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Black Swan Event and The Stock Market Volatility Response to Shocks in Developed, Emerging, Frontier and the BRIC Markets: Lessons from the COVID-19 Pandemic

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ABSTRACT

We study the impact of shocks (news flow) on stock market volatility in different economic regions, namely the developed, emerging, frontier, and BRIC stock markets during the COVID-19 pandemic, which was a'Black Swan Event'. The daily returns of relevant MSCI indices from January 30, 2020 to October 30, 2020 are examined using the EGARCH model's News Impact Curve to gain a perspective on the volatility behaviour in stock markets in the developed, emerging, frontier, and BRIC countries' stock markets. Evidence suggests that the developed markets in the Pacific and Europe, the BRIC countries, the emerging markets in Asia, Europe, and Latin America and the frontier markets in Asia were associated with asymmetric volatility response to shocks. Further, the developed markets in North America, and the frontier markets in Africa were associated with a symmetric volatility response. We observe that the volatility response to shocks in different regions is not uniform and varies according to the size and sign of the shock. The findings of the study provide insights to the investors and the academics in understanding the behaviour of volatility globally during a Black Swan Event, and provides critical inputs in global portfolio decisions.

KEYWORDS

Volatility; BRIC; Emerging markets; Developed markets; Frontier markets.

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1. INTRODUCTION

The COVID-19 outbreak, which was declared as a pandemic on March 11, 2020 by the World Health Organisation (WHO), has been referred to as a "Black Swan Event" (Antipova, 2020). The term "Black Swan" gained relevance in the context of the financial crisis of 2008, a decade ago. It may be mentioned that the term was coined by Taleb (2009) to refer to random events with three key attributes: (a) the event is unexpected; (b) the event has an extreme impact; and (c) the event must be explainable and predictable. Further, Higgins (2013) refer to a "Black Swan Event" as an extraordinary event which can potentially cause large scale damage to economy and the society. The author observed that a "Black Swan Event" cause large shocks leading to "severe challenge to economic activity, social cohesion and even, political stability" and recognised previous virus outbreaks of SARS (2002) and Bird Flu (2008) as "Black Swan" events. It may be mentioned that Antipova (2020) observed that the COVID-19 outbreak has "severely challenged economic activity, social cohesion and even, political stability" and thus, qualifies as a "Black Swan Event". The author notes that the COVID-19 pandemic is not the first, and will perhaps not be the last, such event which the world will witness. Thus, academicians and the investment community need insights on how such events which may arise in health, climate, social, and financial systems may impact stock markets around the world. These events draw parallel to extreme events (high impact, hard to predict phenomenon) which have potential to create large scale impact on social, ecological, and technical systems (McPhillips et al., 2018). Extreme events can create larger stress on the stock markets and stock market participants may be unable to assess the valuation impact of the extreme event rationally (Aktas & Oncu, 2006). It may be noted that Piccoli et al. (2017) observe that extreme events are "market moves that are high in severity, low in frequency, and short term in duration." The authors observed that the stock market crash of 1987 and the 2008-2009 financial crises were instances of extreme events. Further, the authors added that days of macroeconomic or firm specific announcements, geopolictical events or technical trading may be associated with extreme events.

Globally, stock markets have witnessed sell offs and increased volatility as the number of infections and deaths due to COVID-19 increased around the world (e.g. Albulescu, 2020; Ashraf, 2020; Onali, 2020) and governments in different countries of the world imposed restrictions in the form of lock downs and social distancing norms to contain the outbreak (e.g. Baker et al., 2020; Zaremba et al., 2020). It is pertinent to note that as the stock market's volatility reflects the prevailing stress, risks, and uncertainties, it is, consequently, of great significance for market practitioners and policy makers. An increase in volatility can trigger sell offs and lead to increased cost of capital. As Hartwell (2018) observed, volatility has different sources related to economic factors and market uncertainty. Hence, the study of volatility is pertinent to providing insights to investors and portfolio managers toward making investment decisions, and for policy makers who seek to ensure stability of the stock markets. It is pertinent to note that the volatility in stock markets may be influenced by the news flow regarding COVID-19 cases and deaths at both the national and global level, as well as Government interventions to contain the spread of the virus, and corresponding economic package announcements to boost the economy. There are also opportunities and treats arising out of the global supply chain disruptions, COVID-19 vaccine updates, geo political dynamics, and macroeconomic variables during the pandemic. Further, the nature of the influence on the volatility may differ in different economic regions.

To this end, we studied the volatility response to news flows referred to as 'shocks' by Engle and Ng (1993) in stock markets in different economic regions globally during the pandemic.

It is pertinent to mention that Engle and Ng (1993) define 'shocks' as the aggregate measure of news at a particular point in time. We measure the volatility response to shocks (news flow) during the pandemic employing the News Impact Curve proposed by Engle and Ng (1993) in developed, emerging, frontier and the BRIC stock markets. The study period for our work goes well beyond the initial days of the pandemic unlike much of the existing literature on the subject and thus, extends our understanding of the volatility response to news flow during the outbreak. Our work contributes to two strands of extant literature: first, the study adds to the growing literature on the impact of the COVID-19 pandemic on the stock market volatility. Our contribution lies in examining the same in the context of stock markets in different economic regions. Second, our study extends the literature on the relationship between news flows and the stock market volatility (e.g. Mitchell & Mulherin, 1996; Berry & Howe, 1994; Haroon & Rizvi, 2020).

2. LITERATURE REVIEW

The volatility behaviour in stocks markets during the pandemic has been a topic of ongoing research by researchers. Albulescu (2020) investigated the impact of new COVID-19 infections and deaths globally on the volatility in the US stock market using data from the WHO database and S&P Dow Jones Indices database. The study employed a simple Ordinary Least Squares regression and found evidence of increased volatility during the pandemic. Baek et al. (2020) using the Markov switching AR model to identify regime changes from lower to higher volatility, provided an industry level analysis of the subject in the context of the US markets. The study documented volatility to be sensitive to COVID-19 news flows. Both positive and negative news had a significant impact on the stock market volatility. The study found the behaviour of volatility to vary across industries and documented its differential impact on risks across sectors. Baker et al. (2020) observed that, in the history of pandemics, the COVID-19 pandemic has had the greatest impact on volatility in US markets. The study used text based methods, using large daily stock market movements dating back to 1900, and volatility dating back to 1985. The study documented that government restrictions on travel and trade were the main reasons for the increased stock market volatility in US markets during the COVID-19 pandemic as compared to previous pandemics. Mazur et al. (2020) investigated the stock market volatility during the stock market crash triggered by the COVID-19 pandemic in US markets. The study documented asymmetric volatility behaviour in the US markets. Loser sectors such as petroleum, real estate, entertainment and hospitality exhibited extreme asymmetric volatility. Chaudhary et al. (2020) studied the volatility in the top 10 countries in terms of GDP namely Brazil, France, Germany, UK, Italy, Japan, USA, Canada, India and China using the GARCH (1,1) model and documented heightened volatility in all the 10 indices using daily stock returns during the pandemic. Haroon and Rizvi (2020) studied the relation between sentiment generated by COVID-19 news and stock market volatility using EGARCH model. The study identified strongest volatility impact of panic laden news flow related to the COVID-19 pandemic in sectors such as automobile, energy, transportation, and travel and leisure industry while no significant volatility shifts was observed in other sectors examined in the study. Onali (2020) documented significant increase in volatility of US markets due to COVID-19 cases and death in different countries namely the US, China, France, Iran, Italy, Spain and UK using GARCH analysis. The study also documented regime changes (from a low regime to a high regime) in the negative impact of the VIX on the stock market return in the US using the Markov Switching Model. Papadamou et al. (2020) using panel data analysis, studied the impact of COVID-19 pandemic on the volatility of thirteen major stock markets from Asia, Australia, Europe, and the USA. Zaremba et al. (2020), used panel regression, to study the relation between interventions made by the government and the volatility of stock markets in 67 countries and observed that stringent measures increase the volatility. Ibrahim et al. (2020) studied the relation between COVID-19 and stock market volatility in 11 developed and developing economies in the Asia-Pacific region, namely Japan, Vietnam, Malaysia, Laos, China, South Korea, Philippines, Indonesia, Myanmar, Singapore and Thailand using continuous wavelet transformation and GARCH analysis. The study documented stringent government initiatives to fight the COVID-19 pandemic increased stock market volatility in different countries included in the study. Apergis and Apergis (2020) examined the impact of COVID-19 on the volatility of daily stock returns in the Chinese stock market during the period January 27, 2020 to April 30, 2020 using GARCH analysis. The study documented a statistically significant impact on the volatility in Chinese stock market.

The review of available literature on the impact of COVID-19 pandemic on stock market volatility reveals that research on the subject has been largely undertaken in the context of the US stock markets and other stock markets in other parts of the world. However, attempts to explore the impact of the pandemic on volatility in different economic regions, namely the developed, emerging, frontier, and BRIC stock markets are scant. Hence, in this paper, we study the impact of shocks (the aggregate measure of news at a point in time) on volatility using the EGARCH model's News Impact Curve to gain a broad based perspective on the volatility behaviour in developed, emerging, and frontier countries' stock markets along with BRIC stock markets during the pandemic to address the void in existing literature on the subject. By studying the behaviour of volatility, we want be able to understand the susceptibility of the different economic regions of the world to shocks during the pandemic, in terms of the associated episode of volatility with the news flows and thus, provide insights to the market participants in making investment informed decisions.

3. DATA AND METHODOLOGY

Morgan Stanley Capital International (MSCI) provides widely tracked indices which reflect the stock market performance in different economic regions. We examine the daily returns (logarithmic changes in daily closing prices multiplied by 100) on the MSCI World, MSCI Emerging Markets (EM) and MSCI Frontier Markets (FM) to gain insights on volatility in different economic regions of the World, and the MSCI indices for BRIC, Pacific, North America, Europe, EM Asia, EM Europe, EM Latin America, FM Asia, and FM Africa to gain a regional perspective on the volatility in the International stock markets. The economic and country representation of the indices included in the study is provided in Appendix A. The study period starts from January 30, 2020 (the day on which the novel coronavirus outbreak was declared as Public Health Emergency of International Concern by WHO) to October 30, 2020 and the data is taken from the MSCI website (https://www.msci.com/real-time-index-data-search). The study period captures the initiatives to combat the spread of the virus apart from news and speculation about vaccine availability, economic stimulus announced by the governments and other macroeconomic and geo-political developments which could potentially have an impact on the volatility.

The summary statistics for the return data of the MSCI indices included in the study is presented in Table 1. The World index was associated with a mean return of -0.02 percent and a standard deviation of 2.06 percent. The EM index and the FM index were associated with mean returns of 0.01 percent and -0.06 percent and a standard deviation of 1.64 percent and 1.31 percent respectively. Further, the BRIC index was associated with a mean return of 0.04 percent and a standard deviation of 1.71 percent. Among the indices which represented the developed markets, the Pacific, North America and Europe indices were associated with a mean return of -0.03 percent, 0 percent, and -0.08 percent and a standard deviation of 1.43 percent, 2.44 percent, and 2.06 percent respectively. Among the indices which represented the emerging markets, the EM Asia, EM Europe, and EM Latin America indices were associated with a mean return of 0.07 percent , -0.23 percent, and -0.22 percent, and a standard deviation of 1.58 percent, 2.41 percent, and 3.23 percent respectively. The FM Africa and the FM Asia index which represented the frontier markets were associated with mean returns of -0.08 percent, and 0 percent, and a standard deviation of 1.02 percent, and 1.43 percent, respectively. Thus, we observe that the mean returns for the indices under study exhibit a negative bias during the period under study with the exception of the EM, BRIC, and EM Asia indices. Further, we observe that the Index return data series shows excess kurtosis besides being negatively skewed. The return series is not normally distributed as apparent from the Jarque-Bera test statistics.

Table 1
Summary Statistics

MSCI Index	Mean	Std. Dev	Skewness	Kurtosis	Jarque-Bera
World	-0.02%	2.06%	-1.063	10.328	**475.55**
EM	0.01%	1.64%	-1.05	7.644	**212.17**
FM	-0.06%	1.31%	-5.384	48.371	**17758.81**
BRIC	0.04%	1.71%	-1.125	7.18	**184.08**
Pacific	-0.03%	1.43%	- 0.093	6.669	**110.22**
North America	0.00%	2.44%	-0.816	9.638	**381.72**
Europe	-0.08%	2.06%	-1.599	14.482	**1160.31**
EM Asia	0.07%	1.58%	-0.638	6.145	**94.136**
EM Europe	-0.23%	2.4%	-1.119	8.401	**279.25**
EM Latin America	-0.22%	3.23%	-1.247	9.522	**398.28**
FM Africa	-0.08%	1.02%	-2.396	13.969	**1170.32**
FM Asia	0.00%	1.43%	-0.942	6.819	**148.41**

Note: Figures in bold indicates statistical significance at 1 percent level
Source: Author's Own Elaboration

We check if the return data is stationary using the Augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979). We test the null hypothesis that there is unit root in the data. From Table 2, we observe that the test statistic is statistically different from zero which lead to the rejection of the null hypothesis and therefore, we conclude that the data is stationary for all the index return data series.

Table 2
ADF Test Results

MSCI Index	Test Statistic	P-Value	Null Hypothesis
World	-8.296	0.00 *	Reject
EM	-8.229	0.00 *	Reject
FM	-3.653	0.00 *	Reject
BRIC	-15.091	0.00 *	Reject
Pacific	-11.034	0.00 *	Reject
North America	-4.249	0.00 *	Reject
Europe	-13.823	0.00 *	Reject
EM Asia	-14.424	0.00 *	Reject
EM Europe	-14.04	0.00 *	Reject
EM Latin America	-16.324	0.00 *	Reject
FM Africa	-11.785	0.00 *	Reject
FM Asia	-14.589	0.00 *	Reject

Note: * indicated statistical significance at 1 percent level
Source: Author's Own Elaboration

Further, we use the Engle's (1982) Lagrange-multiplier (ARCH-LM) test to check for the presence of the ARCH effect. From Table 3, we conclude that the arch effect is present for all the index return data series as the test statistic is statistically different from zero leading to the rejection of the null hypothesis.

Table 3
ARCH-LM Test Results

MSCI Index	Test Statistic	P-Value	Null Hypothesis
World	4.456	0.03 **	Reject
EM	11.762	0.00*	Reject
FM	17.958	0.00*	Reject
BRIC	3.52	0.06***	Reject
Pacific	16.908	0.00 *	Reject
North America	8.128	0.00 *	Reject
Europe	7.816	0.05 **	Reject
EM Asia	30.043	0.00*	Reject
EM Europe	2.974	0.08***	Reject
EM Latin America	15.283	0.01*	Reject
FM Africa	-11.785	0.00*	Reject
FM Asia	-14.589	0.00*	Reject

Note: ***, ** and * indicates statistical significance at 10 percent, 5 percent and 1 percent level
Source: Author's Own Elaboration

Engle and Ng (1993) introduced the News Impact Curve, which is a measure of how news is incorporated into volatility estimated using an underlying volatility model. The authors evaluated the performance of different GARCH models to model the volatility of stock returns. The authors found that the Exponential GARCH model and the GJR-GARCH model (Glosten et al., 1993; Zakoian, 1994) outperformed all other volatility models in their study. Guided by Engle and Ng (1993), we employed the asymmetric volatility model EGARCH (1,1) (Nelson, 1991) to model the volatility of the stocks markets in different economic regions of the world included in our study. It is established that the normal error distribution does not account for high kurtosis seen in financial time series data efficiently (Bollerslev, 1987; Nelson,1991). Wilhelmsson (2006) observed that the fit of the model may be improved significantly by considering a leptokurtic and skewed return distribution. Therefore, we estimate the model using the maximum likelihood approach under flexible error distribution assumptions namely normal, Student's t and Generalised error distribution (GED). The model captures the asymmetric volatility behaviour through a combination of terms that captures the size and sign of the shock. The model also allows significant news to have a have greater impact on the volatility. Further, the advantage associated with the EGARCH model estimation is that it involves no restriction on the model parameters to achieve positive estimates of the conditional variance, given the logarithmic transformation.

Guided by Engle and Ng (1993), the EGARCH(1,1) may be specified as:

$$\text{Log}(h_t) = \omega + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right] + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta \log(h_{t-1}) \qquad (1)$$

In equation 1, the conditional variance is given by h_t, ω is the constant, α is the ARCH term, β is the GARCH term and γ is the asymmetric term. Asymmetric volatility behaviour exists if $\gamma < 0$ i.e., negative shocks have a greater impact on volatility than positive shocks of the same size. The impact of shocks on volatility is captured by α. A statistically significant positive coefficient of the α means that the relation between the size of the shock and the volatility is positive i.e., the larger the size of the shock, the greater the increase in volatility. If $\alpha > \beta$, volatility is spiky and signifies immediate impact of shocks on volatility while if $\beta > \alpha$, it represents that volatility is persistent i.e., the persistent effect of past shocks on volatility. The sign and statistical significance of the coefficients of the α and γ may be interpreted as follows:

(a)If γ is statistically significant but α is not, it may be interpreted that the size of the shock is not relevant but the sign of the shock impacts volatility.

(b)If γ is not statistically significant but α is, it may be interpreted that the size of the shock impacts volatility irrespective of the sign of the shock.

(c) If γ and α is statistically significant, it may be interpreted that the size, as well as the sign, of the shock impacts volatility.

Further, the prediction model of the return data series: $y_t = m_t + \varepsilon_t$ where y_t is the index return at time *t,* m_t is the conditional mean and the error term ε_t is the deviation of the actual return at time *t* from its mean and represents the aggregate measure of news impact at time *t.* A negative sign of the ε_t implies negative shock (news) and vice-versa. The size of the shock represents the significance of the news. It may be noted that $\sqrt{h_t}$ is the conditional volatility at time *t.*

We also estimate the GJR-GARCH (1,1) model with different distributional assumptions for all the return data series in our study besides the EGARCH model to check if the model performed any better compared to the EGARCH Model in modelling the volatility. Guided by Engle and Ng (1993), the GJR-GARCH model may be specified as:

$$h_t = \omega + \alpha\, \varepsilon_{t-1}^2 + \gamma\, S_{t-1}^{-}\, \varepsilon_{t-1}^2 + \beta\, h_{t-1}\text{, where } S_t^{-}=1 \text{ if } e_t<1,\ S_t^{-}=0 \text{ otherwise} \qquad (2)$$

The model selection is done using the commonly used Akaike Information Criterion (AIC) of Akaike (1974) and Burnham and Anderson (2002).We also use the ARCH-LM test on the residuals to test the goodness of fit of the model.

4. DISCUSSION OF RESULTS

4.1. Model estimation

The results of the model estimation with normal, Student's t and GED distributional assumptions are presented in Table 4.

Table 4
Model Estimation Results

MSCI Index	ω	α	γ	β	AIC	ARCH-LM
World						
Model A	-0.967*	0.395*	-0.111**	0.919*	-5.568	0.412
Model B	**-0.504****	**0.282****	**-0.13*****	**0.964***	**-5.678**	**0.003**
Model C	-0.688**	0.331**	-0.104*	0.947*	-5.649	0.038
EM						
Model A	-0.618***	0.177**	-0.18*	0.944*	-5.789	0.165
Model B	-0.563***	0.165***	-0.166*	0.949*	-5.578	0.23
Model C	**-0.557**	**0.165**	**-0.17***	**0.951***	**-5.791**	**0.226**
FM						
Model A	-0.345*	-0.125*	-0.195*	0.951*	-6.43	0.626
Model B	**-0.156***	**-0.116***	**-0.179***	**0.977***	**-6.836**	**0.008**
Model C	-0.172*	-0.111*	-0.179*	0.976*	-6.79	0.011
BRIC						
Model A	-0.877***	0.217**	-0.157**	0.915*	-5.566	0.210
Model B	-0.763	0.201***	-0.133**	0.928*	-5.570	0.272
Model C	**-0.791***	**0.205****	**-0.14****	**0.925***	**-5.571**	**0.292**
Pacific						
Model A	-0.316**	0.146*	-0.151**	0.976**	-5.951	0.002
Model B	-0.296**	0.135**	-0.15	0.977	-5.941	0.00
Model C	**-0.056***	**-0.023***	**-0.16***	**0.991***	**-5.974**	**0.016**
North America						
Model A	-1.216*	0.592*	-0.084	0.904*	-5.301	0.193
Model B	**-0.607****	**0.377***	**-0.094**	**0.958***	**-5.394**	**0.492**
Model C	-0.89*	0.495*	-0.054	0.935	-5.375	0.079
Europe						
Model A	-0.483*	0.166**	-0.182*	0.95*	-5.275	1.731
Model B	-0.146	0.005	-0.193*	0.982*	-5.37	0.48
Model C	**-0.308*****	**0.081**	**-0.171***	**0.969***	**-5.359**	**1.111**

Table 4
Cont.

MSCI Index	ω	α	γ	β	AIC	ARCH-LM
EM Asia						
Model A	-0.593**	0.162**	-0.148*	0.945*	-5.75	0.611
Model B	-0.569***	0.163***	-0.14**	0.949*	-5.747	0.805
Model C	**-0.56**	**0.156**	**-0.139****	**0.95***	**-5.756**	**0.731**
EM Europe						
Model A	-0.281*	0.094**	-0.171*	0.972*	-5.052	0.789
Model B	**-0.3***	**0.129*****	**-0.143***	**0.974***	**-5.056**	**0.888**
Model C	-0.284*	0.109***	-0.135*	0.974*	-5.054	0.737
EM Latin America						
Model A	**-0.969***	**0.394***	**-0.208***	**0.911***	**-4.598**	**0.003**
Model B	-0.838**	0.373*	-0.171*	0.926*	-4.596	0.000
Model C	-0.902**	0.384*	-0.187**	0.919**	-4.597	0.001
FM Africa						
Model A	-3.261*	0.693*	-0.187*	0.714*	-6.737	0.007
Model B	**-1.268**	**0.388****	**-0.01**	**0.897***	**-6.867**	**0.436**
Model C	-1.683**	0.442*	-0.066	0.859*	-6.831	0.335
FM Asia						
Model A	-0.768	0.034	-0.238*	0.914	-5.95	0.000
Model B	-1.044*	0.232	-0.197**	0.897*	-6.067	0.215
Model C	**-0.809***	**-0.127**	**-0.197****	**0.918***	**-6.083**	**0.107**

Note: Model A represents EGARCH (1,1) with normal error distribution, Model B represents EGARCH (1,1) with Student's t distribution and Model C represents EGARCH(1,1) with Generalised Error Distribution. The figures in bold indicates the best fitting model based on the minimum AIC criterion. ***, ** and * indicates statistical significance at 10 percent, 5 percent and 1 percent level . ARCH-LM indicates the test statistics for heteroskedasticity test on the model residuals. Guided by Burnham and Anderson (1998), a comparison of the EGARCH and GJR-GARCH(1,1) Model with different distributional assumptions reveals that there is no gain in the model performance compared to the EGARCH model based on the minimum AIC criterion. For the sake of brevity, we do not report the parameters of the GJR-GARCH(1,1) Model with different distributional assumptions.
Source: Author's Own Elaboration

The sign and statistical significance of the estimated coefficients (α, γ and β) of the best fitting model based on the minimum AIC criterion are summarised in Table 5.

From Table 5, it is observed that the coefficient of the α term is statistically significant for World, FM, BRIC, Pacific, North America, EM Europe, EM Latin America, and EM Africa indices which signifies the size of the shock impacts the volatility in these markets during the studied period. The statistically significant positive sign of the coefficient of the α term for World, BRIC, North America, EM Europe, EM Latin America and FM Africa indices implies that the relation between the size of the shock and the volatility is positive i.e., the larger the size of the shock, the greater the increase in volatility. The statistically significant negative sign of the α coefficient for FM and Pacific indices implies that the relation between the size of the shock and volatility is negative i.e., the larger the size of the shock, the lesser the increase in volatility. However, the coefficient of α term is not statistically significant for EM, Europe, EM Asia and FM Asia indices which signifies the size of the shock does not impact the volatility in these sectors during the studied period. Further, the negative sign of the statistically significant coefficient of the asymmetric term (γ) for all the indices signifies the asymmetric volatility behaviour in these markets with the exception of North America and FM Africa for which the coefficient of the γ term is negative but not statistically significant**.** The β coefficient is statistically significant and is greater than the α coefficient for all the indices signifying volatility persistence in international stock markets.

Table 5
Summary of Estimated Coefficients

MSCI Index	Size of the Shock (α)	Sign of the Shock (γ)	If β > α
World	+	-	Yes
EM		-	Yes
FM	-	-	Yes
BRIC	+	-	Yes
Pacific	-	-	Yes
North America	+		Yes
Europe		-	Yes
EM Asia		-	Yes
EM Europe	+	-	Yes
EM Latin America	+	-	Yes
FM Africa	+		Yes
FM Asia		-	Yes

Source: Author's Own Elaboration

4.2. Measuring the impact of shocks on the volatility

Guided by Engle and Ng (1993) and Sharma (2012), we used the estimated coefficients of the α and γ term to measure the impact of the sign and size of the shock on the volatility for ±2.58 standard deviations from the mean across the different economic regions under study using the below expressions:

$$\sqrt{e^{(\gamma+\alpha)\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}}}\text{, for } \varepsilon_{t-1} > 0 \text{ and } \sqrt{e^{(\gamma-\alpha)\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}}}\text{, for } \varepsilon_{t-1} < 0 \qquad (3)$$

The impact of negative shock (-2.58 standard deviation from the mean) and positive shock (2.58 standard deviation from the mean) on the volatility for the indices included in the study are presented in Table 6.

From Table 5, we observe that the World index, which represents 23 developed markets, is associated with a 70.14 per cent increase in volatility in response to negative shocks while positive shocks are associated with a 21.66 percent jump in volatility. The EM index, which represents 26 emerging markets, is associated with a 24.52 percent increase in volatility in response to negative shocks while positive shocks were associated with a 19.69 percent drop in volatility. The FM index, which represents 34 frontier markets, is associated with 8.47 per cent increase in volatility in response to negative shocks while positive shocks are associated with 32.65 percent drop in volatility. The BRIC index which represents the BRIC (Brazil, Russia, India, and China) region is associated with a 56.06 percent increase in volatility in response to negative shocks while positive shocks are associated with 8.75 percent jump in volatility. The Pacific index which represents 5 developed markets in the pacific region is associated with a 19.33 per cent increase in volatility in response to negative shocks while positive shocks are associated with a 21.03 percent decrease in volatility. The North America index which represents the US and Canadian stock markets is associated with a 62.63 per cent increase in volatility in response to negative shocks as well as positive shocks. The Europe index which represents 15 developed markets in Europe is associated with a 24.68 per cent increase in volatility in response to negative shocks while positive shocks are associated with 19.8 percent decrease in volatility. The EM Asia index which represents the 9 emerging markets in Asia is associated with a 19.64 per cent increase in volatility in response to negative shocks while positive shocks are associated with a 16.42 percent decrease in volatility. The EM Europe index which represents the 6 emerging markets in Europe is associated with a 42.03 per cent increase in volatility in response to negative shocks while positive shocks are associated with a -1.79 percent decrease in volatility. The EM Latin America index which represents 6 emerging markets *in* Latin America is associated with a 117.4 per cent increase in volatility in response to negative shocks while positive shocks are associated with a 27.12 percent increase in volatility. The FM Africa index which represents 13 frontier markets in Africa is associated with a 64.96 per cent increase in volatility in response to negative shocks as well as positive shocks. The FM Asia index which represents 3 frontier markets in Asia is associated with 28.93 per cent increase in volatility in response to negative shocks while positive shocks are associated with 22.44 percent drop in volatility.

Table 6
Impact of Shocks on Volatility

MSCI Index	Change in Volatility due to Negative Shocks	Change in Volatility due to Positive Shocks	Volatility Response
World	70.14%	21.66%	Asymmetric
EM	24.52%	-19.69%	Asymmetric
FM	8.47%	-32.65%	Asymmetric
BRIC	56.06%	8.75%	Asymmetric
Pacific	19.33%	-21.03%	Asymmetric
North America	62.63%	62.63%	Symmetric
Europe	24.68%	-19.8%	Asymmetric
EM Asia	19.64%	-16.42%	Asymmetric
EM Europe	42.03%	-1.79%	Asymmetric
EM Latin America	117.4%	27.12%	Asymmetric
FM Africa	64.96%	64.96%	Symmetric
FM Asia	28.93%	-22.44%	Asymmetric

Source: Author's Own Elaboration

Thus, we observe the asymmetry in the behaviour of the volatility in response to shocks i.e., the negative shock cause greater volatility increases than positive shocks of the same magnitude in all the developed, emerging, and frontier markets along with the BRIC markets. It may be noted that that both negative and positive shocks cause increases in volatility in the World, BRIC, and EM Latin America indices. On the other hand, negative shocks increase the volatility and positive shocks decrease the volatility in EM, FM, Pacific, Europe, EM Asia, EM Europe, and FM Asia. We observe that there is symmetry in the volatility behaviour i.e., both the negative and positive shock cause increase in the volatility of the same magnitude in North America and FM Africa indices.

5. CONCLUSION

In this paper, we have gained a perspective on the volatility response to shocks in the stock markets of different economic regions, namely the developed, emerging, frontier and BRIC, during the pandemic by using the News Impact Curve of the EGARCH model. Our study adds to the existing literature by describing the volatility response to shocks in different economic regions of the world, especially in the BRIC region, a dimension which has not been explored in the existing literature. The empirical evidence from the study suggests that the volatility behaviour is asymmetric in different economic regions under examination during the period of our study. Among the markets studied, the developed markets in the Pacific and Europe, BRIC, the emerging markets in Asia, Europe, Latin America, and the frontier markets in Asia was associated with asymmetric volatility response to shocks. Among the markets that exhibited asymmetric volatility response,the emerging markets in Latin America, the developed markets, the BRIC markets, and the emerging markets in Europe exhibited greater susceptibility to volatility increases due to negative shocks with 117.4 percent, 70.14 percent, 56.6 percent and 42.03 percent respectively jump in volatility in response to negative shocks during the study period. Further, the developed markets in North America and frontier markets in Africa were associated with a symmetric volatility response. We observed that the volatility response to shocks in different regions is not uniform and varies according to the size and sign of the shock. Further, we find evidence of volatility persistence in stock markets globally during the pandemic signifying the impact of shocks on the volatility decay slowly. The results of the study provide insights to the investment community in effective investment decisions with regard to global portfolio decisions and the academics in understanding the behaviour of the volatility across stock markets in different economic regions during the pandemic, a 'Black Swan Event'. The study sheds light on the volatility response to shocks for the BRIC region during the pandemic. The study is expected to spur research in the context of the BRIC region along with the different economic regions going ahead.

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NOTES

[1]Accessed from https://www.worldometers.info/coronavirus/ on September 30,2020.

AUTHOR'S CONTRIBUTION

First author contributed to the conceptualization, methodology, data analysis and writing of the manuscript. Second author contributed to the conceptualization, reviewed and edited the manuscript.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest in relation to the content exposed in the work.

APPENDIX A: ECONOMIC AND COUNTRY REPRESENTATION OF MSCI INDICES

Serial Number	MSCI Index	Economic Representation	Country Representation
1	World	Developed Markets	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK and the US.
2	Emerging Markets	Emerging Markets	Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, nd, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates.
3	Frontier Markets	Frontier Markets	Bahrain, Bangladesh, Burkina Faso, Benin, Croatia, Estonia, Guinea-Bissau, Ivory Coast, Jordan, Kenya, Kuwait, Lebanon, Lithuania, Kazakhstan, Mauritius, Mali, Morocco, Niger, Nigeria, Oman, Romania, Serbia, Senegal, Slovenia, Sri Lanka, Togo, Tunisia and Vietnam.
4	BRIC		Brazil, Russia, India and China
5	Pacific	Developed Markets	Australia, Hong Kong, Japan, New Zealand and Singapore.
6	North America	Developed Markets	US and Canada.
7	Europe	Developed Markets	Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK.
8	EM Asia	Emerging Markets	China, India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Taiwan and Thailand.
9	EM Europe	Emerging Markets	Czech Republic, Greece, Hungary, Poland, Russia and Turkey.
10	EM Latin America	Emerging Markets	Argentina, Brazil, Chile, Colombia, Mexico, and Peru.
11	FM Asia	Frontier Markets	Bangladesh, Sri Lanka and Vietnam.
12	FM Africa	Frontier Markets	Burkina Faso, Benin, Guinea-Bissau, Ivory Coast, Kenya, Mauritius, Mali, Morocco, Niger, Nigeria, Senegal, Togo, and Tunisia.