“The dynamics of familiarity bias during extreme events: Investor responses across industries”

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THE DYNAMICS OF FAMILIARITY BIAS DURING EXTREME EVENTS: INVESTOR RESPONSES ACROSS INDUSTRIES

Abstract

The efficient market hypothesis is struggling to explain market behavior during rare, high-impact events. In such uncertain times, familiarity guides the decisions, allowing the brain to rely on subconscious processing for optimal outcomes. Therefore, this research aimed to examine the relationship between elevated familiarity bias and abnormal returns during rare events. Data were collected from all companies listed and active on the Indonesia Stock Exchange from 1997 to 2020. A systematic sampling method was used to establish the sample criteria, which led to a total of 5,615 observations derived from the number of trading days over 23 years across nine industries on the Indonesian Stock Exchange. The data collected were analyzed using the traditional Capital Asset Pricing Model, prospect theory and extending the Fama and French three-factor model with the addition of a psychological factor. The results show that familiarity bias behavior does not uniformly occur across all industries in Indonesia during rare events. The industries negatively impacted by these events include agriculture, consumer goods, trade services and investment, finance, basic industry, chemicals, mining, miscellaneous industries, property, real estate and building construction at values of –0.0847, –0.0946, –0.0721, -0.0405, –0.0717, –0.1258, –0.024, and –0.0805, respectively. A positive impact was only found in the infrastructure, utilities, and transportation industry at 0.0028. In conclusion, stock market behavior also affects the economy from a behavioral finance perspective.

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INTRODUCTION

Over the past 23 years, from 1997 to 2020, a total of eleven major economic events have significantly influenced the Indonesian capital market, including the Asian Financial Crisis in 1997, the DotCom Crash in 2000, the September 11 terrorist attacks in 2001, the SARS epidemic in 2002, the Global Financial Crisis in 2008, the European Sovereign Debt Crisis in 2009, the Fukushima nuclear disaster in 2011, the crude oil price collapse in 2014, China's Black Monday in 2015, the Brexit referendum in 2016, and the COVID-19 pandemic in 2020, all of which brought significant and unpredictable impacts to the economy. These events have triggered market fluctuations by over 10% within a brief period, affecting the stability of the capital market. Generally, all occurrences ranging from the Asian Financial Crisis to the COVID-19 pandemic, are often associated with "Black Swan" events. As a result, behavioral economics literature explained market anomalies using psychological methods.

An important psychological factor in financial markets is sentiment towards events influencing the expectations of investors. Positive market sentiment is correlated with stock movements, while negative sen-

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timent is inversely related. Furthermore, significant negative sentiment leads to declining stock performance. For example, during the COVID-19 pandemic, market psychology significantly affected global stock trends, which simultaneously experienced downward movements. In times of economic shocks, psychological responses override rational thinking, particularly in volatile markets driven by panic, while emotional inclusion, preferences, behavior, personality traits, and other related factors often led investors to deviate from rational decision-making. This research aims to determine an investor's tendency to prefer familiar securities, even when such choices may not be optimal from a portfolio diversification perspective. The process, which is known as Familiarity Bias (FB), enables the investors to increasingly rely on psychological defense mechanisms during rare events, potentially leading to abnormal return patterns in the market.

1. LITERATURE REVIEW AND HYPOTHESIS

The field of financial literature is strongly based on the assumption of market efficiency, as postulated in the Efficient Market Hypothesis (EMH) proposed by Fama (1998). The EMH suggested that security prices completely reflected all available information. This theory significantly influenced investors' understanding of how the capital markets respond to new information. The more swiftly a capital market incorporates new information into security prices, the greater the efficiency (Silva, 2022). Preliminary research reported that during periods of crisis or turbulence, market efficiency is temporarily disrupted, although it tends to subsequently return to a more efficient state.

The EMH represents a significant milestone in the advancement of financial theory, serving as a fundamental framework in finance. As a result, it plays a crucial role in analyzing financial market behavior (Nijescu & Anghel, 2022). Generally, EMH is the foundation of classical financial theory, which posits market participants exhibit rational behavior. Rational investors purchase securities when prices decline and sell when it rises (Agarwal et al., 2025). Rational economic agents are seeking ways to maximize utility by achieving the highest possible returns while minimizing risk. Virtually all economic theories share the perspective that investors consistently strive to maximize utility, particularly when making decisions concerning risk and uncertainty.

Empirical research critically examined the EMH concerning the rationality of investors during rare events. Building upon this finding, rare events create uncertain market conditions, which challenge traditional assumptions of market efficiency. Moreover, with the rapid advancement of technology, the EMH requires reconceptualization to accommodate the realities of the big data era, where efficiency is defined in terms of computational capacity and algorithms rather than the availability of information (Martin & Nagel, 2022). The EMH further posited that the price of a security completely reflected all available information. The global market was unable to generate normal rates during the Asian, and Global Financial Crises, alongside health-related issues, such as EMH. This was evident during the COVID-19 pandemic when global stock market reactions to the crisis demonstrated that significant abnormal returns were increasingly rare over time following the similarities displayed by the initial shock, Islamic stock, and conventional indices (Ali et al., 2022). In the early phase of the pandemic, markets exhibited substantial deviations from efficiency, allowing the occurrence of abnormal returns. However, over time, its efficiency was recovered, leading to a decline in abnormal returns.

In this perspective, rare health crises prompted several researchers to examine the EMH in respect to capital markets. Akhtaruzzaman et al. (2020) and Corbet et al. (2020) reported a significant increase in the correlation between returns across stocks, industries, and markets during the pandemic. However, Dima et al. (2021) reported that there were no fundamental changes in market mechanisms or investors' decision-making processes during the pandemic, contradicting the EMH. Dias et al. (2020) reported mixed evidence regarding the validity of EMH. Based on rank variance tests, the random walk hypothesis in the case of stock indices was rejected. The results also indicated that prices

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do not completely reflect available information, and its changes are neither independent nor identically distributed.

The research conducted by Fama and French (1992) extended beyond beta as the sole risk parameter influencing security returns, suggesting that additional variables played a role. This led to the development of the Three-Factor Model, which incorporated other determinants of returns, namely beta, proxied through the risk premium (Capital Asset Pricing Model/CAPM), firm size, and the book-to-market equity ratio. The findings of Fama and French (1992) failed to identify a significant interaction between beta and average returns, indicating that investors did not earn returns solely based on market risk. However, firm size and the book to-market ratio exhibited a more dominant association with returns. This long-term consistency was further reaffirmed by Fama and French (2012) who stated that the observed return patterns persisted over time rather than being temporary anomalies. The consistency with the original 1992 findings also demonstrated that market beta had weak explanatory power in predicting the cross-section of returns in international markets.

The scepticism and debate surrounding the accuracy of market beta as the sole explanatory variable in the CAPM for predicting expected returns led to the prominence of the Fama and French Three-Factor Model (FF3FM). Besides, the FF3FM was perceived as the most influential multifactor model. This was in line with Kaya (2020) who reported that the traditional CAPM exhibited limited explanatory power for stock returns in the Turkish market. The FF3FM asset pricing model was developed in response to the growing body of empirical evidence indicating that the CAPM performed poorly in explaining realized returns. Mukoyi and Ogujiuba (2022) reported that FF3FM was the best model to use in all market conditions. However, several researches outlined the model's limitations in capturing financial market dynamics, particularly during rare events. For example, Hasler and Martineau (2022) reported that CAPM unconditionally failed to explain returns. Building upon the description, the FF3FM conceptualized the relationship between risk and return based on three factors, namely market return, firm size, and book to market equity.

In times of economic turbulence, investors make decisions under rapidly changing information. Moreover, economic fluctuations caused by certain events could lead to cognitive biases, influencing decision-making under uncertain and risky conditions (Tversky & Kahneman, 1992). The prospect theory formulated by Kahneman and Tversky (1992) was used to analyze how individuals overweighed certain outcomes compared to uncertain situations. In this context, investors initially gathered relevant information, subsequently developing multiple decision frames. These enabled the selection of an option that yielded the highest expected utility. The prospect theory was widely used to reflect investors' risk attitudes at the maximum prospect value (Zhong et al., 2022). According to this theory, the alternative with the highest overall perceived value was always selected (Bromiley, 2010). Following the description, instead of maximizing expected utility rankings, choices were made under uncertainty by optimizing a value function that evaluated changes in wealth.

Preliminary research stated that decision-making under uncertain conditions was highly challenging (Bekierman, 2018). Investors evaluated asset volatility based on cumulative prospect theory, using realized volatility as a proxy for daily instability. As a result, the decision-making process significantly influenced the assessment system, depicting a tendency toward irrational behavior where investors were more averse to potential losses than equivalent gains. Previous research had proven that economic agents experienced the impact of losses more intensely and for a longer duration than the effects of gains in the same monetary value, particularly during economic downturns. Moreover, a strong negative correlation existed between financial literacy and behavioral biases among individual investors (Rasool & Ullah, 2020). Rare events, such as health crises, triggered financial market predicaments on a global scale (Kwatra, 2020). In such situations, behavioral economics played a crucial role in panic selling, eventually leading to some of the most significant market crashes in history. Financial markets had encountered these predicaments, particularly during the 2007-2008 global financial crisis, which received widespread attention.

During the COVID-19 pandemic, public health optimization was pursued through large-scale economic closures and extreme social distancing measures (Stewart, 2020). Moreover, virtually all global financial and capital markets experienced downturns as the health crisis unfolded. Market declines during the pandemic influenced investor behavior in Indonesia (Budiarso & Soleman, 2020). EMH, Prospect, and Signaling Theories conformed with the phenomena observed during the COVID-19 pandemic. The economic shock induced by the health crisis was felt globally, affecting both technologically advanced and less developed nations.

In line with the earlier description, FB refers to the tendency of investors to assess, select, and make decisions based on familiar circumstances (Lei & Mathers, 2024). Meanwhile, investors' decisions were not frequently driven by the fundamental value of securities, as proven by traditional financial theories; rather, respective choices were influenced by positive or negative perceptions of those securities. The occurrence of rare events often caused some investors to engage in speculation with greater confidence due to the belief of understanding the situation (Heath & Tversky, 1991). In conditions of ambiguity aversion, investors prefer risks that are well-known and clearly defined over uncertain ones. A manifestation of this bias was the tendency to allocate a significant portion of capital to domestic financial markets rather than diversifying globally (Speidell, 2009). Prior research had shown that investors were generally reluctant to engage in international diversification. Besides, economic agents exhibited home-country bias, preferring to invest in familiar securities (Gaar, 2022). Most investors tend to invest in companies that are geographically close or recognized products. As a result, these investors feel more comfortable and confident investing in familiar assets, even though the investments may not always be objectively optimal.

Familiarity, as a concept, is the cognitive process of quickly and efficiently assimilating new information. The brain uses subconscious neural networks to simplify complex calculations required for effective decision-making. Meanwhile, the fluctuating behavior of foreign and domestic institutional investors is consistent with the familiarity explanation (Hiraki et al., 2003). The strong preference of these institutional investors for large-cap firms was attributed to the familiarity with market conditions or location of clients. Banerjee and David (2024) stated that familiarity played a crucial role in investment decisions and hedging strategies. Furthermore, empirical evidence supporting the familiarity hypothesis, particularly in the insurance sector was also provided. When insurance firms invest in other similar companies, it favors industries that engage in similar operations. This research adopted the return of insurance firms' transaction-based portfolios as an indicator of asymmetric information to investigate the nature of familiarity. Additionally, it examined whether stock trading within the insurance industry yielded superior returns.

Based on the discussion, rare events triggered extreme shifts in economic fundamentals, often driven by global financial, debt, and health crises eventually leading to fiscal turmoil. Empirical evidence over the past century indicates the impact of rare events on per capita gross domestic product (Bacovic et al., 2022). Investors generally exhibited aversion to such rare events, as its occurrence was unpredictable and difficult to forecast. In recent years, the world has witnessed several rare events with catastrophic consequences, including the global financial crisis, and the European sovereign debt crises, alongside the Fukushima nuclear disaster. A common feature of these events was that decision-makers, as well as market participants and regulators, appeared unprepared to respond effectively, giving the impression of panic (Gröschl & Lepoutre, 2022). The lack of preparedness was not solely attributable to irrationality, rather it reflected an optimal response to the limitations in information processing capacity. Decision-makers faced constraints in processing information, resulting in the need for selective attention.

The current research aimed to analyze the complex mechanisms of FB within the dynamics of the Indonesian stock market, particularly in the formation of abnormal returns during rare events. It explicitly identified the structural and temporal conditions that influenced the relationship between the intensification of FB and investment return anomalies. Furthermore, this research explored the variability of market char-

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acteristics over time to determine the extent to which FB contributed to price imbalances during rare events.

The formulation of a single hypothesis led to the use of an in depth quantitative and empirical method to examine existing relationships without the distraction of extraneous factors that could introduce noise in the statistical analysis. Building on the preceding discussion, the following hypothesis was formulated:

H1: *Higher familiarity bias led to abnormal returns during rare events.*

2. METHODOLOGY

The research used daily data for all stocks classified into nine industries by the Indonesian capital market regulator. The data, obtained from 1997 to 2020, included trading volume, bid, market capitalization and ask volumes, price to book value, adjusted closing prices, the LQ45 Index, sectoral indices sourced from the Indonesia Stock Exchange (IDX), and the BI Rate provided by the Central Bank of Indonesia.

The data from 1997 to 2020 were strategically selected to cover several significant economic events that had impacted the Indonesian capital market. This 23-year period provided a comprehensive representation of both bull and bear market cycles, enabling an in-depth analysis of how investors' FB responded to various extreme external shocks. The examination of whether investor behavior remained consistent or evolved offered deeper insights than research limited to only one or two market cycles.

The core research model was developed using the FF3FM framework, combined with insights from prospect theory. The FF3FM was used to evaluate FB as an additional risk factor in the context of IDX during the rare events period. Subsequently, interactive terms were incorporated to enhance the measurement of abnormal returns. This method was consistent with the method proposed by Dawson (2014), stated as follows:

$$\begin{aligned}\pi_t &= \beta_0 + \beta_1 Familiarity_t + \beta_2 RE_t \\ &+ \beta_3 \left[Familiarity \cdot RE\right]_t + \beta_4 SMB_t \\ &+ \beta_5 HML_t + \beta_6 SIZE_t + e_t,\end{aligned} \tag{1}$$

where π_t – abnormal returns, $Familiarity_t$ – familiarity in period t, RE_t – rare events, SMB – difference between the returns of small and large cap stock portfolios, HML – difference between the returns of stock portfolios with high book-to-market ratios and stock portfolios with low book-to-market ratios, $Size_t$ – market capitalization in period t.

The dependent variable used was defined as an abnormal return. In this regard, the returns of industries i in time t (Rt) were used to calculate abnormal return (ARt), deducted from the market returns E[Rt]. The result was equivalent to IDX returns at time t, as stated in the research by Nawangsari and Iswajuni (2019), obtained with the following formula:

$$AR\_t = R\_t - E\left[R\_(i,t)\right]. \tag{2}$$

The calculation adopted the method proposed by Baker and Nofsinger (2010), using the Data-Based Approach as a proxy for measuring FB. This method applied a data-driven technique where the weights of the optimal portfolio were determined through a mean-variance optimization procedure, detailed as follows:

$$w^* = \frac{1}{\gamma} \grave{U}^{-1} \mu, \tag{3}$$

where w^* represents the vector (N×1) of the optimal portfolio weights. Assuming risk aversion remained constant, the optimal weights would only change in response to shifts in the expected excess returns of an asset (μ) or the contribution to the overall portfolio risk (Ω). Considering this perspective, the contribution to the total risk reduced when the expected excess return of an asset increased with optimal weight. Therefore, this research incorporated control variables Small Minus Big, High Minus Low, and company size into the estimation model to isolate the impact of FB on abnormal returns during rare events.

3. RESULTS

The industries with favorable data distributions included the basic materials and chemicals, infrastructure, utilities, transportation, trade, services, and investment. Meanwhile, those with standard

Table 1. Summary statistics

	Agriculture industry					Basic and chemical industry					Consumer goods industry				
Variable	AR	Fam	Size	SMB	HML	AR	Fam	Size	SMB	HML	AR	Fam	Size	SMB	HML
Mean	0.03	15.17	30.67	0.00	0.12	0.20	14.91	32.20	–0.03	0.24	0.57	15.54	32.60	0.03	0.03
Std Dev	2.09	1.63	2.37	1.84	5.33	1.69	0.95	2.23	1.91	4.00	7.21	1.21	2.06	0.84	2.64
	Finance industry					Infrastructure, utilities, and transportation industry					Mining industry				
Mean	0.133	15.89	32.67	0.01	0.03	0.14	15.53	32.31	–0.32	–0.02	0.21	15.79	32.47	0.04	0.07
Std Dev	2.62	1.58	2.63	0.87	2.57	1.74	1.27	2.23	2.16	3.75	2.08	1.57	2.55	1.49	4.42
	Miscellaneous industry					Property, real estate, and construction industry					Trade, services, and investment industry				
Mean	–0.29	15.15	32.21	–0.01	0.03	0.12	15.97	32.05	0.02	0.01	0.03	15.13	32.62	0.05	0.13
Std Dev	2.00	0.88	1.77	1.36	4.79	2.07	1.67	2.06	1.22	3.48	1.47	1.21	2.15	1.02	3.29

deviation values exceeding twice the average consisted of agricultural, consumer goods, financial, mining, property, miscellaneous, real estate, and construction industries. For example, the average abnormal return for agricultural industries, with maximum and minimum values is 0.03%, 18.46%, and -16.73%, respectively. The positive value showed that agricultural industries were capable of generating abnormal returns. However, the negative value suggested that industries do not consistently produce abnormal returns.

Table 2 shows a comprehensive statistical overview of FB associated with abnormal returns for each rare event, exhibiting distinctive characteristics. For example, the average FB during the monetary crisis was 131.67, accompanied by a relatively high abnormal return of 0.14. Similarly, the average FB during the DotCom bubble was 99.16, with an abnormal return of 0.69. These results prove the scientific perspective that periods of rare events must be characterized by increased buying pressure.

In line with the description, the dynamics of financial markets show significant variations in related responses to various economic events. During the global financial crisis, the market experienced strong selling pressure, as indicated by an index and a negative abnormal return of 74.2 and of -0.12, respectively. Considering the oil boom and China's Black Monday event, the market showed varying performances. The oil boom period recorded moderately positive averages for FB and abnormal return, while Black Monday in China showed a statistically significant positive value. These results outlined that market behavior was highly dependent on the specific context of each event. Furthermore, global events such as the oil boom and Black Monday did not directly result in substantial spillover effects on risk-return trade-offs in the Indonesian stock market.

Asides from this description, the phenomenon of FB reflected imperfections in financial markets, as evidenced by several global events namely the War on Terror, SARS epidemic, Fukushima nuclear disaster, Brexit, and COVID-19 pandemic. Statistical analysis reported positive average FB for all five events, namely 36.23 (War on Terror), 6.26 (SARS), 7.66 (Fukushima), 8.51 (Brexit), and 9.03 (COVID-19), illustrating the potential for excessive buying pressure. However, the average abnormal returns showed a different pattern of 0.54 (War on Terror), 1.19 (SARS), 0.20 (Fukushima),

Table 2. Summary statistics of rare events

	Monetary crisis		DotCom		Terror 9/11		SARS 2002	
	FAM	Abnormal return	FAM	Abnormal return	FAM	Abnormal return	FAM	Abnormal return
Mean	131.67	0.14	99.16	0.69	36.23	0.54	6.26	1.19
Std Dev	55.63	5.86	37.46	7.99	118.06	6.98	93.93	7.49
	GFC		Europe debt crisis		Fukushima disaster		Oil cycle	
Mean	74.2	–0.12	–13.76	0.26	7.66	0.20	7.55	0.03
Std Dev	74.19	3.44	73.09	3.50	16.67	1.68	15.16	
	Black Monday China		Brexit		COVID-19			
Mean	9.50	0.02	8.51	0.06	9.03	0.08		
Std Dev	59.78	1.15	22.97	1.26	19.78	2.03		

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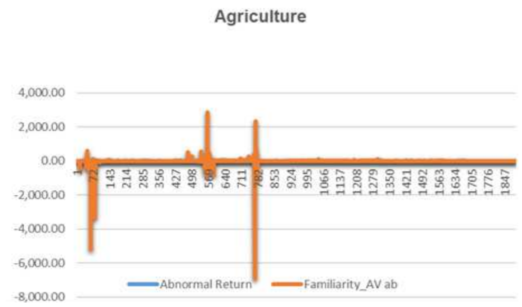
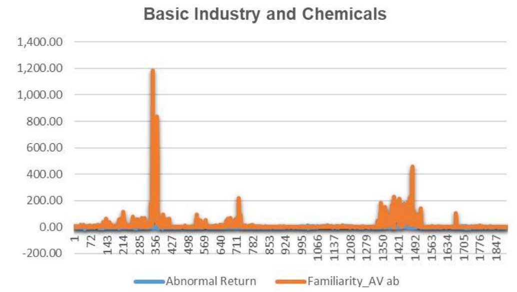
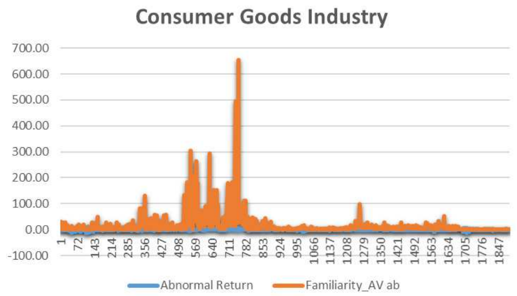


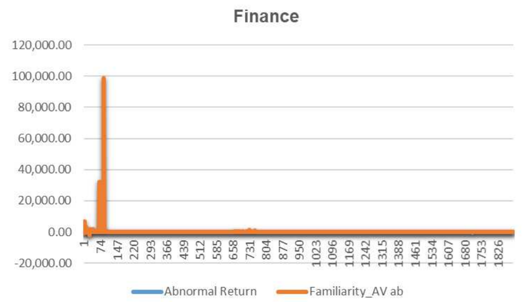
a) Agriculture



b) Basic industry and chemicals



c) Consumer goods industry



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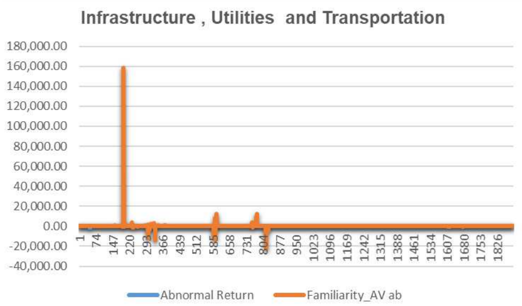
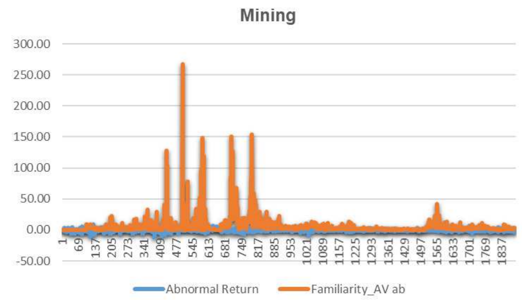
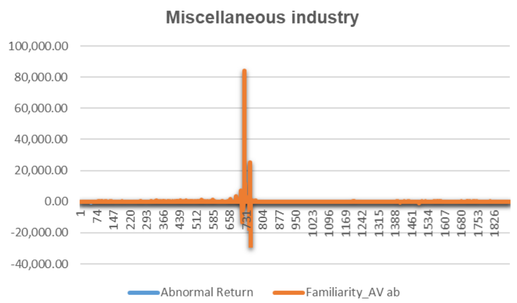


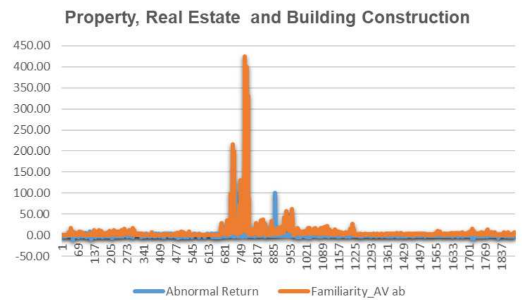
e) Infrastructure, utilities and transportation



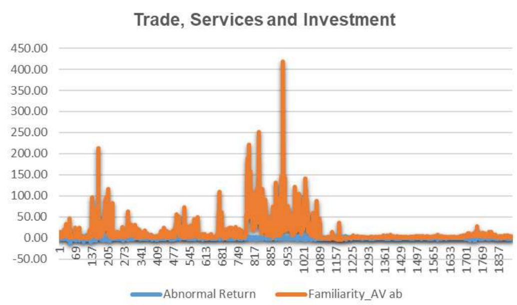
f) Mining



g) Miscellaneous industry

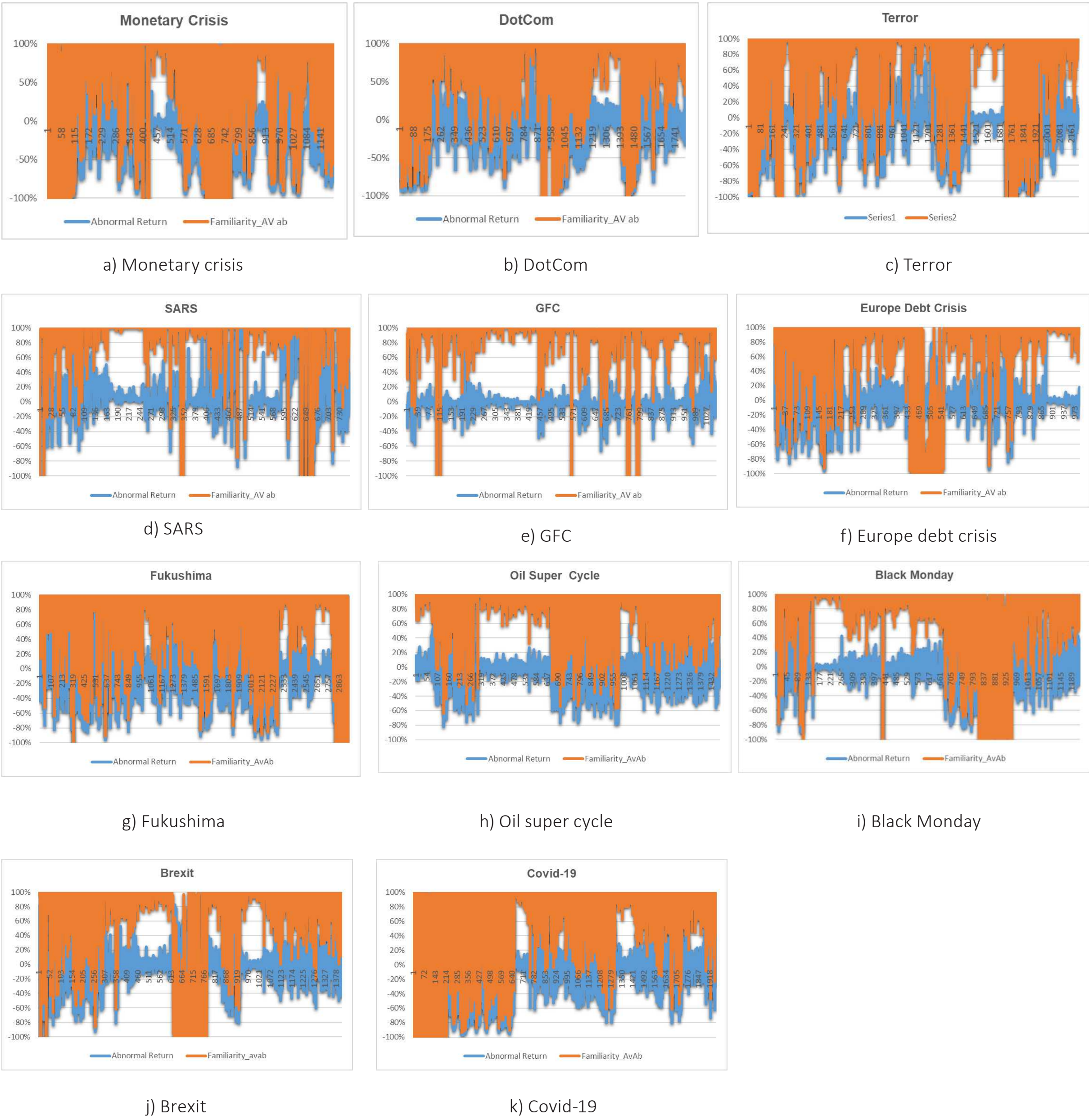


h) Property, real estate and building construction



i) Trade, services and investment

Figure 1. Familiarity bias per quartile returns



a) Monetary crisis b) DotCom c) Terror

d) SARS e) GFC f) Europe debt crisis

g) Fukushima h) Oil super cycle i) Black Monday

j) Brexit k) Covid-19

Figure 2. Familiarity bias in buy and sell imbalances based on rare events and portfolio categories

0.06 (Brexit), and 0.08 (COVID-19). This discrepancy proved the complexity of market dynamics was affected by various factors beyond FB to provide empirical support for the hypothesis of temporal variation in market behavior. The case study on the European debt crisis offered additional insights, showcasing trading characteristics balanced by low FB. Even though abnormal returns approached zero, the level of abnormality remained significant. This phenomenon was explained by the presence of arbitrage opportunities and imperfect market efficiency. Therefore, price anomalies persisted in relatively balanced market conditions, creating strategic opportunities for discerning traders and investors.

Statistical analysis shows a positive average abnormal return of 0.03% in agricultural industries, suggesting the potential for above-average profits. However, the variability in abnormal returns, as illustrated by the occurrence of negative values, provided empirical evidence that challenges the consistency of the EMH. This phenomenon was not confined to agriculture; rather, it reflected a

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complex pattern observed across various economic industries, where the inconsistency of abnormal returns systematically challenged the fundamental assumptions of an efficient capital market.

The empirical analysis of abnormal returns across several industries showed diverse patterns. Agricultural industries reported an average abnormal return of 0.03%, with a significant range of variation, from maximum to minimum values of 18.46% and -16.73%, respectively. The basic materials and chemicals industry exhibited an abnormal return characteristic with an average of 0.20%, fluctuating between 10.57% and -12.83%. Furthermore, consumer goods industries recorded the highest average abnormal return of 0.57%, with an extensive variation range from 100.48% to -17.84%. The financial industries suggested similar dynamics, with an average abnormal return of 0.13% and remarkable fluctuations between 101.41% and -35.29%.

A comprehensive investigation of abnormal returns focused on the complex dynamics of capital markets. The infrastructure, utilities, and transportation industries suggested an average abnormal return of 0.14%, with a variation within the range of 10.37% and -15.96%. Mining industries recorded an average abnormal return of 0.21%, within a significant range of 36.36% and -13.86%. However, miscellaneous industries showed a negative average abnormal return of -0.29%, fluctuating between 21.16% and -12.84%. The property, real estate, and construction industry indicated an average abnormal return of 0.12%, with an extensive variation from 53.31% to -26.98%. Finally, the trade, services, and investment industry had the lowest average abnormal return of 0.03%, ranging from 11.79% to -10.14%.

The coefficient for FB was observed to be negative at -0.08, indicating that the concept was typically observed in agricultural industries. FB was evident across all industries on IDX, including basic materials and chemicals, with a coefficient of -0.07. The consumer goods, financial, mining, miscellaneous, property, real estate, construction, trade, services, and investment industries, showed coefficients of -0.09, -0.04, -0.13, -0.02, -0.08, and -0.07, respectively. The infrastructure, utilities, and transportation industries reported an anomaly with a minimal positive coefficient of 0.00 entirely different from the general trend. The substantial variation in FB coefficients suggested the complexity of investor cognitive behavior, leading to an in-depth investigation to understand the fundamental psychological mechanisms in investment decision-making across different industries.

The agricultural, finance, mining, property, real estate and construction, services, trade, and investment industries recorded that virtually all independent variables significantly correlated with abnormal returns, except for company size. For the basic materials and chemicals industries, this excluded firm size and SMB. In this regard, SMB was also excluded in the consumer goods industries. In the infrastructure, utilities, and transportation industries, the exceptions were FB and firm size. Finally, FB was the only exception in miscellaneous industries. Considering the correlation between abnormal returns and the main independent variables, all industries showed a negative association, except for SMB in agricultural industries. This suggested that a high FB, as well as market consensus and divergence of opinions during bearish and bullish market conditions, were influential factors.

In analyzing the impact of each rare event on the buying patterns driven by FB, this research adopted a robust OLS regression method with appropriately clustered standard errors. A total of three risk factors from the FF3FM were incorporated into the analysis to assess the effect on abnormal returns, isolating the influence of FB as a distinct risk component. According to Dawson (2014), the results of the estimation in Table 3 showed three main aspects, including FB, rare events, and the interactive relationship between both.

The results of hypothesis testing obtained through regression analysis are shown in Table 3. Furthermore, a positive correlation existed between FB and abnormal returns in the agricultural industry ($\beta = 0.264$, $SE = 0.03$). This finding supported the hypothesis that higher FB value resulted in abnormal returns during rare events. The finding was also consistent with Arena and Howe (2008), where the influence of the variable on stocks selected separately produced an abnormal return of 0.80%. A similar pattern was observed in the basic materials

Table 3. The results of hypothesis testing obtained through regression analysis

	Agriculture industry	Basic and chemical industry	Consumer goods industry	Finance industry	Infrastructure, utilities, and transportation industry
FAM	0.264**	0.144**	0.129	0.120**	0.084*
	(0.03)	(0.03)	(0.16)	(0.04)	(0.04)
RE	2.725**	–0.693	–6.943*	1.206	–0.364
	(0.510)	(0.720)	(2.940)	(0.770)	(0.730)
FAM*RE	–0.192**	0.05	0.355*	–0.084*	0.036
	(0.03)	(0.05)	(0.19)	(0.05)	(0.05)
F-value	136.02	119.57	13.01	78.97	95.61
Adj R-squared	0.225	0.202	0.026	0.145	0.168

Table 4. The estimation results of familiarity, rare events and interactions

	Mining industry	Miscellaneous industry	Property, real estate, and construction industry	Trade, services, and investment industry
FAM	0.220**	0.148**	0.107**	0.115**
	(0.03)	(0.03)	(0.02)	(0.02)
RE	2.389**	–0.177	1.252*	0.883*
	(0.640)	(0.850)	(0.530)	(0.480)
FAM*RE	–0.140**	0.005	–0.084*	–0.061*
	(0.04)	(0.06)	(0.03)	(0.03)
F-value	169.41	104.72	68.14	130.68
Adj R-squared	0.265	0.182	0.126	0.220

Note: The numbers represent coefficient values, while the values in parentheses indicate robust standard errors.

and chemicals industries, where a positive relationship existed between FB and abnormal returns (β = 0.144, SE = 0.03). This was also reported in the financial (β = 0.120, SE = 0.04), infrastructure, utilities, transportation (β = 0.084, SE = 0.04), mining (β = 0.220, SE = 0.03), miscellaneous (β = 0.148, SE = 0.03), property, real estate, construction (β = 0.107, SE = 0.02), trade, services, and investment industries (β = 0.115, SE = 0.02) (see Table 4).

Rare events showed a positive effect on abnormal returns (β = 2.73, SE = 0.51), depicting a significant difference of 2.725%. A similar result was observed in the basic materials and chemicals industries, where rare events influenced the relationship between FB and abnormal returns. In this context, the events strengthened the positive relationship between FB and abnormal returns (β = 0.355, SE = 0.19), and the results were consistent with the hypothesis. Similarly, in mining (β = 2.389, SE = 0.64), property, real estate, and construction (β = 1.252, SE = 0.53), as well as trade, services, and investment industries (β = 0.883, SE = 0.48), these events positively influenced abnormal returns. An exception was observed in consumer goods industries, where rare events had a significant negative impact on abnormal returns (β = -6.94, SE = 2.94). This showed a significant difference between the presence and absence of rare events, with a value of –6.943%.

Based on this perspective, rare events moderated the relationship between FB and abnormal returns (β = –0.192, SE = 0.03) in agricultural industries. The negative effect of the variables led to smaller abnormal returns whenever rare events occurred. The interactive effects were also observed in the financial (β = -0.084, SE = 0.05), mining (β = -0.140, SE = 0.04), property, real estate, and construction (β = -0.084, SE = 0.03), including trade, services, and investment industries (β = -0.061, SE = 0.03).

FB significantly affected abnormal returns during rare events, particularly in consumer goods industries. The results were in line with the temporal variation hypothesis, indicating that investors' responses to rare events with FB were not entirely connected to strict rationality. This indicated how investors decision-making diverged from rational economic models, due to the integration of emotional responses and mental shortcuts, particularly during unusual market conditions within a specific industry. More importantly, sub-sampling analysis was conducted for each rare event, and the results shown in Table 5.

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Table 5. Sub-sampling regression analysis results

	Agriculture industry	Basic and chemical industry	Consumer goods industry	Finance industry	Infrastructure, utilities, and transportation industry	Mining industry	Miscellaneous industry	Property, real estate, and construction industry	Trade, services, and investment industry
FAM	0.203	1.009**	0.524	0.127	1.031	0.25	–0.302	0.488*	–0.247
	(0.20)	(0.38)	(0.45)	(0.40)	(2.21)	(0.25)	(0.23)	(0.29)	(0.29)
Intercept	–7.925	5.671	0.631	–3.216	–170.401	–4.398	4.14	–8.191	1.865
	(14.97)	(12.03)	(20.01)	(7.80)	(174.12)	(5.06)	(13.41)	(6.41)	(6.44)
DotCom									
FAM	0.009	0.250*	0.233	–0.066	–1.946	0.287	0.166	–0.012	–0.019
	(0.13)	(0.14)	(0.16)	(0.18)	(1.58)	(0.21)	(0.12)	(0.12)	(0.10)
Intercept	32.837*	–17.304*	–2.813	0.42	675.507*	1.609	–10.711	–3.472	5.497
	(15.74)	(9.03)	(9.11)	(10.11)	(385.36)	(11.21)	(13.36)	(10.20)	(5.10)
Terror									
FAM	0.394**	–0.019	0.172	0.18	0.352	0.388**	0.079	0.152	0.093
	(0.13)	(0.11)	(0.12)	(0.12)	(2.38)	(0.13)	(0.09)	(0.12)	(0.09)
Intercept	25.244	–5.867	–1.245	–5.11	–93.09	0.982	–7.53	–10.638	23.631
	(16.18)	(14.13)	(7.01)	(13.86)	(233.06)	(23.54)	(12.19)	(11.29)	(20.06)
SARS 2002									
FAM	0.775*	0.530*	0.469*	0.720*	–4.663	–0.104	0.646*	0.236	0.135
	(0.39)	(0.24)	(0.18)	(0.30)	(4.03)	(0.64)	(0.25)	(0.30)	(0.15)
Intercept	–35.78	–7.228	–58.144	–154.975	–53.849	6.1	–31.614	–11.714	13.071
	(60.51)	(24.84)	(50.89)	(93.45)	(55.06)	(69.05)	(28.84)	(11.65)	(9.94)
GFC									
FAM	0.216	0.192*	0.079	0.401**	0.222	0.077	0.341	–0.412	0.320*
	(0.14)	(0.11)	(0.19)	(0.13)	(0.18)	(0.23)	(0.21)	(0.41)	(0.16)
Intercept	1.342	22.727	6.599	10.36	2.078	–13.205	35.191	–45.848	0.251
	(16.59)	(16.37)	(19.65)	(27.71)	(41.87)	(17.49)	(24.45)	(39.64)	(13.27)
Europe debt crisis									
FAM	0.489*	0.269**	0.032	0.123	0.001	0.427*	0.147	0.393	0.131
	(0.20)	(0.09)	(0.17)	(0.20)	(0.02)	(0.18)	(0.19)	(0.68)	(0.22)
Intercept	–49.842	–241.658*	–2.134	–90.801	–96.211	–464.367**	–83.529	387.961	–13.458
	(57.74)	(102.28)	(37.08)	(76.36)	(152.14)	(129.09)	(72.64)	(305.54)	(15.85)
Fukushima disaster									
FAM	0.112	0.069	0.223*	–0.041	0.016	–0.053	0.207*	0.279*	0.034
	(0.12)	(0.08)	(0.10)	(0.17)	(0.04)	(0.07)	(0.10)	(0.15)	(0.05)
Intercept	–2.423	–79.862	–19.461	–241.654**	–60.791*	–36.419	–39.99	–1.887	–9.676
	(21.49)	(60.05)	(15.44)	(73.78)	(31.18)	(31.88)	(40.47)	(15.56)	(15.74)
Oil cycle									
FAM	0.264*	–0.001	0.161	0.400*	–0.14	–0.089	–0.034	1.009**	0.818**
	(0.11)	(0.10)	(0.15)	(0.18)	(0.25)	(0.19)	(0.19)	(0.27)	(0.28)
Intercept	–1.201	–1.011	–1.446	–6.272*	1.204	0.829	0.372	–16.872**	–11.805**
	(0.97)	(2.39)	(2.35)	(2.92)	(4.15)	(4.10)	(4.04)	(5.26)	(4.14)
Black Monday China									
FAM	–0.048	–0.125	0.217	0.247	–0.355	0.097	0.152	0.426	0.358
	(0.21)	(0.14)	(0.22)	(0.30)	(0.28)	(0.20)	(0.16)	(0.35)	(0.26)
Intercept	–1.351	1.166	–3.182	–3.939	4.655	–1.618	–3.746	–9.962	–5.085
	(1.72)	(2.02)	(3.32)	(4.99)	(4.32)	(3.44)	(2.66)	(6.57)	(4.01)
Brexit									
FAM	0.061	0.021	–0.295	–0.025	–0.105	–0.18	0.673*	–0.175	0.291
	(0.05)	(0.19)	(0.27)	(0.25)	(0.09)	(0.29)	(0.32)	(0.41)	(0.22)
Intercept	–20.278*	–16.626*	2.047	1.374	15.765	–12.621*	–15.007	–23.089**	–16.487**
	(11.75)	(9.35)	(3.82)	(10.73)	(10.43)	(5.78)	(12.70)	(6.48)	(5.09)
COVID–19									
FAM	–0.028	0.025	–0.233	0.217	0.106	0.132	0.310*	0.145	–0.027
	(0.23)	(0.08)	(0.17)	(0.19)	(0.22)	(0.21)	(0.17)	(0.31)	(0.20)
Intercept	–8.863*	–24.555**	3.826	1.395	–15.122**	–4.842	–8.726	–4.385	–11.284*
	(4.86)	(7.06)	(4.39)	(8.89)	(5.57)	(3.70)	(6.38)	(4.27)	(5.43)

Note: The figures represent coefficient values, with the values in parentheses indicating robust standard errors.

The findings related to the interaction model between the factors of rare events and FB showed a substantial positive effect on abnormal returns. The phenomenon was particularly evident across multiple historical financial disruptions, including the Asian Financial Crisis, collapse of the DotCom bubble, economic aftermath of the War on Terror, SARS outbreak, World Financial Crisis, the European Sovereign Debt Situation, Fukushima nuclear incident, and petroleum market downturn. Each of these distinct events demonstrated a similar pattern of investor behavior. The significance of the positive results implied that a higher level of FB led to abnormal returns, indicating market inefficiency. In these instances, the industry where FB significantly influenced investor behavior was caused by the initial irrational actions of the investors.

4. DISCUSSION

FB showed varying effects, ranging from positive, and negative, to insignificant, supporting and contradicting the EMH. Positive FB was observed in the consumer goods and financial industry. This result was consistent with the research by Seiler et al. (2020), which stated a positive correlation existed between the degree of FB and the subjective probability of investment success. The more familiar an investor is with a company or investment, results in higher FB, less rational market, and significant abnormal returns. However, negative FB was identified in agriculture, mining, property, real estate, building construction, trade, services, as well as investment industries. Its effect in the basic and chemical, infrastructure, utilities, transportation, and miscellaneous industries, were found to be insignificant. The impact of FB varied across rare events and industries, indicating that the effect was not uniform across the market. Furthermore, the magnitude of the impact differed across industries in the capital market of Indonesia.

Building upon the description above, there was substantial evidence that investors preferred familiar issuers when investing in equities. This behavior evolved from FB, where investors were inclined to favor well-known issuers, particularly during periods of market stress, in pursuit of abnormal returns. A major characteristic of issuers that attracted FB was the local presence, particularly in agriculture, consumer goods, finance, mining, property, real estate, construction, services, trade, and investment. These industries were predominantly dominated by local issuers. The finding was in line with the research by Ackert et al. (2005), where investors tended to be more familiar with local and domestic issuers.

The results showed that the influence of FB on the Indonesian stock market varied across industries, during rare events. In this context, FB did not affect certain industries, during specific rare events. For example, in the basic and chemical, infrastructure, utilities and transportation, alongside miscellaneous industries, FB had no significant influence on investment decisions. Therefore, the industry showed no inefficiencies since its absence implied the non-existence of abnormal returns.

Regarding FB, Indonesian investors were more familiar with the basic and chemical, infrastructure, utilities, and transportation, as well as miscellaneous industries. Building upon the finding, these industries mainly included the use of chemicals for the production of raw organic and inorganic materials, alongside businesses related to energy provision, transportation, telecommunication infrastructure, and supporting services, as well as textile and food industries. However, the last three industries were not part of the nine essential commodities required by the general population. During rare events, investors focused more on industries directly connected to essential societal needs. The absence of FB in the three industries under the Indonesian stock market prevented the development of psychological biases.

This research focused on examining FB in respect to the Indonesian capital market, particularly during rare events. The results showed its significant presence was relatively higher compared to several other countries. According to Cao et al. (2011), the degree of FB in Indonesia exceeded that observed in Germany, Japan, the United States, and globally.

Future research should expand its scope to different countries to verify these findings, as well as investigate new areas regarding the psychological biases of individual investors. This should also include respective participation behavior in the stock market, with the possible development of additional psychological bias variables.

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CONCLUSION

This research aimed to examine the relationship between elevated familiarity bias and abnormal returns during rare events.

In conclusion, this research explored the correlation between the increase in FB and abnormal returns in the context of rare events. Industry characteristics, including market capitalization, were incorporated as control variables to isolate the main effects of FB on market behavior. Empirical evidence showed that FB reportedly had positive and negative effects on abnormal returns under upward and downward market conditions. Various events had differing impacts on the behavior of FB, with significant variations across the industry. Meanwhile, moderation analysis suggested a substantive correlation between FB and abnormal returns. In this context, rare events systematically reduced the negative relationship between the variables. FB did not manifest in the basic, chemical, infrastructure, utilities, Transportation, and miscellaneous industries. However, this phenomenon was significantly observed in consumer goods, finance, agriculture, mining, property, real estate, and construction, as well as trade, services, and investment industries. This research showed that FB significantly influenced investment decision-making, leading to temporary deviations from rational principles with the potential for recurring irrational conditions. Each investor had a unique individual response to rare events, considering risk variables and specific potential returns.

AUTHOR CONTRIBUTIONS

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Funding acquisition: Dedi Hariyanto.
Investigation: Dedi Hariyanto.
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Project administration: Wendy Wendy.
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Visualization: Dedi Hariyanto.
Writing – original draft: Dedi Hariyanto.
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