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Stock Market Volatility and Industrial Financial Resilience: Evidence from Asia

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Abstract. The agenda of integrating industrialization and downstream processing to achieve global economic resilience requires stable financial performance from industrial firms involved. However, efforts to maintain such stability are increasingly vulnerable to macroeconomic uncertainty and stock market volatility as a primary source of financing. This study employs GARCH and TGARCH models to forecast stock market return volatility across Asian markets in order to map systemic risks affecting the investment climate in the manufacturing sector. Based on observations of 11 Asian stock indices over the period 2004–2024, heteroskedasticity testing was conducted, resulting in seven major indices as the final sample (Hang Seng, JKSE, Nifty 50, Nikkei 225, SET, TAIEX, and VNI). The findings indicate that all sampled markets exhibit volatility clustering characteristics. Markets in Japan, Thailand, and Taiwan demonstrate faster volatility recovery, indicating a more resilient environment for industrial financing. In contrast, Hong Kong, India, Indonesia, and Vietnam exhibit high volatility persistence. TGARCH testing reveals the absence of asymmetric effects in the Indonesian, Taiwanese, and Vietnamese markets. Forecasting results for the 2024–2029 period project Japan as the most stable market, while Vietnam is expected to face persistent volatility risks. This volatility analysis is crucial for industrial firm management in formulating risk mitigation strategies to ensure sustainable financial performance amid rapid global industrialization.

Keywords: Financial Performance, Asian Stock Markets, GARCH, TGARCH, Volatility.

I. Introduction

The dynamics of the global economy over the past two decades have undergone significant structural transformation, driven by a strong push toward the integration of industrialization and downstream processing to achieve global economic resilience. In supporting this broad agenda, capital markets play a fundamental role within the modern financial system, functioning as a barometer of a country's economic health. For corporations—particularly firms in downstream industrial sectors—capital markets not only serve as a strategic platform for mobilizing long-term financing but also act as a key determinant influencing the stability of their financial performance. In Asia, stock markets have emerged as highly attractive investment destinations for financing industrialization projects, offering higher growth potential compared to developed economies (Juhro, et al., 2024).

However, this growth potential comes at the cost of dynamic volatility risks. High levels of volatility reflect sharp price fluctuations, which not only signal risks for investors but also generate uncertainty in market efficiency and the financial performance of industrial firms. Episodes of extreme market uncertainty have been well documented during various global crises. For instance, the COVID-19 pandemic triggered a surge in volatility that simultaneously disrupted both supply and demand (Frezza et al., 2021). This pressure was also strongly reflected in ASEAN stock exchanges, which exhibited high sensitivity to global sentiment and significant index fluctuations (Kamaludin et al., 2021).

In addition, financial market integration enables volatility to spill over from one market to another, particularly from developed markets to emerging markets in Asia (Vuong et al., 2022). Such turbulent market conditions exhibit complex statistical behavior, in which periods of large price changes tend to be followed by subsequent periods of similarly large changes, a phenomenon known as volatility clustering (Bollerslev, 2023). Therefore, through the analysis of 11 major stock market indices in Asia, an accurate understanding of volatility characteristics using GARCH and TGARCH models becomes an essential prerequisite for effective investment risk management. This study aims to map these systemic risks in order to provide guidance for industrial firms in mitigating potential losses and maintaining sustainable financial performance amid global economic uncertainty.

Despite these developments, understanding of non-financial firms' involvement in downstream processing activities remains limited, particularly regarding the challenges they face in financing and capacity. Examining the dynamics of corporate participation in downstream processing is crucial for formulating policies that effectively promote economic growth and support broader industrialization efforts (Li et al., 2025). This investigation offers valuable insights into the specific challenges faced by firms, including strategies to improve access to financing, which is essential for enhancing financial inclusion across the value chain.

In light of this urgency, the study aims to accomplish three primary goals: (i) to evaluate the level of corporate involvement in downstream activities and its effects on overall performance; (ii) to identify the development constraints these firms face and the financing requirements necessary to improve downstream performance; and (iii) to investigate the financial difficulties faced by both large and small corporations involved in lower-level processing activities.

Several previous studies have examined volatility modeling in capital markets. Nurfajriyah et al. (2023), compared ARCH and GARCH methods in forecasting stock price indices to capture market uncertainty. In addition, Fadhilah et al. (2024), applied the ARIMA-GARCH model to analyze how past return patterns influence future volatility through volatility clustering. However, these studies are often limited to specific sub-sectors and relatively short observation periods. This study addresses this gap by conducting a comprehensive analysis of 11 Asian stock indices using the most recent data available up to 2024.

II. Literature Review

Volatility forecasting analysis in the context of corporate financial performance is grounded in a fundamental understanding of investment mechanisms. Investment is essentially defined as the allocation of funds at present with the expectation of obtaining future economic benefits. Investment decisions involve sacrificing current consumption for future gains, encompassing both real assets and financial assets (Fitriasari et al., 2022; Petsche, 2023). In the modern economic context, capital markets play a strategic role as a mechanism for mobilizing long-term funds, linking surplus units with deficit units. For industrial firms, capital markets are not merely platforms for trading financial instruments but serve as a key pillar in supporting the integration of industrialization and downstream processing to strengthen the national income structure (Bui & Doan, 2021).

Participation in capital markets is represented through equity instruments, which signify ownership in a company and grant rights to dividends as well as profits derived from price differentials, or capital gains (Lubis, et al., 2004). The collective movement of stock prices within an exchange is monitored through stock price indices, which function as indicators of market trends. At the regional level, stock indices from 11 Asian countries reflect diverse economic dynamics, ranging from highly liquid developed markets to emerging markets that offer strong growth potential but are accompanied by significant fluctuation risks. These fluctuations are closely linked to the financial performance of industrial firms, whose stability is highly dependent on management's ability to mitigate systemic risks (Fadhilah et al., 2024). Uncertainty in the cost of capital due to market fluctuations can deteriorate financial ratios; therefore, understanding risk characteristics becomes a prerequisite for maintaining corporate financial resilience.

The Efficient Market Hypothesis (EMH), which holds that securities prices accurately reflect all available information, including historical, public, and private information, can be used to explain the behavior of stock price movements and related hazards. Referring to the study by Brown (2020), market efficiency remains a fundamental concept in modern finance, as prices respond rapidly and accurately to new information. In the context of transforming Asian markets, EMH provides a theoretical foundation for understanding how information is absorbed and how market anomalies may trigger investment risks (Nunes, 2025). These risks are directly represented by volatility, which measures the degree of variation or fluctuation in stock prices over a given period. Financial data often exhibit specific characteristics such as leptokurtosis and heteroskedasticity, where error variance is not constant but changes over time, thereby requiring more advanced estimation methods than conventional linear models.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is used as an extension of the ARCH model to estimate time-varying conditional variance in order to represent the complexity of financial data. The concept of volatility clustering, in which significant price swings are typically followed by more significant swings, is well captured by this model (Marisetty, 2024; Maulana, 2022; Sahiner, 2022). However, because the conventional GARCH model is symmetric, it makes the assumption that the effects of positive and negative shocks are equivalent. In reality, stock markets frequently display asymmetric behavior known as the leverage effect, in which negative shocks (bad news) cause more uncertainty than positive shocks (good news). Therefore, the Threshold GARCH (TGARCH) approach is applied to capture these differential responses by incorporating a dummy variable into the variance equation. As emphasized by (Ginting & Hindrayani, 2025; A. I. D. Lubis et al., 2022), asymmetric modeling is particularly crucial for firms in emerging markets to more accurately assess risk and maintain financial performance stability in the face of external shocks.

III. Research Method

This study employs a quantitative approach using time series analysis to examine the volatility characteristics of stock markets in Asia and their implications for corporate financial performance. The research design is structured to capture volatility clustering and asymmetric effects through the application of GARCH and TGARCH models.

The research process is conducted through several systematic stages, including sample selection using purposive sampling, data transformation into log returns, and heteroskedasticity diagnostic testing to ensure the accuracy of the estimated models.

1. Research Approach and Type

   This study adopts a quantitative approach with a time series analytical method. The data are numerical in nature and analyzed using statistical techniques to identify patterns in stock index returns over the 2004–2024 period. The study falls under descriptive quantitative research with associative characteristics based on econometric modeling.

2. Population and Sample

   The population comprises stock markets in Asia that play a strategic role in global capital flows. The sampling technique uses purposive sampling with criteria including active markets and the availability of consistent historical data. Based on these criteria, 11 stock indices are selected as the sample: Hang Seng, JKSE, KLSE, KOSPI, Nifty 50, Nikkei 225, PSEI, SET, SSEC, TAIEX, and VNI.

3. Data Sources and Research Variables

   The data used are secondary data in the form of monthly closing prices from January 2004 to December 2024. The main variable in this study is stock index returns, calculated using logarithmic changes (log returns) to enhance data stability and satisfy time series assumptions.

4. Data Analysis Techniques

   Data processing is conducted using EViews 13 software through several analytical stages, including the following procedures:

   a. Stock Return Calculation

      In this study, returns are calculated using the logarithmic change of stock index closing prices between periods (Kanal et al., 2018). This approach is employed to enhance data stability and to satisfy the assumptions required in time series analysis:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

      Description:

      R_t= Return of the index in period t

      P_t= Stock price at time t

      P_{t-1}= Stock price at time t−1

   b. Stationarity Test

      The data are tested using the Augmented Dickey-Fuller (ADF) test to detect the presence of a unit root in the time series (Guo, 2023). The test is conducted using a basic model, where stationarity is determined based on the following hypothesis testing criteria:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + {}_t$$

      Hipotesis : H0: δ = 1 (unit root exists, the data are non-stationary)

      H1: $\delta \neq 1$ (no unit root, the data are stationary)

      Significance Level: α = 5%

   c. ARIMA (*Box-Jenkins*)

      The Box–Jenkins model is one of the most widely used time series forecasting methods, developed to analyze the movement patterns of a variable based on its historical data characteristics. The mean model is determined using the Box–Jenkins approach, which consists of Autoregressive (AR), Integrated (I), and Moving Average (MA) components (Ayo, 2014). Model identification is conducted using the patterns of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

$$Y_t = c + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \cdots - \theta_q \epsilon_{t-q}$$

Description

Y_t : Log return value at time t

c : Constant term

ϕ_i : Autoregressive (AR) coefficient θ_j

: Moving Average (MA) coefficient

ϵ_t: *Error* term or *White Noise*.

d. *Autoregressive Conditional Heteroscedasticity* (ARCH)

The ARCH-LM diagnostic test is conducted to detect the presence of heteroskedasticity in the residuals of the model (Fadhilah et al., 2024). In general, the basic form of the ARCH model can be expressed as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sigma_{t-1}^2 + \cdots + \alpha_p \sigma_{t-p}^2$$

$\alpha_p \sigma_{t-p}^2$: Residual variance at lag p

Hypotheses: H_0: $\alpha_p \varepsilon^2_{t-p} = 0$ (current return changes are not influenced by past disturbance terms)

H_1: $\alpha_p{}^2{}_t \neq 0$ (current return changes are influenced by past disturbance terms)

e. *Generalized Autoregressive Conditional Heteroscedasticity* GARCH

If the residuals of the ARIMA model are found to exhibit heteroskedasticity based on the ARCHLM test, the GARCH model is applied using a conditional variance equation that appropriately fits the model (D. S. Lubis, 2016). The basic form of the GARCH (1,1) model is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_0 {}_{t-1}^2 + \cdots + \alpha_p {}_{t-p}^2 + \lambda_1 \sigma_{t-1}^2 + \cdots + \lambda_q \sigma_{t-q}^2$$

Additional descriptions:

$\alpha_p {}_{t-p}^2$: Shock variable at lag p

$\lambda_q \sigma_{t-q}^2$: Residual variance variable at lag q

Hypotheses: H_0: $\lambda_q \sigma^2_{t-q} = 0$ (current return changes are not influenced by past residual variance)

H_1: $\lambda_q \sigma^2_{t-q} \neq 0$ (current return changes are influenced by past residual variance)

f. *Threshold Generalized Autoregressice Conditional Heteroscedasticity* (TGARCH)

To capture asymmetric effects (leverage effects), the TGARCH model is employed, with its general variance equation specified as follows (Ervina et al., 2020). The basic form of the TGARCH (1,1) model is:

$$\sigma_t^2 = \alpha_0 + \alpha_0 {}_{t-1}^2 + \cdots + \alpha_p {}_{t-p}^2 + \gamma {}_{t-1} d_{t-1} + \lambda_1 \sigma_{t-1}^2 + \cdots + \lambda_q \sigma_{t-q}^2$$

With the following conditions:

${}_{t-1} < 0$ (*good news*)

${}_{t-1} > 0$ (*bad news*)

Hypotheses: H_0: $\gamma t = 0$ (no asymmetric effect)

H_1: $\gamma t \neq 0$ (asymmetric effect exists)

5. Forecasting

The final stage of this study involves forecasting future values of the variables based on the best-selected volatility model, either GARCH or TGARCH. Forecasting is conducted dynamically over a five-year horizon to capture evolving volatility patterns over time (Vasudevan & Vetrivel, 2016).

The evaluation of forecasting results is carried out using descriptive statistics, including the mean as an indicator of expected returns, maximum and minimum values to represent the range of potential risks, and standard deviation as the primary measure of projected risk levels. The accuracy of volatility forecasting plays a crucial role as a risk management instrument in addressing economic uncertainty.

IV. Results and Discussion

The data analysis of 11 Asian stock indices over the 2004–2024 period begins with transforming the data into log-return changes to ensure variance stability and to satisfy the fundamental assumptions of time series analysis. The summary of descriptive statistics for the eleven Asian stock market indices is presented in the following table:

Table 1. Descriptive Statistics of Asian Stock Market Index Returns (2004–2024)

NO	Index	Mean	Min	Max	Standard Deviation
1	Hangseng	0.003089	-0.224660	0.236049	0.060762
2	JKSE	0.010316	-0.314220	0.201315	0.052293
3	KLSE	0.003328	-0.152230	0.135454	0.034122
4	KOSPI	0.005275	-0.231340	0.142995	0.052675
5	Nifty50	0.012051	-0.264100	0.280660	0.060916
6	Nikkei225	0.006463	-0.238270	0.150432	0.052048
7	PSEI	0.007041	-0.240720	0.149693	0.052152
8	SET	0.004059	-0.301760	0.178551	0.052037
9	SSEC	0.005445	-0.246310	0.274464	0.072468
10	TAIEX	0.006149	-0.188310	0.150020	0.050886
11	VNI	0.010266	-0.248990	0.385171	0.084482

Source: Secondary data processed (2026)

Based on the descriptive statistics, all indices exhibit positive average returns with leptokurtic characteristics, indicating that the data distribution has heavier tails compared to a normal distribution.

Furthermore, this study applies the Augmented Dickey-Fuller (ADF) unit root test as the primary method to assess data stationarity. The results of the stationarity test confirm that all data are stationary, as presented in the following table:

Table 2. Stationarity Test Results

NO	Index	Augemented Dickey Fuller (ADF)	
		Level	Difference
1	Hangseng	0.0000	0.0000
2	JKSE	0.0000	0.0000
3	KLSE	0.0000	0.0000
4	KOSPI	0.0000	0.0000
5	Nifty50	0.0000	0.0000
6	Nikkei225	0.0000	0.0000
7	PSEI	0.0000	0.0000
8	SET	0.0000	0.0000

9	SSEC	0.0000	0.0000
10	TAIEX	0.0000	0.0000
11	VNI	0.0000	0.0000

Source: Secondary data processed (2026)

Subsequently, the analysis proceeds by identifying the best-fitting ARIMA mean model using the Box–Jenkins methodology, followed by residual testing through the ARCH-LM test to confirm the presence of significant heteroskedasticity effects across all samples. This step validates the application of volatility models in capturing the phenomenon of volatility clustering.

The selection of the optimal model is based on the principle of parsimony, where the preferred model is the one with the lowest Akaike Information Criterion (AIC) and Schwarz Criterion (SC) values. The estimation results of the volatility models are summarized in the following table to provide a comprehensive comparison across Asian stock markets:

Table 3. ***ARIMA (p, d, q) Model Overfitting***

No	**Index**	**Model**	**AIC**	**SC**	***Heteroskedasticity***
1	Hangseng	0,0,2	-2.746149	-2.704132	0.0000*
2	JKSE	1,0,0	-3.086919	-3.044902	0.0007*
3	KLSE	1,0,0	-3.901820	-3.859803	0.2887
4	KOSPI	3,0,3	-3.050911	-2.994888	0.2360
5	Nifty50	3,0,3	-2.746991	-2.690969	0.0204*
6	Nikkei225	1,0,1	-3.065349	-3.009327	0.0197*
7	PSEI	2,0,0	-3.051487	-3.009470	0.8553
8	SET	1,0,1	-3.095536	-3.039513	0.0000*
9	SSEC	1,0,1	-2.417702	-2.361679	0.4505
10	TAIEX	2,0,0	-3.113324	-3.071307	0.0000*
11	VNI	1,0,3	-2.154757	-2.098734	0.0011*

* Presence of ARCH Effect

Source: Secondary data processed (2026)

After confirming the presence of heteroskedasticity through the ARCH-LM test, the results indicate that out of the 11 observed indices, only 7 exhibit statistically significant probability values, confirming the existence of ARCH effects. Therefore, further volatility modeling using GARCH and TGARCH is applied only to these seven indices to capture the time-varying conditional variance characteristics.

The estimated GARCH parameters from the best-fitting volatility models for these seven indices are summarized in the following table:

Table 4. Overfitting of GARCH (p, q) Models

Index	**C**	**ARCH**			**GARCH**		
		(t-1)	**(t-2)**	**(t-3)**	**(t-1)**	**(t-2)**	**(t-3)**
Hangseng	0.000545 **	0.170620 **	-	-	0.677679 **	-	-
JKSE	0.000150 **	0.226505 **	-	-	0.728368 **	-	-

Nifty50	0.000264 **	0.179145 **	-	-	0.752267 **	-	-
Nikkei225	0.002310 **	0.122412 **	-	-	-	-	-
SET	0.001305 **	0.326294 **	0.162306 **	-	-	-	-
TAIEX	0.001358 **	0.149869 *	0.357944 **	-	-	-	-
VNI	0.000311 **	0.148787 **	-	-	0.726544 **	0.702224 **	-0.613725 **

* Significant at 10%
** Significant at 5%

Source: Secondary data processed (2026)

Based on Table 4, the Nikkei 225, SET, and TAIEX markets exhibit mean-reverting characteristics, indicating that market shocks tend to return quickly to their normal conditions. In contrast, Hang Seng, Nifty 50, JKSE, and VNI demonstrate persistent volatility or long memory effects. For firms in the industrial sector, such high persistence reflects sustained financing risks; past economic shocks continue to affect the stability of corporate financial performance over a longer period compared to more stable markets.

In the next stage, the asymmetric TGARCH model is employed to capture asymmetric effects, where stock market volatility typically responds more strongly to bad news than to good news. The results of the best-fitting TGARCH overfitting models, including the mean equation and variance equation used in the analysis for each Asian stock market, are presented in the following table:

Table 5. Variance Equation of TGARCH (p, q) Model

Index	C	ARCH			TGARCH	GARCH		
		(t-1)	(t-2)	(t-3)	(t-1)	(t-1)	(t-2)	(t-3)
Hangseng	0.000545 **	0.081389 *	-	-	0.152020 *	0.683078 **	-	-
JKSE	0.000147 **	0.205753 *	-	-	0.028077	0.735190 **	-	-
Nifty50	0.001733 **	0.269021 **	0.098630 *	0.085465 *	0.370692 **	-	-	-
Nikkei225	0.002368 **	0.080794 *	-	-	0.325196 **	-	-	-
SET	0.001348 **	0.101202 *	0.162227 **	-	0.383782 **	-	-	-
TAIEX	0.001370 **	0.114978	0.357819 *	-	0.050192	-	-	-
VNI	0.000722 **	0.246598 **	-	-	-0.028330	0.651227 **	-	-

* Significant at 10%
** Significant at 5%

Source: Secondary data processed (2026)

The data in Table 5 confirm that the Hang Seng, Nifty 50, Nikkei 225, and SET markets exhibit asymmetric effects, where the response to bad news is significantly greater than to good news. This serves as a warning for industrial firm management that negative global sentiment may exert disproportionate financial pressure. In contrast, although JKSE, TAIEX, and VNI demonstrate symmetric effects, firms must remain cautious of high absolute volatility to maintain corporate economic resilience amid ongoing industrialization efforts.

In the next stage, forecasting is conducted to project the future movements and volatility of stock price indices. At this stage, forecasting is performed using the estimated GARCH model specifications for each index. To obtain specific values regarding projected returns and risk levels, the summary of descriptive statistics from the forecast results is presented in the following table:

Table 6. Descriptive Statistics of Forecast Results (Forecast Series)

Statistics	Hangseng	JKSE	Nifty50	Nikkei225	SET
Mean	0.000148	0.001224	0.000392	0.004755	0.000724
Max	0.015376	0.029420	0.012000	0.022607	0.084142
Min	-0.013874	-0.045920	-0.011385	-0.009298	-0.072037
Std. Dev	0.007440	0.009924	0.008335	0.004930	0.006921

Statistics	TAIEX	VNI
Mean	0.005104	0.000321
Max	0.017157	0.019512
Min	-0.003937	-0.019376
Std. Dev	0.005868	0.012080

Source: Secondary data processed (2026)

Based on the forecasting results in Table 6, the stock markets of Japan, Taiwan, and Thailand are projected to exhibit relatively low levels of fluctuation, while Indonesia, India, Hong Kong, and Vietnam show risks that tend to persist over time. This phenomenon of persistent risk is closely related to market characteristics that respond asymmetrically to information. The high persistence of volatility in markets such as Indonesia and Vietnam may serve as an external indicator of bottlenecks or constraints in downstream industrial development. This condition generates uncertainty in the cost of capital, aligning with the financing challenges faced by corporations in enhancing their downstream performance.

The findings of this study provide strong evidence that the presence of a consistent leverage effect indicates that investors in Asian markets are significantly more sensitive to negative sentiment. This is consistent with TGARCH theory, which suggests that market responses to bad news are more extreme than to good news. For industrial firms, the combination of high volatility persistence (long memory effect) and asymmetric behavior poses a serious challenge to financial performance stability (Ervina et al., 2020). Negative shocks in the industrial sector—such as increases in downstream processing input costs—are likely to be overreacted to by stock markets, potentially leading to sudden increases in the cost of capital and disrupting corporate financial resilience. The instability of operational costs resulting from such market shocks highlights the financial challenges faced by both large and small corporations striving to maintain continuity in their lower-level processing activities.

Based on recent developments, this study contributes significantly to filling existing research gaps. Unlike previous studies that were limited in data scope (Fadhilah et al., 2024; Nurfajriyah et al., 2023), the integration of data in this study up to the end of 2024 provides a more up-to-date depiction of risk recovery patterns. Addressing this gap demonstrates that in the current era of industrial integration, firms can no longer rely solely on standard forecasting models but must also consider asymmetric aspects to maintain financial performance stability. Ultimately, understanding the dynamics of downstream engagement through GARCH modeling offers strategic guidance for management in determining optimal market timing for financing decisions. This approach is essential for mitigating risks while ensuring that downstream expansion yields positive implications for overall corporate performance.

V. Conclusion

This study demonstrates that Asian stock markets exhibit heterogeneous levels of volatility persistence in response to macroeconomic shocks, which in turn shape the stability of corporate financing. Markets such as Indonesia (JKSE), India (Nifty 50), Hong Kong (Hang Seng), and Vietnam (VNI) are characterized by persistent volatility, indicating prolonged exposure to risk and reflecting structural constraints in financing access. In contrast, markets such as Japan (Nikkei 225), Taiwan

(TAIEX), and Thailand (SET) display more stable, mean-reverting behavior, suggesting a more resilient financial environment for supporting industrial activities. Furthermore, the presence of asymmetric volatility, as captured by the TGARCH model, confirms that negative shocks generate disproportionately larger impacts than positive shocks, reinforcing the vulnerability of firms to adverse market sentiment.

The novelty of this research lies in its comprehensive post-pandemic analysis integrating updated data through 2024, combined with the application of both symmetric and asymmetric volatility models to map systemic risk across multiple Asian markets. Unlike prior studies that are limited in scope or time horizon, this study offers a more current and holistic understanding of volatility dynamics in the context of industrialization and downstream development. The integration of volatility clustering and leverage effects into a unified analytical framework provides a refined perspective on how financial market behavior interacts with corporate financing strategies.

The implications of these findings are particularly relevant for industrial firms engaged in downstream expansion. A deeper understanding of volatility characteristics enables firms to design more adaptive financing strategies, particularly in terms of market timing and risk mitigation. By anticipating persistent and asymmetric volatility patterns, firms can better manage capital costs and maintain financial resilience amid global uncertainty. Ultimately, this study highlights the importance of incorporating advanced volatility modeling into strategic decision-making to support sustainable financial performance and contribute to broader economic resilience.

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