Jurnal Aplikasi Manajemen dan Bisnis, Vol. 8 No.3, September 2022
Permalink/DOI: http://dx.doi.org/10.17358/jabm.8.3.802

Available online
http://journal.ipb.ac.id/index.php/jabm

THE EFFECT OF RATIONAL AND IRRATIONAL SENTIMENTS OF INDIVIDUAL AND INSTITUTIONAL INVESTORS ON INDONESIA STOCK MARKET

Elly Zunara[*)1], Noer Azam Achsani[*)], Dedi Budiman Hakim[**)], Roy Sembel[***)]

[*)] School of Business, IPB University
Jl. Padjajaran, Bogor, Indonesia 16151, Indonesia
[**)] Faculty of Economics and Management, IPB University
Jl. Agatis Kampus IPB Darmaga, Bogor 16680, Indonesia
[***)] IPMI Business School
Jl. Rawajali Timur No.1, Jakarta 12750, Indonesia

Article history:
Received
23 March 2022

Revised
13 June 2022

Accepted
9 August 2022

Available online
30 September 2022

Abstract: The study's goal is to explore the relationship between investor sentiment, stock return, and volatility in Indonesian markets, with a focus on the Indonesia Stock Exchange (IDX). This research looked at the Indonesia Stock Exchange's (IDX) monthly statistics on stock trading volume from January 2015 to January 2021 to infer the attitudes of both institutional and retail investors. The analysis also uses a variety of well-known and accepted factors from the literature on asset pricing, such as the Covid-19 index, a reliable indicator of Indonesia's underlying market conditions. Error Correction Model was used to analyze a regression between investor sentiment and fundamentals in the Indonesian stock market in order to determine the impact of macroeconomic and Covid-19 risk variables on sentiment (ECM). Next, it looked at how unexpected shifts in Indonesian investor sentiment affected stock returns and IDX volatility with the help of Impulse response functions (IRFs) derived from a Vector Error Correction Model (VECM) model. Individual and institutional investors' stock market returns and IDX volatility were found to be affected more by rational than by irrational attitudes, according to the empirical findings.

Keywords: investor sentiment, IDX, stock returns, volatility, VECM

Abstrak: *Penelitian ini bertujuan untuk mengeksplorasi hubungan antara sentimen investor, return saham, dan volatilitas di pasar Indonesia, dengan fokus pada Bursa Efek Indonesia (BEI). Penelitian ini melihat statistik bulanan Bursa Efek Indonesia (BEI) pada volume perdagangan saham dari Januari 2015 hingga Januari 2021 untuk menyimpulkan sikap investor institusi dan ritel. Analisis ini juga menggunakan berbagai faktor yang dikenal dan diterima dari literatur tentang harga aset, seperti indeks Covid-19, indikator yang dapat diandalkan dari kondisi pasar yang mendasari Indonesia. Error Correction Model digunakan untuk menganalisis regresi antara sentimen investor dan fundamental di pasar saham Indonesia untuk mengetahui pengaruh variabel makroekonomi dan risiko Covid-19 terhadap sentimen (ECM). Selanjutnya, melihat bagaimana perubahan tak terduga dalam sentimen investor Indonesia mempengaruhi return saham dan volatilitas BEI dengan bantuan Impulse Response Functions (IRFs) yang diturunkan dari model Vector Error Correction Model (VECM). Return pasar saham investor individu dan institusi dan volatilitas BEI ditemukan lebih dipengaruhi oleh sikap rasional daripada irasional, menurut temuan empiris.*

Kata kunci: *sentimen investor, IDX, return saham, volatilitas, VECM*

[1] Corresponding author:
Email: elly_zunara@yahoo.com

INTRODUCTION

The potential relationship between investor conduct and stock performance has been the subject of increased discussion in recent years. 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 understood by considering scenarios in which certain participants are not totally rational. In particular, it investigates situations in which one or both of the principles supporting people's rationality are disregarded, as proposed by Barberis and Thaler (2003).

In their work on behavioral capital asset pricing, Shefrin and Statman (1994) create a framework in which noise traders and information traders engage in a two-way dialogue. They focus on certain cognitive errors and show how these errors affect how much the market is influenced by noise traders. They claim that attitudes of noise traders function as a second driver, in addition to information, and so lead the market away from efficiency.

An alternative to the efficient market hypothesis, the noise trader technique is the foundation of this research. This strategy rests on two primary premises. To begin, not all investors are perfectly rational, and the demand for hazardous assets is impacted by investors' views or sentiments that are not totally supported by basic news. Second, Shleifer and Summers were constrained in their approach because arbitrage, defined as "trading by totally rational investors not subject to any sentiment," carries a certain degree of danger (1990). Limits to arbitrage, as espoused by Uygur and Tas in the language of contemporary behavioral finance, reflect the high costs and high risks associated with wagering against sentimental investors (2012).

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

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

To prove that noise traders can outperform rational investors in the long run, De Long et al. (1991) developed a model of portfolio allocation by noise traders. Noise traders are able to succeed in the long run despite their high levels of risk taking and conspicuous consumption. They contend that the evidence against noise traders' long-term viability is not as solid as is usually believed. Campbell and Kyle (1993) build on the ideas presented by Black (1986) to provide a model in which stock prices are influenced by the interplay between noise traders and information traders. Stock prices can be affected by noisy traders, as the utility-maximizing investors are risk-averse.

An alternative to the efficient markets paradigm is presented by Shleifer and Summers (1990), who highlight the importance of investor emotion and constrained arbitrage in setting stock prices. They demonstrate that the complete arbitrage assumption upon which the market efficiency theory rests is unrealistic and that the assumption of restricted arbitrage is a more realistic description of markets for hazardous assets. This suggests that arbitrageurs may not be able to fully offset the effects of shifts in investor sentiment on stock returns.

Several empirical studies, following the "noise trader model" of De Long et al. (1990), analyze how investor emotions affect stock performance (DeBondt, 1993; Solt and Statman, 1988; Clarke and Statman, 1998; Fisher and Statman, 2000; Lee et al. 2002; Brown and Cliff, 2004, 2005). Overall, the research support the idea that the emotions of individual institutional investors tend to shift in tandem with stock market gains.

These studies reveal that investors are susceptible to the sway of popular opinion and that some market participants may overlook a company's fundamentals while making investment decisions. As a result, stock prices can react dramatically to sudden and unexpected shifts in the emotions of impulsive traders. Baker and Wurgler (2006), 2007; Barberis et al. (1998), Black (1986), De Long (1990), Fisher (2000), Kumar and Lee (2006), and Trueman (1988) all point to the importance of irrational investors' trading actions in influencing 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 terms of purchasing power and public consumption. In addition, another aspect that can be used as a source of Indonesia's economic growth is an increase in investment activities, especially 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 carry out activities in the Indonesian stock market, especially local investors, both institutional investors and individual or retail investors. Local ownership in the stock market has increased since 2016 by 51.77% to 56.85% in 2020. The increase in share ownership by local investors in Indonesia was mainly due to the increase in ownership of institutional investors driven by an increase in funds managed by institutional investors such as Pension Funds. Meanwhile, the increase in the ownership of individual local 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 have a significant influence on stock market activities in Indonesia, compared to other countries it is still very low. The ratio of the involvement of the Indonesian population who invests in the capital market is less than 5%, far behind the United States (US) with a ratio of 55%, Singapore reaching 26%, and even Malaysia reaching 9%. Therefore, Survey data such as the American Association of Individual Investors (AAII) and Investors Intelligence (II), whilst a popular sentiment proxy, is no suitable for this research because the data are not available and may be built in in a different way in emerging markets like Indonesia.

In this research, we use data available in the Indonesian capital market and can represent investor sentiment, namely trading volume. One possible indicator of investor attitude is the volume of trades, often known as liquidity. When impulsive investors are optimistic and buying rising stocks, rather than when they are gloomy and buying falling equities, they are more likely to desire to trade and, thus, add liquidity, as shown by prior study by Baker and Stein (2004). Several researchers, including Liao et al. (2011), Baker and Wurgler (2006), and Chen et al. (2013), have used trading volume as a surrogate for investor sentiment.

Brown and Cliff (2004, 2005) and Lee et al. (2002) among others have hypothesized a systemic relationship between stock market outcomes and investor emotion. This is why the VAR model developed by Sims (1980) was selected as the econometric strategy to use in examining the hypothesized connections. We also factor in the following concerns prior to the estimating phase.

In a perfectly competitive financial market, only the unexpected part of explanatory factors would cause the stock market to move. All the variables in a multi-index model, according to Elton and Gruber (1991), should be surprises or innovations and should not be expected from their prior values. Consequently, the novel element (innovations) of explanatory variables is used by asset-pricing models like Arbitrage Pricing theory.

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 to one another. If you produce such an estimate, you risk jumping to the wrong conclusion because you are ignoring the effect of variations in unpredictable aspects of investor sentiment and stock market returns. To avoid such misspecification problems, we employ the VAR model to generate robust impulse response functions (the predicted pattern of unexpected changes or innovations). Furthermore, throughout the course of the previous two decades, VAR models have been shown to surpass structural models in terms of prediction performance (Litterman and Supel, 1983; Hakkio and Morris, 1984; Litterman, 1984; Lupoletti and Webb, 1986; Webb, 1999).

To set ourselves apart from the prior literature, we first use the ECM Model to analyze the fundamental and irrational components of investor attitudes, as well as their possible effects on stock market returns and volatility. Second, unlike other studies, we use a unified model to assess the impact of investor sentiment on stock market returns, both for individual and institutional investors. Finally, using the generalized impulse response functions (IRFs) and forecast error variance decomposition (FEVD) of the VAR/VECM model, we examine the effect of unexpected changes and contributions in the mood of Indonesian investors on the return and volatility of the IDX's stock price.

The following empirical findings are derived from the generalized impulses produced by a vector autoregression (VAR) or vector error correction model (VECM) model. To begin, research has shown that institutional investors are more influenced by rational sentiments than irrational ones, whereas individual investors are more influenced by the reverse. While prior research (De Long et al. 1990; Shleifer and Summers, 1990) has portrayed investor sentiments as entirely irrational, we find in this research that both individual and institutional investor sentiments are driven by rational and irrational factors, each of which has a unique impact on stock market return. Second, institutional and individual investors' irrational sentiments should have a larger impact on stock market volatility than their rational sentiments. Those prior research by Sayim et al (2013). Third, negative reactions in stock market returns and volatility to reasonable investor sentiments are followed by positive reactions in subsequent time periods. This observation contradicts the conclusions of prior research by Verma et al (2008). Finally, JCI returns had the most impact on JCI returns, whereas illogical sentiment was more important than rational sentiment in determining JCI returns.

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

METHODS

In this work, we utilize a method for gauging investor mood in Indonesia that is analogous to that developed by Verma and Soydemir for gauging person attitude (2006). 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, Huang, and Wu (2011), Baker and Wurgler (2006), and Chen et al. (2013). For the purpose of this analysis, we use the trading volume of institutional investors (SENT1t) and trading volume of individual investors (SENT2t) as proxies for local investor sentiment.

In the asset pricing literature, we include the following variables as fundamentals that carry nonredundant information: the rate of expansion of the Indonesian economy as indicated by the Fama/Cost Index's estimate of the percentage increase or decrease in industrial production in Indonesia during any (1970). The Index of Industrial Production (IIP) measures the level of production across numerous industries. Industrial Production (IIP) is a widely followed economic statistic for the manufacturing sector. Campbell (1991) defines the short-term interest rate as the interbank offered rate multiplied by 12 and 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. Sharpe (2002) defines inflation as the monthly change in the Indonesia consumer price index, and uses this to determine the real return earned by investors. Differences in exchange rates Changes in the exchange rate between the Indonesian rupiah and the US dollar, as calculated by Elton and Gruber (1991). (EXCR). Asian oil prices for 2019 are tracked via monthly changes in the West Texas Intermediate price (WTI). The cost of WTI served as a useful economic indicator. variable that indicates if the time period is before or after the Covid-19 period (Collins 2020). As a result of its widespread effects on the world economy, Covid 19 has also affected Indonesian investment operations (DUMC19). We collect information monthly beginning in January 2015 and ending in February 2021.

Fundamental and noise components of sentiments may influence stock returns since sentiments comprise reasonable expectations-based risk variables (Shleifer and Summers, 1990; Brown and Cliff, 2005). It's worth noting that Hirshleifer (2001) draws parallels between expected returns and both 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 based on the facts, and (ii) an irrational component based on the noise. We use the ECM to simulate the rational and irrational effects of fundamentals and noise on investor sentiment, and then we formulate Equations 1 and 2:

$$SENT1_t = \alpha_0 + \alpha_j \sum_{j=1}^{j} FUND_j + \xi_t \qquad (1)$$

$$SENT2_t = \beta_0 + \beta_j \sum_{j=1}^{j} FUND_j + \zeta_t \qquad (2)$$

Where α_0 and β_0 are constants, α_j and β_j the parameters to be estimated; ξ_t and ζ_t are the random error terms. $SENT1_t$ and $SENT2_t$ represent the shifts in sentiments of institutional and individual investors, respectively, at time *t*. $FUND_{jt}$ is the set of fundamentals representing rational expectations based on risk factors that have been shown to carry nonredundant information in conditional asset pricing literature. The fitted values of Equations 1 and 2 capture the rational component of sentiments (i.e., $SENT1_t$ and $SENT2_t$). On the other hand, the residual of Equations 1 and 2 capture the irrational component of sentiments (i.e. ξ_t and ζ_t).

When dealing with variables that are nonstationary but are cointegrated, ECM was used despite the fact that this method has limitations. Since the data is not stationary but does exhibit cointegration, ECM employs this constraint on the preexisting long-term variable relationships to hasten their convergence into their cointegration relationships while still permitting dynamic changes in the near term (Firdaus, 2011).

The next part of the research looks at how investor mood can effect JCI returns. Given that investor sentiment can be both reasonable and irrational (Verma and Soydemir, 2006). Accordingly, Equation (3) is used to separate rational and illogical components of sentiment variables, and the following regression equation is applied in the return-generating process:

$$R_t = \gamma_0 + \gamma_1 SENT\hat{1}_t + \gamma_2 SENT\hat{2}_t + \gamma_3 \xi_t + \gamma_4 \zeta_t + \mu_t$$

where γ_0 is a constant while γ_1, γ_2, γ_3 and γ_4 are the parameters to be estimated; *t* is the random error term. Specifically the parameters γ_1 and γ_2 capture the effects of sentiments induced by fundamental trading on the part of individual and institutional investors, respectively; while γ_3 and γ_4 capture the effects of sentiments-induced noise trading by individual and institutional investors, respectively.

Using economic theory (structural models) for numerical information analysis, Juanda and Junaidi (2012) showed how most econometric models of time series are constructed. Sometimes the complexity of economic theory or the apparent 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 instead the use of dynamic models that independently influenced each variable. For time series data, the Vector Autoregressive (VAR) model provided an alternate approach. This model's data were static, hence it was given the name "unrestricted VAR" (VAR unlimited). As there are several variables in this research, the VAR equation is used to describe the associations between them (Juanda and Junaidi, 2012). For a bivariate problem (two-variable equation) with a simultaneous causality relationship, we can write the VAR model as (Enders, 2014)

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

$$z_t = b_{20} - b_{21} \gamma_t + \gamma_{21} y_{t-1} + \gamma_{22} z_{t-1} + e_{zt} \text{ ....(2)}$$

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

$$\underset{B}{\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}} \underset{X_t}{\begin{bmatrix} y_t \\ z_t \end{bmatrix}} = \underset{\beta_0}{\begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix}} + \underset{\beta_1}{\begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{2} \end{bmatrix}} \underset{X_{t-1}}{\begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix}} + \underset{e_t}{\begin{bmatrix} e_{yt} \\ e_{zt} \end{bmatrix}}$$

or it can be written to be:

$$X_t = \hat{a}_0 + \hat{a}_1 X_{t-1} + e_t \ldots..(3)$$

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).

$$X_t = A_0 + A_1 X_{t-1} + \varepsilon_t \ldots(4)$$

Where: A_0 is $B^{-1}\beta_0$ (intercept), A_1 is $B^{-1}\beta_1$ (vector autoregressive), ε_t (error).

The dynamic nature of the interaction between the variables is demonstrated by Equation 4. The shocks experienced by certain variables can be counteracted by their impulses against other variables. One further thing 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. In addition, there is a chance that they are cointegrated. The model under these constraints is known as restricted VAR. One solution to this issue is to employ a model known as vector error correction (VECM).

This model restricts the long-term linkages of endogenous variables to cointegration relationships while taking into account the short-term dynamics. The following equation sums up the VECM model, as presented by Firdaus (2011). (all variables were in the natural logarithm form).

$$\Delta y_t = \mu_{0x} + \mu_{1xt} + \Pi_x y_{t-1} + \sum_{k=1}^{1=1} \Gamma_{ix} \Delta y_{t-1} + \varepsilon_t \quad (5)$$

Where: Δy_t is variable vector JCIR, JCIV, $SENT_{1t}$, $SENT_{2t}$, μ_{0x} is intercept vector, μ_{1x} is regression coefficient vector. t is time trend. Π_x is $\alpha_x\beta$' where b' contains a long-term cointegration equation. y_{t-1} is variable in level. Γ_{ix} is the regression coefficient matrix. k-1 is a VECM order of VAR ε_t is error term.

By running policy simulations with the VAR specification, researchers can use Monte Carlo techniques to establish confidence bands around the estimated parameters in Hamilton (1994). Impulse response functions are used to 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 held constant. Confidence intervals are built around the mean response because impulse responses are highly nonlinear expressions of the anticipated parameters. When both the lower and upper bands have the same sign, a result is declared statistically significant at the 95% level of confidence.

Theoretically, it is well established that results of conventional orthogonalized estimated error variance decomposition based on the often employed Cholesky decomposition of VAR innovations are susceptible to variable ordering Pesaran and Shin (1998). To solve these types of misspecification issues, we use the recently discovered generalized impulses technique described by Pesaran and Shin (1998), which applies an orthogonal set of innovations without relying on the VAR ordering.

The following are the steps that were taken to complete this research: One, a unit root test with the help of the Augmented Dickey Fuller (ADF). 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, and (5) Optimal lag analysis. (5) We will employ Johansen's Co-integration approach if the variables are stationary at initial difference. We shall employ a VECM strategy if the data suggests the presence of co-integration. Further analysis is required in the absence of co-integration, therefore we proceeded to step 6 (analyzing the Impulse Response Function) before moving on to step 7 (analyzing the Forecast Variance Error Decomposition) (FEVD).

RESULTS

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 shown in Table 1. We observed that none of the variables were level, but all were first difference stationary.

Where *SENT1* is sentiments of institutional investor, *SENT2* is sentiments of individual investor. *JCIR* is monthly returns on JCI, JCIV is monthly volatility on JCI, *LN_EXCR* is exchange rate between Indonesia

Rupiah and the US dollar, *LN_IPI* is industrial production index of Indonesia, *INT* is interest rate, *INF* is inflation,LN_OILP is oil price.

The Impact of Fundamental Variable for Local Investor Sentiment

Using Error Correction Model (ECM), we explore how fundamental including effect of Covid-19 in the form of a dummy variable may affect local investor sentiment. Indonesia market fundamentals are regressed uses Equations 1 and 2 on investor sentiments in order to capture the effects of macroeconomic and Covid 19 risk factors on investor sentiments.

Table 2 show that the institutional investor sentiments are significantly related to industrial production index, inflation, oil price and pandemic Covid-19. Similarly, Table 3 reports that individual investor sentiments are significantly related to industrial production index, interest rate, inflation and oil price. In addition, individual investor sentiments have a more influenced pandemic Covid-19 than institutional investor sentiments. These findings corroborate Brown and Cliff's (2005) contention that investor attitudes may have a mix of rational and irrational components in addition to noise.

The variables are institutional investor sentiments (SENT1), individual investor sentiments (SENT2) exchange rate between Indonesia Rupiah and the US dollar (LN_EXCR), industrial production index of Indonesia (LN_IPI), interest rate (INT), inflation (INF), oil price (LN_OILP), dummy Covid-19 (DUMC19).

The Causal Relationship between rational and irrational local investor sentiments on stock market returns and volatility

For each regression, we compute the rational and irrational components of individual and institutional investor sentiment using ECM derived from Equations 1 and 2. For this research, we estimate a six-variable VECM to examine the relative impacts of rational and irrational local investor attitudes on stock market returns and volatility, as shown in Equation 3. IDX returns and volatility, as well as the reasonable and irrational sentiments of institutional and individual investors, are the variables under consideration.

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 present in the multivariate time series data, making the estimation result credible thanks to this test (Gujarati and Porter, 2010).

Table 1. Unit root tests

Variable	Level		First difference	
	ADF test result	Prob	ADF test result	Prob
SENT1	-2.111	0.241	-14.012	0.0001*
SENT2	-2.596	0.099	-9.975	0.0001*
JCIR	-7.147	0.000*	-6.590	0.0000*
JCIV	-5.623	0.000*	-8.824	0.0000*
LN_EXCR	-2.987	0.790	-9.561	0.0000*
LN_IPI	-2.755	0.571	-3.449	0.0000*
INT	-0.422	0.899	-5.183	0.0000*
INF	-1.413	0.125	-6.438	0.0000*
LN_OILP	-2.478	0.070	-3.449	0.0130*

*) stationary with prob < 5%

Table 2. Effects of fundamentals on institutional investor sentiments based on Equations 1.

Dependent variable: SENT1t				
Variable	Coefficient	SE	t-Statistic	Prob.
LN_EXCR	-0.82	1.15	-0.71	0.48***
LN_IPI	3.06	0.89	3.44	0.00***
INT	-0.04	0.06	-0.65	0.52***
INF	-0.08	0.04	-2.11	0.04***
LN_OILP	0.52	0.17	3.04	0.00***
DUMC19	-0.31	0.18	-1.71	0.09***
C	16.54	9.37	1.76	0.08***
R-squared	0.57			
AIC	0.53			
SC	0.75			
Sum squared resid	6.00			
Log likelihood	-12.39			
F-statistic	14.42			
Prob(F-statistic)	0.00			

*, **, *** Significance at the 10, 5, and 1 percent levels, respectively.

Table 3. Effects of fundamentals on individual investor sentiments based on equation 2.

Dependent variable: SENT2t				
Variable	Coefficient	SE	t-Statistic	Prob.
LN_EXCR	-1.81	1.44	-1.26	0.21
LN_IPI	2.22	1.11	2.00	0.05**
INT	-0.18	0.07	-2.37	0.02**
INF	-0.10	0.05	-2.19	0.03**
LN_OILP	0.48	0.21	2.28	0.03**
DUMC19	-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			
Sum squared resid	9.33			
Log likelihood	-28.48			
F-statistic	12.44			
Prob(F-statistic)	0.00			

*, **, *** Significance at the 10, 5, and 1 percent levels, respectively.

None of the variables were 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 results shown in Table 1. We observed that none of the variables were level, but all were first difference stationary. These results demonstrated the existence of a link between the two imbalances studied here throughout the course of a relatively brief period of time. If we wanted to know how things will settle out in the long run, we had to execute a co-integration test.

Optimum VAR Lag was at 8 Lag of 1

Roots of the characteristic polynomial for all the variables utilized 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 a variety of techniques. Table 4 displays the Lag Length Criteria and Ar Roots Graph that were 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 best for the VAR model. This check was formerly used to remedy autocorrelation issues in VAR systems. For a model involving VAR and co integration, the optimal lag proved effective.

There were 2 Cointegrating Vectors Between All Variables

According to the results in Table 5, a long-term equilibrium relationship among variables was established through the linear combination of two or more non-stationary variables, a phenomenon known as cointegration. The Johansen Cointegration Test was utilized for analysis. Table 5 displays the results of a Johansen cointegration test on IDX returns and volatility, as well as the rational and irrational sentiments of institutional and individual investors. The results of the test indicate that the null hypothesis can be accepted at the 5% level, and that two positive relationships exist. It 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.

Local Investor Sentiment Affected to Return and Volatility IDX in the Long Run

The volatility and returns on the IDX were both exogenous factors. Exogenous factors included local investor sentiment, classified as rational, irrational, institutional, and individual, respectively. Table 6 presents the VECM estimation results, which reveal that local investor sentiment has a large impact on return and volatility in the long run but has no effect on 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 at the coefficients in the regression equations is a challenging task. As Sims (1980) and Enders (2014) demonstrate, doing t-tests on individual coefficients is not a good way to find out what the relationships are between the variables. Consider the system's reaction to typical random shocks, or IRFs, as suggested by Sims (1980).

Where *SENT1_R* is rational sentiments of institutional investor, *SENT1_IR* is irrational sentiments of institutional investor, *SENT2_R* is rational sentiments of individual investor, *SENT2_IR* is irrational sentiments of individual investor, *JCIR* is monthly returns on JCI, JCIV is monthly volatility on JCI.

Table 4. Determine lag intervals for endogenous with lag length criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
1	208.2432	NA	1.86e-10*	-5.382600	-4.168228*	-4.904197*
2	241.8010	54.53150	2.05e-10	-5.306282	-2.877539	-4.349478
3	273.7000	45.85480	2.49e-10	-5.178126	-1.535011	-3.742919
4	314.7265	51.28307*	2.45e-10	-5.335203	-0.477716	-3.421593
5	353.2882	40.97186	2.89e-10	-5.415257	0.656601	-3.023245
6	392.4757	34.28906	3.94e-10	-5.514866	1.771364	-2.644452
7	438.7358	31.80383	5.60e-10	-5.835495	2.665107	-2.486679
8	538.4564	49.86029	2.33e-10	-7.826763*	1.888210	-3.999545

Table 5. Results of cointegration test

(a) Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.432383	108.7944	83.93712	0.0003
At most 1 *	0.375597	68.58656	60.06141	0.0080
At most 2	0.265687	35.14841	40.17493	0.1464
At most 3	0.127631	13.22223	24.27596	0.6028
At most 4	0.033494	3.527683	12.32090	0.7778
At most 5	0.015497	1.108885	4.129906	0.3403
(b) Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.432383	40.20786	36.63019	0.0183
At most 1 *	0.375597	33.43815	30.43961	0.0205
At most 2	0.265687	21.92618	24.15921	0.0975
At most 3	0.127631	9.694543	17.79730	0.5179
At most 4	0.033494	2.418798	11.22480	0.8720
At most 5	0.015497	1.108885	4.129906	0.3403

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 6. VECM estimation results

Variable	Coefficient	t-Statistic
Short Term		
D(JCIR (-1))	-0.13224	[-0.791]
D(JCIV (-1))	0.01330	[0.941]
D(SENT1_R (-1))	0.05637	[0.527]
D(SENT1_IR (-1))	0.02882	[1.308]
D(SENT2_R (-1))	-0.06331	[-0.505]
D(SENT2_IR (-1))	-0.01209	[-0.555]
CointEq1	-0.54829	[-2.415]*
Long Term		
SENT1_R (-1)	0.05346	[1.795]*
SENT1_IR (-1)	0.05093	[2.988]*
SENT2_R (-1)	-0.05294	[-1.843]*
SENT2_IR (-1)	-0.02859	[-2.282]*

*) significant with T-stat > T-table (1.65). Where SENT1_R is rational sentiments of institutional investor, SENT1_IR is irrational sentiments of institutional investor, SENT2_R is rational sentiments of individual investor, SENT2_IR is irrational sentiments of individual investor, JCIR is monthly returns on JCI, JCIV is monthly volatility on JCI.

The Effect of The Rational Sentiment Institutional Investors Are Positive for IDX Returns

In order 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 the immediate and long-term impulse reaction of one variable to the shock of another is known as an Impulse Response Function (IRF). In general, short-term reactions were highly noticeable and volatile, while long-term ones were quite stable. Figure 1 displays the outcome.

The impulse responses of IDX returns to a one-time SD rise in rational and irrational attitudes of institutional investors are shown in Figure 1(a) and (b), respectively. IDX returns did not react to shocks in rational investor attitude in the first month, but dropped by -0.003 units in the second month, fluctuated until the tenth month, and then remained relatively stable at around 0.01 units for the rest of the period. This results is in line with research by Verma et al. (2008), who found that institutional rational emotions favorably impacted future IDX returns.

IDX returns did not react to irrational sentiment investor institutional shocks in the first month, but they climbed in the second month to 0.0007 unit and continued to increase until the tenth month, after which they remained rather stable at around -0.004 unit. This suggested that institutional investors' irrational outlooks have a major future impact on IDX results.

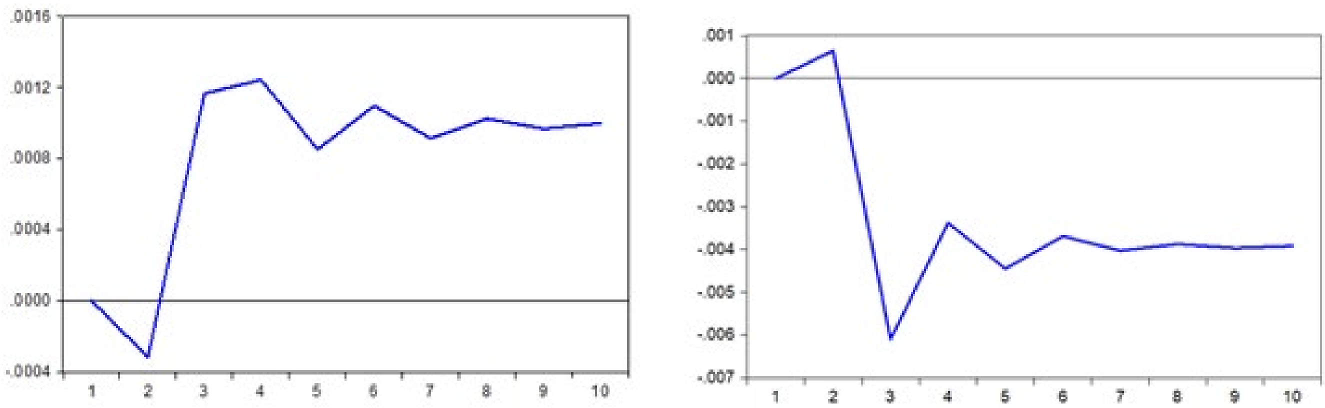
The response for the rational component of institutional investors is much greater than the response for the irrational component, which may suggest that sentiments-induced fundamental trading by institutional and individual investors has a much greater impact on stock market returns than sentiments-induced noise trading.

The Effect of Individual Investors Sentiment Are Positive for IDX Returns

The impulse responses of IDX returns to a one-time SD rise in rational and irrational investor sentiment are shown in Figure 2(a) and (b), respectively. IDX returns did not react to individual shocks in rational investor mood in the first month, but they dropped by -0.0015 units in the second month, fluctuated until the tenth month, and then remained generally stable at around 0.015 units thereafter. This suggested that individuals' sane expectations had a large, beneficial effect on future IDX returns.

IDX returns did not respond to irrational emotion investor institutional shocks in the first month, but climbed and fluctuated thereafter until the tenth month, after which they remained rather stable at around 0.004 unit. This suggested that irrational optimism had a materially favorable effect on future IDX results.

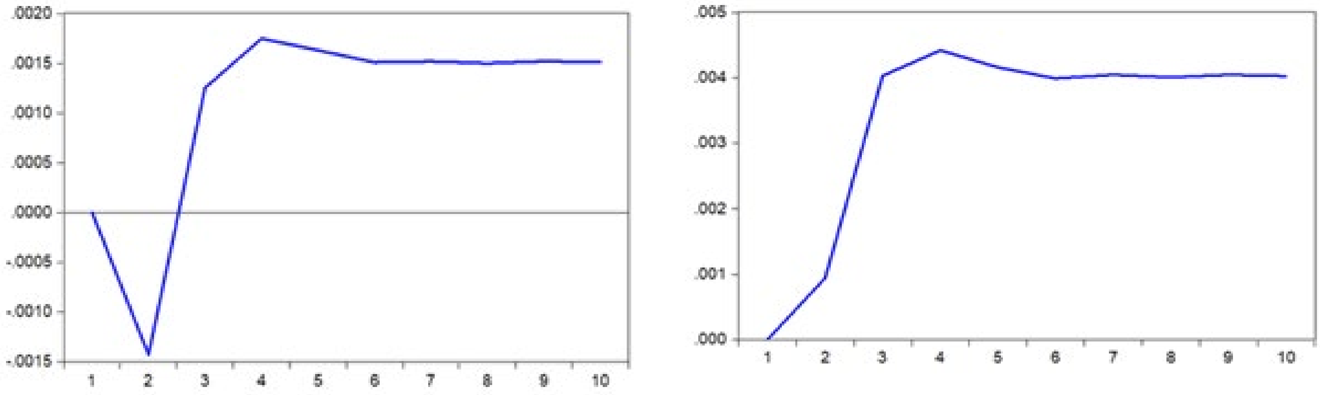
If the irrational aspects of investors have a larger impact than the rational aspects, this could mean that sentiments-induced noise trading has a considerably larger impact on stock market returns than sentiments-induced fundamental trading.



(a) rational sentiments

(b) Irrational sentiments

Figure 1. Response of IDX returns to the rational and irrational sentiments of institutional investors



(a) rational sentiments

(b) Irrational sentiments

Figure 2. Response of IDX returns to the rational and irrational sentiments of individual investors

The Effect of The Rational Sentiment Institutional Investors Are Positive for IDX Volatility

The impulse responses of IDX volatility to a one-time SD rise in rational and irrational attitudes among institutional investors are displayed in Figure 3(a) and (b). While IDX volatility did not react to shocks to rational investor mood in the first month, it did so in the second month, dropping by -0.001 unit, oscillating until the tenth month, and then remaining relatively stable at around 0.007 unit. This suggested that the future IDX volatility was strongly altered in a good way by the rational attitudes of institutional investors.

IDX volatility did not react to irrational mood among investors and institutional shocks in the first month, but it did respond negatively and then fluctuated until the tenth month, after which it remained relatively stable at around -0.063 unit. This suggested that irrational emotions have a major, negative impact on IDX volatility.

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

The Effect of The Rational Sentiment Individual Investors Are Positive for IDX Volatility

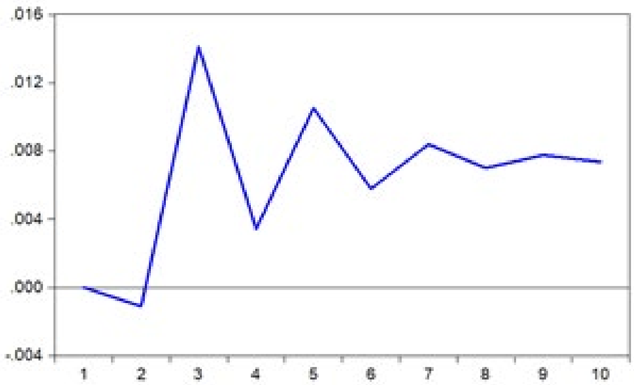
The impulse responses of IDX volatility to a one-time SD rise in rational and irrational investor sentiment are shown in Figure 4 (a) and (b). IDX volatility did not respond to individual shocks in rational investor mood in the first month, but did so in the second month with a loss of -0.03 units, then fluctuated in response until the tenth month, and then remained relatively stable at around -0.005 units. This suggested that the future IDX volatility was strongly impacted negatively by the rational attitudes of institutional investors.

IDX volatility did not respond to individual shocks in irrational investor attitude in the first month, but it did grow and fluctuate in response from the second through the tenth month, after which it remained rather stable at around 0.027 units. This suggested that future IDX volatility was considerably influenced positively by individuals' irrational views.

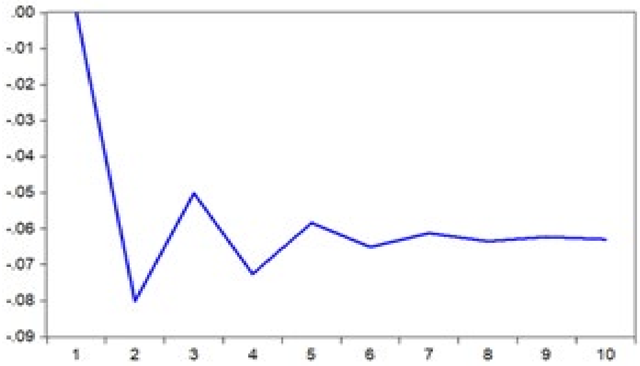
Irrational Sentiment Had a Bigger Contribution than Rational Sentiment for JCI Return

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. Multivariate causation among the VAR model's variables was illustrated by the FEVD pattern. Table 7 displays the findings of the FEVD.

According to Table 7, the JCI's (JCIR) contribution to the return itself ranged from 100% in the first month to 76.26% in the tenth month. Institutional investors' rational sentiment (SENT1 R) increased from zero to twenty-one basis points (bps) of return in the tenth month, whereas irrational sentiment (SENT1 IR) increased from zero to six point nine seven basis points (bps) of return in the tenth month.

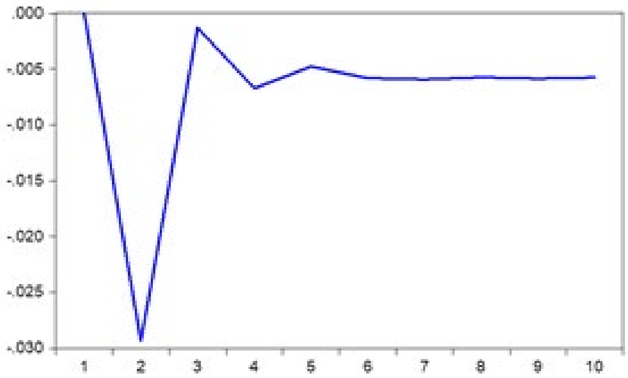


(a) rational sentiments

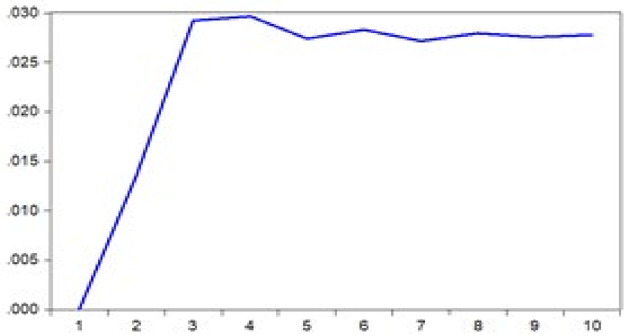


(b) Irrational sentiments

Figure 3. Response of IDX volatility to the rational and irrational sentiments of institutional investors



(a) rational sentiments



(b) Irrational sentiments

Figure 4. Response of IDX volatility to the rational and irrational sentiments of individual investors

Table 7. FEVD results

T	S.E.	JCIR	SENT1 R	SENT1 IR	SENT2 R	SENT2 IR
1	0.04	100.00	0.00	0.00	0.00	0.00
2	0.04	98.84	0.09	0.09	0.87	0.12
3	0.05	93.04	0.15	2.52	1.08	3.22
4	0.05	90.37	0.16	2.93	1.10	5.44
5	0.05	87.42	0.17	3.92	1.12	7.37
6	0.05	84.96	0.18	4.54	1.13	9.19
7	0.05	82.53	0.19	5.24	1.15	10.89
8	0.05	80.32	0.20	5.84	1.17	12.48
9	0.05	78.22	0.21	6.43	1.18	13.97
10	0.05	76.26	0.21	6.97	1.19	15.36

Where T is period, SENT1_R is rational sentiments of institutional investor, SENT1_IR is irrational sentiments of institutional investor, SENT2_R is rational sentiments of individual investor, SENT2_IR is irrational sentiments of individual investor, JCIR is monthly returns on JCI.

Investors' rational sentiment (SENT2 R) increased from 0% to 1.19 % in the 10th month, whereas institutional investors' irrational sentiment (SENT2 IR) increased from 0% to 15.36%.

Each period's total contribution from all these factors was always 100%. This FEVD study revealed that while JCI returns contributed more to the JCI return itself, irrational sentiment contributed more to the JCI return than rational sentiment.

Where *T* is period, *SENT1_R* is rational sentiments of institutional investor, *SENT1_IR* is irrational sentiments of institutional investor, *SENT2_R* is rational sentiments of individual investor, *SENT2_IR* is irrational sentiments of individual investor, *JCIR* is monthly returns on JCI.

Managerial Implication

The findings of this research have substantial policy and investment policy implications. Unlike prior research, which placed all of the blame for negative stock market sentiment on the irrational actions of investors, the new data lends credence to the thesis that stock market returns are driven by underlying economic fundamentals. When developing investing strategies, it is important for investors to understand the role played by both rational and irrational investor sentiment.

Researchers hope that policymakers may use the findings of this research to calm investor fears and steady the stock market. The findings of this research were meant to aid the Jakarta Stock Exchange (IDX) and the Financial Services Authority in their efforts to build out Indonesia's capital markets for the future.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

Based on the data, we examine how individual and institutional investors' rational and irrational sentiments affected IDX returns and volatility during the timeframe of our research. Unlike prior research, which posits that investor emotions are entirely irrational, we demonstrate that both individual and institutional investor sentiments are driven by rational and irrational causes.

Overall, after estimating a six-variable VECM model, we discover the following. To begin, research has shown that institutional investors are more influenced by rational sentiments than irrational ones, whereas individual investors are more influenced by the reverse. Second, institutional and individual investors' irrational sentiments should have a larger impact on stock market volatility than their rational sentiments. Third, negative reactions in stock market returns and volatility to reasonable investor sentiments are followed by positive reactions in subsequent time periods. Lastly, JCI returns had the dominant contribution to JCI return itself, on the other hand irrational sentiment had a bigger contribution than rational sentiment for JCI return.

REFERRENCES

Asianto A. 2019. The price determinants of west Texas intermediate crude oil. *Jurnal Aplikasi Manajemen dan Bisnis* 5(1):153-162

Baker M, Stein, JC. 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets* 7(3):271–299

Baker M, Wurgler J. 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance* 61(4):1645-1680.

Baker M, Wurgler J. 2007. Investor sentiment in the stock market. *Journal of Economic Perspectives* 21(2):129-151.

Barberis N, Shleifer A, Vishny RW. 1998. A model of investor sentiment. *Journal of Financial Economics* 49:307–43.

Barberis N, Thaler R. 2003. A survey of behavioral finance. *In Handbook of the economics of finance* 1:1053-1128.

Black F. 1986. Noise. *Journal of Finance* 41(3) 529-543.

Brown GW, Cliff MT. 2004. Investor sentiment and the near-term stock market. *Journal of Empirical Finance* 11:1–27.

Brown GW, Cliff MT. 2005. Investor sentiment and asset valuation. *Journal of Business* 78(2): 405-440.

Campbell J. 1991. A variance decomposition for stock returns. *Economic Journal* 101(405):157-179.

Campbell J, Kyle A. 1993. Smart money, noise trading and stock behavior. *Review, Economic Studies* 60(1):1-34.

Clarke RG, Statman M. 1998. Bullish or bearish?.

Financial Analysts Journal 54:63–72.

Collins CN. (2020). Effect of covid-19 pandemic on global stock market values: a differential analysis. *Acta Universitatis Danubius* (*Economica*) 16 (2).

DeBondt W. 1993. Betting on trends: intuitive forecasts of financial risk and return. *International Journal of Forecasting* 9:355–71.

De Long J, Shleifer A, Summers L, Waldman, R. 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98(4):703-738.

De Long J, Shleifer A, Summers L, Waldman, R. 1991. The survival of noise traders in financial markets. *Journal of Business* 64:1–19.

Elton E, Gruber M. 1991. *Modern Portfolio Theory and Investment Analysis*. New York: John Wiley & Sons.

Enders W. 2014. *Applied Econometric Time Series.* 4th ed. New Jersey: John Wiley and Sons.

Fama E. 1970. Efficient capital markets: a review of theory and empirical work. Journal of Finance 25(2):383-417.

Firdaus M. 2011. *Aplikasi Ekonometrika Untuk Data dan Time Series*. IPB Pres. Bogor

Fisher KL, Statman M. 2000. Investor sentiments and stock returns. *Financial Analysts Journal* 56:16–23.

Gujarati DN, Porter DC. 2010. *Essentials of Econometrics. 4th ed.* New York: McGraw-Hill

Hakkio MS. and Morris CS. 1984. *Autoregressions: A User's Guide*. Kansas City: Federal Reserve Bank of Kansas City.

Hamilton JD. 1994. *Time Series Analysis*. Princeton: Princeton University Press.

Hirshleifer D. 2001. Investor psychology and asset pricing. *Journal of Finance* (56):1533–97.

Juanda B, Junaidi. 2012. *Ekonometrika Deret Waktu: Teori dan Aplikasi*. Bogor: IPB Press

Kumar A, Lee CM. (2006). Retail investor sentiment and return comovements. *Journal of Finance* 61(5):2451-2485.

Lee WY, Jiang CX, Indro DC. 2002. Stock market volatility, excess returns, and the role of investor sentiments. *Journal of Banking & Finance* 26: 2277–99.

Liao TL, Huang CJ, Wu CY. 2011. Do fund managers herd to counter investor sentiment?. *Journal of Business Research* 64(2):207–212.

Litterman RB. 1984. Forecasting with Bayesian vector autoregressions. *Federal Reserve Bank of Minneapolis* 95.

Litterman RB. and Supel TM. 1983. Using vector autoregressions to measure the uncertainty in Minnesota's revenue forecasts. *Federal Reserve Bank of Minneapolis Quarterly Review* 1:10-22.

Lupoletti WM. and Webb, R. H. 1986. Defining and improving the accuracy of macroeconomic forecasts: contributions from a VAR model. *Journal of Business* 59:263–85.

Pesaran MH, Shin Y. 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters* (58)17–29.

Sayim M, Morris PD, Rahman H. 2013. The effect of US individual investor sentiment on returns and volatility. Review of Behavioral Finance. 5(1):1–19.

Shefrin H, Statman M. 1994, Behavioral capital asset pricing theory, *Journal of Financial and Quantitative Analysis* 29(3):323-349.

Sharpe S. 2002. Reexamining stock valuation and inflation: the implications of analysis' earning forecasts. *Review of Economics and Statistics* 84(4):632-648

Shleifer A, Summers L. 1990, The noise trader approach to finance. *Journal of Economics Perspective* 4(2):19-33.

Sims C. 1980. Macroeconomic and reality. *Econometrica* 48(1):1-49.

Solt ME, Statman M. 1988. How useful is the sentiment index?. *Financial Analysts Journal* 44:45–55.

Trueman B. 1988. A theory of noise traders in securities markets. *Journal of Finance* 43(1):83-95.

Uygur U, Tas O. 2012. Modeling the effects of investor sentiment and conditional volatility in international stock markets. *Journal of Applied Finance & Banking* 2(5):239-260.

Verma R, Soydemir G. 2006. The impact of US individual and institutional investor sentiment on foreign stock markets. *Journal of Behavioral Finance* 7(3):128-144.

Verma R, Baklaci H, Soydemir G. 2006. The impact of rational and irrational sentiments of individual and institutional investors on DJIA and S&P500 index returns. Applied Financial Economics 18(16):1303-1317

Webb RH. 1999. Two approaches to macroeconomic forecasting, Economic Quarterly. *Federal Reserve Bank of Richmond* 85:23–40.