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Stock Market Volatility and Persistence: Evidence from High-Income and Middle-Income Economies

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Abstract

This study examines the volatility of stock market indices in high-income and middle-income economies. Relying on daily closing prices from January 4, 2005 to May 4, 2021 and using the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model with one ARCH term and one GARCH term, the study finds evidence of long memory and mean reversion, suggesting that volatility persists but that it returns to its mean. In addition, the study finds that the latest news and prior information about volatility influence the volatility of indices, but prior information exerts greater influence. By providing a deeper understanding of stock market volatility in high-income and middle-income economies, this study contributes to the literature and provides investors, policymakers, and regulators additional insight.

Keywords: stock markets, volatility, mean reversion, GARCH

1. Introduction

The stock market has long been identified as susceptible to volatility, which is a situation involving deviations in stock prices (Mallikarjuna & Rao, 2019; Mamtha & Srinivasan, 2016). High volatility is characterized by stock prices increasing and then decreasing unexpectedly. On the other hand, low volatility is characterized by a gradual change in stock prices (Mamtha & Srinivasan, 2016). Volatility has impacts that extend beyond the stock market. For instance, elevated risk and uncertain returns in volatile markets could diminish investors' confidence, rattle the financial system, and hinder overall economic performance (Bhowmik & Wang, 2020; Mala & Reddy, 2007). As such, an understanding of factors that influence stock market volatility is pertinent. By providing an enhanced understanding of stock market volatility, investors, and policymakers are empowered with additional knowledge for better decisions.

Although stock market volatility can vary by country, the possibility of contagion and spread from one country or group of countries to another (Uludag & Khurshid, 2019; Natarajan, Singh, & Priya, 2014) makes delineating the factors that impact volatility in high-income economies (HIEs) and middle-income economies (MIEs) important for new insights to be generated. In addition, by shedding light on stock market volatility and the level of persistence in HIEs and MIEs, the study enhances policy makers' ability to predict the volatility of stock markets and/or be proactive in mitigating the risks associated with it. The findings show that indices in MIEs offer better average returns than indices in HIEs, but the risk to investors is higher in MIEs. In addition, the study finds that the latest news and prior information influence volatility, however, prior information exerts more influence. Furthermore, the study shows evidence of long memory and volatility persistence. The mean reversion finding in the study indicates that volatility reverts to its long-term averages, but the time it takes for volatility to dissipate varies by index. The remainder of the article is organized as follows. Section 2 provides a brief overview of the existing literature on stock market volatility. The empirical study methodology and data are described in section 3, with results presented in section 4. Section 5 concludes the article.

2. Review of Literature

Stock market volatility is associated with uncertainty relating to stock prices. In a volatile stock market, prices rise and fall rapidly (Haider, Hashmi, & Ahmed, 2017; Ahmad & Ramzan, 2016). Studies (e.g., Bhownik & Wang, 2020; Arestis, Demetriades, & Luintel, 2001) reveal that stock market volatility has economic implications. Given that wide swings in prices affect investors' confidence (Joo & Mir, 2014), consumer confidence and spending (Mala & Reddy, 2007), and investment (Haider, Hashmi, & Ahmed, 2017), it suffices to say that stock markets play an important role in the economy. A plethora of theoretical and empirical studies suggest that stock market volatility is driven by uncertainties. On the theoretical front, outlooks differ on the cause(s) of volatility. For example, Arestis, Demetriades, and Luintel (2001) and Kumari and Mahakud (2015) link volatility to uncertainty in macroeconomic conditions whereas Kumari and Mahakud (2016) and Rehman (2013), Orlitzky (2013) remark that it is driven by investors' psychology and sentiments. Other studies (e.g., Abdennadher & Hellara, 2018; Asaturov, Teplova, & Hartwell, 2015; Natarajan, Singh, & Priya, 2014) attribute volatility to contagion or spillover effects.

Empirically, there is a broad acknowledgment that stock markets can be volatile in developed and developing economies, but studies seem to differ on the level of volatility and persistence. Joseph, Vo, Mobarek, and Mollah (2020) suggest that volatility persists in developed economies than in less developed countries in central and eastern European markets. A similar outlook is expressed in Mallikarjuna and Rao (2019), which hints that stock markets in developed countries are more sensitive to information than their counterparts in developing countries. However, the inference in Uludag and Khurshid (2018) reveals a contrary view. The study's suggestion that investors should consider holding more stocks from markets in G7 countries than emerging markets creates the impression that stock markets in G7 countries are less volatile. This sentiment is buttressed by Khandaker and Farooque (2021) observation that stock markets in emerging economies exhibit higher volatility than those in developed economies. Additionally, notwithstanding the focus on countries in the same region and/or economic bloc, empirical studies parade an array of approaches and models with a substantial amount of conflicting findings. For example, Hepsag (2016) examination of Central and Eastern European stock markets reveals high variability of volatility and high volatility persistence in Poland and Lithuania, but the study shows that Czech and Hungary have lower variability of volatility. Sosa and Ortiz (2017) study of stock exchanges in Canada, the U.S., and Mexico find that the Canadian stock market exhibited a high level of volatility, however, the inference in Mallikarjuna and Rao (2019) shows that the US has a higher level of volatility than Canada. It is conspicuous that several studies (e.g., Mallikarjuna & Rao, 2019; Abdennadher & Hellara, 2018; Kumari & Mahakud, 2016; Engle, Ghysels, & Sohn, 2013; Mala & Reddy, 2007) rely on AutoRegressive Conditional Heteroskedasticity (ARCH) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models or a variation of it, some (e.g., Alqahtani, Wither, Dong, & Goodwin, 2020; Khalid & Khan, 2017) favour other models, which may have contributed to the observation of conflicting outcomes. In addition, differences in approach adopted, data type, and study period may have elicited inconsistencies in findings.

Furthermore, the broad categorization of countries in studies (e.g., Spulbar, Trivedi, & Birau, 2020; Mallikarjuna & Rao, 2019) limits relevance to high-income economies (HIEs) and middle-income economies (MIEs). To uncover details unique to HIEs and MIEs, this study focuses on stock market volatility and persistence in HIEs (i.e., Canada, Eurozone, France, Germany, Hong Kong, Japan, Korea, Taiwan, UK, and the U.S.) and MIEs (i.e., Argentina, Brazil, China, India, Indonesia, Mexico, and Pakistan). Additionally, the increased importance and contribution of MIEs to the global economy makes comparison with HIEs appealing. Also, studies indicate that negative shocks generate higher volatility than positive shocks of the same magnitude, (Kumari & Mahakud, 2016), but little is known about the length of time it takes for volatility to wane in HIEs and MIEs. By Examining the context of HIEs and MIEs, this study provides insight and contributes to a better understanding of stock market volatility.

3. Methodology and Data

To estimate stock market volatility, studies (e.g., Bhowmik & Wang, 2020; Kumari & Mahakud, 2016; Uyaebo, Atoi, & Usman, 2015) use ARCH, GARCH, or an extension of the GARCH model. Mallikarajuna & Rao (2019) noted that the ARCH model as proposed by Engle (1982) is appropriate when there is volatility clustering, which is a situation that occurs when large changes in volatility are accompanied by large changes and small changes in volatility are accompanied by small changes (Sosa & Ortiz, 2017). The ARCH model as expressed in Poon (2005, pp. 36-37) is:

$$r_t = \mu + \varepsilon_t \tag{1}$$

$$\text{Where } \varepsilon_t \sim N(0, \sqrt{h_t}) \quad \text{and} \quad \varepsilon_t = z_t \sqrt{h_t}$$

Where r_t is the stock market index return at time t, μ is the average return, and ε_t is the residual. z_t as standardized residual returns is i.i.d (i.e., independent and identically distributed) random variable with a mean of zero (0) and variance of one (1)

The conditional variance (h_t) is a function of past squared residual returns (σ_t^2) and it is written as:

$$h_t = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{2}$$

For h_t to be considered strictly positive variance, the constant term (ω) has to be greater than zero (i.e., $\omega > 0$) and α_j, which is the coefficient of lagged squared residuals (i.e., the ARCH term) must be at least zero (i.e., $\alpha_j \geq 0$). Although the ARCH model can be estimated by using the maximum likelihood of $\{\varepsilon_t\}$ (Poon, 2005), it requires a large number of lags (i.e., high order q) to be effective (Hasan & Zaman, 2017; Alberg, Shalit, & Yosef, 2008). Studies (e.g., Onakoya, 2013; Alberg, Shalit, & Yosef, 2008) indicate that the GARCH model proposed by Bollerslev (1986) addresses the limitation of the ARCH model and that GARCH model with a small number of terms provides a better result than the ARCH model with several terms. The GARCH (p, q) model as expressed in Poon (2005, p. 38) is:

$$h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{3}$$

Where ω is a constant term, α_j is the coefficient of the lagged squared residuals (i.e., the ARCH term) that highlights the short-run persistence of shocks and sensitivity to the latest news or information about prior volatility. β_i is the coefficient of the lagged conditional variance (i.e., the GARCH term) that signals the long-run persistence of shocks (Uludag & Khurshid, 2019; Tripathy, 2017; Joo & Mir, 2014). In addition, while a high value of α_j suggests high sensitivity to new information, a high value of β_i indicates that more time would be required for the volatility to wane (Chaudhary, Bakhshi, & Gupta, 2020). For the most common GARCH (1, 1) model that consists of one ARCH term and one GARCH term, ω must be greater than zero (i.e., $\omega > 0$) and α_1 and β_1 have to be at least zero (i.e., $\alpha_1 \geq 0$ and $\beta_1 \geq 0$) for h_t to be strictly positive (Sosa & Ortiz, 2017; Poon, 2005). In addition, for the GARCH (1, 1) process to be weakly stationary, the sum of α_1 and β_1 has to be less than one (i.e., $\alpha_1 + \beta_1 < 1$). Since the sum of the ARCH term and GARCH terms provides insight into volatility persistence over time, volatility persistence is acknowledged if the sum is close to one (Mallikarjuna & Rao, 2019).

A measure of volatility persistence is the half-life, which is the time it takes for volatility to move halfway back towards its unconditional mean (Ahmed, Vveinhardt, Streimikiene, & Channar, 2018; Engle & Patton, 2001). Similar to Ahmed, Vveinhardt, Streimikiene, & Channar (2018, p. 187), the half-life based on GARCH (1, 1) model in this study is determined by using the expression:

$$\mathrm{HL} = \log[(\alpha + \beta)/2] \;/\; \log(\alpha + \beta) \tag{4}$$

Where HL is the half-life of volatility, and α and β are the ARCH and GARCH terms respectively. To understand the volatility of stock market indices in HIEs and MIEs, this study uses GARCH (1, 1) which is considered the simplest and robust form of the GARCH model (Engle 2001). The model, which consists of one ARCH term and one GARCH term involves estimating the mean and conditional variance as indicated below:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{5}$$

The stock market volatility is estimated using daily closing price data of major indices in HIEs and MIEs from January 4, 2005 to May 4, 2021. The data is sourced from Yahoo Finance and Oxford-Man Institute of Quantitative Finance databases. The data is transformed into daily returns using the expression:

$$r_t = \ln(P_t / P_{t-1}) \tag{6}$$

Where r_t is the stock market index return at time *t*, ln is the natural logarithm, P_t is the closing stock market price index at the end of day t, and P_{t-1} is the closing price lag one period (i.e., preceding day's closing price). Studies that utilized daily data and approaches similar to this study include Chaudhary, Bakhshi, and Gupta (2020), Mallikarjuna and Rao (2019), and Uludag and Khurshid (2019). The indices relating to the HIEs category include TSX (Canada), Euronext 100 (Eurozone), CAC 40 (France), DAXI (Germany), HIS (Hong Kong), N225 (Japan), KOSPI (Korea), TSEC (Taiwan), FTSE 100 (UK), and NYSE (US). Indices in the MIEs group are MERVAL (Argentina), IBOVESPA (Brazil), Shenzhen (China), BSESN (India), JKSE (Indonesia), MXX (Mexico), and KSE (Pakistan).

4. Results and Discussion

4.1 Descriptive Statistics

Table 1A and Table 1B are displays of the descriptive statistics of the indices in HIEs and MIEs. The mean returns were positive in all markets but with some differences. The mean return in MIEs is higher than the average returns in HIEs. Among the HIEs group, Korea's KOSPI produced the highest returns while UK's FTSE generated the least returns (Table 1A). In the MIEs category, MERVAL, which is Argentina's main stock market index produced the highest returns whereas Mexico's MXX showed the lowest mean return (Table 1B). The standard deviation of indices in the MIEs category is relatively higher than the HIEs group. Indices in the two groups showed negatively skewed returns, which indicates that they are not normally distributed. In addition, the negative skewness suggests a sharp decline in prices and a high degree of possibility that investors incurred losses (Abonongo, Oduro, Ackora-Prah, & Luguterah, 2016; Jondeau & Rockinger. 2003). Furthermore, Canada's TSX and Argentina's MERVAL are the most negatively skewed in their respective categories, signalling that they experienced more extreme losses than the rest of the indices. Kurtosis of the indices deviates from 3 (Table 1A and Table 1B), indicating a leptokurtic distribution with a high peak and fatter tail, which is typical of distributions with large deviations from the mean (Abonongo, Oduro, Ackora-Prah, & Luguterah, 2016). For the Jarque-Bera of the indices in Table 1A and Table 1B, the p-values indicate that the assumption of normality is rejected at 5 percent level of significance, providing more evidence that the stock market returns in HIEs and MIEs are not normally distributed. The stationarity test was carried out using the Augmented Dickey-Fuller (ADF) test with the null hypothesis (H_0) that the indices have a unit root. The results in Table 2, which reject the null hypothesis (H_0) that the indices have unit root at the significance level of 1 percent affirm that each of the stock market return series in HIEs and MIEs is stationary.

Table 1A. Descriptive statistics for High-Income Economies (HIEs)

	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera
Canada (TSX)	0.0001808	0.0113597	-1.063315	23.22158	70,646
Eurozone (Euronext 100)	0.0001453	0.0126347	-0.398079	12.50236	15,806
France (CAC 40)	0.0001154	0.0137854	-0.287079	11.59056	12,886
Germany (DAXI)	0.0002999	0.0135852	-0.252077	11.45767	12,347
Hong Kong (HIS)	0.0001766	0.0145525	-0.046669	12.06675	13,761
Japan (N225)	0.0002296	0.0147917	-0.487086	11.07035	10,997
Korea (KOSPI)	0.0003142	0.0125212	-0.516775	12.05615	13,954
Taiwan (TSEC)	0.0002554	0.0114074	-0.477475	7.553233	3,612
UK (FTSE)	0.000087	0.011455	-0.31347	11.96486	12,924
US (NYSE)	0.0002024	0.0128152	-0.691114	16.89629	33,397

Source: Authors' computations.

Table 1B. Descriptive statistics for Middle-Income Economies (MIEs)

	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera
Argentina (MERVAL)	0.0009023	0.0230284	-2.628342	52.53197	411,751
Brazil (BVSP)	0.0003858	0.0177524	-0.443205	11.99433	13,723
China (Shenzhen)	0.0003944	0.0184024	-0.525414	6.114298	1,784
India (BSESN)	0.0004898	0.0142259	-0.224367	14.14855	20,992
Indonesia (JKSE)	0.0004453	0.0131331	-0.591058	11.18006	11,297
Mexico (MXX)	0.0003252	0.0121897	-0.030082	9.224575	6,605
Pakistan (KSE)	0.000491	0.0130081	-0.59385	6.937077	2,808

Source: Authors' computations.

Table 2. Augmented Dickey-Fuller (ADF) test

High-Income Economies (HIEs)		Middle-Income Economies (MIEs)	
	ADF Statistics	ADF Statistics	
Canada (TSX)	-47.222***	Argentina (MERVAL)	-44.449***
Eurozone (Euronext 100)	-46.411***	Brazil (IBOVESPA)	-46.100***
France (CAC 40)	-47.018***	China (Shenzhen)	-44.565***
Germany (DAXI)	-45.830***	India (BSESN)	-44.733***
Hong Kong (HSI)	-44.781***	Indonesia (JKSE)	-42.860***
Japan (N225)	-45.059***	Mexico (MXX)	-45.400***
Korea (KOSPI)	-43.641***	Pakistan (KSE)	-40.339***
Taiwan (TSEC)	-42.538***		
UK (FTSE)	-47.505***		
US (NYSE)	-47.805***		

Source: Author's computations.

Note. p-Values are in parentheses. *** indicates statistical significance at the 1 percent level (i.e., $p \leq 0.01$).

4.2 GARCH Model

The Autoregressive Conditional Heteroscedasticity (ARCH) effect test conducted reveals the existence of the ARCH effect in the residuals of the data, suggesting that the estimation process involving the GARCH model is appropriate (Kumari & Mahakud, 2016). The outputs of the GARCH (1, 1) model for HIEs and MIEs are presented in Table 3A and Table 3B. The estimates show ARCH term (α) for indices in HIEs and MIEs are statistically significant, suggesting that news about volatility in the previous period influences the volatility of indices in the two categories of countries. Among HIEs, NYSE in the US has the highest ARCH term (α) coefficient (Table 3A), signifying that it is greatly influenced by information about volatility in the previous period than the rest of the indices in HIEs. Hang Seng Index (HSI) in Hong Kong is the least affected by information about volatility in the previous. In the MIEs category, Argentina's MERVAL has the highest ARCH term (α) coefficient (Table 3B), indicating that it is greatly affected by news about volatility in the prior period than the other indices in the group. The low ARCH term (α) coefficient displayed by China's Shenzhen Index (Table 3B) shows that it is the least affected by information about the prior period's volatility. Also, the GARCH term (β) is significant (Table 3A and Table 3B), which shows that prior volatility influences current volatility (Joo & Mir, 2014). Among indices in HIEs, Hong Kong's HSI has the highest GARCH term (β) coefficient, suggesting that its volatility is greatly influenced by volatility that occurred in the previous periods. Japan's N225 is an index in HIEs in which volatility from the preceding period has the least influence on the current volatility. In the case of MIEs, because China's Shenzhen displays the highest GARCH term (β) coefficient and Argentina's MERVAL the lowest, the volatility of China's Shenzhen can be said to be greatly influenced by prior periods' volatility, which is consistent with Tripathy (2017). Similar to Mallikarjuna & Rao (2019), the ARCH (α) and GARCH (β) terms are greater than zero (0) but less than one (1), signifying the presence of volatility clustering in each stock market. This implies that any observed volatility shocks will be expected to influence volatility in future periods (Engle & Patton, 2001). Consistent with remarks in Poon (2005), the finding that volatility clusters suggest that turbulence in the stock market in HIEs and MIEs will be accompanied by a turbulent period while a period of calm will be accompanied by a calm period. Results in Table 3A and Table 3B show that the sum of ARCH (α) and GARCH (β) terms is less than one for the indices in HIEs and MIEs. This signals evidence of mean reversal, which is consistent with Ahmed, Vveinhardt, Streimikiene, and Channar (2018) and Engle and Patton (2001). However, the sum of ARCH (α) and GARCH (β) terms for China and India in the MIEs category and Canada in the HIEs group is closer to one than the rest of the indices, implying a high degree of volatility persistence in China, India, and Canada. Furthermore, the magnitude of the GARCH term (β) is greater than the magnitude of the ARCH term (α) (Table 3A and Table 3B). This indicates that indices in HIEs and MIEs are more responsive to past volatility than information about volatility in the previous period, creating the expectation that volatility would require more time to dissipate (Chaudhary, Bakhshi, & Gupta, 2020). Given that indices with a high level of persistence tend to exhibit high half-life and weak mean reversion and that those with low persistence show low half-life and strong mean reversion (Abonogo, Oduro, Ackora-Prah, & Luguterah, 2016), the half-life was evaluated to determine the degree of volatility persistence. The results in Table 3A and Table 3B signify the persistence of volatility. Among the HIEs category, the volatility of Canada's TSX takes the longest (79 days) to return halfway back to its long-term average. On the other hand, Japan's N225 has the fastest mean reversion. Its half-life of 32 days indicates that unlike other indices in the HIEs category, its volatility will take 32 days to return halfway back to its mean. In the MIEs group, China's Shenzhen index and India's BSESN have the slowest mean reversion with half-lives of 87 days and 82 days respectively, suggesting that volatility is more persistent in China and India than in the other indices in MIEs and HIEs. Argentina's MERVAL and Brazil's BOVESPA have the fastest mean reversion. The half-life of 20 days for Argentina's MERVAL and 23 days for Brazil's BOVESPA (Table 3B) show low volatility persistence and faster dissipation of volatility than the other indices.

Table 3A. GARCH (1, 1) Output for High Income Economies (HIEs)

	α	**β**	**α + β**	**Half-life (Days)**
Canada (TSX)	0.1226763	0.8684571	0.9911334	79
	(0.000)	(0.000)		
Eurozone	0.1267751	0.8570303	0.9838054	43
(Euronext 100)	(0.000)	(0.000)		
France (CAC 40)	0.1214581	0.8634227	0.9848808	46
	(0.000)	(0.000)		
Germany (DAXI)	0.0981111	0.8848533	0.9829644	41
	(0.000)	(0.000)		
Hong Kong (HSI)	0.0654458	0.924049	0.9894948	67
	(0.000)	(0.000)		
Japan (N225)	0.1268247	0.8509159	0.9777406	32
	(0.000)	(0.000)		
Korea (KOSPI)	0.0861785	0.9003654	0.9865439	52
	(0.000)	(0.000)		
Taiwan (TSEC)	0.0805469	0.9031794	0.9837263	43
	(0.000)	(0.000)		
UK (FTSE)	0.1202217	0.8636764	0.9838981	44
	(0.000)	(0.000)		
US (NYSE)	0.1330854	0.8519221	0.9850075	47
	(0.000)	(0.000)		

Source: Authors' computations.

Note. α represents the ARCH term coefficient; β represents the GARCH term coefficient. p-values are in parentheses.

Table 3B. GARCH (1,1) Output for Medium Income Economies (MIEs)

	α	**β**	**α + β**	**Half-life (Days)**
Argentina (MERVAL)	0.2152769	0.7479822	0.9632591	20
	(0.000)	(0.000)		
Brazil (BOVESPA)	0.082062	0.8862929	0.9683549	23
	(0.000)	(0.000)		
China (Shenzhen)	0.0590705	0.932919	0.9919834	87
	(0.000)	(0.000)		
India (BSESN)	0.0936486	0.8978195	0.99146681	82
	(0.000)	(0.000)		
Indonesia (JKSE)	0.1340747	0.8478837	0.9819584	39
	(0.000)	(0.000)		
Mexico (MXX)	0.0983023	0.8879811	0.9862834	51
	(0.000)	(0.000)		
Pakistan (KSE)	0.0930019	0.891655	0.9846569	46
	(0.000)	(0.000)		

Source: Authors' computations.

Note. α represents the ARCH term coefficient; β represents the GARCH term coefficient. p-values are in parentheses.

5. Conclusion

This study examines the volatility of stock market indices in HIEs and MIEs. It used daily closing data from January 4, 2005 to May 4, 2021 on ten (10) indices in HIEs and seven (7) indices in MIEs and applied the GARCH (1, 1) model. The kurtosis is greater than three (3) for each of the indices, indicating a leptokurtic distribution. This suggests that stock market returns are highly volatile in HIEs and MIEs. Nonetheless, the study finds that mean returns in MIEs are higher than the average returns in HIEs, but the finding that MIEs as a group have higher standard deviation reveals that the high returns in MIEs are accompanied by high risk. Results of the GARCH (1, 1) model showing that the ARCH term (α) and GARCH term (β) are significant indicate that information about volatility in the previous period and past occurrence of volatility influence the volatility of stock markets. Furthermore, the finding that the magnitude of the GARCH term (β) is greater than the magnitude of the ARCH term (α) shows that indices in HIEs and MIEs are mostly influenced by prior volatility, suggesting evidence of volatility persistence in the two categories of countries. The mean reversion findings show that volatility dissipates and that indices in HIEs and MIEs return to their mean but the time it takes for volatility to dissipate varies by index. Given that investors gravitate toward markets with high volatility persistence and weak mean reversal when positive shocks cause volatility but seek markets with low volatility persistence and strong mean reversal when negative shocks generate volatility (Abonogo, Oduro, Ackora-Prah & Luguterah, 2016), the mean reversal results suggest that in periods when negative shocks trigger volatility, indices in HIEs and MIEs with a strong mean reversal and low persistence (i.e., short half-life) would witness less turbulence due to investors' expectation of quick dissipation of volatility. However, in periods of positive shocks eliciting volatility, such indices would lose activities to indices with a weak mean reversal and high volatility persistence (i.e., high half-life) due to investors' expectations that the resultant volatility from the positive shocks will persist. The finding that the time it takes for volatility to dissipate varies by index signifies that if markets received similar information, reactions would differ. Given this, future studies should examine macroeconomic factors and market-specific events that impact the volatility of stock markets. This study is limited to HIEs and MIEs, for a more generalizable result, future research should consider expanding the sample size and include fast and slow-growing economies.

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