and restricted arbitrage in setting stock prices. They demonstrate that the complete arbitrage speculation upon which the market efficiency theory rests is unrealistic and that the hypothesis of restricted arbitrage is a better realistic portrayal of markets for hazardous assets. Therefore, arbitrageurs may not neutralize the impacts of differences in investor presumptions on stock returns.

Several empirical studies, following the De Long et al. (1990) noise trader model, analyze how investor emotions affect stock performance (Lee et al., 2002; Brown & Cliff, 2004). Overall, the research supports the idea that retail investors' emotions tend to shift in tandem with stock market gains

The studies show investors' susceptibility to changes in popular opinion and that a company's fundamentals may be overlooked by some market participants while making investment decisions. Subsequently, stock prices could react dramatically to unexpected shifts in impulsive traders' emotions. Baker and Wurgler (2007), Barberis et al. (1998), Black (1986), De Long et al. (1990), Kumar and Lee (2006), Trueman (1988) highlighted the essence of irrational investors' trading actions in affecting stock prices.

Indonesia is a developing country with good economic growth possibilities since it has more than 270 million people and is the largest economy in Southeast Asia. Indonesia is one of the largest countries in purchasing power and public consumption. Additionally, another aspect that can be used as a basis for Indonesia's economic growth is an increase in investment activities, particularly in the capital market.

The development of JCI's market capitalization in the last five years cannot be separated from the role of growing ownership of investors who conduct activities in the Indonesian stock market, especially retail or retail investors. The number of Indonesian retail investors has increased significantly, where at the end of 2021, the number of retail investors amounted to 3.45 million or an increase of 103.60% YoY (The Indonesia Central Securities Depository (KSEI). The increase in the ownership of local retail investors is driven by the increasing awareness and knowledge of the public about investment, and the presence of information technology makes it easier to invest in the capital market.

Although local investors significantly influence stock market activities in Indonesia, compared to other countries, it is still very low. The ratio of the Indonesian population investing in the capital market is less than 5%. This is significantly behind the United States (US), Singapore, and Malaysia, with ratios of 55%, 26%, and 9%, respectively. Survey data, including the American Association of Individual Investors (AAII) and Investors Intelligence (II), are popular sentiment proxies. However, the data are unsuitable for this study because they are unavailable and may be developed differently in emerging markets, such as Indonesia.

In this research, we used data available in the Indonesian capital market and can represent retail investor sentiment. Retail investor sentiment as an object of research has criteria, namely stock trading volume activity carried out by individual investors registered on the IDX. One possible indicator of investor attitude is the volume of trades, often known as liquidity. When impulsive investors are promising and buy rising stocks, preferably than when they are gloomy and buy declining equities, they are more probable to desire to trade and, therefore, add liquidity, as shown by a prior study by Baker and Stein (2004). Several researchers, including Liao et al. (2011), Baker and Wurgler (2007), have used trading volume as a surrogate for investor presumption.

Investors regulate expectations based on new information, significantly influencing their trading volume. Information is implanted in prices and returns as well as could be noticed regarding the transformation in returns. Therefore, it is intriguing to analyze the relationship between the returns and trading volume in stock markets. The first approach authorizes supervising investors' over-confidence (Baker & Stein, 2004), while the stock market liquidity is supervised based on trading volume (Chordia et al., 2001). Otherwise, investor over-, under-confidence, and stock market liquidity empirically move jointly.

Firm characteristics are critical in determining how returns are impacted by sentiment. For instance, Lee et al. (1991) stated that sentiment affects undersized firms the most. Baker and Wurgler (2007) found that sentiment could influence harder-to-value stocks. Lemmon and Portniaguina (2006) developed a portfolio with a short and long position on large and small stocks in the US market. The high sentiment makes the returns for small stocks descend more than for large stocks in the following period. Nevertheless, Brown and Cliff (2004) did not discover an improved tendency for sentiment toward small stock returns. Berger and Turtle (2012) showed that sentiment significantly affects stocks in transparent firms. According to Zhu and Niu (2016), firms experiencing high information indecision are more influenced by sentiment. This supports Tuyon et al. (2016) that the sentiment's effect on stock prices varies based on firm size. Therefore, this study included firm-level controls in the analysis.

Brown and Cliff (2004) have hypothesized a systemic relationship between stock market outcomes and investor emotion. This is why the VAR model designed by Sims (1980) was selected as the econometric strategy for examining the hypothesized connections. We also factor in the following concerns before the estimating phase. In a perfectly competitive financial market, only the unexpected part of the explanatory factors would cause the stock market to move. Elton and Gruber (1991) stated that the multi-index model variables should be surprises unexpected from the prior values. Consequently, asset-pricing models such as arbitrage pricing theory use novel elements (innovations) of explanatory variables.

Since the formulated models are multi-index models, the knowledge gained from the current round of direct estimating is limited to how the predicted components are related. If one produces such an estimate, they risk jumping to the wrong conclusion because they dismiss the variations' effect on unpredictable aspects of investor sentiment and stock market returns. To avoid the misspecification problems, we employ the VAR model to generate robust compulsion response functions (the expected pattern of unexpected innovation or changes). Furthermore, throughout the previous two decades, VAR models surpass structural models in terms of prediction performance (Litterman, 1984; Webb, 1999).

To answer the objectives in this study, it is necessary to involve several stages, we first use the ECM model to analyze the fundamental and unreasonable components of investor attitudes and the possible impacts on stock market returns. Second, a unified model was employed to analyze how investor sentiment impacts stock market returns for retail investors. Third, the study used the generalized impulse response functions (IRFs) as well as forecast error variance decomposition (FEVD) of the VAR/VECM model. It examined how unexpected changes and Indonesian retail investors' moods affect the all-stock market return index based on firm size.

The following steps were taken to complete this research: (1) A unit root test with the help of the augmented Dickey-Fuller (ADF) test; (2) Model for Correcting Errors, Version 2 (ECM): If the variables are level-stationary in Stage 1 (ADF), then we proceed to VAR analysis; (3) VAR stability analysis; (4) Optimal lag analysis; (5) Optimal lag analysis. We will employ Johansen's co-integration approach if the variables are unmoving at the initial distinction. We shall employ a VECM strategy if the data suggest the presence of cointegration. Further analysis is required in the absence of cointegration. Therefore, we proceeded to Step 6 (analyzing the Impulse Response Function) before moving on to Step 7 (analyzing the forecast variance error decomposition) (FEVD).

The following empirical findings are derived from the error correction model (ECM) and the generalized impulses produced by a vector autoregression (VAR) or vector error correction model (VECM) model. To begin, research has shown that retail investor sentiments are navigated by rational and irrational factors, each of which has a unique impact on stock market return. While prior research (De Long et al., 1990; Shleifer & Summers, 1990) has portrayed investor sentiments as entirely irrational. Second, retail investors' irrational sentiments should have a larger impact on all stock market return indexes (i.e., big, middle, small stock) than their rational sentiments. Retail investors' irrational sentiments had the largest impact on the middle stock return index. Prior similar research by Lee et al. (1991) asserts that sentiment affects small firms (not big firms) most. Third, it showed that the all-stock returns index is significantly and negatively impacted by one-standard-deviation growth in Indonesia's rational and irrational investor sentiment. However, this observation contradicts Brown and Cliff (2004), Verma and Soydemir (2006). Finally, returns on all stock market return indexes had the most impact on all stock market return indexes itself. In contrast, the illogical sentiment was more important than rational sentiment in determining all stock market return indexes.

The findings of this research have substantial policy and investment policy implications. Unlike prior research, which placed all of the blame for the negative stock market sentiment on the irrational actions of investors, the new data lends credence to the thesis that underlying economic fundamentals drive stock market returns. Since both rational and irrational emotions affect stock returns, investors can enhance their portfolio performance by considering both. This research lends credence to the theory that investor sentiment affects the stock market return, which will aid policymakers in developing measures to stabilize investor sentiment and lessen market uncertainty and volatility.

2. Methods

In this work, we use a method for gauging investor mood in Indonesia that is analogous to that developed by Verma and Soydemir (2006) for gauging a person's attitude. The volume of trades, representing the market's liquidity, has been proposed as a barometer of investors' optimism (Baker & Stein, 2004). Trading volume has been used as a stand-in for sentiment in numerous studies, including those by Liao et al. (2011), Baker and Wurgler (2007).

For this analysis, we operate the trading volume of retail investors (SENTIt) as a sentiment of retail investors. In the asset pricing literature, we contain the following variables as fundamentals that carry nonredundant information: the rate of expansion of the Indonesian economy as indicated by the index's estimate of the percentage increase or decrease in industrial production in Indonesia. The Index of Industrial Production (IIP) measures the production level across numerous industries. Industrial Production (IIP) is a widely followed economic statistic for the manufacturing sector (Fama, 1970). The short-term interest rate is the interbank offered rate is expressed as a monthly percentage rate. The interest rate is a key metric used by investors to determine the monetary worth of their capital gains (Campbell, 1991). Sharpe (2002) defines inflation as the monthly change in the Indonesian consumer price index and uses this to determine the real return earned by investors, differences in exchange rates, and changes in the exchange rate between the Indonesian rupiah and the US dollar, as calculated by Elton and Gruber (1991). According to Asianto (2019), oil prices are tracked via monthly changes in the West Texas Intermediate price (WTI). The cost of WTI serves as a useful economic indicator. This variable indicates if the period is before or after the Covid-19 period (Ngwakwe, 2020). Because of its widespread effects on the world economy, Covid-19 has also affected Indonesian investment operations (DVC19) (Wijaya & Zunairoh, 2021). We collect information monthly beginning in January 2015 and ending in February 2021.

The fundamental and noise components of sentiments may influence stock returns since sentiments comprise reasonable expectations-based risk variables (Shleifer & Summers, 1990). It is worth noting that Hirshleifer (2001) draws parallels between expected returns, hazards, and investor misvaluation. Bullish or bearish sentiment on the part of an investor may be a reflection of the investor's reasonable expectations for the upcoming period, an expression of the investor's irrational exuberance, or a combination of the two. Thus, we begin by dissecting investor attitudes into their constituent parts: (i) a rational component founded on the facts and (ii) an irrational component founded on the noise. We use the ECM to simulate the rational and irrational consequences of fundamentals and noise on investor sentiment, then formulate Equation 1:

$$SENTI_t = \alpha_0 + \alpha_j \sum_{j=1}^{j} FUND_{jt} + \xi_t \quad (1)$$

where α_0 and β_0 are constants, α_j and β_j are the parameters to be evaluated, ξ_t while ζ_t are the random error terms. $SENTI_t$ are the changes in retail investors' sentiments at time $_t$. $FUND_{jt}$ are the fundamentals defining rational expectations founded on the risk factors carrying nonredundant information in the conditional asset pricing literature. The fitted and residual values $SENTI_t$ and ξ_t capture the rational and irrational sentiments, respectively

ECM was used when dealing with nonstationary but cointegrated variables, although this method has limitations. Since the data is not stationary but exhibits cointegration, the ECM employs this constraint on the preexisting long-term variable relationships to hasten their convergence into their cointegration relationships while permitting dynamic changes in the near term (Juanda & Junaidi, 2012).

The next part of the research examines how investor mood affects all index stock returns, given that investor sentiment can be both reasonable and irrational (Verma & Soydemir, 2006). Accordingly, Equation (2) is used to separate the rational and illogical components of sentiment variables, and the subsequent regression equation is applied in the return-generating method:

$$R_{it} = \gamma_0 + \gamma_1 SENTI_t + \gamma_2 \xi_t + \mu_t \qquad (2)$$

where R_{it} is the stock return based on firm size, γ_0 is a constant, γ_1 and γ_2 are the parameters to be evaluated, and t is the random error term. The parameters γ_1 and γ_2 capture the effects of sentiments caused by fundamental and noise trading by retail investors, respectively.

Juanda and Junaidi (2012) used economic theory for numerical information analysis of how most time series economic models are constructed. Sometimes the complexity of economic theory or the clear complexity of the current phenomena prevented the exact specifications for the model from being determined.

There were cases where the relationships between variables could not be modeled using a static set of equations, necessitating dynamic models that independently influenced each variable. The Vector Autoregressive (VAR) model provided an alternate approach for time series data. This model's data were static. Hence, it was given the name "unrestricted VAR" (VAR unlimited). As several variables exist in this research, the VAR equation describes their associations (Juanda & Junaidi, 2012). For a bivariate problem (two-variable equation) with a simultaneous causality relationship, we can write the VAR model (48).

$$y_t = b_{10} - b_{11}z_t + \gamma_{11}y_{t-1} + \gamma_{12}z_{t-1} + e_{yt} \cdots \ldots (3)$$

$$z_t = b_{20} - b_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{12}z_{t-1} + e_{zt} \cdots \ldots (4)$$

There is a mutual influence between y and z in the system. The following is a matrix notation for the two equations shown above.

$$\underbrace{\begin{bmatrix} 1 & b_{11} \\ b_{21} & 1 \end{bmatrix}}_{B} \underbrace{\begin{bmatrix} y_t \\ z_t \end{bmatrix}}_{X_t} = \underbrace{\begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix}}_{\beta_0} + \underbrace{\begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}}_{\beta_1} \underbrace{\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix}}_{X_{t-1}} + \underbrace{\begin{bmatrix} e_{yt} \\ e_{zt} \end{bmatrix}}_{et}$$

It can be written to be

$$BX_t = \beta_0 + \beta_1 X_{t-1} + e_t \ldots\ldots (5)$$

The standard form or reduced form of the VAR system is the following Equation, which is obtained by multiplying equation 3 by B^{-1} (inverse B).

$$X_t = A_0 + A_1 X_{t-1} + \varepsilon_t \ldots (6)$$

where A_0 is $B^{-1}\beta0$ (intercept), A_1 is B^{-1} $\beta1$ (vector autoregressive), εt (error).

The dynamic nature of the interaction between the variables is demonstrated by Equation 6. The shocks felt by certain variables could be neutralized by impulses against other variables. Another item that can be studied is the relative importance of different endogenous variables.

Sometimes, time series variables are not level-stationary but are first-difference-stationary. Additionally, there is a chance that they are cointegrated. The model under these constraints is known as a restricted VAR. One solution to this issue is employing a vector error correction model (VECM).

This model limits the endogenous variables' long-term linkages to joint-term relationships and incorporates the short-term dynamics. The following Equation summarizes the VECM model presented by Juanda and Junaidi (2012). Here, all variables assumed the natural logarithm form.

$$\Delta y_t = \mu_{0x} + \mu_{1xt} + \Pi_x y_{t-1} + \sum_{k=1}^{1=1} \Gamma_{ix} \Delta y_{t-1} + \varepsilon_t \ldots \ldots (7)$$

where Δyt is the variable vector BSIR, MSIR, SSIR, $SENT_{1t}$, $SENT_{2t}$, $\mu 0x$ is the intercept vector, μ_{1x} is the regression coefficient vector, and t is the time trend. Πx is $\alpha_{x\beta'}$ where b' includes a long-term cointegration equation, and yt_{-1} is variable in level. Γ_{ix} is the regression coefficient matrix, while k-1 is a VECM order of VAR $_{\varepsilon t}$ is an error term.

By running policy simulations with the VAR specification, researchers can use Monte-Carlo techniques to establish confidence bands around the estimated parameters (Hamilton, 1994). Impulse response functions describe how one variable is expected to react to a single unitary shock in another variable. They show how the series will react to pure shocks when all other variables are consistent. Confidence intervals develop almost the mean response. This is because impulse responses are the anticipated parameters' highly nonlinear expressions. The result is significant at 95% confidence when the lower and upper bands have the same sign.

The results of conventional orthogonalized estimated error variance based on the Cholesky decomposition of VAR innovations are susceptible to variable ordering (Pesaran & Shin, 1998). These misspecification issues were solved using the generalized impulses technique defined by Pesaran and Shin (1998). The technique applies orthogonal innovations independent of VAR ordering.

3. Results

3.1. Data Stationarity Test

Each variable's time-series attributes are verified using unit root tests before moving on to the main results. Checks for unit roots using the Augmented Dickey-Fuller (ADF) test are displayed in Table 1. We observed that the variables of stock index return (big, middle, and small) were level, but all were first difference stationary.

Table 1. Unit root tests (Developed by the authors)

Variable	**Level**		**The first difference**	
	ADF test result	**Prob**	**ADF test result**	**Prob**
SENTI	-2.11	0.24	-14.01	0.00*
BSIR	-7.36	0.00*	-6.88	0.00*
MSIR	-8.41	0.00*	-6.81	0.00*
SSIR	-7.74	0.00*	-8.48	0.00*
LNECR	-2.99	0.79	-9.56	0.00*
LNIPI	-2.76	0.57	-3.45	0.00*
INTR	-0.42	0.89	-5.18	0.00*
CPI	-1.41	0.13	-6.44	0.00*
LNOP	-2.48	0.07	-3.45	0.01*

Notes: * Stationary with prob < 5%; *SENTI* is the sentiments of the retail investor, BSIR is the monthly returns on the big stock index, MSIR is the monthly returns on the middle stock index, SSIR is the monthly returns on the small stock index, LNECR is the exchange rate between the Indonesian rupiah and the US dollar, LNIPI is the industrial production index of Indonesia, INTR is the interest rate, CPI is inflation, and LNOP is the oil price.

3.2. The Impact of Fundamental Variables on Retail Investor Sentiment

Using the error correction model (ECM), we explore how the fundamentals, including the effect of Covid-19 in the form of a dummy variable, may affect retail investor sentiment. This study regressed Indonesia's market fundamentals using Equation 1 on retail investor sentiments. The aim was to capture the impacts of market fundamentals and Covid-19 risk factors.

Table 2 shows a significant relationship between retail investor sentiments, industrial production index, interest rate, inflation, and oil price. The R2-value of 0.53 signifies that market fundamentals explain more than half of the variation in the retail investor sentiment. The results support previous studies that market fundamentals influence investor sentiment (Brown & Cliff, 2004; Verma & Soydemir, 2006). Additionally, these findings corroborate Brown and Cliff (2004) that investor attitudes may have rational and irrational components, as well as noise.

Table 2. The fundamentals on retail investor sentiment effect based on Equation 1 (Developed by the authors)

Dependent variable: SENTIt				
Variable	**Coefficient**	**SE**	**t-Statistic**	**Prob**
LNECR	-1.81	1.44	-1.26	0.21
LNIPI	2.22	1.11	2.00	0.05**
INTR	-0.18	0.07	-2.37	0.02**
CPI	-0.10	0.05	-2.19	0.03**
LNOP	0.48	0.21	2.28	0.03**
DVC19	-0.35	0.23	-1.55	0.12
C	32.19	11.69	2.75	0.01**
R-squared	0.53			
AIC	0.97			
SC	1.19			
Log-likelihood	-28.48			
F-statistic	12.44			
Prob (F-statistic)	0.00			

Notes: The variables are retail investor sentiments (SENTI), the exchange rate between the Indonesia Rupiah and the US dollar (LNECR), the industrial production index of Indonesia (LNIPI), interest rate (INTR), inflation (CPI), oil price (LNOP), and dummy Covid-19 (DVC19); *, **, *** Significance at the 10, 5, and 1 per cent levels, respectively.

3.3. The Causal Relationship between Rational and Irrational Retail Investor Sentiments on Stock Market Returns

We compute the rational and irrational components of retail investor sentiment for each regression using an ECM derived from Equation 1. A six-variable VECM was estimated to examine how rational and irrational retail investors' attitudes impact stock market returns based on firm size, as indicated in Equation 3. The variables considered are the big, middle, and small stock return index, as well as the retail investors' rational and irrational sentiments.

It was important to conduct unit root tests, VAR stability tests, and optimal lag tests on the pre-estimate before doing the VECM analysis. Importantly, the unit root was displayed in the multivariate time series data, making the estimation result credible thanks to this test (Juanda & Junaidi, 2012).

None of the variables was at rest at the level, but they were all at rest at the first difference. To begin, we presented the unit root of all variables using the augmented Dickey-Fuller (ADF) test, with the outcomes shown in Table 1. We observed that none of the variables was level, but all were first difference stationary. These results demonstrate a link between the two imbalances studied here throughout a relatively brief period. If we wanted to know how everything would settle out in the long run, we had to execute a cointegration test.

3.4. The Optimum VAR Lag Was at 8 Lag of 1

Roots of the characteristic polynomial for all the variables used multiplied by the delays of each VAR were used to perform the VAR stability test. Stability in a VAR system of equations is indicated if the modulus of all roots of characteristic polynomials is less than 1.

The ideal lag period for a VAR model can be found using various techniques. Table 4 displays the Lag Length Criteria and Ar Roots Graph used to establish the Lag Intervals for the Endogenous in this paper. Table 4 shows that when Lag Length Criteria are compared, a lag order of 1 is the best for the VAR model using the Schwars criterion (SC) value. This check was formerly used to remedy autocorrelation issues in VAR systems. The optimal lag proved effective for a model involving VAR and cointegration.

3.5. Three Cointegrating Vectors between All Variables

Table 5 shows that a long-term equilibrium relationship among variables was established through cointegration, implying the linear combination of nonstationary variables. The Johansen Cointegration Test was used for analysis. Table 5 displays the outcomes of a Johansen cointegration test on the big, middle, and small stock return indexes, as well as retail investors' rational and irrational sentiments. The test results indicate that the null hypothesis can be accepted at the 5% level and that three positive relationships exist. This implies that the relationships between the variables are stable and lasting. It is possible to proceed with VEC modeling if cointegration linkages are assumed to exist.

Table 4. Determining the lag intervals for the endogenous with lag length criteria (Developed by the authors)

Lag	LogL	LR	FPE	AIC	SC	HQ
1	374.3263	NA	1.25e-11	-10.91645	-10.07313*	-10.58422*
2	394.2088	33.55162	1.49e-11	-10.75652	-9.069897	-10.09208
3	426.2906	49.12531	1.23e-11	-10.97783	-8.447890	-9.981160
4	454.1305	38.27988	1.20e-11	-11.06658	-7.693324	-9.737683
5	479.1645	30.51016	1.34e-11	-11.06764	-6.851072	-9.406521
6	525.8319	49.58408*	8.12e-12	-11.74475	-6.684863	-9.751402
7	562.8786	33.57362	7.32e-12	-12.12121	-6.218011	-9.795639
8	606.1788	32.47515	6.24e-12*	-12.69309*	-5.946578	-10.03530

Table 5. Results of the cointegration test (Developed by the authors)

(a) Unrestricted Cointegration Rank Test (Trace)				
Hypothesized		**Trace**	**0.05**	
No. of CE(s)	**Eigenvalue**	**Statistic**	**Critical Value**	**Prob.****
None *	0.532993	121.1212	60.06141	0.0000
At most, 1 *	0.365711	67.06099	40.17493	0.0000
At most, 2 *	0.306479	34.73817	24.27596	0.0017
At most 3	0.105157	8.753993	12.32090	0.1839
At most 4	0.012114	0.865379	4.129906	0.4069
(a) Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized		**Max-Eigen**	**0.05**	
No. of CE(s)	**Eigenvalue**	**Statistic**	**Critical Value**	**Prob.****
None *	0.532993	54.06018	30.43961	0.0000
At most, 1 *	0.365711	32.32282	24.15921	0.0032
At most, 2 *	0.306479	25.98418	17.79730	0.0024
At most 3	0.105157	7.888614	11.22480	0.1817
At most 4	0.012114	0.865379	4.129906	0.4069

Notes: Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level; * denotes rejection of the hypothesis at the 0.05 level; ** The MacKinnon-Haug-Michelis (1999) p-values

3.6. Retail Investor Sentiment Affected Return Stock Index in the Long Run

Big, middle, and small stock return indexes were exogenous factors. Exogenous factors included retail investor sentiment, classified as rational, irrational, and retail. The VECM estimation results in Table 6 display that the return stock index is significantly and positively impacted by rational retail investor sentiment. In contrast, irrational retail investor sentiment has no effect. Rational and irrational retail investor sentiments do not affect the return stock index in the short run.

Authoritative autoregressive systems are notoriously tricky to define in a few words, according to Sims (1980). In particular, interpreting them by looking in the coefficients at the regression equations is challenging. As Sims (1980) demonstrated, doing t-tests on retail coefficients is not a good way to determine the relationships between the variables. Consider the system's reaction to typical random shocks, or IRFs, suggested by Sims (1980).

Table 6. VECM estimation results (Developed by the authors)

Variable	Coefficient	t-Statistic
D(BSIR (-1))	-0.43966	[-2.448]*
D(MSIR (-1))	0.46007	[1,252]
D(SSIR (-1))	-0.26090	[-0.965]
D(SENTI_R (-1))	-0.00887	[-0.178]
D(SENTI_IR (-1))	-0.01751	[-0.668]
CointEq1	-0.02173	[-2.083]*
Long Term		
SENTI_R (-1)	0.00614	[1.918]*
SENTI_IR (-1)	-0.10425	[-0.402]

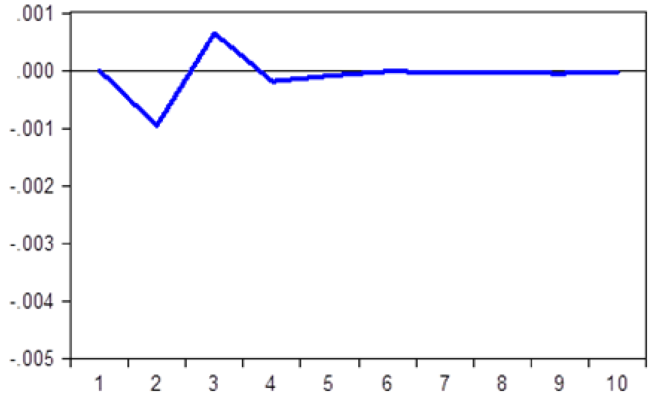
Notes: * Significant with T-stat > T-table (1.65); *SENT1_R* is the rational sentiment of the retail investor, *SENT1_IR* is the irrational sentiment of the retail investor, *BSIR* is monthly returns on the big stock index, *MSIR* is monthly returns on the middle stock index, and *SSIR* is monthly returns on the small stock index.

3.7. The Effect of the Retail Investors' Sentiments is Negative on Big Stock Index Returns

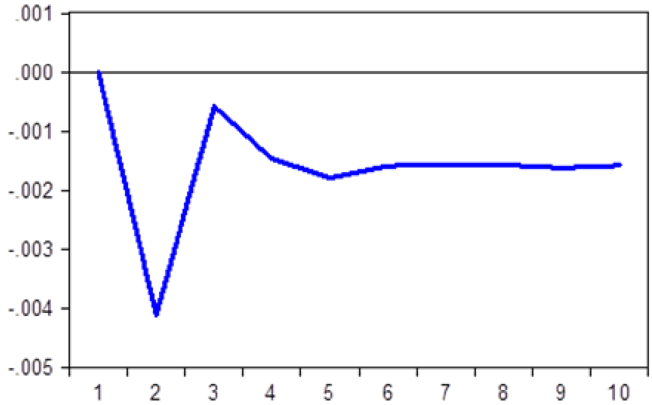
To determine how a given variable in the system reacts to a shock of magnitude one standard deviation (SD), we use the VAR model to create the generalized impulse responses. A simulation of one variable's short and long-term impulse reaction to another variable's shock is the impulse response function (IRF). Generally, short-term reactions were highly noticeable and volatile, while long-term ones were quite stable. Figure 1 displays the outcome.

Figures 1(a) and (b) show the big stock index returns' impulse responses to a one-time SD increase in the rational as well as irrational attitudes of retail investors. Big stock index returns did not react to shocks in rational retail investor attitude at the first month but dropped by -0.001 units at the second month and increased at the third month to 0.0007, fluctuated until the tenth month, and then remained relatively stable at around -0.00003 or closed to 0 units for the rest of the period. Big stock index returns did not react to irrational sentiment retail investor shocks in the first month. Still, they decreased at the second month to -0.004 units and continued to increase until the tenth month, after which they remained rather stable at around -0.0016 units. This suggested that retail investors' irrational outlooks have a major future impact on big stock index results.

The response for the retail investors' irrational attitudes significantly exceeds the response for the rational component. This means that sentiment-induced noise trading impacts big stock index returns more than fundamental trading. This finding supports De Long et al. (1990), concerning irrational investors that grow market risk by not applying the firm's fundamentals in trading.



a



b

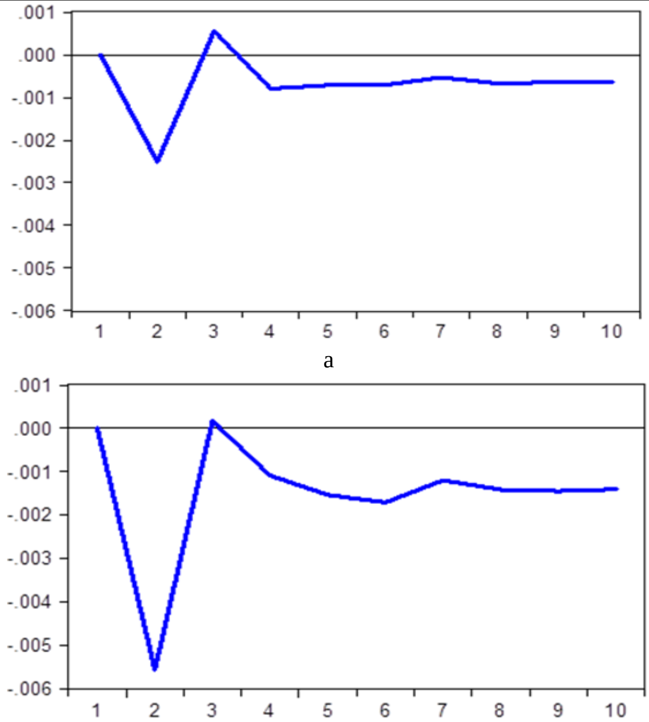
Figure 1. Response of the big stock index returns to the retail investors' rational and irrational sentiments: (a) Rational sentiments; (b) Irrational sentiments (Developed by the authors)

3.8. The Effect of Retail Investors' Sentiments is Negative on Middle Stock Index Returns

Figures 2(a) and (b) show the middle stock index returns' impulse responses to a one-time SD increase in the retail investors' rational and irrational attitudes. While middle stock index returns did not react to shocks to rational investor mood in the first month, they did so in the second month, dropping by -0.0025 units, oscillating until the tenth month, and remaining relatively stable at around 0.0006 units. This suggested that the future middle stock index returns were strongly altered in a good way by the irrational attitudes of retail investors.

Middle stock index returns did not react to irrational sentiment investor retail shocks in the first month. Still, it did respond negatively and then fluctuated until the tenth month, after which it remained relatively stable at around -0.0014 units. This means that future middle stock index returns are significantly and negatively impacted by irrational emotions.

The irrational component of retail investors owns a far larger impact on middle stock index returns than the rational component, suggesting that noisy trading driven by investor sentiment is more influential than fundamental trading driven by investor sentiment.



a

b

Figure 2. Response of the middle stock index returns to the retail investors' rational and irrational sentiments: (a) Rational sentiments; (b) Irrational sentiments (Developed by the authors)

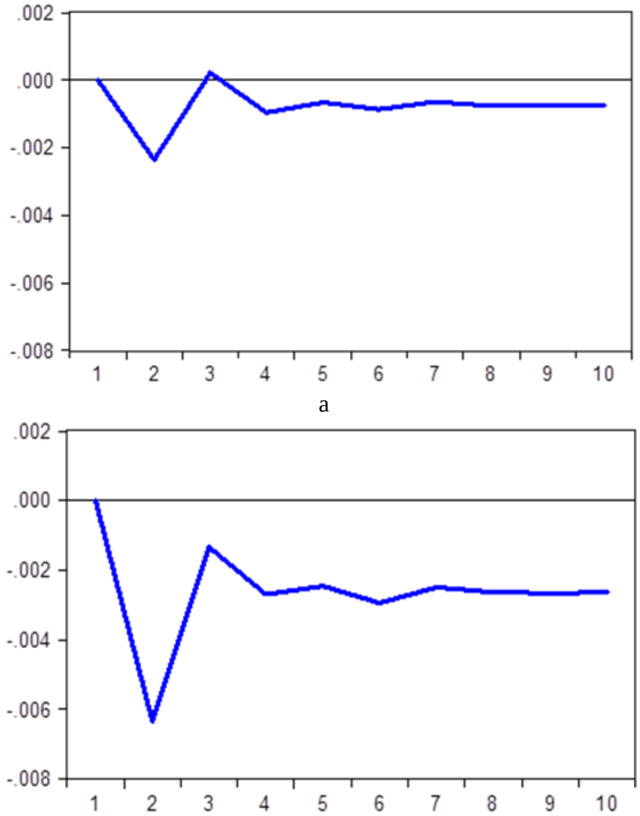
3.9. The Effect of Retail Investors' Sentiments is Negative on Small Stock Index Returns

Figures 3(a) and (b) show the small stock index returns' impulse responses to a one-time SD growth in the retail investors' rational and irrational sentiments. The small stock index did not react to retail shocks in a rational investor mood in the first month. Still, they dropped by -0.0024 units in the second month, fluctuated until the tenth month, and remained generally stable at around -0.0007.

Small stock index returns did not respond to irrational sentiment investor retail shocks in the first month, but climbed and fluctuated until the tenth month, after which they remained rather stable at around -0.003 units. This suggested that irrational optimism had a materially favorable effect on future small stock index returns.

Suppose the irrational aspects of retail investors have a larger impact than the rational aspects. In that case, this could mean that sentiment-induced noise trading has a considerably more significant impact on stock market returns than sentiments-induced fundamental trading (Alrababa'a & Saidat, 2022).

Figures 1-3 show that small stock has the greatest response compared to big and middle stocks if shocks occur from investor sentiment. This is in line with the results by Yang et al. (2017) that investor sentiment has a stronger effect on smaller companies and stocks that are heavily traded by individual investors.



a

b

Figure 3. Response of small stock index return to retail investors' rational and irrational sentiments: (a) Rational sentiments; (b) Irrational sentiments (Developed by the authors)

3.10. Irrational Sentiment Had a Bigger Contribution than Rational Sentiment to All-Stock Index Return

To foretell how much variance each variable in the VAR system will contribute to the main variable, researchers used a Forecast Error Variance Decomposition (FEVD) analysis. The FEVD pattern illustrated multivariate causation among the VAR model's variables. Table 7 displays the findings of the FEVD.

According to Table 7, the all-stock index return contribution to the return itself ranged from 100% in the first month to 94,28% (big stock index), 89,95% (middle stock index), and 89,95% (small stock index) in the tenth month. Retail investors' rational sentiments increased from 0 to 1 basis point (big stock index), 3 basis points (middle stock index), and 6 basis points (small stock index) of return in the tenth month. In contrast, irrational sentiment increased from 0 to 22 basis points (big stock index), 27 basis points (middle stock index), and 31 basis points (small stock index) of return in the tenth month.

Each period's total contribution from all these factors was always 100%. This FEVD study revealed that while all stock index returns contributed more to the all-stock index return, irrational sentiment contributed more to the all-stock index return than rational sentiment. This result is in line with research by Zunara et al. (2022), who found that JCI returns contributed more to the JCI return itself and irrational sentiment contributed more to the JCI return than rational sentiment. Furthermore, the result from FEVD is the biggest contribution of irrational sentiment is in the small stock index. According to Lee et al. (1991), sentiment affects small firms the most.

Table 7. FEVD results of contribution sentiment retail investor for stock index (Developed by the authors)

	Big stock index				**Middle stock index**				**Small stock index**			
T	**S.E.**	**BSIR**	**SENTI R**	**SENTI IR**	**S.E.**	**MSIR**	**SENTI R**	**SENTI IR**	**S.E.**	**SSIR**	**SENTI R**	**SENTI IR**
1	0,06	100,00	0,00	0,00	0,06	100,00	0,00	0,00	0,06	100,00	0,00	0,00
2	0,07	97,23	0,02	0,35	0,07	99,40	0,10	0,50	0,07	98,66	0,06	0,44
3	0,08	95,32	0,02	0,28	0,08	91,02	0,08	0,39	0,08	97,37	0,05	0,34
4	0,09	95,07	0,02	0,25	0,09	91,09	0,08	0,36	0,09	97,53	0,05	0,34
5	0,10	95,06	0,02	0,25	0,10	91,28	0,07	0,33	0,10	97,85	0,04	0,32
6	0,10	94,71	0,01	0,24	0,10	90,75	0,07	0,32	0,10	97,95	0,04	0,33
7	0,11	94,55	0,01	0,23	0,11	90,41	0,07	0,30	0,11	98,06	0,04	0,32
8	0,12	94,45	0,01	0,22	0,12	90,26	0,06	0,29	0,12	98,15	0,04	0,31
9	0,12	94,36	0,01	0,22	0,12	90,11	0,06	0,28	0,12	98,23	0,03	0,31
10	0,13	94,28	0,01	0,22	0,13	89,95	0,06	0,27	0,13	98,29	0,03	0,31

Notes: T is period, *SENTI_R* is the rational sentiment of the retail investor, *SENTI_IR* is the irrational sentiment of the retail investor, *BSIR* is monthly returns on the big stock index, *MSIR* is monthly returns on the middle stock index, and *SSIR* is monthly returns on the small stock index.

3.11. Managerial Implications

Previous studies have shown that investor sentiment is essential in financial market returns. For instance, investor sentiments drive phenomena such as bubbles, crashes, and herding crashes more than market fundamentals. The investor sentiment's significance on stock market returns could help domestic and international investors improve asset valuation models. This could be realized by merging investor sentiment into the return-generating process. Furthermore, the stock market is the economics and financial health barometer driven by investor sentiment. This study showed the relationship between investor sentiment and returns based on firm size characteristics in the Indonesia Stock Market. Therefore, the results could help aid in designing policies that stabilize sentiment and decrease market uncertainty as well as volatility.

4. Conclusion

This study investigated how the retail investors' rational and irrational sentiments affect the stock returns based on firm size characteristics such as big, middle, and small stock indexes in Indonesia. The findings showed that investor sentiment is significantly affected by market fundamentals. Furthermore, the Indonesian market fundamentals impact the retail investor sentiment. The R^2-value of 0.53 indicates that market fundamentals explain more than half of the variation in retail investor sentiment. These findings support previous results that market fundamentals influence investor sentiment (Verma & Soydemir, 2006).

The paper also documents that retail investors' irrational sentiments should have a larger impact on all stock market return indexes (i.e., big, middle, small stock) than their rational sentiments. Retail investors' irrational sentiments had the largest impact on the small stock return index. According to Lee et al. (1991), sentiment affects small firms the most. This study found that a one-standard-deviation increase in rational, as well as irrational investor sentiment significantly and negatively affect the all-stock returns index. However, this finding contradicts Verma and Soydemir (2006). Finally, returns on all stock market return indexes had the most impact on all stock market return indexes itself. In contrast, the illogical sentiment was more important than rational sentiment in determining all stock market return indexes.

This study filled a gap in the investor sentiment literature by examining the impact of investor sentiment on stock markets and identifying the importance of investor sentiment in influencing stock prices and their volatility. From a practical perspective, the findings of this paper may be relevant for individual investors to guide their investment decisions, especially in the Indonesian stock market.

This study has potential limitations. In developed countries, investor sentiment can be accurately measured through data surveys such as the American Association of Individual Investors (AAII) and Investors Intelligence (II), which are popular as proxies for investor sentiment. However, these data are not suitable for this study because they are not available and could be developed differently in emerging markets, such as Indonesia. In this study, we use trading volume data that can represent retail investor sentiment. Therefore, it is suggested for further research to use other proxies to represent investor sentiment to add to the literature regarding the influence of investor sentiment in Indonesia.

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