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Market Shocks and Stock Volatility: Evidence from Emerging and Developed Markets

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Abstract: Market turbulences and their impact on the financial market, particularly on the stock market, is a financial topic that has received significant research attention recently. This study compared the characteristics of stock return and volatility in selected developed and emerging markets between the 2008 financial crisis and the 2019 worldwide pandemic. In this sense, we seek to answer two concerns. First, do the developed and emerging markets behave similarly during crisis periods? Second, does economic strength always shield markets from poor economic circumstances? For this purpose, the daily return data of E7 (Emerging 7) and G7 (Developed 7) countries for two sample periods—namely, the financial crisis period of 2007–2009 and the global pandemic period of 2019–2021—were chosen. By using univariate GARCH models, namely GARCH, EGARCH, and TGARCH, the study discovered that developing and developed markets reacted differently to these two financial crises. While emerging markets responded similarly to these two crises, developed economies acted differently, being more volatile and sensitive to the worldwide pandemic of 2019 than the financial crisis of 2008. Moreover, a country's economic prowess does not always shield it from economic turmoil. This study will help investors identify diversification opportunities among the developed and emerging markets during a crisis period. Additionally, this will help portfolio and fund managers understand the behaviour of stock markets during times of market crisis and thus give advice to investors.

Keywords: risk–return; volatility; asymmetric volatility; financial crisis; global pandemic; emerging markets; developed markets; GARCH models

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1. Introduction

The global market has been affected by a series of market crises, and each market crisis has varied effects on the stock market and the economy as a whole (Figure 1). By looking into the nature of these market crises, the 2008 fall of the Lehman Brothers served as the catalyst for the global financial crisis, which had been building more in recent decades. The U.S. Federal Reserve reduced interest rates to 1% after the dot-com bubble crashed in 2000, providing banks with low-cost capital. Armed with considerable financial weight, banks and financial firms supported officials and authorities to hold key positions in important financial regulatory bodies around the world. They also supported their own top executives to hold these positions. The financial sector became the most powerful and the least regulated in the world as a result of these acts. In 2020, the novel coronavirus (COVID-19) outbreak caused widespread economic and financial harm that is far greater than the harm caused by prior significant public health crises. The stock market of the U.S.A. was more reactive to COVID-19 at an earlier stage (Gao et al. 2022). In the case of India, as of 29 May 2020, the number of COVID-19 cases had surpassed the 165,000 milestone there (Verma and Sinha 2020). The epidemic is therefore the largest global shock countries have faced in recent decades, and the development of the world economy is predicted to decline by up to 5.2%, marking the sharpest depression in decades (Insaidoo et al. 2021). In this situation, it is important to understand and compare the impact of different market crises on the stock market to explore their nature and impact on the stock market.

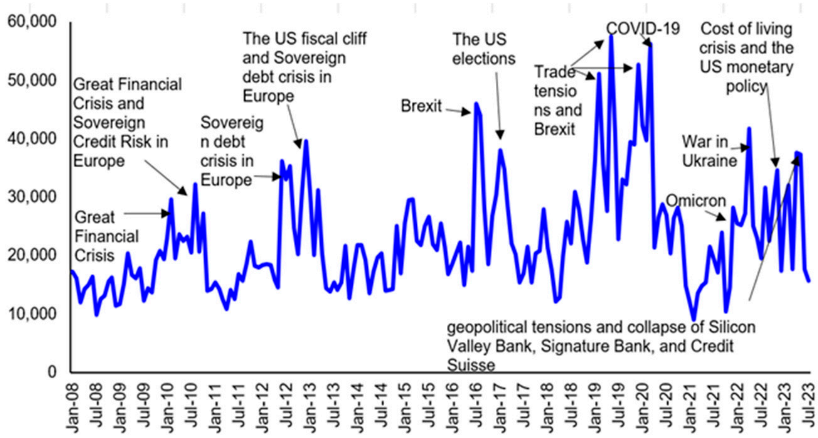

Figure 1. Major events that affected stock markets. Source: (Economic Policy Uncertainty Index 2023).

Market turbulences and their impact on the financial market, particularly on stock market volatility, is one of the relevant financial topics that has received the most research during recent times. According to the capacities of the various markets, this volatility may also be regionally distinct and handled in different ways. Numerous studies have examined the variables that could lead to volatile markets. However, the influence of the financial crises—particularly those that had the greatest negative effects, such as 2008's global financial crisis and the recent pandemic—on the volatility in established and emerging markets has not received enough attention. The present study evaluates the impact of two well-known market crises, namely the 2008 financial crisis and the recent global pandemic COVID-19, on the stock markets of G7 (developed markets) and E7 (emerging markets). The market behaviour to different market crises may not be the same all the time. The primary concerns of this study are to investigate whether developed and emerging markets behave similarly in these crises and whether the economic strength of developed markets always protects them from the worst market conditions, as well as whether these markets are cointegrated during the times of market turbulences? By investigating these facts, investors and stock market participants will obtain more insight on the effect of a market crisis on stock volatility, the behaviour of different markets, and their interaction.

By comparing the effects of the financial crisis of 2008 on these two economies, the results show that emerging markets are impacted more severely than established ones. In addition, established markets were more affected by the latest pandemic than the emerging markets. Varied market crises have varied effects, some of which are more severe than others. This demonstrates that a nation's economic might is not necessarily a guarantee against economic turbulence. In the same way, this study finds a significant presence of asymmetric volatility on emerging and mature markets. This study confirms the findings of previous researchers that negative news has a higher impact on stock volatility than positive news. This will assist them in making better investment decisions, especially at the time of the worst market conditions, so that they can minimise their risk.

The following sections comprise the remaining text of this article. The data and research technique are described in Section 2. After reporting the empirical results in Section 3, Section 4 offers closing remarks and research recommendations.

2. Literature Review

2.1. Volatility in Emerging and Developed Markets

The emerging markets are identified using traits that set them apart from developed economies. The majority of emerging markets have low per-capita incomes and are heavily dependent on a small number of industries. Political unpredictability, abrupt regime changes, exchange rate volatility, external pricing fluctuations, etc. cause erratic economic growth (Umar et al. 2021) (Su et al. 2020). The stock markets in emerging nations have experienced a remarkable expansion in recent years in terms of value and volume, opening up investment opportunities (Raza et al. 2016). Due to the high projected returns, low market efficiency, and rapid expansion, the emerging nations are desirable locations for Foreign Institutional Investors (FIIs) to diversify their portfolios. However, higher predicted rewards are accompanied by higher risk due to political and economic unrest (Sharma et al. 2021). Furthermore, the financial markets of developing countries are susceptible to events and news happening throughout the world, creating a volatile and unsettling atmosphere.

The emerging market's equities returns' volatility structure were modelled by different studies. Between 2006 and 2020, Umar et al. (2021) examined the volatility patterns of stock returns on the Pakistan Stock Exchange using GARCH family models in various symmetric and asymmetric forms along with the News Impact Curve. They show that the daily returns showed asymmetry, suggesting that market news affects investors' emotions and behaviour on a continual basis. Between January 2000 and December 2019, Sharma et al. (2021) used linear and non-linear GARCH models to analyse the symmetric and asymmetric volatility of five significant emerging economies, including India, China, Brazil, Indonesia, and Mexico, with a focus on the pre- and post-crisis. The effects of the global financial crisis on the stock market volatility in Hong Kong, Japan, China, and India amid the subprime mortgage crisis and the Eurozone debt crisis using the EGARCH model (Singhania and Anchalia 2013), in contrast to Hong Kong, where it had no effect, the sub-prime crisis had a favourable effect on the return volatility of China, India, and Japan. The analyses of Eichengreen and Park (2008) and Eichengreen et al. (2012) on the financial crisis 2008 indicated that emerging markets had failed to prevent the U.S. economic disaster. Furthermore, Dooley and Hutchison (2009) demonstrate that the emerging economies' response was insufficient in the early stages of the subprime crisis, which occurred between June 2007 and August 2008. When the markets were under stress during the 2007–2009 financial crisis, high volatility retention was demonstrated but not as much during the euphoric time before the crisis (Wang and Yang 2018). According to the study, significant unfavourable returns have a stronger impact on volatility persistence than favourable returns do. Volatility levels also affect volatility persistence more (Su and Wang 2020). This implies that volatility persistence is systematically influenced by returns and volatility levels.

Following an initial period in which the growth rates of developed and developing nations appeared to be going in different directions, the crisis reached its most critical stage after in the United States, Lehman Brothers went into bankruptcy in September 2008, and its impact on emerging markets began to be felt more strongly (Bianconi et al. 2013). However, after the financial crisis, Baruník et al. (2016) found that the overall intra-market connectivity of U.S. stocks significantly increased during the most recent financial crisis. This was determined by simulating the asymmetries in volatility spill-overs between U.S. stocks over the distinctly diverse times before, during, and after the financial crisis. The relationships between the greater China, US, and Japanese stock markets were examined in the study conducted by Wang and Wang (2010). While focusing on the three well-established markets of New York, Tokyo, and London, Koutmos and Geoffrey Booth (1995) asserted that more than advantageous innovations, unfavourable innovations in one market increase volatility in the subsequent market to trade. They accomplish this by incorporating the asymmetric impact of favourable and unfavourable news on volatility transmissions into the model.

In the recent past, the investigation of the impact of exogenous and endogenous shocks on different financial markets by using different approaches/methods has attained major attention in the finance literature. By taking the sample from 2007 to 2021, Awijen et al. (2023) forecasted the oil prices during the time of crisis. They used two approaches: support vector machine and long–short memory approaches. Madani and Ftiti (2024) examined the effects of investment or sentiment related to oil and stock markets on extreme movement in oil price dynamics during the early COVID-19 period. Ftiti et al. (2021a) investigated the effect of non-fundamental news on stock returns. They found that non-fundamental pandemic news increased return volatility and liquidity risk. In line with this, several scholars (Pacheco 2022; Inacio and David 2022; Le et al. 2021; Jawadi et al. 2020) evaluated the impact of market shock on oil price and oil-exporting countries. Similarly, market shock on the crypto-currency market (Bhatnagar et al. 2023; Fernandes et al. 2022; Agosto and Cafferata 2020; Ftiti et al. 2021b) and exchange rate market (Narayan 2020, 2022; Jawadi et al. 2019) has been well investigated in the literature from the classical approach of measuring volatility using univariate GARCH models (Alberg et al. 2008; Teräsvirta 2009; Awartani and Corradi 2005; Franses and Van Dijk 1996) to modern methods (Bouzgarrou et al. 2023) such as the NARDL model, vector machine model (Awijen et al. 2023), quantile regression (Živkov et al. 2020), and artificial neural networks (Sarfaraz et al. 2023). The evaluation of different market shocks on financial markets is still continuing.

2.2. Financial Crisis 2008 and Stock Market Volatility

Early in 2008, the USA experienced a financial collapse that set off the global crisis, which spread fast to the rest of the world. As real estate values fell in 2007, huge international banks that had overinvested in hazardous real estate mortgages incurred significant losses in the early phases of the crisis (Assaf 2016). Following the crisis, the US government and other sovereign officials changed regulations and provided bailouts to lessen the negative effects on the economies of the countries (Luchtenberg and Vu 2015). On 8 October, the benchmark portfolio's volatility closed at 68.01 percentage points, compared to just 24.72 points on 8 September 2008, for the yearly standard deviation of return (Schwert 2011).

Through the 2008's financial crisis, many authors looked into the effect of the GFC (global financial crisis) on stock market variation from different perspectives as investors may experience severe consequences as a result of financial or economic crises; therefore, this topic has generated a great deal of attention among academic scholars. Luchtenberg and Vu (2015) looked at the frequency of contagion among foreign markets in order to identify the mechanism by which any identified contagion is spread. The GFC and Asia's central role in the global money flow are the direct causes of the volatility. Western financial markets are a primary driver of Asian economies, and stock exchanges have an important influence on their rate of expansion. Singhania and Anchalia (2013) and Karunanayake et al. (2010) assessed the effect of the sub-prime crisis and the European debt crisis and showed that the Asian crisis and more subsequent global financial crises had a major impact on returns in the selected markets. Furthermore, (Syriopoulos et al. 2015) examined the volatility spill-over among BRICS (Jin and An 2016) and emerging markets during the financial crisis. Mazumder and Ahmad (2010) examined the root causes of the US stock market volatility, mortgage and liquidity crises, and their consequences on the global economy from 2007 to 2009.

Along with changes in company value, the value of a company's risky investments relative to its less risky investments is likely to shift (Duffee 2002). The proportion of debt and equity rises with a decline in the stock's value, making it riskier and more volatile. According to Campbell and Hentschel (1992), if volatility is priced, then its asymmetrical characteristics could simply be due to the presence of time-varying risk premiums. The existence of volatility feedback was proposed as a different explanation by Bekaert and Wu (2000). This phenomenon is reliant on volatility persistence, wherein the realisation of big news, whether favourable or unfavourable, raises both present and future volatility. Additionally, it assumes that expected return and conditional variance have a favourable intertemporal relationship. Volatility rises when there are good news events and falls when there are negative events because rising volatility lowers current stock prices and increases expected returns. This is accordance with comments made by Glosten et al. (1993).

H_1: *The global financial crisis has a significant impact on the market volatility of developed and emerging markets.*

2.3. Global Pandemic and Stock Market Volatility

Due to its suddenness and severity, the novel coronavirus pandemic, which has had an influence on practically every element of human existence and the economy, has been called a "black swan event". The epidemic has considerably uplifted market volatility around the globe (Uddin et al. 2021; Zaremba et al. 2020). The global stock markets experienced uncertainty and an increase in volatility as a result of the COVID-19 pandemic outbreak. Engelhardt et al. (2021) demonstrate that the capital markets' volatility in response to COVID-19 case releases is much lower in high-trust countries after analysing a sample of leading economies' stock market indexes. The world's economy, both established and developing, notably those of the United States (Albulescu 2021), United Kingdom (Ozkan 2021; Kusumahadi and Permana 2021), South Africa (Szczygielski and Chipeta 2023), Brazil and India (Sahoo 2021; Bora and Basistha 2021) have been significantly impacted by the pandemic's high levels of uncertainty and risk.

Different aspects of the impact of the global pandemic on different financial markets have been investigated in the literature; particularly, stock market volatility has been investigated by many authors. The stock markets in emerging economies were significantly more negatively impacted by the recent pandemic than those in developed countries (Harjoto and Rossi 2021). He also discovered that compared to the 2008 financial crisis, the equity markets in both emerging and developed countries recovered from the COVID-19 epidemic more quickly. Uddin et al. (2021) looked at how COVID-19 affects stock market volatility and whether economic strength could lessen any possible adverse effects on 34 established and emerging markets. It was discovered that the economic traits and aspects at the national level do contribute to reducing the volatility caused by the virus pandemic. They propose that in order to mitigate the impact in the world's financial markets, it is beneficial to enhance the economic strength. Furthermore, Bentes (2021) examined the impact of the global pandemic on G7 countries, while Mazur et al. (2021) and Baek et al. (2020) examined the US market, Insaidoo et al. (2021) analysed the Ghana stock market, Zehri (2021) examined the East Asia stock market, Bora and Basistha (2021) and Verma and Sinha 2020) analysed the Indian stock market, and Mishra and Mishra (2021) studied Asian markets. The US stock market's uncertainty and the effects of the first and second waves of the continuing COVID-19 epidemic are first compared and evaluated by Yousfi et al. (2021). Market events have different effects on the economy, industry and companies. Not only macro-economic events but also micro-economic events (industry and company-specific events) may affect the valuation, performance of industry and companies and thus the economy as a whole. Rababah et al. (2020) and Shen et al. (2020) suggested that small and medium-sized businesses are the ones most impacted by this pandemic. Additionally, they highlighted that serious impact sectors and industries that were most negatively affected by the COVID-19 pandemic saw a more dramatic fall in financial performance than other industries. Ozdemir et al. (2022) and Hasan et al. (2023) investigated how a supply chain (SC) interruption affected a semiconductor company's performance outcomes during the COVID-19 pandemic and offers suitable risk mitigation measures to address the issue.

H_2: *COVID-19 has a significant influence on the market of volatility of developed and emerging markets.*

Multiple studies have looked at various facets of stock market volatility in various developed, developing, and emerging markets. The models used in several of these research studies were of the GARCH type, albeit some of them made considerable changes. The majority assessed two or more factors with volatility persistence and volatility asymmetry being the most frequently rated ones. There is a gap in the literature regarding studies comparing the impact of different financial crises on multiple financial markets. The present study tries to evaluate the extend of asymmetric volatility of developed and emerging markets with regard to two major financial crises: the financial crisis of 2008 and the recent global pandemic related to COVID-19 by using different GARCH models and market integration during the crisis period. The present study tries to answer the following research questions:

1. Has there been any impact on the volatility of developed and emerging markets from the financial crisis of 2008 and the COVID-19 epidemic?

2. Do the volatility patterns of developed and emerging markets during the COVID-19 epidemic and the 2008 financial crisis resemble one another?

3. Does economic strength always shield and safeguard the market from adverse market conditions?

3. Data and Methodology

The broad market indices from developed and emerging nations were employed in the study (Table 1). Seven broad market indices from emerging and developed economies that are labelled as emerging 7 (E7) and developed 7 (G7) were employed in the study. The selection of such economies was underpinned by their high levels of stability, relative economic development, developed capital markets, comprehensive regulations and laws, and favourable liquidity. The sample period as a whole was separated into two time periods: the financial crisis period (2008) and the global pandemic period (2020). The period of the 2008 crisis is represented by the sample period of 2007–2010 and the global pandemic is represented by the sample years 2019–2021.

Table 1. Stock indices selected for the study.

Panel A: Emerging Markets			Panel B: Developed Markets		
No	**Country**	**Stock Index**	**No**	**Country**	**Stock Index**
1	Brazil	BOVESPA	1	Italy	FTSE Italia All Share
2	China	SSE Composite Index	2	Canada	S&P/TSX
3	India	S&P BSE Sensex	3	France	CAC 40
4	Indonesia	IDX Composite	4	Germany	DAX
5	Mexico	S&P/BMV IPC	5	Japan	Nikkei 225
6	Russia	MOEX 10	6	UK	FTSE 100
7	Turkey	BIST 100	7	USA	Nasdaq 100

The study used volatility models in order to explore and contrast the effects of two events (Financial crisis 2008 and Global pandemic 2020) that might have affected emerging and developed stock markets. First, to analyse the data attributes for all the variables, a descriptive analysis utilising the average, variance, skewness, kurtosis, and Jarque–Bera statistic was carried out. Additionally, the extent of return volatility and asymmetric volatility has been verified using GARCH, EGARCH and TGARCH.

The daily stock returns were determined using the following formula to assess stock return volatility:

$$\mathrm{rt} = \ln\left(\mathrm{P_t}/\mathrm{P_{t-1}}\right) \tag{1}$$

where rt is the daily return, $\mathrm{P_t}$ is the share price index at period t, and $\mathrm{P_{t-1}}$ is the share price index at period $\mathrm{t}-1$, respectively.

3.1. Unit Root Test

Before employing an econometric technique for regression analysis, it is necessary to check the stationarity of the series by employing the unit root testing. As the non-stationary time series of financial returns may limit the usefulness of successful forecasting models in informal testing (Timmermann and Granger 2004), the Augmented Dickey–Fuller test (Cheung and Lai 1995) has been employed to see if the series stayed stationary at the level and first difference.

3.2. Econometrics Models

In general, stock market returns react to economic shocks like pandemics, political upheaval, and natural disasters, especially when the news is bad or negative, because huge unfavourable returns are more common than large favourable returns, and there are asymmetries in the interdependence of markets (Baruník et al. 2016). Asymmetries in volatility show that bad news's repercussion upsets exert a larger influence on boosting future volatility as contrasted with good return shocks brought on by news that is good, as argued by Christie (1982) as well as Koutmos and Geoffrey Booth (1995). Due to the fact that a decline in stock market value increases the overall debt-to-equity ratio, which increases leverage, this return effect is frequently referred to as the "leverage effect". GARCH models established by Engle (1982) and Bollerslev (1987) have proven useful for simulating the conditional volatility of equities securities and the markets in which they trade. Volatility is known to spread in an asymmetrical way; this fact was formalised in Nelson's (1991) exponential generalised autoregressive conditional heteroscedasticity (GARCH) model and later in Glosten et al.'s (1993) model as well as in Zakoian's (1994) threshold ARCH model. The use of these models produced a sizable amount of empirical evidence that supports the asymmetry between the returns on volatility that are negative and positive.

3.2.1. GARCH (1,1) Model

To describe the dynamics of the conditional variance, Engle (1982) developed the autoregressive conditional heteroskedasticity (ARCH) model, which calculates return variance as a straightforward quadratic function of the lagged values of innovations.

Performing diagnostic tests on the return series' properties, including stationarity, normality, autocorrelation, and heteroscedasticity, was the initial stage in the analysis. The later application of GARCH models was justified by the presence of ARCH effects. The ARCH model's frequent need for numerous parameters and a high order q to accurately reflect the volatility process is one of its flaws. To overcome the weakness of the ARCH model, Bollerslev (1986) suggests the GARCH model. Bollerslev et al. (1994) demonstrated that the GARCH (1,1) specification effectively performs in the majority of applicable scenarios. The GARCH model's ability to efficiently reduce excess kurtosis in returns is a useful characteristic (Franses and Van Dijk 1996). They could be seen as a simple and dynamic method for estimating and diagnostic testing (Drakos 2010). In the conventional GARCH model, the conditional variance has been projected onto its own prior lags. As a foundational model structure, GARCH (1,1) has been employed (Brooks et al. 2001).

The variance in a general GARCH model is written as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2 \tag{2}$$

3.2.2. Nonlinear GARCH models

The financial markets frequently experience a more significant declining trend in conjunction with an increase in asset prices. In order to try and explain this occurrence, Engle and Ng (1993) built asymmetric information curves under the influence of good news and bad news, respectively. The market's response to shocks is fundamentally expressed by the asymmetry effect. It also goes by the name "leverage effect", which is a crucial aspect of many investment alternatives. Market analysts frequently discover that the asymmetry effect, which refers to the fact that a stock's volatility is considerably higher when it experiences negative shocks than when it experiences positive shocks, also affects stock price movement in the capital market (Lin 2018).

To account for the effects of asymmetric leverage and long- and short-memory volatility, nonlinear GARCH models have been developed as well as other stylized characteristics of financial markets. Glosten et al. (1993) contributed the GJR model, while Nelson (1991) established the EGARCH model, and the APARCH model was introduced by Ding et al.

(1993). This study employs the following nonlinear GARCH-class models to predict the volatility of stock return.

3.2.3. EGARCH (1,1)

The research looked at whether a downturn affected volatility more than a positive surprise for the chosen time series using the asymmetric GARCH model known as EGARCH by Nelson (1991) and TGARCH by Zakoian (1994).

The assumption that positive and negative events with identical actual values result in stock price fluctuations of comparable magnitude underlies the conditional variances in the linear GARCH model. However, in practise, both favourable and adverse shocks of equivalent scale typically result in swings of varying intensities, especially in the financial markets. A share price decline frequently has a bigger influence on the stock market than a share price rise, and the decline process appears to be more volatile and unpredictable. Nelson (1991) developed the exponential GARCH model (EGARCH model) based on the GARCH model and made the following improvements

$$\text{Mean equation} = r_i = \mu + \varepsilon_t \tag{3}$$

$$\text{Variance equation } ln\left(\sigma_t^2\right) = a_0 + \beta_1 ln\left[\sigma_{t-1}^2\right] + a_1\left[\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right] - \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{4}$$

where the coefficient γ describes the volatility leverage effect.

3.2.4. TGARCH (1,1)

The threshold GARCH (TGARCH) model is another GARCH version that can simulate leverage effects. Zakoian (1994) and Glosten et al. (1993) introduced the TGARCH model, which aims to pinpoint the leverage effect in the financial time series. All that is required to determine whether a statistically significant difference exists when shocks are negative is to simply include a multiplicative dummy variable in the variance equation. Additionally, it is based on the hypothesis that unexpected information shocks may have an impact on the volatility of stock returns. The following can be used to specify the model's form:

$$\sigma_t = \omega + \alpha\sigma_{t-1}[|\varepsilon_t| - c\varepsilon_t] + \beta\sigma_{t-1} \tag{5}$$

$$\sigma_t = \omega + \alpha I[\varepsilon_{t-1} \geq 0]\varepsilon_{t-1} + \gamma I[\varepsilon_{t-1} < 0]\varepsilon_{t-1} + \beta\sigma_{t-1} \tag{6}$$

The asymmetry exists if $\gamma > 0$. The unfavourable shocks' impulse $(\alpha + \gamma)$ being higher than the favourable shocks' impulse (α), is how the asymmetry is visible.

The table lists the selected nations along with their respective primary stock market indices. Panel A represents selected emerging markets and respective stock indices, whereas panel B represents the selected developed markets and respective stock indices.

4. Results and Discussion

The descriptive statistics for the emerging and developed market indices during the financial crisis of 2008 and global pandemic of 2019 are shown in Table 2. It is found that the mean return of developed markets is higher than the emerging market return during both crisis periods. Through the period of the financial crisis of 2008, the average return of all emerging market indices have negative values except for Russia. All the developed market indices have a positive mean return during this period. Among developed markets, Germany is showing a higher mean return of 0.000913 followed by the USA with 0.000661. Meanwhile, comparing the variation in return, the standard deviation of emerging market indices is higher than that of the developed market. It means that during the financial crisis period of 2008, the emerging market produced a negative return, and the volatility in return is also higher than matured markets. All the indices show excess kurtosis, and some of the emerging and developed markets show negative skewness.

Table 2. Descriptive statistics.

	Financial Crisis 2008													
	Emerging Markets							**Developed Markets**						
	Brazil	China	India	Indonesia	Mexico	Russia	Turkey	Italy	Canada	France	Germany	Japan	UK	USA
Mean	−0.00016	−0.0001	−0.0006	−0.00016	0.00115	0.00451	−0.00014	0.000639	0.000364	0.000639	0.000913	0.00097	0.000622	0.000661
Std. Dev.	0.02013	0.02461	0.02392	0.02013	0.02290	0.04496	0.02167	0.016917	0.01925	0.016917	0.022076	0.019971	0.018603	0.018618
Skewness	0.52851	0.29322	−0.2414	0.52851	−0.50268	−0.26875	−0.00709	0.346537	0.529006	0.346537	0.337511	−0.21279	−0.00176	−0.13567
Kurtosis	7.47020	4.27715	7.30864	7.47020	6.51196	6.59539	5.92288	5.558396	7.673469	5.558396	9.052083	8.248362	7.715285	8.427461
Jarque-Bera	532.776	49.178	479.336	532.776	142.898	769.509	238.152	177.9855	581.6712	177.9855	939.4451	702.4027	563.2593	748.1174
	Global Pandemic 2020													
	Emerging Markets							**Developed Markets**						
	Brazil	China	India	Indonesia	Mexico	Russia	Turkey	Italy	Canada	France	Germany	Japan	UK	USA
Mean	−0.0001	−0.00036	−0.00066	−0.0001	−0.0003	−0.00041	−0.0004	−0.00015	−0.00043	−0.00015	−0.0004	−0.0004	−0.00025	−0.00051
Std. Dev.	0.01339	0.01119	0.01625	0.01339	0.01283	0.01390	0.01281	0.014091	0.015348	0.014091	0.013967	0.015579	0.014159	0.017092
Skewness	−0.0606	0.8642	1.7477	−0.0606	0.5295	0.8386	0.7821	1.328546	1.779271	1.328546	−0.10913	1.406124	1.209096	1.063167
Kurtosis	11.6080	10.2188	20.0065	11.6080	6.04577	11.8588	10.8211	14.36878	30.79849	14.36878	7.165834	17.08043	16.03325	20.28078
Jarque-Bera	1500.782	1115.752	6104.162	1500.784	2100.567	1646.16	1401.47	2998.804	17082.87	2998.804	368.3384	4587.221	3851.051	6631.334

Source: Author's Calculation. The table provides descriptive statistics of daily stock return data of selected emerging and developed markets during two sample periods: the global financial crisis of 2008 and global pandemic of 2019. The main descriptive statistics include the mean, standard deviation, skewness and kurtosis.

With regard to the global pandemic of 2019, the average returns of all indices from developed and emerging markets were negative and the variation in return was approximately the same for both markets. The global pandemic of 2019 affected both emerging and developed markets similarly, or we can say that both markets reacted to the global pandemic in the same way.

While comparing the behaviour of developed and emerging markets regarding the financial crisis of 2008 and the global pandemic of 2019, we can conclude that developed markets do not always have the strength to face the financial crisis, as the behaviour of the return and volatility is varying with regard to these crisis periods. Even though the developed markets created a positive return and showed less volatility during the financial crisis of 2008, the same markets were negative and had higher volatility during the global pandemic of 2019. In case of emerging markets, the behaviour is quite similar for each of these crisis periods. The global pandemic crisis had much more impact on the financial market as compared with the GFC 2008.

The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests are used to check for the unit root in the index returns. The initial criterion for applying any regressive model to a time series is data stationarity. The result of a stationarity test using ADF and the PP test for the financial crisis of 2008 and global pandemic of 2019 are documented in Table 3. The test statistics and the corresponding p-values have been shown at first difference of the data. The results of both tests indicate that the data set is stationary at first difference.

Table 3. Unit root test.

	ADF		**PP**	
	T Statistics	**Probability**	**T Statistics**	**Probability**
Financial Crisis 2008				
Panel A: Emerging markets				
Brazil	−20.99	0.000 ***	−20.99	0.000 ***
China	−24.77	0.000 ***	−24.78	0.000 ***
India	−22.87	0.000 ***	−22.81	0.000 ***
Indonesia	−20.99	0.000 ***	−20.99	0.000 ***
Mexico	−14.25	0.001 ***	−14.32	0.001 ***
Russia	−14.75	0.001 ***	−14.72	0.001 ***
Turkey	−18.32	0.000 ***	−20.12	0.000 ***
Panel B: Developed markets				
Italy	−26.71	0.000 ***	−26.71	0.000 ***
Canada	−28.11	0.000 ***	−28.23	0.001 ***
France	−26.71	0.000 ***	−26.71	0.000 ***
Germany	−26.05	0.001 ***	−26.24	0.001 ***
Japan	−12.62	0.000 ***	−27.97	0.000 ***
UK	−12.29	0.001 ***	−27.68	0.000 ***
USA	−21.94	0.000 ***	−29.44	0.000 ***
Global Pandemic 2019				
Panel A: Emerging markets				
Brazil	−11.11	0.000 ***	−21.78	0.000 ***
China	−21.81	0.000 ***	−21.81	0.000 ***
India	−17.16	0.000 ***	−24.72	0.000 ***
Indonesia	−11.11	0.000 ***	−21.78	0.000 ***
Mexico	−22.82	0.000 ***	−22.82	0.000 ***
Russia	−22.38	0.001 ***	−22.53	0.000 ***
Turkey	−20.46	0.000 ***	−22.20	0.000 ***

Table 3. *Cont.*

	ADF		PP	
	T Statistics	**Probability**	**T Statistics**	**Probability**
		Global Pandemic 2019		
		Panel B: Developed markets		
Italy	−11.37	0.000 ***	−28.87	0.000 ***
Canada	−11.38	0.000 ***	−28.81	0.000 ***
France	−13.77	0.000 ***	−21.74	0.000 ***
Germany	−14.42	0.000 ***	−28.48	0.000 ***
Japan	−17.13	0.000 ***	−23.55	0.000 ***
UK	−18.01	0.000 ***	−23.95	0.000 ***
USA	−16.71	0.000 ***	−23.18	0.000 ***

Source: Authors' calculation. The table summarizes the stationarity test of stock return data of developed and emerging markets during two sample periods, namely the global financial crisis of 2008 and COVID-19. The result of an ADF (Augmented Dickey–Fuller) test and PP (Philips–Perron) test are used for checking the stationarity. *** indicates significance at the 1% level.

Along with the descriptive statistics, the selected broad market indices were subjected to an ARCH effect and autocorrelation test, and the results showed that there was serial correlation in both returns and squared returns. To ascertain whether ARCH effects exist, the Lagrange multiplier (LM) test is typically used. To test for first-order ARCH, regress the squared regression residuals $\hat{e}^2$ on their lags $\hat{e}^2_{t-1}$.

The null hypothesis is $H_0 = \gamma_1 = 0$ against $H_1 = \gamma_1 \neq 0$

$$\hat{e}^2_{t-1} = \gamma_0 + \gamma\hat{e}^2_{t-1} + v_t$$

The testing equation will fit poorly with a low R^2 if there is no ARCH impact, as 1 = 0. If there is an ARCH effect, we anticipate that its lagged values will have a significant impact on the magnitude of $\hat{e}^2$ and that the R^2 will be large.

Table 4 provides an overview of the results of the ARCH-LM test. We reject H_0—that the series has an ARCH effect on the residuals—because all the LM statistic values are significant at a 1% threshold of significance, which suggests that the variance of the return of all the market indices is not constant. The squared returns' serial correlation shows that there is heteroscedasticity because the second moments of the series are time varying.

The application of GARCH (1,1) to test the volatility in the return series (Table 4) and asymmetric EGARCH (1,1) and TGARCH (1,1) models to determine the asymmetric effect in the conditional volatility were both prompted by the presence of the ARCH effect (Tables 5 and 6). The variance equation showed that for both crisis periods, all coefficients were significant at the 1% level of significance for all return series from established and emerging markets.

The primary concern of this study is to assess how emerging and developed markets respond to the financial crisis of 2008 and global pandemic of 2019. By analysing the volatility of emerging markets, the β coefficient was highest during the period of the 2008 financial crisis as compared with the global pandemic of 2019, showing that the financial crisis of 2008 had a greater impact on emerging markets than the recent global pandemic. Among emerging markets, China has been the most volatile during both crisis periods, as it has the highest β coefficient. By examining the impact of the financial crisis of 2008 on each of the emerging markets, China and Turkey were the most volatile markets and Indonesia is the least volatile, followed by Brazil. The recent global pandemic had a greater impact on the Chinese market as it exhibited higher volatility, which was followed by Russia. Brazil and India are the least affected markets during this recent crisis. In the case of developed markets also, the financial crisis of 2008 has a greater impact on market volatility than the pandemic of 2019. During the period of the financial crisis of 2008, among the developed markets, the United States of America shows high volatility as it has a high β coefficient, which was followed by Japan. Italy and France are the least volatile markets.

Among the developed markets, Canada and the UK are the most affected countries of the recent pandemic crisis of 2019. Germany and the USA are the least affected markets. The examination of the behaviour of emerging and developed markets during above two crisis periods revealed that the behaviour of markets is different for these crisis periods. In summary, we can say that the α coefficient for each index demonstrates the presence of volatility clustering throughout the course of the series. A long memory in the variance is suggested by the estimate of the β coefficient. This suggests that long-term changes in the current volatility will have an impact on future volatility or that the long-term effects of old news will have an impact on future volatility. As the total of the ARCH and GARCH terms is less than 1 ($\alpha_1 + \beta < 1$), volatility shocks are clearly highly persistent.

The study uses EGARCH and T-GARCH models to examine the asymmetric effect of various types of news on volatility (or leverage effect). The EGARCH and T-GARCH estimates are statistically significant, as seen in Table 6. For all indices during the two sample periods, the leverage coefficient γ is either negative (for EGARCH) or positive (for T-GARCH), suggesting the existence of an asymmetric behaviour. This indicates that within the study period, negative shocks (bad news) have a greater effect on the volatility of the following period than positive shocks (good news) of a similar magnitude.

During the first sample period (the global financial crisis of 2008), the leverage coefficient λ is significant for all the emerging and mature markets with EGARCH and TGARCH models. The magnitude of the global financial crisis on volatility is varied from one model to another. Among emerging markets, China is most affected by the financial crisis of 2008 with a λ value of −0.172 in the EGARCH model, while in the TGARCH model, Brazil and Indonesia are the most affected countries with a γ value of 0.296. The least affected countries among emerging markets are Russia and Turkey. Coming to the developed market, the effect of the global financial crisis is different from that on the emerging market, particularly the magnitude is less. Among developed markets, Germany is most affected in both models with a λ value of −0.168 and γ value of 0.228. The least affected countries are the UK and Canada.

Table 4. ARCH-LM test.

	Financial Crisis 2008		**Global Pandemic 2019**	
	ARCH LM Statistics	**Prob. Chi Square (1)**	**ARCH LM Statistics**	**Prob. Chi Square (1)**
Panel A: Emerging Markets				
Brazil	23.66	0.000 ***	30.03	0.000 ***
China	24.65	0.000 ***	36.62	0.000 ***
India	27.51	0.000 ***	24.71	0.000 ***
Indonesia	28.61	0.000 ***	30.03	0.000 ***
Mexico	47.32	0.000 ***	41.10	0.000 ***
Russia	35.77	0.000 ***	30.81	0.000 ***
Turkey	28.21	0.000 ***	32.01	0.000 ***
Panel B: Developed Markets				
Italy	37.18	0.000 ***	65.36	0.000 ***
Canada	95.66	0.000 ***	65.65	0.000 ***
France	37.18	0.000 ***	65.36	0.000 ***
Germany	51.55	0.000 ***	66.02	0.000 ***
Japan	24.00	0.000 ***	36.56	0.000 ***
UK	21.84	0.000 ***	36.66	0.000 ***
USA	22.39	0.000 ***	33.24	0.000 ***

Source: Authors' calculation. The table presents the results of the ARCH–LaGranger Multiplier test for checking the ARCH effect in the return series of selected emerging and developed markets during two sample periods, namely the global financial crisis of 2008 and COVID-19. *** indicates significance at the 1% level.

Table 5. GARCH analysis.

GARCH (1,1)			
	α_0	α_1	**B**
Financial Crisis 2008			
Panel A: Emerging markets			
Brazil	0.00027 ***	0.0111 ***	0.747 ***
China	0.00097 ***	0.0018 ***	0.970 ***
India	0.00011 ***	0.0146 ***	0.851 ***
Indonesia	0.00021 ***	0.0011 ***	0.746 ***
Mexico	0.00054 ***	0.0053 ***	0.844 ***
Russia	0.00053 ***	0.0051 ***	0.868 ***
Turkey	0.00012 ***	0.0018 ***	0.911 ***
Panel B: Developed markets			
Italy	0.00053 ***	0.0032 ***	0.850 ***
Canada	0.00024 ***	0.0121 ***	0.872 ***
France	0.00053 ***	0.0031 ***	0.850 ***
Germany	0.00046 ***	0.0042 ***	0.852 ***
Japan	0.00029 ***	0.0103 ***	0.891 ***
UK	0.00021 ***	0.0021 ***	0.879 ***
USA	0.00013 ***	0.0094 ***	0.903 ***
Global pandemic 2019			
Panel A: Emerging markets			
Brazil	0.00012 ***	0.0051 ***	0.664 ***
China	0.00034 ***	0.0083 ***	0.892 ***
India	0.00045 ***	0.0119 ***	0.701 ***
Indonesia	0.00012 ***	0.0025 ***	0.664 ***
Mexico	0.00045 ***	0.0015 ***	0.824 ***
Russia	0.00065 ***	0.0035 ***	0.825 ***
Turkey	0.00014 ***	0.0121 ***	0.812 ***
Panel B: Developed Markets			
Italy	0.00051 ***	0.0069 ***	0.716 ***
Canada	0.00060 ***	0.0004 ***	0.789 ***
France	0.00057 ***	0.0013 ***	0.775 ***
Germany	0.00025 ***	0.0098 ***	0.654 ***
Japan	0.00081 ***	0.0070 ***	0.728 ***
UK	0.00068 ***	0.0184 ***	0.784 ***
USA	0.00053 ***	0.0015 ***	0.620 ***

Source: Authors' calculation. The table illustrates the result of the symmetric GARCH (1,1) model of return series of selected emerging and developed markets during two sample periods: the global financial crisis of 2008 and the 2019 global pandemic COVID-19. *** indicates the significant presence of the GARCH effect at 1%.

In the second sample period of COVID-19, the leverage effect coefficient is significant for all the markets, and its magnitude is almost the same for both emerging and developed markets in contradiction to the case of the 2008 financial crisis. Among emerging markets, India has a higher leverage coefficient in both the models with a λ value of -0.250 and γ value of 0.456, and Mexico is the least affected one. In case of mature markets, the UK and USA are the most affected countries. From this, we can generalize that the impact of different market crisis is not similar; some events have a higher impact than other events. Also, the reaction of different markets towards such events is different.

The next concern of this study is to examine whether economic strength helps protect developed markets from the worst economic conditions. By evaluating the impact of the financial crisis of 2008 on both of these types of markets, it has a greater impact on emerging markets than on developed markets. At the same time, the recent pandemic has impacted developed markets more than emerging markets.

Table 6. Modelling asymmetric volatility.

	EGARCH				TGARCH			
	α_0	α_1	β	γ	α_0	α_1	B	Γ
Financial crisis 2008								
Panel A: Emerging markets								
Brazil	0.0027 ***	0.159 ***	0.757 ***	−0.151 ***	0.00012 ***	0.053 ***	0.806 ***	0.296 ***
China	0.0051 ***	0.179 ***	0.968 ***	−0.172 ***	0.00021 ***	0.041 ***	0.826 ***	0.106 ***
India	0.0051 ***	0.212 ***	0.777 ***	−0.094 ***	0.00061 ***	0.051 ***	0.874 ***	0.182 ***
Indonesia	0.0170 ***	0.159 ***	0.857 ***	−0.151 ***	0.00012 ***	0.053 ***	0.804 ***	0.296 ***
Mexico	0.0012 ***	0.150 ***	0.888 ***	−0.143 ***	0.00052 ***	0.034 ***	0.915 ***	0.258 ***
Russia	0.0153 ***	0.148 ***	0.880 ***	−0.105 ***	0.00038 ***	0.093 ***	0.877 ***	0.102 ***
Turkey	0.0011 ***	0.131 ***	0.812 ***	−0.101 ***	0.00032 ***	0.081 ***	0.902 ***	0.112 ***
Panel B: Developed markets								
Italy	0.0018 ***	0.113 ***	0.817 ***	−0.153 ***	0.00095 ***	0.022 **	0.887 ***	0.222 ***
Canada	0.0017 ***	0.123 **	0.816 ***	−0.135 ***	0.00012 ***	0.018 **	0.897 ***	0.209 ***
France	0.0018 ***	0.013 **	0.807 ***	−0.153 ***	0.00095 ***	0.022 ***	0.887 ***	0.222 ***
Germany	0.0086 ***	0.085 ***	0.896 ***	−0.168 ***	0.00017 ***	0.032 ***	0.902 ***	0.228 ***
Japan	0.0057 ***	0.103 ***	0.881 ***	−0.150 ***	0.00013 ***	0.040 **	0.911 ***	0.174 ***
UK	0.0092 ***	0.116 ***	0.898 ***	−0.145 ***	0.00096 ***	0.063 ***	0.925 ***	0.164 ***
USA	0.0019 ***	0.011 ***	0.907 ***	−0.139 ***	0.00012 ***	0.023 ***	0.949 ***	0.172 ***
Global pandemic 2019								
Panel A: Emerging markets								
Brazil	0.0082 ***	0.036 ***	0.941 ***	−0.099 ***	0.00031 ***	0.060 **	0.919 ***	0.262 ***
China	0.0031 ***	0.117 ***	0.856 ***	−0.139 ***	0.00056 **	0.059 ***	0.849 ***	0.242 ***
India	0.0142 **	0.051 ***	0.876 ***	−0.250 ***	0.00023 ***	0.054 ***	0.824 ***	0.456 ***
Indonesia	0.0080 ***	0.136 ***	0.741 ***	−0.099 ***	0.00031 ***	0.060 ***	0.919 ***	0.262 ***
Mexico	0.0087 ***	0.109 **	0.875 ***	−0.087 ***	0.00035 ***	0.025 ***	0.876 ***	0.164 ***
Russia	0.0060 ***	0.100 ***	0.886 ***	−0.154 ***	0.00051 ***	0.135 ***	0.825 ***	0.273 ***
Turkey	0.0081 ***	0.030 ***	0.810 ***	−0.181 ***	0.00024 ***	0.110 ***	0.811 ***	0.172 ***
Panel B: Developed markets								
Italy	0.0021 **	0.101 ***	0.888 ***	−0.216 ***	0.00013 ***	0.056 ***	0.933 ***	0.282 ***
Canada	0.0041 **	0.142 ***	0.791 ***	−0.215 ***	0.00034 ***	0.051 ***	0.916 ***	0.019 ***
France	0.0012 ***	0.141 ***	0.788 ***	−0.216 ***	0.00013 ***	0.057 ***	0.935 ***	0.292 ***
Germany	0.0047 ***	0.105 **	0.863 ***	−0.094 ***	0.00014 ***	0.054 ***	0.941 ***	0.228 ***
Japan	0.0029 ***	0.153 ***	0.808 ***	−0.277 ***	0.00011 ***	0.022 ***	0.855 ***	0.521 ***
UK	0.0061 ***	0.016 ***	0.918 ***	−0.161 ***	0.00092 ***	0.046 ***	0.949 ***	0.251 ***
USA	0.0057 ***	0.030 ***	0.911 ***	−0.351 ***	0.00030 ***	0.038 ***	0.841 ***	0.262 ***

Source: Authors' calculation. *** indicates the significant presence of the GARCH effect at 1%. ** indicates significance at 5%. The table reports the result of non-linear GARCH models, exponential GARCH and threshold GARCH for two sample periods. *** indicates the significant presence of asymmetry in volatility of return series of selected developed and emerging markets at the 1% level.

5. Conclusions and Policy Implications

The connection between the financial crisis and the stock market is a topic of growing academic interest. A significant amount of economic anguish was brought on by the 2008 financial crisis in the United States, and it appeared that this distress had spread to other nations. Most of the studies either concentrated on the impact of financial crisis on the developed market or the emerging market. To address this gap, this study compared the characteristics of stock return volatility in E7 (Emerging 7) and G7 (Developed 7) markets in response to two major financial crises: the financial crisis of 2008 and the global pandemic surrounding COVID-19. With the use of GARCH models, the study discovered indications of volatility persistence and asymmetry in both emerging and developed markets. By evaluating the impact of the financial crisis of 2008 on both of these markets, it has a greater impact on emerging markets than developed markets. At the same time, the recent pandemic has impacted developed markets more than emerging markets. The impact of different market crises is not similar, some events having a higher impact than other events. In this essence, it can be asserted that a country's economic strength does not always shield it from economic turmoil. A claim was made by Muguto and Muzindutsi (2022) through the comparative evaluation of developed and emerging market reactions to the COVID-19 pandemic that developed markets are more informationally efficient than emerging markets. Here, this study finds that the market behaviour towards different financial crises is not similar, and the mature market is not always informationally efficient. If the market is informationally efficient, this market should always show less reaction to a market crisis.

5.1. Implications of the Study

The findings may aid in understanding the nature of the financial crisis of 2008 and the COVID-19 epidemic as well as their effects on various stock markets in developed and emerging economies. This will help investors to understand the nature of developed and emerging markets especially during times of market turbulence. Additionally, diversification into international markets might aid in reducing risk during the market crisis periods. The study will help fund managers comprehend global portfolio diversity better and to advise investors as a result.

5.2. Limitation and Scope for Future Research

This study investigates the asymmetric volatility of developed and emerging markets by taking the two most affected market crises—namely, the global financial crisis of 2008 and the global pandemic surrounding COVID-19. To generalize the study's findings, more studies need to conducted in this area. Research can be conducted by including the recent Russia–Ukraine war and its impact on European countries. Moreover, the market integration and asset integration can be studied in the future. By focusing on particular markets, the factors which affect the asymmetric volatility during the time of market crisis can also be investigated further.

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