"Market crash factors and developing an early warning system: Evidence from Asia"

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MARKET CRASH FACTORS AND DEVELOPING AN EARLY WARNING SYSTEM: EVIDENCE FROM ASIA

Abstract

Market crashes pose significant risks to the stability and performance of financial markets, making the development of an early warning system crucial. This study utilizes exchange rate volatility and investor sentiment to predict market crashes. While several studies have examined factors affecting market crashes in developing countries. This study aims to develop an early warning system for investors to minimize investment risk using Exchange Rate Volatility and Investor Sentiment. The study focused on seven countries: Indonesia, Malaysia, Singapore, the Philippines, Thailand, Vietnam, and Mongolia. The stock exchanges examined included Jakarta Stock Exchange Composite, FTSE Malaysia KLCI, FTSE Singapore, SET Index, PSEi, HNX/HNXI, and MNE Top 20/MNETOP20. The analysis involved assessing early warning systems to provide valuable supplementary information for decision making and evaluating market vulnerabilities. The logistic regression equation was utilized to model market crashes, incorporating variables such as exchange rate volatility and investor sentiment while considering their interactions as moderating factors. The results indicate that exchange rate volatility and investor sentiment have a significant negative effect on market crashes, with probabilities of 0.0082 and 0.000 Furthermore, investor sentiment acts as a mediator for exchange rate volatility, amplifying its impact on market crashes. This suggests that higher exchange rate volatility and negative investor sentiment increase the likelihood of market crashes. Exchange rate volatility and investor sentiment can serve as early warning indicators, emphasizing the importance of monitoring these factors for market participants and policymakers.

Keywords	financial market stability, sentiment analysis, investment risk management, market volatility, developing countries, logistic regression
JEL Classification	G01, G32, E44

INTRODUCTION

Market crashes pose significant risks to investors and profoundly affect financial stability and economic growth. Recognizing the importance of early warning systems in mitigating such risks, this study focuses on developing an innovative approach to anticipate market crashes by utilizing two key indicators: exchange rate volatility and investor sentiment. The relevance of this research topic stems from the need to enhance the understanding of the dynamics and triggers of market crashes, particularly in the context of a globalized and interconnected financial system. Market crashes can result in severe economic downturns, leading to financial distress, loss of investor confidence, and even systemic risks. By developing an effective early warning system, investors and policymakers can take proactive measures to minimize the adverse effects of market crashes and safeguard financial stability. This paper addresses a crucial research question about the correlation between exchange rate volatility and investor sentiment on

market crashes. This research question is important because it will be used as an early warning system for market crashes, benefiting investors, policymakers, and other stakeholders in the financial sector. In addition, the findings of this study will contribute to the existing literature on market crashes and early warning systems and provide valuable insights for stakeholders in the financial sector.

1. LITERATURE REVIEW

The study of Early Warning Systems is important because it can predict crash risk and prevent investors from losing money. In this case, the exchange rate and stock return volatility are often used as a basis during the emergence of crash risk. Moreover, the early warning system needs to be implemented as part of risk management to avoid crash uncertainty. In Klopotan et al. (2018), thirty-four papers on macroeconomics (such as exchange rates) and stock exchange crises were analyzed. This emphasized the importance of the factors affecting market crashes, enabling the early warning system to prevent investor losses. Truong et al. (2022) developed a framework for an early warning system capable of being applied in diverse Asian nations, such as Malaysia, Singapore, the Philippines, Thailand, and Indonesia. The global market crash was also a potential systemic risk and macroeconomic (exchange rate) instability source (Samitas et al., 2020), where a better understanding of the influence of increased connectedness on its risk probability was emphasized.

Global and regional issues were also influential in the occurrence of market crashes. Based on Yang et al. (2019), the financial turmoil unfolding on a global scale led to the occurrence of the most severe market crashes in 1998. This historical event showed that investor panic played a significant role in initiating market crashes. In 2008, the Subprime Mortgage financial crisis also caused market crashes. According to Song et al. (2020), the business distresses 2018 were attributed to the trade war between the USA and China. In 2020, these distresses were attributed to the COVID-19 pandemic, with a significant downturn in global stock markets starting from February 20, 2020, resembling the magnitude of the 2008 Great Recession. During this period, the stock market crash was largely attributed to the widespread pandemic and had far-reaching consequences. This led to the exertion of a substantial influence on various aspects of society, including the economy, public health, and daily life. The

financial crises in Europe, the Middle East, and Asia also negatively affected the stock price volatility of a country, indicating that global or regional issues or events impacted the market crashes.

In March 2020, the stock market experienced its most significant crash, characterized by a rapid DJIA index. This emphasized a significant drop in value by 6,400 points within four trading days, marking a steep 26% decrease (Mazur et al., 2020). During the initial phase of the pandemic in the United States, the stock price also experienced heightened levels of volatility, which was noticeable through the VIX, a widely used business indicator. This attained the levels comparable to those witnessed during notable historical crashes, such as the Black Monday in 1987, as well as the Great Depression and Crash in 1933 and 1929, respectively (Contessi & Pace, 2021). Moreover, financial crises and pandemics had far-reaching consequences across all sectors of the economy, with effects lasting for months to years (Rai et al., 2021). Based on Liu et al. (2021), a trend of decreasing conditional skewness was observed in the stock price with the increasing daily count of confirmed COVID-19. This indicated that the patient increased susceptibility to stock market crashes. When a heightened fear sentiment was determined, the effect of the pandemic became more prioritized on the probability of stock price distress.

According to Moradi et al. (2021), market crashes were found to detrimentally affect the exchange rate. Ali et al. (2020) also showed a negative correlation between the exchange rate and the stock market's daily (monthly) overall performance. This proved that fluctuations in currency exchange rates were considered a detrimental indicator, reacting negatively to stock price volatility. The study by Febriandika et al. (2023) reveals that the USD has a positive impact on the stock index in both the short and long term, while the JPY and HKD have a negative influence. Based on Asekome dan Agbonkhese (2015), the exchange rate insignificantly affected market crashes. Based on Tian et al. (2021), exchange rate reforms and stock market crashes were carried out between
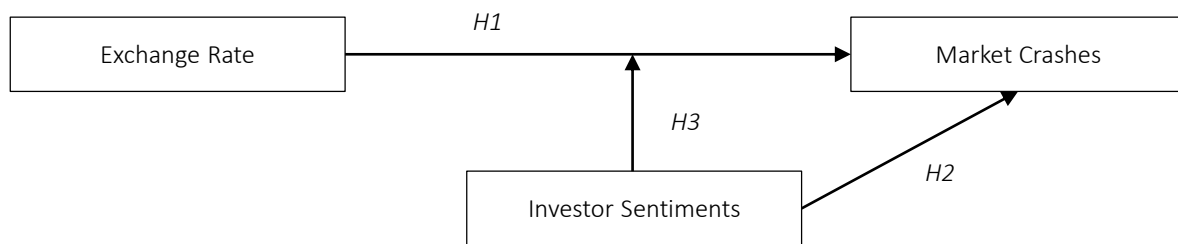
Figure 1. Research framework

2014 and 2016. This led to a notable positive impact on the transmission of uncertainty within the stock market in China, as well as the exchange rate between the country and another nation exhibiting a considerable strengthening. In this case, the positive impact was statistically significant in the short run, although its significance gradually declined as time progressed. Besides macroeconomic factors, investor sentiment also significantly and positively impacted market crash risk, as highlighted by Cui and Zhang (2019).

Pan (2019) indicated that negative investor sentiment positively affected market crashes. Besides, irrational sentiments also caused a significant excess of market volatility (Haritha & Rishad, 2020). In Yin and Tian (2015), a direct relationship was determined between investor sentiment and the likelihood of future market crashes, indicating a positive correlation between the two variables. Meanwhile, Gong et al. (2016) stated that investor sentiment did not influence stock price volatility. Investor sentiment also examined various financial issues, focusing on bubbles, market crashes, and financial crises prediction. Based on Cui and Zhang (2019), investor sentiment substantially positively impacted the likelihood of market crashes. This specifically focused on investigating the influential patterns of foreign investor sentiment on the likelihood of the individual stock prices entering a bearish trend. Fu et al. (2020) also implemented a dataset containing investor sentiment in US companies. This discovered that a rise in investor sentiment amplified the likelihood of market crashes. In Zouaoui (2011), the influence of investor sentiment on the global stock market was investigated. The results showed that the sentiment variable enhanced the probability of a stock market crisis occurring within a one-year timeframe. These signals had several implications for both the market and investor involved. Furthermore, using an extensive dataset of U.S. companies from 1991 to 2014, Cui and Zhang

(2019) discovered that several companies exhibited a heightened probability of stock price crashes during elevated investor sentiment periods. This indicated the influence of investor sentiment on the likelihood of market crashes. In this case, the probability of a significant decline in stock prices was subsequently increased. The correlation between the sentiment of investors and market crashes occurrences were also established in Cui and Zhang (2019) and Fu et al. (2020).

The literature review highlights the theoretical perspectives, empirical evidence, and methodological approaches used to test the relationship between exchange rate volatility, investor sentiment, and market crashes. While previous studies have contributed valuable insights, the literature lacks comprehensive research specifically focused on the market crashes in the companies, not countries. This study addresses these gaps and provides additional evidence on the relationship between exchange rate volatility, investor sentiment, and market crashes, contributing to theoretical knowledge and practical implications for investors. The purpose of the study is to examine the relationship between exchange rate volatility and investor sentiment to market crashes. The study also aims to investigate whether investor sentiment acts as a moderating factor that influences the exchange rate volatility and market crashes. Regarding the theoretical review, Figure 1 served as a research framework.

Furthermore, the following hypotheses are developed:

H1: High levels of exchange rate volatility are expected to raise the likelihood of market crashes.

H2: Negative investor sentiment is anticipated to amplify the probability of market crashes.

H3: *When investor sentiment acts as a mediator for exchange rate volatility, it is expected to subsequently heighten the probability of market crashes.*

2. METHOD

The algorithm of this study will use the logistic regression equation, which is as follows:

$$Log\left[\frac{C}{1-C}\right] = \beta_0 + \beta_1(ER) + \qquad (1)$$
$$+ \beta_2(IS) + \beta_3(ER \cdot IS) + e,$$

where C – Market crashes, $1-C$ – Non-Market Crashes, β_0 – Constant, β_1 – Exchange Rate regression coefficient, ER – Exchange Rate, β_2 – Investor Sentiment regression coefficient, IS – Investor Sentiment, β_3 – Moderating variables coefficient, $ER \cdot IS$ – Exchange Rate x Investor Sentiment, e – error.

This study was carried out by emphasizing a specific set of countries, namely Indonesia, Malaysia, Singapore, the Philippines, Thailand, Vietnam, and Mongolia, which provided the comprehensive data readily available for analysis in the developing countries. The stock exchanges examined were also Indonesia (Jakarta Stock Exchange Composite), Malaysia (FTSE Malaysia KLCI), Singapore (FTSE Singapore), Thailand (SET Index), the Philippines (PSEi), Vietnam (HNX /HNXI), and Mongolia (MNE Top 20/MNETOP20). Furthermore, extensive analysis was conducted on the early warning systems alerting market participants and policymakers about potential financial sector crises.

These systems were comprehensively studied to understand their practical value, due to providing valuable supplementary information for decision-making processes and assessing market vulnerabilities.

Binary logistic regression (logit model) was a formal and concise method used to describe and model categorical outcomes with two distinct categories, namely market and non-market crashes. In this method, the dependent variable represented the occurrence of market crashes, where 1 and 0 indicated market and non-market crashes. Furthermore, the probability of a market crash occurrence was calculated based on the average log daily return in period t, compared to the average log daily return during the study time. To quantify investor sentiment, the difference in logarithmic returns between periods t and t–1 was also calculated. From this context, the assessment of exchange rate volatility involved the analysis of the local currency value fluctuations relative to the United States dollar (USD).

3. RESULTS

The following is the output analysis of binary logistic regression, using the EViews software. Based on Table 2, the samples experiencing and not encountering market crashes were 176 and 188 from a total of 364 people, respectively. For the variable investor sentiment, exchange rate volatility also had negative and positive means during the presence and absence of a crash, respectively. For example, the means of –0,0004 and 0,0001 were observed for the presence and absence of the ex-

Table 1. Operational variables

Variables	Concept	Scale	Unit	Measurement
Market Crashes	The probability of a market crashes was calculated based on the average log daily return in period t, compared to the average log daily return during the study time. where 1 and 0 indicated market and non-market crashes	Nominal	Nominal	1 for the composite index that experiences one or more daily returns, falling by 2.5 standard deviations below the average daily return over a one-month period, with 2.5 chosen to yield a frequency of 0.1% in the normal distribution during the fiscal year period; and 0 otherwise.
Exchange Rate Volatility	Monthly volatility of the US Dollar value against local currencies.	Ratio	%	$ER_{it} = \frac{ER_{it} - ER_{it-1}}{ER_{it-1}}$
Investor Sentiment	Investor sentiment is measured by calculating the difference in returns.	Ratio	%	The difference in log returns between period t and period t-1.

Table 2. Descriptive analysis

Variables	Y	N	Mean	Min	Max	Standard Deviation
Exchange Rate Volatility	**Crash**	**176**	**−0,0004**	**−0,0788**	**0,0758**	**0,0163**
Investor Sentiment	No Crash	188	0,0001	−0,0634	0,0464	0,0144
	Crash	176	−0,0168	−0,1926	0,0754	0,0357
	No Crash	188	0,0173	−0,1039	0,1019	0,0296
Exchange Rate Volatility		364	−0,0001	−0,0788	0,0758	0,0153
Investor Sentiment		364	0,0008	−0,1926	0,1089	0,0369
Moderating		364	−0,0001	−0,0119	0,0059	−0,0001

Table 3. Correlation matrix

Variables	Market Crashes	Exchange Rate Volatility	Investor Sentiment	Moderating
Market Crashes	1			
Exchange Rate Volatility	−0,017	1		
Investor Sentiment	−0,463	−0,207	1	
Moderating	−0,011	−0,266	0,137	1

change rate volatility crash, respectively. The existence and non-existence of investor sentiment crash also had mean values of 0,0168 and 0,0173, respectively. Moreover, higher standard deviation was observed for the samples experiencing market crashes for exchange rate volatility and investor sentiment variables, compared to those not encountering the distresses. In this case, the exchange rate volatility SD for crash and normal periods were 0,0163 and 0,0144, respectively.

Table 3 displays the output correlation matrix, indicating that all variables were free from highly correlated data, with the relationship values below 0.9 (Alamsyah & Zhu, 2021).

Based on Table 4, the binary logistic regression analysis was observed, where model 4 was better than the other platforms. From this context, Model 1 showed that the exchange rate was insignificant on market crashes (0,7485 > alpha 0,05). This was accompanied by the analysis of Model 2, where the statistical outputs were negative and significant between investor sentiment and market crashes, with the coefficient 0,000 and the p-value less than 0,05. Meanwhile, Models 3 and 4 indicated that exchange rate volatility and investor sentiment negatively and significantly affected market crashes. The moderating variable also positively and significantly influenced market crashes, with investor sentiment amplifying the effect of currency exchange rate volatility on market crashes, at a significance level of 0,0474. In this case, Model 4 was a determinant for market crashes compared

to other models. Exchange rate variables and investor sentiment were also early warning indicators before the occurrence of market crashes.

According to Table 4, the matrix of the constant Markov transition probabilities showed the likelihood of transitioning from one state to another. This prioritized a 2x2 matrix with two states (1 and 2) and showed that the probability of staying in the same state (state 1 or state 2) was high (0.991681 and 0.974802) or low (0.008319 and 0.025198). The constant expected durations matrix also exhibited the expected duration (in days) of staying in a specific state before transitioning to the other form.

$$P(I,k) = P(s(t) = K \cdot I \cdot s(t-1) = i), \quad (2)$$
$$(row = i/column = k).$$

Table 4. Matrix of constant Markov transition probabilities

Constant Transition Probabilities		
	1	2
1	0,991681	0,008319
2	0,025198	0,974802
Constant Expected Durations		
	1	2
1	120,2024	39,68549

In Table 4, the anticipated duration of staying in state 1 was longer (120,2024 days) compared to state 2 (39,68549 days). However, the constant transition probabilities matrix indicated a high

Table 5. Binary logit regression output

Variables	Expected Sign	Model 1		Model 2		Model 3		Model 4	
		Coefficient	Prob	Coefficient	Prob	Coefficient	Prob	Coefficient	Prob
C		−0,0662	0,5277	0,0124	0,9188	0,0072	0,9532	0,0372	0,7663
Exchange Rate Volatility	Negative	−2,1947	0,7485			−24,6196	0,0083	−24,3254	0,0082
Investor Sentiment	Positive			−48,9619	0,000	−52,224	0,000	−53,7141	0,000
Moderating	Negative							423,0391	0,0474
McFadden R–squared		0,0002		0,2168		0,232		0,2367	
S.D. dependent var		0,5004		0,5004		0,5004		0,5004	
Akaike info criterion		1,3959		1,0959		1,0803		1,0792	
Schwarz criterion		1,4173		1,1173		1,1124		1,1221	
LR Statistic		0,103		109,3209		117,0019		119,3703	
N		364		364		364		364	
%Correct		97%		74%		74%		76%	
%Incorrect		3%		26%		26%		24%	
Obs with Dep = 0		188		188		188		188	
Obs with Dep = 1		176		176		176		176	

probability of remaining in the same state, suggesting a stable market. The expected stay in State 1 was also more extended than in State 2, proving its capability in highly representing a better stable market. Based on the results, market conditions changed rapidly and was essential to continuously monitor trading risks using early warning systems, to mitigate potential losses.

The algorithm of this study based on binary logistic regression is expressed as follows:

$$Log\left[\frac{C}{1\text{-}C}\right] = 0,0372 - 24,3254 \cdot ER - \qquad (3)$$
$$-53,7141 \cdot IS - 53,7141 \cdot ER \cdot IS + e.$$

The coefficient –24.3254 suggests that an increase in exchange rate volatility decreases the probability of market crashes. This indicates that higher exchange rate volatility tends to lower the likelihood of market crashes. The coefficient –53.7141 suggests that an increase in investor sentiment decreases the probability of market crashes. This implies that positive investor sentiment reduces the likelihood of market crashes. The coefficient –53.7141 indicates that the combined effect of higher exchange rate volatility and positive investor sentiment further decreases the probability of market crashes. The justification for using this model is to estimate the impact of exchange rate volatility, investor sentiment, and their interaction on the likelihood of market crashes. By analyzing the coefficients, can determine the direction and significance of these variables in predicting market crashes.

According to the results of binary logistic regression, the exchange rate volatility and investor sentiment negatively and significantly affected market crashes at significance levels of 0,0082 < 0,005 (alpha) and 0,000 < 0,005 (alpha), respectively. Regarding the significance value of 0,0474, less than 0,05, investor sentiment evidently enhanced the impact of exchange rate fluctuations on the occurrence of market crashes, indicating that all hypotheses were accepted.

In Model 1, exchange rate volatility, the coefficient is –2,1947, but it is not statistically significant. However, in Model 3 and Model 4, the coefficients are –24,6196 and –24,3254, respectively, and both are statistically significant with probabilities of 0,0083 and 0,0082. This indicates that higher exchange rate volatility is associated with an increased likelihood of market crashes. when exchange rates are more volatile, it creates uncertainty and instability in the market, potentially leading to higher risks and a higher probability of market crashes.

In Model 2, Model 3, and Model 4, the coefficient for investor sentiment is statistically significant with probabilities of 0. This suggests that more negative investor sentiment is associated with a higher probability of market crashes. When investor sentiment is negative, it may lead to excessive optimism and risk-taking behavior, which can contribute to market instability and an increased likelihood of market crashes.

Because investor sentiment acts as a mediator for exchange rate volatility, it amplifies the effect of

exchange rate volatility on market crashes. This implies that when exchange rate volatility increases, it creates uncertainty and potential risks in the market. However, the impact of this volatility on market crashes depends on the level of investor sentiment. If investor sentiment is negative, it may lead to increased market participation, risk-taking, and potentially speculative behavior. As a result, the combination of high exchange rate volatility and negative investor sentiment could create a situation where market crashes are more likely to occur.

The first hypothesis (H1) stated that high levels of exchange rate volatility would increase the likelihood of market crashes. The second hypothesis (H2) suggested that negative investor sentiment would amplify the probability of market crashes. Lastly, the third hypothesis (H3) proposed that when investor sentiment acted as a mediator for exchange rate volatility, it would subsequently heighten the probability of market crashes.

The findings of the study indicated that all three hypotheses were supported. The statistical analysis revealed significant results, with H1 having a significance of $0.0082 <$ alpha 0.05, H2 with a significance of $0.000 <$ alpha 0.05, and H3 with a significance of $0.0474 <$ alpha 0.05. These results provide empirical evidence supporting the notion that high levels of exchange rate volatility, negative investor sentiment, and the mediating effect of investor sentiment on exchange rate volatility contribute to an increased probability of market crashes. The study's findings emphasize the importance of considering both exchange rate volatility and investor sentiment as crucial factors in understanding and predicting market crashes, which has implications for risk management and investment decision making.

4. DISCUSSION

The results obtained were supported by Moradi et al. (2021), Ali et al. (2020), and Asekome and Agbonkhese (2015), where a significant negative association was shown between exchange rate and market crashes. These results contributed to Syahri and Robiyanto (2020), where the Composite Stock Price Index exhibited an inverse association with exchange rate. The investor seeking to optimize the returns should also exercise caution when confronted with abrupt fluctuations in the variable (Salisu et al., 2022). Before a crisis, investor often responded to both favorable and unfavorable exchange rate shocks, while overlooking negative suddenness shortly after the hazard (Sheikh et al., 2020). This was due to exchange rate during the 2020 analysis, where the market crashed due to COVID-19, leading to the relative stability of the comparative prices of two currencies from different nations. Fan et al. (2021) also stated that investor sentiment was able to magnify the influence of exchange rate volatility on market crashes. in this case, unfavorable investor sentiment stimulated increased participation in stock investments, leading to heightened market crashes. When this variable became negative, subsequently contributing to a higher occurrence of market crashes. However, Ali et al. (2020) and Moradi et al. (2021) exhibited the relationship regarding exchange rate and market crashes.

This results were in line with Fu et al. (2020), Peng and Hu (2020), Bouteska (2020), Cui and Zhang (2019), Pan (2019), Zhang et al. (2019), and Zouaoui (2011), where investor sentiment influenced the occurrence of market crashes. These results were consistent with Fu et al. (2020a), Yin and Tian (2015), Alnafea and Chebbi (2022), and Haritha and Rishad (2020), where investor sentiment strengthened the effect of market crashes. From this context, the Panic Index was a reliable predictor of future stock price drops.

The findings from this study provide valuable insights for researchers and practitioners in the field of financial markets and risk management. The identified relationships between variables and their impact on market crashes can serve as a foundation for further research and practical applications. One avenue for future research is to delve deeper into the moderating variable and its role in the occurrence of market crashes. Understanding how this variable interacts with investor sentiment can provide a more comprehensive understanding of the underlying mechanisms driving market instability. Further investigation can explore additional factors that may influence the moderating variable and its impact on market crashes, such as regulatory policies, economic conditions, or mar-

ket-specific characteristics. Additionally, it would be beneficial to examine the temporal dynamics of the relationships identified in this study. Market conditions and investor sentiment can change over time, and it is important to capture these dynamics to enhance the accuracy of early warning systems for market crashes. Longitudinal studies and time-series analysis can help uncover patterns and trends, enabling the development of more robust and accurate predictive models.

CONCLUSION

This study aimed to develop an early warning system for investors to minimize investment risk by using Exchange Rate Volatility and Investor Sentiment as predictors of market crashes. The results indicated that high levels of exchange rate volatility and negative investor sentiment were associated with an increased likelihood of market crashes. Moreover, when investor sentiment acted as a mediator for exchange rate volatility, it further heightened the probability of market crashes. These findings align with previous research emphasizing the significance of these variables in predicting market downturns. The study also highlighted the importance of exchange rate volatility as an early warning system in evaluating investments in the capital market. Depreciation of a currency was associated with a tendency for stock prices to decline, indicating the need for caution when confronted with abrupt fluctuations in exchange rates. Investor sentiment provided additional valuable information, showing that perceptions of stockholders can deviate from fundamental information and influence market crashes. Understanding investor sentiment can contribute to predicting future stock price drops and evaluating market conditions. The study's results were supported by previous research that established a negative association between exchange rate and market crashes. The stability of exchange rates in various countries during the analyzed period further emphasized their role as predictors of market crashes. Similarly, investor sentiment's influence on market crashes was consistent with previous studies, highlighting its ability to magnify the effect of exchange rate volatility.

The findings from this study have practical implications for investors, policymakers, and risk managers. By incorporating exchange rate volatility and investor sentiment into decision-making processes, market participants can mitigate risks and make more informed investment choices. The study's results also contribute to the development of early warning systems for market crashes, enabling proactive risk management strategies.

The study acknowledged its limitations, including the consideration of only two independent variables (exchange rate and investor sentiment) and the focus on a specific time period and set of countries. Future investigations should incorporate additional macroeconomic variables and expand the study period to provide a more comprehensive understanding of the relationships being studied. Additionally, further exploration of the moderating variable and its role in market crashes is recommended. Understanding the interaction between the moderating variable, investor sentiment, and other factors can enhance the understanding of market instability. Furthermore, examining the temporal dynamics of these relationships and incorporating additional factors such as regulatory policies and economic conditions can lead to more accurate predictive models.

AUTHOR CONTRIBUTIONS

Conceptualization: Rachmat Sudarsono, Nury Effendi.
Data curation: Lisa Kustina, Rachmat Sudarsono, Nury Effendi.
Formal analysis: Lisa Kustina, Rachmat Sudarsono, Nury Effendi.
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Visualization: Lisa Kustina
Writing – original draft: Lisa Kustina.
Writing – review & editing: Lisa Kustina, Rachmat Sudarsono, Nury Effendi.

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