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Stock Market Volatility: A Pre-Post Covid19 Analysis of Emerging Markets

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Abstract

Using several volatility estimations, researchers investigate the stock volatility on pre and post COVID19 announcements among emerging (E7) countries. The correlation coefficient matrix finding shows that low, moderate, and negative correlation in pre-COVID19 and post-COVID19 has a highly positive correlation found between the selected volatility estimators. RogersSatchell, Standard deviation has the first rank, and Garman-Klass has the last position in the pre-post covid19 analysis volatility estimators. However, the authors find that the significant effect of pre-post covid19 on E7 countries in the world. The findings key implication is the volatility of post-covid-19 gets higher than that of pre-COVID19. It suggests that investors need to adjust their financial portfolio to focus on which sectors are less influenced by COVID19. Moreover, it gives an early warning signal for investors and the government to take precautionary action for possible it even occurs in the future.

Keywords: Coronavirus, Emerging Stock Market Indices, Volatility Estimators

1. Introduction

As of March 11, 2020, the coronavirus's announcement date, the World Health Organization (WHO) officially declared the coronavirus as a Nobel disease and breakout to be a global pandemic. The cases of coronavirus were surpassed 500,000, and its rises continue. The whole world is suffering from this disease; over 170 countries, confirmed coronavirus cases (WHO, 2020). The COVID-19 breakout has had identified a significant impact on the world economy. Different countries were applying different strategies to protect their people, resources, and economy as well. Some countries used short-term quarantine policies strictly, followed them, and blocked all-economy resources throughout the country. It observed in long-term mass unemployment, industrial breakdown, business failure, aviation, and tourism stuck thought the world. The people certainly faced hardships due to coronavirus (Zhang, Hu, & Ji, 2020). The new regime work on the intraday volatility plays a role in the substantially, and the historical volatility is going slow in the covid19 event. It has been proven that intraday volatility within pre and post-trade has difficulty deciding the order of stocks (Mitchell & Catalano, 2021). Substantially affected the behavior and performance of different algorithmic (algo) strategies, which means the increase in the volatility of effect to limit stocks' price. Before the crisis, data is less helpful in forecasting the future related decision performance of algos. It is better to have more options in the portfolio and weigh the distribution of gathered data under the market's new condition (Cree, 2020).

Yes, historical events affect the stock market volatility and liquidity, which will be crucial to the financial analyst to recommend and suggest to the client. Covid19 has proven the market's friction due to the market's information flow and causes significantly deviate from their equilibrium value. The results, first observation is that covid19 leads to the industry's volatility like Meals, Games, and Mines related market (Baek, Mohanty, & Glambosky, 2020). Second, Covid19 has significant liquidity deterioration in the market of ElcEq, Carry, and Other (Christensen, 2020). Due to Covid19, disruption has taken place in the financial market in which India has witnessed sharp volatility in the stock market (Bora & Basistha, 2021). The study focused on the period of Sept 2019 to July 2020. Comparative analysis of returns of pre and post Covid19. GARCH model has used the judge the volatility of the Indian stock market. It witnessed that pre-Covid19 returns are higher than the post-covid19 returns and stated that BSE and NSE returns are reached the bottom line during the first lockdown time from March 24 to March 06, 2020 (Bora & Basistha, 2020).

Generally, volatility stems from the new arrival information in the market, whether it is public, private, and semi-public private. It can be calculated using the standard deviation of stock price changes from close to close of trading going back a certain number of days, often used 5, 10, 20, and 90 days. Indeed, the historical price volatility is computed as a standard deviation based on the stock price's daily returns (Oyelami & Sambo, 2017). Volatility is the statistical

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measurement of the risk. It is used to measure the market risk on a single script or an entire portfolio. It can also have expressed a different definition that finance is called the standard deviation of a variable. Volatility is playing an essential role in the stock market by threw of historical data. This data used with a change in stock price, which reflected from yesterday's price comparison with today's price. Stock price or future contract movement and speed measured by change rate. This change will have reflected on a daily, weekly basis, quarterly basis, and yearly basis. The higher the volatility, measure the more stock price experience; it also identifies a trend's direction (John Summa, 2016).

Many research articles have carried out the estimation of the volatility of the stock market worldwide. Volatility measures the risk in the stock market of a particular script, and it also focused on increasing the trading profit and reducing the risk to investors. Traditionally, volatility is associate with chaos and instability. A few things are consistent enough not to exhibit volatility (Fontanills & Gentile, 2003). The volatility estimation is the central importance of the pricing, portfolio analyses, portfolio construction, and risk management of any portfolio efficient frontiers. Many authors tried to improve the classical standard deviation of daily basis return to estimate the assets' volatility (Brandt & Kinlay, 2003). Their many volatility estimators are developed by Parkinson (Parkinson, 1980), Garman and Klass (Garman & Klass, 1980), Rogers and Satchell (Rogers & Satchell, 1994), and make the information available for the daily traders. The volatility estimators, sometimes called by financial professionals "the investor's gauge of fear," have developed over time to become one of the modern-day financial market highlights.

This paper aims to compare the performance of six volatility estimators (Stdev, Close-to-close, Rogers & Satchell, Parkinson, Garman-Klass, and Yang-Zhang), which employs open, high, low, and close (OHLC) values of daily prices of emerging countries (E7) in the world. For this purpose, we collected data of the event window; an event called the announcement date of COVID19 by the world health organization (WHO); the researcher preferred to measure the event study on behalf of the pre-post event covid19, which called the event window. Numerous studies have been published on the volatility estimators to know the efficiency and accuracy of volatile data. Range-based estimators of volatility, realized volatility, implied volatility, extreme value volatility, and historical volatility (Vipul & Jacob, 2007), open with drastic jumps these methods already published in reputed journals. E7 addressed the famous economist's John Hawksworth and Gordon Cookson, which reflected in the PwC report in 2006 (Hawksworth & Cookson, 2008). The purpose of making this group is to identify the largest economy globally; it also predicted that the E7 is larger economies compared to the G7 in 2030 (John Hawksworth, 2017). E7 has based on purchasing power parity. PwC expected its E7 would be 75% larger than the G7 in the purchasing power parity in 2050 (Thornton, 2006). The future of E7 Countries Economy in 2050 stated that China is the highest in the USD of 70,710. Tukey will be the last in economic growth. India secured the second position in the economic growth, i.e., 37,668 USD, Brazil played the third position in the successful growth in the economy; Mexico would be the fourth rank with 9,340 USD in the economy of E7 countries. Russia will be in the fifth position in the queue of economic growth 8,580. Indonesia would be the sixth rank in the growth series of emerging economies of E7 countries Sources: PwC Report (John Hawksworth, 2017). This study tries to determine the impact of the pre-post covid19 volatility measured by six volatility estimators to establish all volatility estimators' relationship pre-post covid19.

1.1. Impact of Covid19 on Emerging Countries in the World

COVID19 is becoming a risk for the people and economies; this pandemic is still unfolding for every country. The economic impact on the Covid19 has far exceeded by the global financial crisis. Even the conventional policies and orthodox policies are not limited to this risk of a pandemic. IMF stated, "Emerging markets are likely to face an uphill battle". Multiple shocks have buffeted the emerging market economies. Domestic containment measures the effect of external demand, which has declined in the market (Mühleisen, Gudmundsson, & Ward, 2020).

China stock market value erosion is lowest compared to the MSCI emerging market, USA, Europe, and India, in which India has the highest in vales deterioration of market performance. China originated from coronavirus even the stock market fell only 3-4 percent, emerging markets fell down 13-16 percent, and the Europe stock market fell 19-20 percent, where the USA has also decreased by 14 percent, in series India is highest down in the stock market, i.e., 26 percent (Sharma, 2020). Indian stock market dropped for a temporary period; each dip will allow investors to enjoy the high returns from the market with a long-term horizon. An analysis of pre-post covid19 observed that Sensex and Nifty had shown the spike pre covid19, i.e., respectively, 12,362 and 42,273 with consideration blue-chip companies like HDFC Bank, HDFC, TCS, Infosys, Reliance, Hindustan Unilever, ICICI Bank, and Kotak Bank. A Comparison of Pre and Post COVID View of Indian Stock Markets, Sensex and Nifty50 fell down 38 percent; total market capitalization has lost 27.3 percent from the start year. India's stock market has reflected the pandemic's sentiments unleashed upon investors, foreign and domestic alike (Ravi, 2020).

In Russia, coronavirus impacted lives and economies. It indicated that the Russian economy depended upon oil prices. The time observed oil price was dramatically going down from around \$60/barrel to around \$15/barrel in the coronavirus time. Russian stock market and exchange market goes down along with the oil price (Becker, 2020). Brazil's economies significant fall in the consumer goods and services industries, but Euro monitor the forecasting growth in Brazil's economies of 2020. It has been seen as a short-term negative impact on sales in 2020. Sales concertation does not repeat like Q1 and Q2 of 2020. It will reframe the consumption of the occasion of Brazil (Euromonitor, 2020). Mexico's stock market has a slow recovery in emerging markets with trade. Mexican banks were also awakening slowly compared to Brazil, Peru, and Chile and have limited support supported by the industries (Perez-Gorozpe, 2020).

The Indonesian economy has fallen due to coronavirus in IHSG and the Rupiah. Organizations have stopped production and international activities as well. At the same time, the corporate has started work from home to protect their people. Indonesia suffered from the outbreak of COVID19 (PwC Indonesia, 2020). Turkey had a headwind on the COVID19, the weak awakening of the economy, and social gain. Turkey's government has provided financial support to firms and households. The economic outlook was more uncertain; it will depend upon the unprecedented crisis that has entered the country (The World Bank Group, 2020).

1.2. Objectives of the Study

The present study focused on the volatility of the estimator's analysis of pre-post Covid19 in emerging countries (E7) of the world. The objective of the study is to find out the pre-post COVID19 enhances the estimators of volatility. It does it give results immediately or take considerable time by computing and comparing before and after Covid19 volatility performance by using volatility estimator's models on Standard Deviation (STDEV), The Close to Close (CC), The Rogers & Satchell (RS), Parkinson (PERK), Garman-Klass (GK) and Yang Zhang (YZ).

1. To analyze the impact of Covid19 on the estimation of the volatility of emerging countries in the world during the pre- and post-announcement period.
2. To measure the volatility estimators of emerging countries during the pre and post the announcement of Covid19 in the world.

All the six volatility estimators were used for the study with emerging seven countries globally, which are as followed, China, India, Brazil, Mexico, Russia, Indonesia, and Turkey. (Hawksworth & Cookson, 2008) Stated these seven countries are more prevalent in the abbreviation of emerging seven countries "E7".

2. Literature Review

The literature review depends on the two parts' first background theory of concept and the second point-based on previous studies.

2.1. Background Theory

This standard stock price used for the study and logarithm follows the stock price's random walk, which seems to be an excellent approximation. The diffusion characterizing the constant walk. This works the same as the variance of return work; hence, it becomes a critical quantity to calculate the traditional estimation to calculate the stock price. It is shown that the extreme value of high and low to provide the best estimate (Parkinson, 1980). Volatility formulated by the improvements in stock price. These estimators used data readily available on any company's financial page like open, close, high, low, and transaction value. These new estimators considered it more efficient compared to the standard estimators (Garman & Klass, 1980). This study is based on the volatility estimator, which applies the different period time series of high, low, open, and close. This deals in three distinct movements, the unbiased in the continuous limit, independent of the drift, consistent in dealing with opening price jumps, using the variance among all estimators. The accuracy has shifted from historical close-to-close volatility estimators to entire lifetime series (Yang & Zhang, 2000).

Prior volatility measured by standard deviation, then extended to range-based volatility, has featured the Monte Carlo simulation to measure the volatility. An alternative has emerged the estimation of the volatility of the stock price. Now efficiency word has added in the volatility estimation to improve the simple standard deviation. Alizadeh-Brandt-Diebold volatility estimators produced a biased estimate of the actual process of volatility unless the high frequency observation, performance of these estimates has deteriorated in the presence of the other departures (Brandt, & Kinlay, 2003). This study has reviewed the expansion of realized volatility; a simple discrete-time series has been used to motivate this study. Continues time series provides the theoretical foundation in all literature. The case studies of with and without microstructure noise are considered, it has found the serval problems inconsistent estimate the daily-realized volatility. Simple properties are discussed in the comparison of the asymptotic properties in the data. The multivariate model is concluded the realized the co-variance; it focused on the forecasting (Mcaleer & Medeiros, 2008). This study has explained the volatility estimators based on open, low, high, and close to the stock price. Methods have been used in the survey like, Close to Close, Exponentially Weighted, Parkinson, Garman-Klass, Rogers-Satchell, and Yang and Zhang (Bennett & Gil, 2012).

2.2. Previous Studies

The kernel function of spot volatility has been used in the paper to check the data's microstructure noise. Itô semi martingale model has proved that Central Limit Theorems for the estimation error with an optimal rate and study the problems of optimal bandwidth and kernel selection. Observed that the asymptotic variance of the pre-averaging. The feasible implementation has worked optimal bandwidth and Monte Carlo experiments confirm the superior performance in the proposed method (Figueroa-López & Wu, 2020). This study is based on the G7 stock market indices. First, standard deviation has been used the find the impact of market volatility. Second, identify the daily case to the growth of the G7 countries.

Third, find out the impact of Covid19 by the GJR-GARCH model. It found that all G7 indices have low prices in March 2020. It also observed that low price during March 2020 in comparison to the 20 years of data. Only one exceptional case of the Japan index (Nikkei 225), whose minimum returns in October 2008. The regression analysis has interpreted a significant positive response to the G7 stock market. Finally, GJR-GARCH has a significant positive impact on all G7 stock markets; it indicates the Covid-19 increased market volatility (Yousef, 2020). Range-based volatility has been applied in the study with more precision; Garman-Klass volatility has followed the low and high stock price volatility. Data has normalized by their standard deviation is approximately working with a normal distribution. High-frequency data is recognized but not for the low-frequency data, which is essential to build a more straightforward and precise calculation of volatility models (Molnar, 2012).

Paper focused on the method of the volatility risk premium and risk aversion on the indices. For this purpose, authors used free realized and option-implied volatility measurements. The Monte Carlo experiment proved that procedure work, implemented on the S&P 500 index option implied volatilities and high frequency were judged by realized volatility. Short-term dependencies work on the estimation of volatility risk premium, which turned to the macro variables. It proved that the volatility risk premium predicts the future of stock market returns (Bollerslev, Gibson, & Zhou, 2011). Volatility estimators used historical data on open close low high (OHLC) value.

Another variance squared has calculated, meaning that standard deviation. This method has been applied to the VIX in the USA and VDAX in Germany and compared these indices' volatility. The empirical study observed that autocorrelation exists in both indices, cross-correlation functions of building blacks with the variance decrease potentially in both series. The observation of the EWMA style of estimators has a higher prediction capacity than the GARCH model of Volatility (Jaresova, 2010). This paper has identified the overnight-realized volatility that takes 24 hours a day. Several methods have been used for overnight returns that affect the results. S&P 500 index has used for this study, realized volatility applied based on existing literature. First, a statistical test of Patton, which gives the weightage squared of overnight returns and sum of intraday squared returns, is the most accurate measure of the realized volatility on the over the night returns (Ahoniemi & Lanne, 2010).

This paper estimated the integrated variance of a general jump-diffusion with volatility. The study exploited the relationship between speeds and passed the time of the Brownian motion. Duration based volatility estimation identified the robustness for the jumps and microstructure noise (Andersen, Dobrev, & Schaumburg, 2008). The study examined the market risk due to stock price and interest rate movement for portfolio trading. The standard deviation identifies risk exposure; another way identified the risk by implied volatility, which estimates the future volatility. Data played an essential role in the standard point's efficiency, where time-series fill the grease of several problems (Soczo, 2003). This paper focused on the relationship between implied and realized volatility S&P 500 Index volatility, data used from 1995-1999. Estimate realized volatility methods of standard deviation, Parkinson, Yang and Zhang, and range estimators, for the implied volatility had used the Black-Scholes model, to checking the option pricing model. They found the improvement in the implied volatility and realized volatility had soundly predicted the future. Hence, there is no significant difference between the realized and implied volatility; however, in the model of Black-Scholes and Heston model (Shu & Zhang, 2003). This study contains an empirical finance method of volatility is called range based multivariate volatility. The CARR model incorporates the superiority of range in forecasting volatility, and elasticity volatility has marked by the GARCH model. DCC model of range-based volatility measured the multivariate data; high and low volatility has measured the efficient estimators. The range-based volatility has estimated the sensitivity of outliers in the data. The finding of the utility of quantile range to replace the standard range to get the data's robustness (Chou, Chou, & Liu, 2002). This study examined the asymptotic analysis for rolling sample variance estimators on the different sets of information with a different frequency called integrated volatility, reflecting the cumulative integral instantaneous volatility in the other data groups. Also applied optimal weightage schemes for the integrated volatility estimators and Monte Carlo simulations (Andreou & Ghysels, 2002).

3. Research Methodology

This paper consists of the methodology section into three-parts. First, data used, second, research model, and third, the method used.

3.1. Data

The current study shows that the Covid19 pre-post analysis of the volatility of emerging stock markets globally and find the impact on the coronavirus on the individual country. Data collected from Google finance (https://in.finance.yahoo.com/).

Table 1. Emerging Stock Markets on Google Finance

E7 Countries	Emerging Stock Markets	Yahoo Finance
China Stock Market	SSE Composite Index (000001.SS)	https://finance.yahoo.com/quote/000001.ss?ltr=1
Indian Stock Market	S&P BSE SENSEX (^BSESN)	https://in.finance.yahoo.com/quote/%5EBSESN/
Brazil Stock Market	IBOVESPA (^BVSP)	https://finance.yahoo.com/quote/%5EBVSP/
Mexico Stock Market	IPC MEXICO (^MXX)	https://finance.yahoo.com/quote/%5EMXX/
Russia Stock Market	MOEX Russia Index (IMOEX.ME)	https://finance.yahoo.com/quote/IMOEX.ME/
Indonesia Stock Market	Jakarta Composite Index (^JKSE)	https://finance.yahoo.com/quote/%5EJKSE/
Turkey Stock Market	MSCI Turkey (TUR)	https://finance.yahoo.com/quote/TUR/

The present study used the event window for the data collection, methodology, and data for finding out whether such an announcement of Covid19 on March 11, 2020. The pre-post data of all (Emerging Seven Countries) E7, which is 142 days plus and minus from the announcement date of covid19, find a significant impact on the emerging stock market performance.

3.2. Model Development

The data extracted of E7 countries of world from the premier source for global media property i.e., Yahoo! network special from the Yahoo! Finance. Volatility estimators can be measured with various methods ranging from the ordinary method standard deviation to a sophisticated estimator method. The present study used the well-known techniques of estimating emerging countries' volatility (E7) with particular reference to the pre and post. The Day 0, event window has been defined as the day on which the COVID19 announcement was made by the World Health Organization (WHO). The event window comprises 284 days, the Days -142 form announcement of COVID19, i.e., March 11, 2020, and Days +142. The pictorial representation of the event window, Figure 1 below.

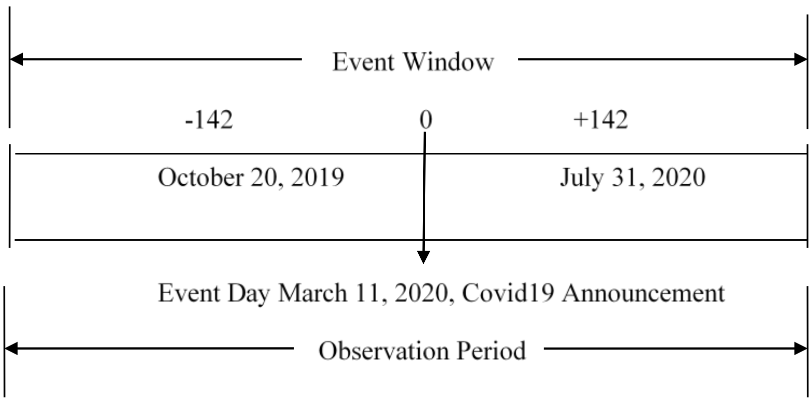


Fig. 1. Event Study Periods

Solely this study used secondary data; the study sample consists of E7 emerging stock markets globally, i.e., China, India, Brazil, Russia, Mexico, Indonesia, and Turkey. The study aims to identify the impact of coronavirus on the volatility of emerging market stock prices.

For the accomplishment of the objectives of the study, the following null hypotheses are set:

- H01 = There is no significant effect on the Volatility Estimator's of China before and after Covid-19.
- H02 = There is no significant effect on the Volatility Estimator's of India before and after Covid-19.
- H03 = There is no significant effect on the Volatility Estimator's of Brazil before and after Covid-19.
- H04 = There is no significant effect on the Volatility Estimator's of Mexico before and after Covid-19.
- H05 = There is no significant effect on the Volatility Estimator's of Russia before and after Coivd-19.
- H06 = There is no significant effect on the Volatility Estimator's of Indonesia before and after Covid-19.
- H07 = There is no significant effect on the Volatility Estimator's of Turkey before and after Covid-19.

3.3. Method

As per the way path of the objective of the study based on the time-series data. There is a requirement of smooth showing the data to estimate emerging stock markets' volatility with various well-known methods (Bennett & Gil, 2012). There are several benchmark volatility estimators follows:

1. Standard Deviation (STDEV)

It measures the dispersion data relative to its mean after that calculated as the square root of variance. Which reflects the deviation from the mean? If the data set far from the mean, meaning that there is a higher deviation within the data set, the higher the standard deviation, the more spread out (Feller, 1951). In continuation of Michael (Parkinson, 1980) has given volatility definition in terms of the high and low prices of stocks as a deviation from the mean. The standard deviation formula has given: -

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

2. Close to Close (CC)

The Close-to-Close historical volatility estimator is a standard method of calculation of historical volatility. It is calculated by the through of logarithmic returns over a given period of observation. CC volatility reflects the historical price movements of the underlying stock. It is called the assets' actual volatility (Harbourfront Technologies, 2020).

$$\textit{Close to Close Volatility } \sigma = \sqrt{\frac{1}{N}\sum_{t=1}^{N} x_i^2}$$

3. Parkinson Volatility (PARK)

Parkinson volatility is the part of classic historical volatility that summarizes the price behavior of the stock. This volatility has been realized on the close-to-close prices. This volatility does not incorporate all the happenings during the day (Breaking Down Finance, 2020). Parkinson's volatility extended version of the standard calculation of volatility using the low and highsecurity matric price and summarized the data range. It will work more efficiently than the closeto-close volatility in the intraday (Parkinson, 1980).

$$\textit{Parkinson Volatality } \sigma = \sqrt{\frac{1}{4\ln(2)}\sum_{t=1}^{N}\left(\ln\left(\frac{Ht}{L_t}\right)\right)^2}$$

4. **Garman and Klass (GK)**

Garman and Klass have viewed the volatility estimator using the open, close, low, and high price of the security. It has demonstrated a much high efficiency than the close-to-close volatility (Garman & Klass, 1980). The following formula is here:-

$$\text{Garman and Klass Volatility} \quad \sigma = \sqrt{\frac{z}{n}\sum\left[\frac{1}{2}\left(\log\frac{H_i}{L_i}\right)^2 - (2\log 2 - 1)\left(\log\frac{C_i}{O_i}\right)^2\right]}$$

5. Yang Zhang (YZ)

Yang and Zhang have used volatility in the high jump opening in the stock price, which is constant, unbiased, and drift-independent. This is a unique feature of Yang and Zhang's stock price volatility (Yang & Zhang, 2000).

$$\sigma = \sqrt{\sigma_o^2 + k\sigma_c^2 + (1-k)\sigma_{rs}^2}$$

$$\sigma_o^2 = \frac{1}{N-1}\sum_{i=1}^{N}(\ln\frac{o_i}{c_{i-1}})^2$$

$$\sigma_c^2 = \frac{1}{N-1}\sum_{i=1}^{N}(\ln\frac{c_i}{o_{i-1}})^2$$

$$\sigma_{rs}^2 = \frac{1}{N-1}\sum_{i=1}^{N}\{(ln\frac{h_i}{c_i})(ln\frac{h_i}{o_i}) + (ln\frac{l_i}{c_i})(ln\frac{l_i}{o_i})\}$$

$$k = \frac{0.34}{1.34 + \frac{N+1}{N-1}}$$

In 2000, Yang and Zhang created a volatility measure that handles both opening jumps and drifts. The sum of the overnight volatility (close-to-open volatility) and a weighted average of the RogersSatchell volatility and open-to-close volatility. The assumption of continuous prices does mean the measure tends slightly to underestimate the volatility.

6. Rogers-Satchell

Rogers-Satchell measures the volatility estimator of security price when the average return of a security is not equal to zero. Rogers-Satchell drift is also called Rogers-Satchell has used drift term, (which is mean return is not equal to zero). The results have given the better volatility estimation when showing the trending line of securities (Rogers & Satchell, 1994). The following formula has driven: -

$$\text{Rogers} - \text{Satchell Volatality} \quad \sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\{(ln\frac{h_i}{c_i})(ln\frac{h_i}{o_i}) + (ln\frac{l_i}{c_i})(ln\frac{l_i}{o_i})\}}$$

7. Paired T-test

The paired t-test was used to compare with the two groups of series. Another way, it is used where two values for the same sample (Shier, 2004). It provides a hypothesis test on a pair of random sample population means. The difference between the two means is approximately normally distributed (Kim, 2015). The paired t-statics is calculated:

$$Paired\ t - test = \frac{\bar{d}}{\sqrt{S^2/n}}$$

4. Results and Analysis

4.1. Results

Historical time series data analysis will carry the explained empirical finding, followed by the policy, implication, and amendments. This will also unlock new opportunities in a broad area of emerging stock in the world.

Table 2. Volatility Estimators of Chinese Stock Market of Pre-Post COVID19

Volatility Estimators	China	
	Pre	Post
STDEV	0.89%	1.25%
CC	1.31%	1.42%
PARK	0.79%	1.07%
GK	1.09%	1.48%
RS	0.72%	0.97%
YZ	1.30%	1.27%

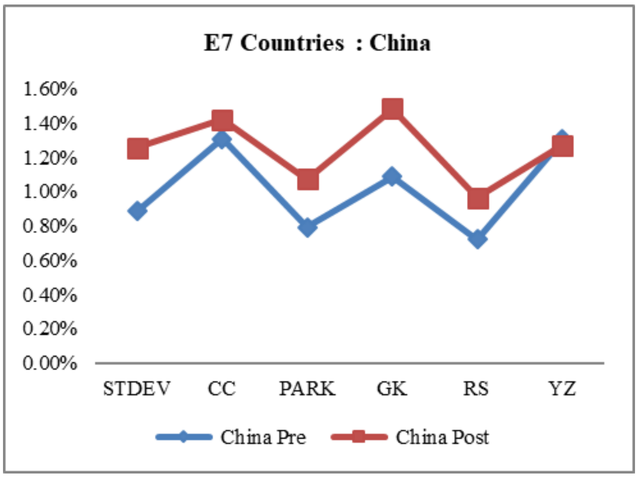


Table 2 explained the volatilities estimators of China stock market pre-post analysis. It was observed that the post-COVID19 China stock market was more volatile in comparison to the pre covid19. Garman and Klass volatility are highest, and Rogers -Satchell is lowest compared to all the volatility estimators in the post covid19. Close to close volatility is highest, and RogersSatchell is lowest in the pre COVID19 than all estimators of volatility, which means that RogersSatchell is less volatile in pre-post covid19 in comparison to all volatility estimators. RS has a perfect combination of all parameters of price moments in a market that is high of close & open and low of close & open.

Table 3. Volatility Estimators of Chinese Stock Market of Pre-Post COVID19

Volatility Estimators	India	
	Pre	Post
STDEV	0.81%	2.39%
CC	1.54%	2.97%
PARK	0.79%	2.24%
GK	1.05%	3.02%
RS	0.81%	2.13%
YZ	1.37%	2.82%

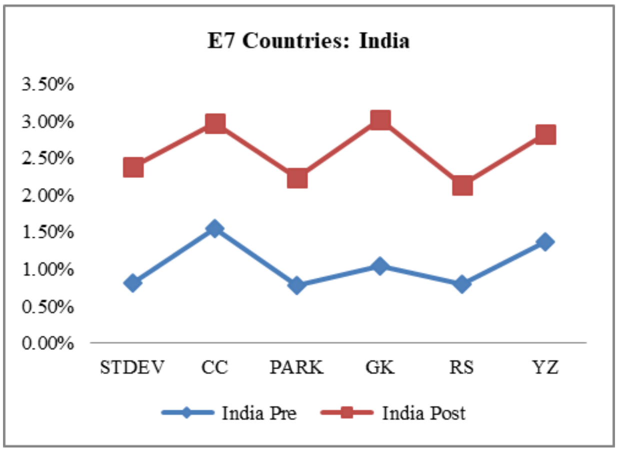


Table 3 interpreted the Indian stock market volatility estimators of pre-post covid19. It found that the post Covid19 Indian stock market was more volatile in comparison to the pre Covid19. Pre-Covid19 research found that Parkinson's volatility is less volatile in comparison to all volatility estimators. The close-to-close volatility was the highest performer in the pre covid19 scenario. Post-covid19 measurement identified the Garman-Klass volatility as an efficient measurement of volatility estimators; Rogers-Satchell has interpreted the low volatility in the post covid18 scenario. The central observation was post-COVID19 Indian stock market had fluctuated more in comparison to the pre-COVID19.

Table 4. Volatility Estimators of Brazil Stock Market of Pre-Post COVID-19

Volatility Estimators	Brazil	
	Pre	Post
STDEV	1.97%	3.78%
CC	2.14%	3.77%
PARK	1.44%	3.33%
GK	2.09%	4.60%
RS	1.09%	2.98%
YZ	1.47%	3.11%

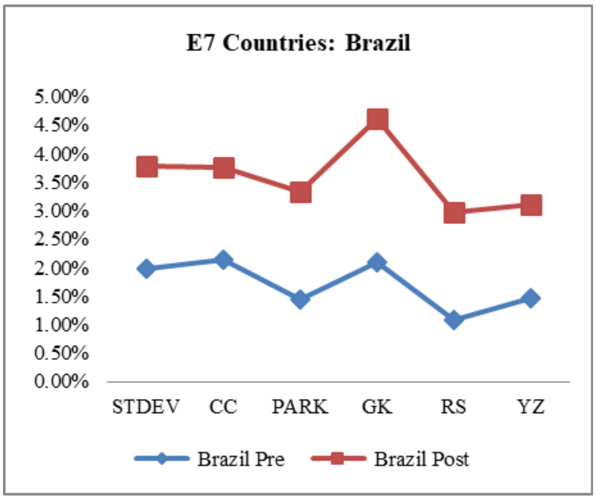


Table 4 interpreted the Indian stock market volatility estimators of pre-post covid19. It found that the post Covid19 Indian stock market was more volatile in comparison to the pre Covid19. Pre-Covid19 research found that Parkinson's volatility is less volatile in comparison to all volatility estimators (Aslam , Ferreira, Mughal, & Bashir , 2021). The close-to-close volatility was the highest performer in the pre covid19 scenario. Post-covid19 measurement identified the Garman-Klass volatility as an efficient measurement of volatility estimators; Rogers-Satchell has interpreted the low volatility in the post covid19 scenario. The significant observation was postcovid19 Indian stock market has more fluctuated in comparison to the pre-covid19.

Table 5. Volatility Estimators of Mexico Stock Market of Pre-Post COVID19

Volatility Estimators	Mexico	
	Pre	Post
STDEV	0.95%	1.50%
CC	1.03%	1.93%
PARK	0.78%	1.55%
GK	1.08%	2.06%
RS	0.75%	1.67%
YZ	0.83%	1.81%

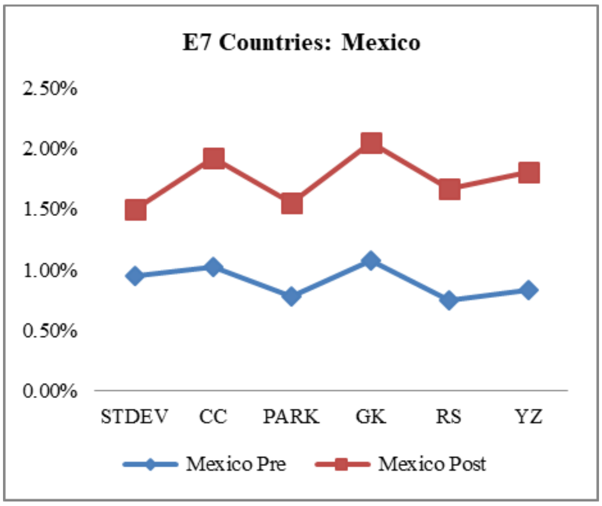


Table 5 summarized the Mexico stock market less volatile in Rogers-Satchell estimator of volatility in comparison all estimators in the pre-post data series. Garman-Klass was the highest volatile in the series of pre-post covid19 data in the volatility estimators.

Table 6. Volatility Estimators of Russia Stock Market of Pre-Post COVID-19

Volatility Estimators	Russia	
	Pre	Post
STDEV	0.69%	1.95%
CC	1.38%	2.33%
PARK	1.70%	2.09%
GK	2.25%	2.74%
RS	1.76%	2.15%
YZ	2.12%	2.37%

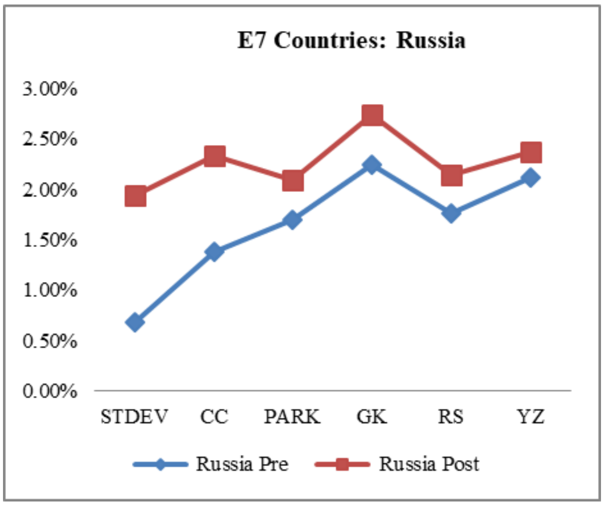
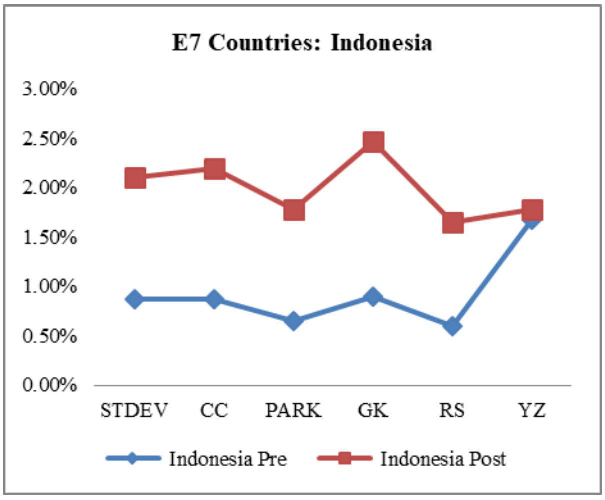


Table 6 estimated the volatility with different methods. STDEV is low volatile in the pre-post COVID19 volatility estimator's series, and Garman-Klass was the highest fluctuated volatility estimators in the pre-post covid19 data series.

Table 7. Volatility Estimators of Indonesia Stock Market of Pre-Post COVID-19

Volatility Estimators	Indonesia	
	Pre	Post
STDEV	0.87%	2.10%
CC	0.87%	2.19%
PARK	0.64%	1.78%
GK	0.89%	2.46%
RS	0.60%	1.65%
YZ	1.67%	1.77%



The performance of the Indonesia stock market in terms of fluctuation tabulated in table 7, the low volatility estimator was Rogers-Satchell in the data series of pre-post covid19. Yung-Zhang was the highest volatile estimator in pre-covid19 analysis, and the Garman-Klass volatility estimator was in the post-covid19 series.

Table 8. Volatility Estimators of Turkey Stock Market of Pre-Post COVID-19

Volatility Estimators	Tukey	
	Pre	Post
STDEV	0.81%	1.37%
CC	1.54%	2.54%
PARK	0.79%	1.47%
GK	1.05%	1.93%
RS	0.81%	1.55%
YZ	1.37%	2.51%

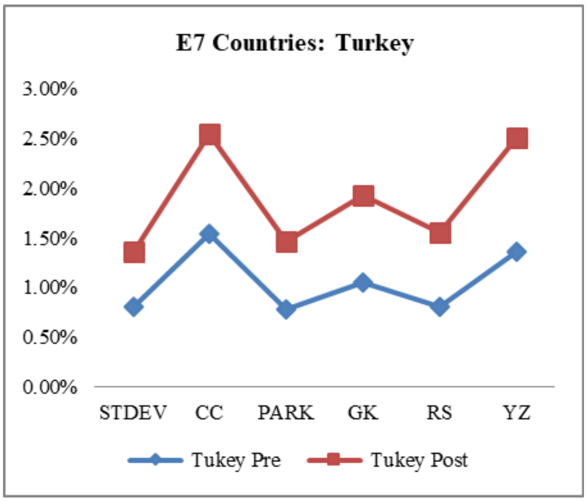


Table 8 shows that volatility estimators of the Turkey stock market, Parkinson Volatility, measure the low estimator in pre-post covid19 analysis. Close to close volatility was the highest volatility in the pre-post COVID19 study.

Table 9. Pre-COVID19 Correlation of Volatility of Emerging Countries (E7)

Estimator	STDEV	CC	PARK	GK	RS	YZ
STDEV	1					
CC	0.71	1				
PARK	0.35	0.54	1			
GK	0.44	0.58	0.99	1		
RS	0.02	0.33	0.94	0.90	1	
YZ	-0.16	-0.07	0.45	0.42	0.52	1

Table 9, the idea of using measuring the correlation between estimators is to determine the interrelationship of the various volatility estimators of pre-covid19. Here, moderate, low, and negative correlation applied to the estimators on pre-covid19 analysis.

Table 10. Post-COVID19 Correlation of Volatility of Emerging Countries (E7)

Estimator	STDEV	CC	PARK	GK	RS	YZ
STDEV	1					
CC	0.89	1				
PARK	0.98	0.93	1			
GK	0.99	0.92	0.98	1		
RS	0.92	0.92	0.98	0.97	1	
YZ	0.74	0.95	0.83	0.81	0.87	1

Table 10, Correlation coefficient shows a highly significant correlation between all the volatility estimators in post-covid19. Meaning that after covid19 highly positive correlation was found in the volatility estimators.

Table 11. Pre-COVID19 Volatility Estimators Rank of Emerging Countries (E7)

E7 Countries	STDEV	CC	PARK	GK	RS	YZ	Rank in Ascending order
China	0.89%	1.31%	0.79%	1.09%	0.72%	1.30%	RS, PARK, STDEV, GK, YZ, CC
India	0.81%	1.54%	0.79%	1.05%	0.81%	1.37%	PARK, RS, STDEV, GK, YZ, CC
Brazil	1.97%	2.14%	1.44%	2.09%	1.09%	1.47%	RS,PARK, YZ, STDEV, GK, CC
Mexico	0.95%	1.03%	0.78%	1.08%	0.75%	0.83%	RS, PARK, YZ, STDEV,CC, GK
Russia	0.69%	1.38%	1.70%	2.25%	1.76%	2.12%	RS, PARK, YZ, STDEV, CC, GK
Indonesia	0.87%	0.87%	0.64%	0.89%	0.60%	2.00%	STDEV, CC, PARK, RS, YZ, GK
Turkey	0.81%	1.54%	0.79%	1.05%	0.81%	1.37%	RS, PARK, STDEV, CC, GK, YZ

The ranking of volatility estimators is requires treating differently in the forecasting of emerging stock market indices. To determine whether these changes affect the ranking of competing in volatility estimators. The order is using for determining high-frequency data; it referred to the scales using the valid latent target variable in all sample data.

The volatility estimation performance observed that the majority of Rogers-Satchell volatility has 1st rank in the ascending order of volatility estimators table 11, Parkinson, and standard, respectively. Most of the 2nd position of volatility estimators was Parkinson, Rogers-Satchell, and close-to-close. The last place was Garman-Klass, Close-to-close, and Yung-Zhang.

Table 12. Post-COVID19 Volatility Estimators Rank of Emerging Countries (E7)

E7 Countries	STDEV	CC	PARK	GK	RS	YZ	Rank in Ascending order
China	1.25%	1.42%	1.07%	1.48%	0.97%	1.27%	RS, PARK, STDEV, YZ, CC, GK
India	2.39%	2.97%	2.24%	3.02%	2.13%	2.82%	RS, PARK, STDEV, YZ, CC, GK
Brazil	3.78%	3.77%	3.33%	4.60%	2.98%	3.11%	RS, YZ, PARK, CC, STDEV, GK
Mexico	1.50%	1.93%	1.55%	2.06%	1.67%	1.81%	STDEV, PARK, RS, YZ, CC, GK
Russia	1.95%	2.33%	2.09%	2.74%	2.15%	2.37%	STDEV, PARK, RS, YZ, CC, GK
Indonesia	2.10%	2.19%	1.78%	2.46%	1.65%	1.77%	STDEV, PARK, RS, CC, YZ, GK
Turkey	1.37%	2.54%	1.47%	1.93%	1.55%	2.51%	RS, YZ, PARK, STDEV,CC, GK

Rank was the performance measurement of volatility among the estimators in table 12, which found Rogers-Satchell was the 1st rank, respectively Standard Deviation. The majority has supported to identify the last position out of all the volatility estimators was Garman-Klass.

Table 13. Pre-Post T-test of Volatility Estimators of Emerging Countries (E7)

Emerging 7 Countries	Paired Differences				t - test	df	Sig. (2tailed)
	Mean	Std. Devi.	Std. Error Mean	95% Confidence Interval of the Difference			

					Lower	Upper			
Pair 1	China Pre - China Post	-.0023	.0016	.0007	-.0040	-.0006	-3.41	5	.019
Pair 2	India Pre - India Post	-.0154	.0023	.0009	-.0178	-.0130	-16.46	5	.000
Pair 3	Brazil Pre - Brazil Post	-.0190	.0032	.0013	-.0224	-.0156	-14.31	5	.000
Pair 4	Mexico Pre - Mexico Post	-.0085	.0017	.0007	-.0102	-.0067	-12.39	5	.000
Pair 5	Russia Pre - Russia Post	-.0062	.0039	.0016	-.0104	-.0021	-3.86	5	.012
Pair 6	Indonesia Pre - Indonesia Post	-.0107	.0051	.0021	-.0160	-.0054	-5.17	5	.004
Pair 7	Turkey Pre - Turkey Post	-.0084	.0022	.0009	-.0106	-.0061	-9.48	5	.000

The paired T-test compares the two means that were of the same stock market table 13. Average difference of pre-post covid19 data of all the emerging stock markets. Standard has shown the difference score, standard deviation divided by the square root of the sample. The confidence interval of both upper and lower bound, a significant average difference between pre-post covid19 of emerging market stock prices. The other hand result shows that nearly all the volatility estimators show that post-covid19 is always higher than pre-covid19, and the statistical evidence shows a significant difference.

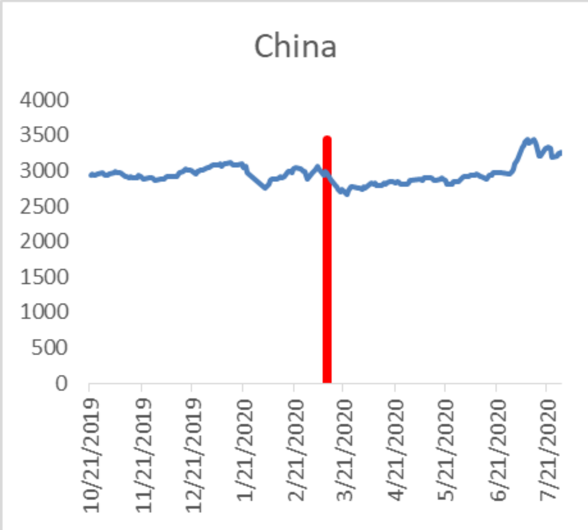
4.2. Analysis

The study's objective is to evaluate the volatility estimator among the emerging stock markets in the pre-post covid19. The volatility estimators used the volatility to check the efficiency in the time series data of event window (-142 days, Event Day (Announcement of COVID19 by WHO, March 11, 2020, +142 days) pre-post covid19. Volatility estimators are Standard Deviation, Historical Close-to-Close, Parkinson, Garman-Klass, Rogers-Satchell, and Yang Zhang volatility estimators, E7 countries (China, India, Brazil, Mexico, Russia, Indonesia, and Turkey) by using daily prices of open, high, low, and close (OHLC) to identify the efficient volatility estimators in the emerging stock market of pre-post covid19. Garman-Klass and Close to close volatility estimators are highest in pre-post covid19 of the China stock market; Rogers- Satchell is less volatile in pre-post covid19 than all volatility estimators. It is the perfect combination, all the parameters of price moments of the market. It followed that the high, open, low, and close. Indian stock market is post-covid19 more volatile in comparison to the pre COVID19. Pre-post COVID19, the research observed that Parkinson volatility and Rogers-Satchell are less volatile, the close to close and Garman-Klass are the highest performer in the pre-post covid19 scenario (Bora & Basistha, 2020).

Brazil stock market is measured volatility of all estimators found double from pre to post Covid19. Rogers-Satchell was low volatile in pre-post covid19, close to close and Garman-Klass volatility was the highest fluctuated volatility in pre-post covid19 data in the Brazilian stock market. Mexico stock market less volatile in the Rogers-Satchell, the estimator of volatility in comparison to all estimators in the pre-post data series. Garman-Klass volatility estimator was the highest volatility in the series of pre-post covid19 analyses. Russia stock market estimated the volatility, STDEV is low volatile in pre-post covid19 volatility estimator's series, and Garman-Klass was the highest fluctuated volatility estimators in pre-post covid19. Indonesia stock market the low volatility estimator was Rogers-Satchell in the pre-post COVID19 data set. Yung-Zhang was the highest volatile estimator in pre-covid19 analysis, and the Garman-Klass volatility estimator was in the post-COVID19 series. The performance of volatility estimators of the Turkey stock market, Close to close volatility was the highest volatility in pre-post covid19 analysis. Parkinson Volatility is a measurement of the low estimator in pre-post covid19 analysis. The correlation matrix has shown that the inter-relationship of the various volatility estimators of pre-covid19. It found a low, moderate, and negative correlation among all estimators of volatility on pre-covid19 analysis. The correlation coefficient after COVID19 has a highly positive correlation found in the volatility estimators. Rogers-Satchell and Standard deviation have 1st rank in the ascending order of volatility estimators of pre-post COVID19; the Last position was Garman-Klass in pre-post covid19. This paper found that rejection of the null hypothesis, there is a significant impact of pre-post COVID19 on E7 countries in the world (Yousef, 2020).

4.2.1. E7 Countries Stock Markets -Pre-Post Covid19 Analysis

The event window of COVID19 pre and post, which reflected 142 days before and after data of E7 countries stock market. All the seven countries' stock market has reacted separately, as a line diagram of China's stock market shows that the minor effect of coronavirus in the event window compared to the Indian stock market has a substantial negative impact on covid19. The Brazilian stock market has a downturn due to coronavirus in the initial 60 days. Mexico's stock market is less volatile in comparison to the Brazil stock market. Russia's stock market has a deep downturn in the first 45 days and comes back to perform well. Jakarta stock market hurts by the coronavirus. It continues for the down for an extended period after two months of the covid19 announcement picked up the market's market position. Rightly, discussed Turkey stock market followed the negative impact.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3500
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2500
2000
1500
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500
0
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11/21/2019
12/21/2019
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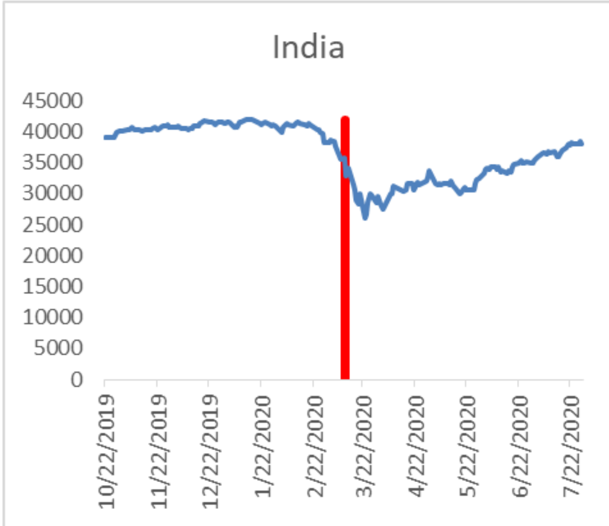
7/21/2020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2/22/2020
3/22/2020
4/22/2020
5/22/2020
6/22/2020
7/22/2020


Brazil
140000
120000
100000
80000
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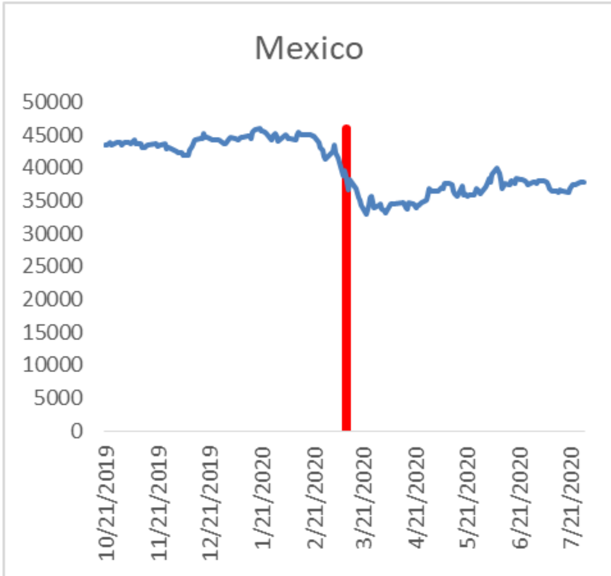
7/21/2020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2/21/2020
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4/21/2020
5/21/2020
6/21/2020
7/21/2020


Russia
160
140
120
100
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40
20
0
10/21/2019
11/21/2019
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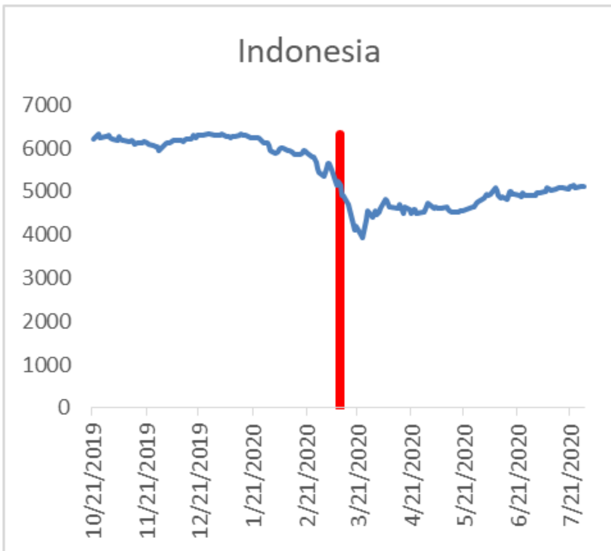
7/21/2020


Indonesia
7000
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3/21/2020
4/21/2020
5/21/2020
6/21/2020
7/21/2020

5. Conclusion and Recommendation

5.1. Conclusion

We can conclude that the emerging stock market (E7), i.e., One high low close (OHLC), has various volatility estimators to forecast the degree of efficiency in the daily basis time-series data. However, to know the pattern of up and down by the standard deviation and historical close-to-close volatility, which is the most common method to use the volatility (Petnehazi & Gall, 2018). Another way to judge the volatility which defines the drift in the time series, i.e., open with high jumps in underlying stock market price. Which are classical estimators of volatility called close-to-close (Yang & Zhang, 2000). Historical volatility among the volatility estimators is the statistical significance of pre-post covid19 in the emerging market volatility. It is proven in the Grauman-Klass volatility estimator are systemically higher than remaining estimators (Stdev, Close to close, Parkinson, Rogers-Satchell, and Yung-Zhang) in pre-post COVID19 analysis (Duque & Paxson, 1997). Historical volatility has explanatory power over implied volatility for predicting future value; a historical value reflected by implied volatility and open market information plays a vital role in market efficiency (Shu & Zhang, 2003). The correlation coefficient among the financial market will predict the relationship if there was no technical error in the sample data (Soczo, 2003). Topcua and colleagues stated that the official response time emerging stock market and the government's size stimulus package offset the effect of COVID19. It also observed that the Asian emerging market had been the highest impact, and emerging markets in Europe have a low hit from COVID19 (Topcua & Gulalb, 2020). The study related to the G7 countries emerging economies has been a negative effect on the stock markets. All G7 stock markets stated that the covid19 had affected the FTSE MIB most compared to the Nikkei 500. Due to the coronavirus, all the seven countries' financial markets are severe with high external debt (Pata, 2020).

5.2. Recommendation

Previous studies suggested that the standard deviation is given limited to the best performance measurement of the stock market's price moments. Statistically, the measure of volatility has defined the cross check-in between the different volatility estimation methods, which is equally essential for the diagnostic analysis of research data. Which will confirm the prediction of volatility in the future (Oyelami & Sambo, 2017). In this study, it has been proven that Yang-Zhang and Rogers-Satchell model recently developed a model of volatility that identified the more efficient analysis in the emerging stock market in the world. Finally, the results conclude that the COVID-19 outbreak has affected the emerging stock market indices, increased volatility, and affected the economy and financial system. This study provides original statistics of the COVID19 pandemic on emerging stock market indices. The coronavirus has demised the life of millions of people throughout the world, and significant challenges to the economy, unemployment, movement of the financial market unprecedented. Emerging market risk increases substantially in the response of the COVID19. Individual countries negatively reacted due to the pandemic. COVID19 overserved that GDP down has caused by a highly volatile market due to uncertainty. The respective government will take the policy amendment after seeking the nation's pandemic situation (Zhang, Hu, & Ji, 2020).

This study has witnessed that 64 countries of stock markets reacted more proactively to the growth of predicted numbers of cases than the change in the numbers of deaths. It depicts that adverse market reaction was strong in the initial 60 days of COVID19. The finding reveals that the stock market has a quick response to the pandemic; this response varies due to the depending on time of the COVID-19 (Ashrafa, 2020). The capital market operators, research analysts, stockbrokers, professional brokers, and sub-brokers have limited knowledge of volatility estimators; this study will help them identify open, high, low, and close (OHLC) for the analysis of their stock price. Therefore, the understanding of volatility of the price stock becomes pertinent. Hence, this paper seeks to demonstrate the volatility of indices, portfolios, and stock prices using the various volatility estimators' methods since investment decisions cannot be made worthless.

References

Ahoniemi, K., & Lanne, M. (2010). Realized volatility and overnight returns. Bank of Finland Research Discussion Papers, 19, 1-24.

Andersen, T. G., Dobrev, D., & Schaumburg, E. (2008). Duration-Based Volatility Estimation. Global COE Hi-Stat Discussion Paper Series, 08-034.

Andreou, E., & Ghysels, E. (2002). Rolling-Sample Volatility Estimators: Some New Theoretical, Simulation and Empirical Results. Journal of Business & Economic Statistics, 20(03), 363-376.

Ashrafa, B. N. (2020, December). Stock markets’ reaction to COVID-19: cases or fatalities? Research in International Business and Finance, 54. doi:https://doi.org/10.1016/j.ribaf.2020.101249

Aslam , F., Ferreira, P., Mughal, K. S., & Bashir , B. (2021). Intraday Volatility Spillovers among European Financial Markets during COVID-19. International Journal of Financial Studies, 9(1). doi:https://doi.org/10.3390/ijfs9010005.

Baek, S., Mohanty, S. K., & Glambosky, M. (2020, Nov). COVID-19 and stock market volatility: An industry level analysis. Elsevier Public Health Emergency Collection, 37, 12-23. doi:10.1016/j.frl.2020.101748.

Becker, T. (2020, April 15). Russia Economic Update — Brace for the Covid-19 Impact! Retrieved from https://freepolicybriefs.org/: https://freepolicybriefs.org/2020/04/15/russia-economic-covid-19-impact/

Bennett, C., & Gil, M. A. (2012, February 03). Measuring Historical Volatality. Santander: Global Banking and Markets, 1-13.

Bollerslev, T., Gibson, M., & Zhou, H. (2011). Dynamic Estimation of Volatility Risk Premia and Investor Risk Aversion from Option-Implied and Realized Volatilities. Journal of Econometrics, 160(1), 235-245.

Bora, D., & Basistha, D. (2020, August 14). The outbreak of COVID-19 pandemic and Its Impact on Stock Market, Research Square. doi:10.21203/rs.3.rs-57471/v1

Brandt, M. W., & Kinlay, J. (2003). Estimating Historical Volatality. Journal of Business & Economic Statistics, 146-153.

Breaking Down Finance. (2020, September 02). Parkinson-Volatility. Retrieved from https://breakingdownfinance.com: https://breakingdownfinance.com/finance-topics/riskmanagement/parkinson-volatility/

Khalifa, H. K. H., Al Tawalbeh, A., & Almoslmani, W. M. (2022). Covid-19 Pandemic and TV Shows: Social Responsibility in Forming the Massive Awareness as Perceived by the Bahraini Public. Journal of Hunan University Natural Sciences, 49(4).

Chou, R. Y., Chou , H., & Liu, N. (2002). Range Volatility Models and Their Applications in Finance. In Quantitative Finance and Risk Management (pp. 1273-1281). Taiwan: Springer.

Christensen , C. (2020). The Relative Industry Specific Effects of COVID-19 on Market Volatility and Liquidity. US: All Graduate Plan B and other Reports. Retrieved from https://digitalcommons.usu.edu/gradreports/1470

Cree, A. (2020). Intraday Volatility in the COVID Era: Why it Matters. US: https://flextrade.com. Retrieved from https://flextrade.com/intraday-volatility-in-thecovid-era-why-it-matters/

Duque, J., & Paxson, D. A. (1997). Empirical Evidence On Volatility Estimators. 1-38.

Euromonitor. (2020, 04 14). The Impact of Coronavirus in Brazil: Uneven Prospects Across Industries. Retrieved from https://blog.euromonitor.com/: https://blog.euromonitor.com/the-impact-of-coronavirus-in-brazil-uneven-prospectsacross-industries/

Feller, W. (1951). The Asymptotic Distribution of the Range of Sums of Independent Random Variables. Annals of Mathematical Statistics, 22, 427-432.

Figueroa-López, J. E., & Wu, B. (2020). Kernel Estimation of Spot Volatility with Microstructure Noise Using Pre-Averaging. Econometrics: Cornell University, 1-39.

Fontanills, G. A., & Gentile, T. (2003). The Volatality Course Workbook. New Jersey: John Wiley & Sons Inc.

Garman, M. B., & Klass, M. J. (1980). On the Estimation of Security Price Volatilities from Historical Data. The Journal of Business, 53(1), 67-78.

Gujarati, D. (2004). Basic of Econometrics (4th ed.). NewYork: McGraw-hill.

Harbourfront Technologies. (2020, April 30). Close-to-Close Historical Volatility Calculation. Retrieved from http://tech.harbourfronts.com/:
http://tech.harbourfronts.com/trading/close-close-historical-volatility-calculationvolatility-analysis-python/

Hawksworth, J., & Cookson, G. (2008). The World in 2050. England: Price WaterHouse Coopers.

Khalifa, H. K. H. (2022). A Conceptual Review on Heuristic Systematic Model in Mass Communication Studies. International Journal of Media and Mass Communication (IJMMC), 4(2), 164-175.

Jaresova, L. (2010). EWMA Historical Volatility Estimators. Acta University Carolinae – Mathematica ET Physica, 51(2), 17--28.

John Hawksworth. (2017). The World Economy in 2050. UK: Price Water Coopers .

John Summa. (2016). Option Volatility. Investopedia. Retrieved from http://www.investopedia.com/university/optionvolatility/default.asp

Khan, M. A., & Ahmad, E. (2019). Measurement of Investor Sentiment and Its Bi-Directional Contemporaneous and Lead–Lag Relationship with Returns: Evidence from Pakistan. Sustainability, 20.

Kim, T. K. (2015). T test as a parametric statistic. Korean Journal of Anesthesiology, 68(6), 540546.

Mcaleer, M., & Medeiros, M. C. (2008). Realised Volatality: A Review. Econometric Reviews, 27(1-3), 10–45.

Medeiros, O. R., Van Doornik, B. F., & Oliveira, G. R. (2011). Modeling and forecasting a firm’s financial statements with a VAR –VECM Model. Brazilian Business Review, 8(3), 20-39. doi:http://dx.doi.org/10.15728/bbr.2011.8.3.2

Mitchell , C., & Catalano, T. J. (2021, May 3). TRADING STRATEGIES. Retrieved from Rules for Picking Stocks When Intraday Trading: https://www.investopedia.com/daytrading/pick-stocks-intraday-trading/

Molnar, P. (2012, June). Properties of range-based volatility estimators. International Review of Financial Analysis, 23, 20-29.

Mühleisen, M., Gudmundsson, T., & Ward, H. P. (2020, August 06). COVID-19 Response in Emerging Market Economies: Conventional Policies and Beyond. Retrieved from https://blogs.imf.org/: https://blogs.imf.org/2020/08/06/covid-19-response-in-emergingmarket-economies-conventional-policies-and-beyond/

Oyelami, B. O., & Sambo, E. E. (2017). Comparative Analysis of Some Volatility Estimators:
An Application to Historical Data from the Nigerian Stock Exchange Market. International Journal of Computational and Theoretical Statistics, 13-35.

Parkinson, M. (1980). The Extreme Value Method for Estimating the Variance of the Rate of Return. The Journal of Business, 53(1), 61-65.

Pata, U. K. (2020, May). Is the COVID-19 Pandemic a Financial Disaster for G7 Countries? Evidence from a Fourier Cointegration Test. SSRN. doi:http://dx.doi.org/10.2139/ssrn.3603068

Perez-Gorozpe, J. M. (2020, May 26). Mexican Toll Roads Remain Vulnerable Amid COVID-19; Recovery Could Come Quickly As Restrictions Ease. Retrieved from https://www.spglobal.com/: https://www.spglobal.com/ratings/en/research/articles/200204-coronavirus-impact-keytakeaways-from-our-articles-11337257

Petnehazi, G., & Gall, J. (2018, March 19). Exploring the predictability of range-based volatility estimators using RNNs. Intelligents Systems in Accounting Finance & Management, 1-11. doi:arXiv:1803.07152v1 [q-fin.CP] March 19 2018

PwC Indonesia. (2020, APRIL 26). COVID-19: Considering the potential business impacts for Indonesia. Retrieved from https://www.pwc.com/: https://www.pwc.com/id/en/covid-19potential-business-impact-for-indonesia.html

Ravi, S. (2020, May 11). Impact Of COVID 19 On The Indian Stock Markets. Retrieved from http://www.businessworld.in/: http://www.businessworld.in/article/Impact-Of-COVID-19-On-The-Indian-Stock-Markets/11-05-2020-191755/

Rogers, L. G., & Satchell, S. (1994). Estimating the Volatility of Stock Prices: A Comparison of Methods That Use High and Low Prices. Applied Financial Economics, 4(3), 241-47.

Sharma, A. (2020, April 13). Coronavirus impact: India worst hit stock market; China leastaffected. Retrieved from https://www.businesstoday.in/: https://www.businesstoday.in/markets/stocks/coronavirus-impact-india-worst-hit-stockmarket-china-least-affected/story/400890.html

Khalifa, H. K. H. (2020). Media Dependency during COVID-19 Pandemic and Trust in Government: The Case of Bahrain. International Journal of Management, 11(11).

Shier, R. (2004). Statistics: Paired t-tests. UK: Mathematics Learning Support Centre. Retrieved from Paired t-tests: http://www.statstutor.ac.uk/resources/uploaded/paired-t-test.pdf

Shu, J., & Zhang, J. E. (2003, Jan). The Relationship Between Implied and Realized Volatility of S&P 500 Index. Wilmott magazine, 1, 83-91.

Sims, C. A. (1980). Macroeconomics and Reality. The Econometric Society, 48(1), 1-48.

Soczo , C. (2003, 2003). Estimation of Future Volatality. Periodica Polytechnica Ser. Soc. Man. SCI, 11(02), 201–214.

The World Bank Group. (2020, April 16). The World Bank in Turkey. Retrieved from https://www.worldbank.org/: https://www.worldbank.org/en/country/turkey/overview

Topcua, M., & Gulalb, O. S. (2020, July). The impact of COVID-19 on emerging stock markets. Finance Research Letters, 12-23. doi:https://doi.org/10.1016/j.frl.2020.101691

Thornton, P. (2006, March 03). New E7 nations will overtake G7 by 2050. Retrieved from https://www.independent.co.uk/:https://www.independent.co.uk/news/business/news/new-e7-nations-will-overtake-g7-by-2050-6107791.html

Vipul, & Jacob, J. (2007, Nov). Forecasting performance of extreme-value volatility estimators. The Journal of Future Markets, 27(11), 1085-1105. doi:10.1002/fut.20283

WHO. (2020). Coronavirus disease 2019 (COVID-19). World Health Organisation (WHO). Retrieved from https://www.who.int/docs/default-source/coronaviruse/situationreports/20200327-sitrep-67-covid-19.pdf?sfvrsn=b65f68eb_4

Yang, D., & Zhang, Q. (2000). Drift-Independent Volatility Estimation Based on High, Low, Open, and Close Prices. Journal of Business, 73(3), 477-491.

Yousef, I. (2020). Spillover of COVID-19: Impact on Stock Market Volatility. International Journal of Psychosocial Rehabilitation, 24(6), 18069-18081.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. Finance Research Letters. doi:https://doi.org/10.1016/j.frl.2020.101528