Volatility Response to "Black Swan Event" of Covid-19 in Asian Stock Market: An Empirical Study Using EGARCH Model

Dr. Neeru Gupta
Maharaja Agrasen Institute of Technology, Delhi, INDIA

Corresponding Author: doctorneerugupta@gmail.com

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ABSTRACT

By detailing the volatility response to shocks in several Asian nations, a dimension that has not been examined in the existing literature, our study contributes to the body of literature. The empirical data from the study indicate that volatility displayed asymmetric behavior in a few select Asian stock markets over the study period. In relation to this study, we saw that the volatility reaction followed a consistent pattern in the Asian region. For all but a few select markets, shocks are homogeneous in size and sign. Additionally, there is evidence that volatility responses are persistent across all Asian stock markets, which suggests that the impact of volatility will gradually diminish. This study offers helpful information to the investor community to help them make informed decisions about their investments.

***Keywords*—** Volatility, Covie-19, EGARCH, Black Swan

I. INTRODUCTION

Black swan events are characterized by their extreme rarity, severe impact, large negative consequences and the widespread insistence in world. Covid 19 outbreak may be referred as a black swan event due to its sever impact and worldwide impact. Antipova (2020) analyzed the situation Reports of World Health Organization during Covid 19 and found the signs of Black Swan event Standard forecasting tools and investment models can both fail to predict and potentially increase vulnerability to black swans by propagating risk and offering false security. Based on observations and report by Antipova covid 19 can be considered as black swan event.

After the first case of the novel corona virus (COVID 19) was detected in Wuhan City, Hubei Province, China in December 2019, the quick and enormous spread of COVID 19 caused the World Health Organization (WHO) to declare COVID 19 as a global pandemic on March 11, 2020 (Gössling *et al.*, 2020). The COVID 19 pandemic catastrophe has wreaked havoc on several economies around the world.The financial markets in the world are shaken violently during covid 19 pandemic. The stock market's reaction reflects this effect, with major fluctuations in trading volume and price indices (Ashraf, 2020). The first half of the year 2020 saw one of the most dramatic stock market crashes in history Many countries imposed strict lockdowns to contain the further spread of the virus and halted all major economic operations, which ultimately were received negatively by stock markets, hence the inevitable market crash in March 2020. Stocks across the sectors reacted differently to COVID-19 based on the effect it has on the operations of the business, for example, in S&P 1,500 sample sectors like natural gas, food, healthcare, and software stocks earned positively higher returns as compared to shares in petroleum, real estate, entertainment, and hospitality sectors which fell drastically (Mazur et al., 2020). Similarly, the effect of COVID-19 on the US economy is more lethal than that of the Spanish Flu of 1918–1919 (Baker et al., 2020). As per the report of the World Economic Forum (WEF, 2020), by the end of February 2020, the volatility in financial markets had increased many fold due to the sell-off by investors and traders to protect their capital. This led to a crash in equity markets amounting to a loss of 30% to market capitalization which is higher compared to the global financial crises of 2009.

The news flow during the covid 19 such as announcement of cases, launch of Vaccine, mutation of virus, death rate, economic announcements by government etc has varied impact on volatility on stock market. These news flows has been referred as "Shocks" by Engle and Ng (1993). Negative shocks create negative reactions. Negative overreaction often led to panic selling. It is possible to describe panic sales as a sudden rise in sales orders for a specific investment, which drives down the stock price (Dreman and Lufkin, 2000). "shock" is an aggregate measure of news at a particular point in time.

Here in this paper the author has tried to measure the volatility response to shocks (news flow) during Covid 19 pandemic in seven Asian Countries. The study period is November 2019 to September 2022 that includes the some early and later days of Covid 19 spread. This work contributes in two ways to extant literature: first, the study adds to the growing literature on the impact of the

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COVID-19 pandemic on the stock market volatility. This contribution lies in examining the same in the context of stock markets in different Asian countries. Second, this 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).

Covid 19 pandemic kind of events is neither the first nor the last which has ever impact on financial markets. Such events will keep on happening. Therefore, the academician, investors and corporate need insights on how such events may impact financial market around the world. Stock market being the most volatile and most sensitive financial market the participants here may be unable to assess the impact of such extreme events market. Piccoli et al. (2017) observe that extreme events are “market moves that are high in severity, low in frequency, and short term in duration.”

II. REVIEW OF LITERATURE

Volatility is a statistical measure of the dispersion of returns for a given security or market index. In most cases, the higher the volatility, the riskier the security. Volatility is often measured from either the standard deviation or variance between returns from that same security or market index.

In the securities markets, volatility is often associated with big swings in either direction. For example, when the stock market rises and falls more than one percent over a sustained period of time, it is called a "volatile" market. An asset's volatility is a key factor when pricing options contracts.

Generally, volatility of stock return in earlier studies was calculated using standard deviation or variance but seminal work of Engle (1982) [16] proposed the notion of conditional volatility and since then a battery of extended models like GARCH, EGARCH(Exponential GARCH), GJR-GARCH etc. have been proposed in literature where the dynamic concept of volatility is explored. Unlike simple volatility, as measured by standard deviation, conditional volatility is expressed as random variable which is conditioned upon a given value of another variable and it is dynamic in nature. Advantages of using conditional volatility models are well documented in empirical finance and it is found to chronicle volatility of financial market more successfully.

The existing studies are mostly focused on particular geographic areas like the United States (Albulescu, 2021; Baek et al.,2020; Choi, 2020; Onali, 2020), while others also include Europe (Mirza et al., 2020), Australia (Gunay et al., 2021), and the Asia Pacific Region (Ibrahim et al., 2020). Other studies concentrate on a mix of developed and emerging market countries around the globe (Ashraf, 2020; Zaremba, 2020). Harjoto et al., (2020) conducted multivariate regressions, while Uddin et al. (2021) applied an EGARCH model, to test the impact of daily COVID-19 cases and deaths on the volatility of stock markets in emerging and developed markets separately. Others have focused their studies solely on emerging markets or developed markets. Both include a comparison of similarities and differences between the two markets. Uddin et al. (2021) further explore the effects of capital market and country-level variables on stock market volatility. Walid Bakery, et al (2022) find major differences between emerging and developed markets in how investors interpret risk based on government responses to COVID-19. Relationship of stock market volatility and COVID-19 information being conditioned differently by the contexts of developed and emerging markets will provide useful insights into risk assessment to managers of global portfolios Cevik (2022)Studied the impact of investor sentiments on volatility in Group of 20 countries using various methods, including panel regression with fixed effects, panel quantile regressions, a panel vector auto regression (PVAR) model, and country-specific regressions. The effect of investor sentiment on volatility is consistent across the distribution: negative sentiment increases volatility, whereas positive sentiment reduces volatility. analyzed the influence of COVID-19 on the return and volatility of the stock market indices of the top 10 countries based on GDP using a widely applied econometric model—generalized autoregressive conditional heteroscdasticity (GARCH). Volatility remains higher than in normal periods, signaling a bearish tendency in the market. The COVID variable, as an exogenous variance repressors in GARCH modeling, is found to be positive and significant for all market indices. Jabran K., Iqbal A.(2021) examined volatility spillover effects between stock market and foreign exchange market in selected Asian countries; Pakistan, India, Sri Lanka, China, Hong Kong and Japan. This study considered daily data from 4th January, 1999 to 1st January, 2014. The results reveal bidirectional asymmetric volatility spillover between stock market and foreign exchange market of Pakistan, China, Hong Kong and Sri Lanka and unidirectional transmission of volatility from stock market to foreign exchange market of India and no volatility transmission between the two markets in reference to Japan. Miyakoshi T. (2003) studied the magnitude of return and volatility spillovers from Japan and the US to seven Asian equity markets. Volatility of the Asian market is influenced more by the Japanese market than by the US. Third and there exists an adverse influence of volatility from the Asian market to the Japanese market. This paper considers a different volatility spillover model from Ng (2000), noting the strong relationship between Japan and

Asian markets. This study reveals that only the influence of the US is important on the Asian market returns; there is no influence of Japan.

Many earlier studies on the capital market reaction of infectious virus epidemics might be referenced as we analyze COVID 19's impact. Prior literature exhibited varied results in terms of the stock market's reaction to pandemics. One of the initial studies argued that the 2003 SARS pandemic cost as much as the Asian financial crisis, with losses estimated at $3 trillion in GDP and $2 trillion in financial market equity. Macciocchi *et al.* (2016). The meagre financial performance of the economy has resulted in a bearish stock market. For any nation, the feel-good factor in the stock market is a key driver that displays the potential return from the capital market in that nation. During an initial crisis period, this feel-good factor quickly turns into a fear factor for shareholders, resulting in a bearish market without much change in the fundamentals of companies (**Totir and Dragotă 2011**).

III. DATA AND METHODOLOGY

In the Asian region, there are multiple stock exchanges. As per data from World Federation of Exchanges Top seven stock exchanges are selected from Asian countries. These are South Korea(KRX index), China (Shanghai Composite), Japan (TOPIX Index), India (BSE-Sensex), Hongkong (HKEX Index), Taiwan (TWSE index), Thailand (SET index). The investigation was done by taking daily stock price data from Yahoo Finance website for the period 1st Nov 2019 to 9th September 2022 The daily return (logarithmic changes in daily closing prices multiplied by 100) of the select Asian stock exchanges are used to get insights on the volatility in Asian stock markets during Black swan events of Covid-19. The study period captures the various news/shocks such as travel ban, lockdown, new cases, vaccine availability, economic benefits announcements by governments and others which could potentially have varied impact on volatility of stock market. The considered period for this study will give a superior comprehension of stock markets' behavior.

Estimation Technique

In this study, the analysis is carried out through various statistical techniques such as Descriptive Statistics, the Unit Root Test, the ARCH effect test and the Exponential generalized autoregressive conditional heteroscdasticity (EGARCH) model to gain perspective on volatility behavior in Asian stock markets EGARCH model studies the impact of past shocks on current volatility. An asymmetric behavior of volatility revels that negative news has a larger impact on volatility than a positive news has an impact on volatility.

IV. RESULTS AND DISCUSSION

Descriptive Statistics

The summary statistics of the return data is presented in Table-1.

Table 1: Results of Descriptive Statistics

Stock Market	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
RET_KOREA	0.024025	0.11117	8.251268	-8.766972	1.356709	-0.188002	9.386192	1198.756
RETBSE	0.000525	0.001	0.085947	-0.141017	0.014843	-1.642733	20.39647	9102.574
RETCHINASAN	0.009093	0.047085	5.554206	-8.039159	1.114373	-0.906131	9.163589	1208.988
RETHK	0.051073	0	11.14215	-9.191087	2.025258	0.323864	6.071167	288.5704
RETJPTOKIO	-0.0149	0.052693	12.88479	-20.46609	1.691088	-1.742987	47.7832	59101.41
RETTHI	0.002002	0.035879	7.653075	-11.42818	1.271317	-1.991118	23.95866	13217.55
RETTIWAN	0.035782	0.083437	6.172618	-6.005489	1.194203	-0.467656	6.754858	438.6066

Source: Author's compilation

The Highest mean return is in Hongkong stock market i.e. 0.05% with highest standard deviation 2.025 followed by Taiwan stock exchange return of 0.03% and a standard deviation of 1.27. The Japan's Tokio stock exchange has a negative mean return of -0.015% with S.D. of 1.69. The Bombay Stock exchange has a mean return of 0.0005% with the least standard deviation of 0.0148. the return data series also exhibits that the returns has excess kurtosis besides being negatively skewed in all Asian markets under study except Hongkong stock exchange. The Jarque-Bera test statistics also shows that data is not normally distributed. **The Jarque-Bera test statistic is always positive and if it is not close to zero, it shows that the sample data do not have a normal distribution.**

Unit-Root Test

Augmented Dickey-Fuller (ADF) test of Dickey and Fuller (1979) is applied to test if the return series are stationary. The null hypothesis(H01) i.e. there is s unit root in the series. The results in table 2 shows that ADF statistics are significant at 1 percent level as the ADF test statistics is much less than the test value at 1%. Also the p value is significant at 1% level. Therefore, null hypothesis is rejected for all indices. It is concluded that the data series on stock Index return is stationary.

Table 2: Results of Unit-Root Test

Stock Index	ADF stats	P Value	Null Hypothesis
RET_KOREA	-16.59751	0.0000*	Reject
RETBSE	-8.339089	0.0000*	Reject
RETCHINASAN	-25.93259	0.0000*	Reject
RETHK	-27.11296	0.0000*	Reject
RETJPTOKIO	-12.39558	0.0000*	Reject
RETTHI	-9.016625	0.0000*	Reject
RETTIWAN	-25.73025	0.0000*	Reject

Note: *Indicate statistical significant at 1% level
Source: Author's own elaboration

ARCH-LM Test

Further, ARCH-LM test is used to check for the presence of ARCH effect in return series. Presence of RCH effect indicates presence of conditional volatility in the data series. Before estimating further GARCH family model the test of ARCH Effect is necessary. If ARCH effect exists only than we can model volatility using GARCH models. The testing for presence of Arch effect in residuals is given by equation

$\mu_t^2 = b_0 + b_1 \mu_{t-1}^2$

If $b_1 = 0$;it indicates there is no ARCH effect (conditional volatility). The significant value of b_1 indicated the presence of conditional volatility.

Table 3: Results of ARCH-LM Test

Stock Index	LM Statistics(obs r Square	P Value	b_1	Null Hypothesis
RET_KOREA	270.5139	0.0000	0.621173	Reject
RETBSE	18.99268	0.0000	0.166031	Reject
RETCHINASAN	12.33432	0.0004	0.132652	Reject
RETHK	24.8436	0.0000	0.188249	Reject
RETJPTOKIO	296.2916	0.0000	0.650132	Reject
RETTHI	8.693556	0.0032	0.112351	Reject
RETTIWAN	113.7621	0.0000	0.402852	Reject

From table -3 it is observed that the LM statistics is significant in all the return series with p value less than 0.01. The null hypothesis is rejected here at 1%significance level. Also the b_1 value for all return series is greater than 0 which indicated the presence of conditional volatility in the returns. The Null hypothesis i.e. there is no ARCH effect in the series is rejected here. It is concluded that all return series have the presence of conditional volatility and it can be modeled through GARCH family models.

EGARCH

Many researches around the world has been done to model the volatility in stock markets returns. It is found that GARCH family model outperform all the volatility models. An asymmetric volatility model EGARCH (1,1) (Nelson, 1991) to model the volatility of the stocks markets in different Asian countries during black swan event of covid 19. The model has been estimated under the three error distribution assumptions namely normal (Gaussian), Student's t and Generalised error distribution (GED). This model captures the asymmetric behavior of volatility by measuring the size and sign of shocks. 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:

$$LOG(ht) = \omega + \alpha *ABS(RESID(-1)/@SQRT(GARCH(-1))) + \gamma *RESID(-1)/@SQRT(GARCH(-1)) + \beta *LOG(GARCH(-1))$$

In the above equation, the conditional variance is given by ht ,ω is the constant, α is the ARCH term, β is the GARCH term and γ is the asymmetric term. Asymmetric volatility behavior 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 significant positive value of α indicates that the size of shocks and volatility are positively related i.e larger the size of shocks greater the volatility. If $\alpha> \beta$ it indicates that volatility is spiky there is an immediate impact of shocks on volatility and if $\beta > \alpha$, it signifies that the impact of shocks on volatility is persistence. 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. The results of EGARCH(1,1) model with normal error distribution, Student's t test and GED distribution assumptions are presented in table-4. Model selection is done on the basis of Alkaike Information Criteria (AIC). The model with minimum AIC value is considered as best fitted model.

Table 4: Results of EGARCH model

Stock Index		ω	Α	Γ	Β	AIC
RET_KOREA	**Model A**	**-0.272**	**0.3809**	**-0.1694**	**0.888**	**3.0737**
	Model B	-0.2640	0.3702	-0.1718	0.8906	3.0757
	Model C	-0.2685	0.3762	-0.1712	0.8891	3.0759
RETBSE	Model A	-0.3883	0.1343	-0.1467	0.9680	-6.19057
	Model B	**-0.3851**	**0.1242**	**-0.1560**	**0.9685**	**-6.2292**
	Model C	-0.3833	0.1288	-0.150	0.96	-6.2149
RETCHINASAN	Model A	-0.2523	0.3596	-0.1594	0.8088	2.9198
	Model B	**-0.1513**	**0.2191**	**-0.1163**	**0.8676**	**2.850**
	Model C	-0.1961	0.2760	-0.1341	0.8377	2.8577
RETHK	Model A	-0.0884	0.2771	-0.0216	0.9118	4.1591
	Model B	-0.0536	0.2874	-0.0499	0.8828	4.1085
	Model C	**-0.0697**	**0.2796**	**-0.03877**	**0.896**	**4.1072**
RETJPTOKIO	Model A	-0.2959	0.3885	-0.1347	0.9450	2.8780
	Model B	**-0.2832**	**0.3722**	**-0.095**	**0.94**	**2.8450**
	Model C	-0.2908	0.3773	-0.1132	0.943	2.8504
RETTHI	Model A	-0.135	0.1871	-0.0671	0.977	2.793
	Model B	0.754	0.0939	0.0614	-0.8637	2.8007
	Model C	**-0.1229**	**0.1638**	**-0.0707**	**0.9807**	**2.6848**
RETTIWAN	Model A	-0.0967	0.1463	-0.1818	0.889	2.9786
	Model B	**-0.1221**	**0.1684**	**-0.1870**	**0.8988**	**2.9352**
	Model C	-0.1097	0.1549	-0.1831	0.8963	2.9452

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.
Source: Author's own Exploration

Table 5: Summary of Estimated Coefficient

Stock Index	Size of shock((α)	sign of shock(γ)	If $\beta > \alpha$
RET_KOREA	+	-	Y
RETBSE	+	-	Y
RETCHINASAN	+	-	Y
RETHK	+	-	Y
RETJ+TOKIO	+	-	Y
RETTHI	+	-	Y
RETTIWAN	+	-	Y

Source: Author's own Exploration

The sign of estimated coefficients (α , γ and β)of best fitted model is presented in table-5. It is observed that the coefficient of the α term is statistically significant for all Asian stock market indices which signifies the size of the shock impacts the volatility in these markets during study period. Positive sign of the coefficient of the α term indicated that the size of shocks and the volatility are positively related. Larger the shock, greater the volatility. Further, the negative sign of the statistically significant coefficient of the asymmetric term (γ) for all the indices signifies the asymmetric volatility behavior in Asian stock markets. The negative news has a larger impact on volatility than the positive news. The β coefficient is statistically significant and is greater than the α coefficient for all the indices signifying that there is no volatility spike and indicates volatility persistence in Asian stock markets.

V. CONCLUSION

In this paper the author gains the perspective on volatility response to shocks during Covid 19 in seven Asian stock markets namely South Korea(KRX index), China (Shanghai Composite), Japan (TOPIX Index), India (BSE-Sensex), Hongkong (HKEX Index), Taiwan (TWSE index), Thailand (SET index). Our study adds to the existing literature by describing the volatility response to shocks in different Asian countries, a dimension which has not been explored in the existing literature. The empirical evidence of the study suggest that there is asymmetric behavior of volatility in all select Asian stock markets during study period. We observed that volatility response follow a uniform pattern in Asian region with respect to this study. The size and sign of shocks are also uniform for all select markets. Further, there is evidence that the volatility response is persistence in all Asian stock markets means the impact of volatility will decay slowly. This study provides useful insights to the investor community to take wise and effective investment decision with regards ti their investments in Asian countries. This study is also an addition to the academics to understand the stock market volatility response in different economic regions during Covid 19 kind of Pandemic-Black swan Event.

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