The Persistence of Volatility in Nifty 50

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Abstract

The market participants trade in the Nifty index to mitigate the risk, as trading in Nifty leads to wealth and exposes the market participants to external shocks. Normally, market participants disfavor volatility as it is a serious concern. So, volatility measures the magnitude of the information's impact on any index or stock. The unpredictability of external shock toward the market was a cause for concern because it had adverse effects on the market. The index values worldwide had been substantially sensitive to the external stock. With several factors contributing to the stock market's performance, distilling volatility is impossible. In addition, the COVID-19 pandemic was the starlight in fuelling the unpredictability in the security markets. The study empirically investigated the impact of events (shocks) on the Nifty 50 index. To achieve our objective, we applied the GARCH model for estimating the volatility of daily returns of the closing price of the Nifty 50 index from January 1, 2019 to December 15, 2021. A total of 732 observations were sourced from the NSE website and transformed into natural log returns for volatility pattern analysis. The findings revealed that the Indian secondary market had experienced unanticipated volatility during the study period. The shock was strong even when the positive information arrived. The existing negative information had a stronger hold over the market movement.

Keywords : COVID-19, GARCH, Nifty 50, shock, volatility

JEL Classification Codes : G10, G17, O16

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Volatility refers to rapid and unpredictable changes in an asset value or capital market indices. The term "volatility" relates to higher fluctuation and risk. The higher the volatility, the higher will be market turmoil. Volatility can designate the potency or genuineness behind a price move. The extent of fluctuation in stock prices is known as stock market volatility. Finding out when does market behaves more unpredictably is quite a tedious task as it is backed by various facets like political stability, global pandemics, economic fundamentals, government budget policies, corporate performance, and so on.

The COVID-19 global pandemic has rattled the stock markets across the world and also caused robust movements in the Indian stock markets. Governments worldwide ran from pillar to post without knowing where the chequered flag was waving. The economic disturbances and COVID-19 outbreak have severely affected the

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financial market. Nicolas Firzli (2020)[1] referred to the global pandemic as "the greater financial crisis and is bringing down many pent-up financial and geopolitical dysfunctions." As a result of the pandemic, the global financial market risk has grown significantly (Zhang et al., 2020). The stock bourses were in mayhem following the corona outbreak in Wuhan in December 2019. Azimli (2020) found out that due to the COVID-19 attack, investors could not enjoy the benefits of diversification, and increased uncertainty affected the required rate of return and the current market value of stocks. When WHO declared COVID-19 a pandemic, the financial markets became Black Swan whose impact may be deeper and longer on the economy. When the first nationwide lockdown in India was declared on March 22, 2020, the entire economic activities of the country came to a standstill. Global market fluctuations have provoked volatility in the Indian financial market (Raja Ram, 2020). As soon as the Janta Curfew (2020) was proclaimed, BSE SENSEX shed by 13.2%, and NSE Nifty slipped by 29% on March 23, 2020 (Bora & Basistha, 2021). These were the highest dip in the indices in a single day after the Harshad Mehta Scam (Mondal, 2020). The blood-shedding of the share market proved that no one could resist the rage of COVID-19. Nevertheless, as only the fittest could survive during financial anarchy, the Indian capital market survived the turmoil due to its positive growth rate in the past two decades prior to COVID-19 (Tulsian & Shrivastav, 2020).

Fractions of the capital market are volatile, which ignites the curiosity among the researchers to solve the volatility and to capture the magnitude of spread among the events. However, volatility is the inevitable element of the capital market, which makes it livelier. In other words, when market volatility is excessive, the market does not function efficiently, resulting in market turbulence — high volatility in the market and the turmoil of the market participant's ensembles as conjoint twins. The volatility in the stock market was first captured by Engle (1982), who observed the presence of an autoregressive influence in conditional variance and came up with the autoregressive conditional heteroscedasticity (ARCH) process. In order to capture the dynamic behavior of conditional variance among ARCH, Bollerslev (1986) presented a Generalized ARCH model as an extension of the ARCH model.

Review of Literature

The stock market behaves asymmetrically for the good and bad news spreading across different countries. Kanas (1998) proved this by analyzing the volatility spillovers across London, Frankfurt, and Paris stock markets using EGARCH. The impact of bad news in one market on the volatility of another market is larger than the impact of good news in another market. Ng (2000) found volatility spillovers from Japanese and US markets to Malaysia, Singapore, Taiwan, and Thailand. Kaur (2004) employed EGARCH models to prove the asymmetrical volatility movement in the stock market. The effect of desirable and terrible information is not equal to the volatility. There was a volatility spillover between India (Sensex and Nifty) and the US (NASDAQ and S&P 500) markets.

Raju and Ghosh (2004) identified that volatility in the Indian stock marketplace was much less compared to other global stock markets. The performance in the Indian inventory marketplace accelerated over the years, and intraday volatility was under control. Mavuluri and Boppana (2006) analyzed the relevance of transaction counts for the Indian stock market. Every five-minute intraday data for Nifty and Nifty Junior was used to analyze the influence of trading frequency on stock market volatility. Trading frequency has more impact on stock market volatility than market size. Mehta and Sharma (2011) examined the time-varying volatility of NSE. According to their findings, historical volatility has a more significant impact on current volatility. Moreover, conditional volatility assists investors in forecasting their returns from the equity market. To capture the influence of volatility on the Indian securities market, Rastogi and Srivastava (2011) used a time-varying variance-based GARCH approach. In conditional volatility, there was no significant co-movement in either market.

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https://signal2forex.com/2020/03/22/ecr-risk-experts-contemplate-another-financial-crisis/

Sakthivel et al. (2012) found that as two economies are tightly integrated through international trade and investment, a bivariate GARCH model indicated bidirectional volatility spillover between the US and Indian stock markets. In addition, there was a one-way volatility spillover from Japan and the United Kingdom to India. Singh (2017) found that the Indian stock market's volatility is significantly higher than that of the major developed and emerging stock markets. Models from the ARCH family outperform OLS models. The TARCH model fits better than the other models based on AIC and SC criteria.

Cepoi (2020) analyzed the relationship between COVID-19-related news and stock market returns. According to the pane quantile regression, the stock market has asymmetric dependence on COVID-19-related information. Therefore, authenticated information through strong media channels has to spread to reduce the financial problems created by COVID-19. Ozili and Arun (2020) found that lockdown, monetary policy, and international travel restrictions had a negative impact on economic activity and increased the volatility of major stock market indices. In addition, the increase in COVID-19 cases and death rates increased the global inflation rate, unemployment rate, and energy commodity index.

Shehzad et al. (2020) applied the asymmetric power GARCH model and proved that COVID-19 had affected the US and Japan's market returns. However, the Asian markets were able to make better prospects due to their portfolio optimization. Hence, European and US markets were more affected by COVID-19 than Asian markets. Bora and Basistha (2021) studied the influence of COVID-19 on stock market volatility in India using the GARCH model. According to the study, the Indian stock market exhibited substantial volatility during the pandemic. The indices returned more during the pre-COVID-19 period than during COVID-19.

Dey and Brown (2021) examined the performance of BSE & NSE amid the COVID-19 pandemic in India from the beginning until the end of the first wave. The moving average method was used to measure the volatility of the stock markets. The results showed that the stock markets experienced high volatility during the peak pandemic period and recovered from unsteadiness with reduced volatility after the lockdown was lifted. Faniband and Faniband (2021) analyzed volatility spillover between bonds issued by the Government of India and Nifty using GARCH. The broad total return index of Clearing Corporation of India Limited did not Granger cause Nifty, but vice-versa was not true. The volatility in Nifty did not influence volatility in the broad total return index.

Prakash (2021) analyzed the impact of oil & gold prices, foreign exchange reserves, foreign institutional investment, and balance of payments on Nifty. The study revealed that except for oil prices, no other mentioned factors had any relationship with the movement of NIFTY. Vevek and Selvam (2021) studied the volatility in Nifty by employing various GARCH family models and provided empirical evidence on conditional volatility. The study period was from January 2006 to October 2017. The study revealed that the EGARCH (1,1) model was the best fit for capturing volatility.

Saud et al. (2022) proposed that Aroon Indicators help investors identify the buying and selling points of stocks. As a result, the investors can generate a 3.91% to 40.07% greater annual rate of return if they adopt Aroon Indicators. In addition, the proposed trading method was a better and safer trading mechanism than the classical technique. Lakshmanasamy (2022) examined the volatility relationship between oil prices, foreign exchange rates, and BSE SENSEX in India. Using GARCH Model, the author found that volatility and volatility spillovers in oil and exchange rates cause volatility in BSE SENSEX. In addition, the internal shocks of the stock market also triggered volatility in BSE SENSEX.

Objective of the Study

The main aim of the research is to probe the persistence of volatility of Nifty returns in the Indian stock market by adopting different models of the GARCH family.

Research Methodology

The research paper was an analytical study focused on finding the prolonged existence of volatility in Nifty 50. For the study, Nifty index daily closing value data are sourced from the NSE website (https://www.nseindia.com/). The Nifty index value is a weighted index calculated using top performing 50 equity stocks already listed in NSE. The study was entirely based on secondary data sourced from NSE from January 1, 2019 to December 15, 2021. A total of 732 observations were transformed into natural log returns.

$$\textit{Nifty return (LRN)} = \ln (P_t / P_{t-1}) \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where, *LRN* is the daily natural log return of the Nifty index, P_t is the present value of *LRN*, and P_{t-1} is the previous day value of *LRN*. As a result of using natural logarithm, the mean and variance of the lower frequency data are easier to derive from higher frequency data.

The ARCH (1) and GARCH (1, 1) models were employed in this study via EViews 9 software to measure Nifty 50 index volatility. The generalized autoregressive conditional heteroscedasticity is known as the GARCH (1, 1) model, proposed by Engle (1982). GARCH is used to capture the volatility clustering among the squared residuals. Bollerslev (1986) used the GARCH model to troubleshoot the problem with high ARCH orders.

Analysis and Results

Table 1 exhibits the descriptive statistics of the Nifty index return series. The average return over the study period is 0.06%. The standard deviation is 1.39%, reflecting a high level of volatility in the Nifty index return. The wide-ranging gap between the maximum (0.084003) and minimum (–0.139038) supports the high variability of price change in the Nifty index. Jarque–Bera value is 13218 with significance at 1% level, which denotes 13218 deviations from the normal distribution. Therefore, the normal distribution null hypothesis in Jarque-Bera should be zero. Negative skewness (–1.724503) showcases that the distribution has a longer left tail and deviates entirely from normality. Naturally, positive or negative skewness implies the presence of asymmetry in the series. Likewise, if the kurtosis value is greater or lesser than 3, it indicates the peaked or flatness of the series. The kurtosis value is 23.53016, which is highly peaked and does not follow the rule of normal distribution. Overall, the descriptive statistics of the Nifty return series have negative skewness and leptokurtic distribution (highly peaked kurtosis); hence, the series has an asymmetric distribution, creating uncertainty in the prediction and price discovery process.

Figure 1 presents the natural log data of the Nifty return series for 732 observations starting from January 1, 2019 to December 15, 2021. In Figure 1, the Nifty 50 return series have volatility clustering, which means high volatility is followed by a high and low is followed by a low. So, the graph represents the series as highly volatile with rough and tranquil periods.

Table 1. ***Descriptive Summary of Daily Nifty 50 Return Series (LRN)***

Mean	0.000624	Min.	–0.139038	Kurtosis	23.53016
Std.	0.013902	Max.	0.084003	Skewness	–1.724503
Median	0.001284	Jarque–Bera	13218.19*	Observations	732

Source: Constructed value from EViews 9. After analyzing the daily log return of Nifty 50 (LRN), the above numerical values have been considered. Data extracted from www.nseindia.com.

Note. ***, **, & * denote 10%, 5%, & 1% significance levels.

Figure 1. *Line Plot of LRN Daily Return Series*

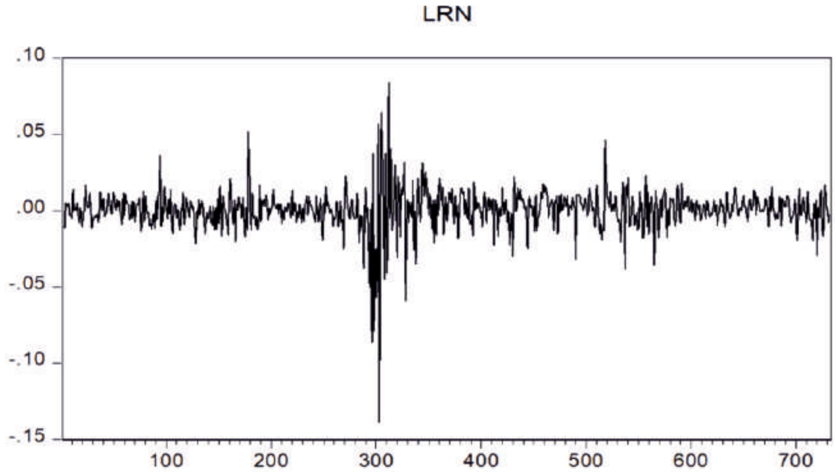

Table 2. ***Results of Augmented Dickey-Fuller (ADF) Unit Root Test***

Value	ADF.	Critical Value	
t-statistics	–8.734424	1% level	–3.439142
Probability	0.000	5% level	–2.865310
		10% level	–2.568834

Source : Constructed value from Eviews 9. The above numerical values have been considered after analyzing the daily return of Nifty (LRN). Data extracted from www.nseindia.com.

Table 2 showcases the ADF unit root test. This test is performed to capture the presence of unit root in the daily Nifty 50 return series. The *p*-value of the ADF test is below 0.05. Hence, the test output is that the series was stationary at the level.

Table 3 is the output of the least square regression of lagged Nifty return with a constant, one-day lagged return, AR, MA and ARMA, LRNARMA. The second column explains the regression equation of LRN C, and the result displays that the constant (alpha variable) has no significant impact on LRN. So, the test failed to reject the H_0. Regression's null hypothesis (H_0) is there is no impact on LRN by constant. The third column's result displays the regression equation of LRN C LRN (–1). The constant does not have a significant impact. Still, the LRN (–1) has a negative (–0.072) influence at a 1% significant level, which explains that one-day lagged Nifty return (previous day) is influencing the Nifty (present-day). The fourth and fifth columns display the equation of LRN C AR (1) and LRN C MA (1), the result is a negative influence of AR (1), and MA (1) is significant at 1%. The model AR (1) is a one-day lagged autoregressive, and the model MA (1) is a one-day lagged moving average term of Nifty return. The sixth column reveals the regression equation of LRN CARMA (1, 1), and the result displays that constant (alpha variable) and ARMA (1, 1) have no significant impact on LRN. So, the test failed to reject the H_0.

Regression's null hypothesis (H_0) is that constant and ARMA (1, 1) have no impact on LRN. The seventh column shows the result of regression equation LRN CARMA (2, 1), and the result displays that constant (alpha variable) has no significant impact, but ARMA (1, 1) has a significant impact on LRN at a 5% level. So, H_0 is rejected. Regression's null hypothesis (H_0) is that constant and ARMA (2, 1) have no impact on LRN. The final and eighth column reveals the regression equation LRN C LEN (–1) ARMA (1, 1); the result exhibits the existence of significant influence at a 1% level of LEN (–1) ARMA (1, 1) on LRN. So, H_0 is rejected. Regression's

Table 3. *Fitting Regression Model and Testing for Heteroscedasticity*

LRN	C	LRN (–1)	AR (1)	MA (1)	ARMA (1,1)	ARMA (2,1)	LRN-ARMA (–1,1,1)
C	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006
LRN (–1)		–0.072***					–0.091*
AR (1)			–0.072*		–0.247	0.030**	–0.966*
MA (1)				–0.068*	0.175	–0.071***	0.997*
AIC	–5.712	–5.714	–5.712	–5.712	–5.709	–5.709	–5.718
SIC	–5.706	–5.701	–5.569	–5.594	–5.684	–5.684	–5.686
HQC	–5.710	–5.709	–5.704	–5.598	–5.699	–5.700	–5.705
LRN ARMA (–1,1,1) Engle's ARCH-LM Test for Heteroscedasticity							
ARCH-LM test *F*- statistics		16.445			Prob. *F* (1,728)	0.0001	
Observed *R*-square		6.127			Probability χ^2 (1)	0.0001	

Source : Constructed value from Eviews 9. The above numerical value has been considered after analyzing the daily return of Nifty 50 (RNIF). Data extracted from www.nseindia.com.

Note. ***, **, & * denotes 10%, 5%, & 1% significance levels.

LRN is Nifty return, C is constant, LRN (–1) is lagged Nifty return (Previous days RNIF), AR is autoregressive, MA is moving average, Engle's ARCH-LM test is ARCH–Lagrange Multiplier test, HQC is Hannan – Quinn criterion, SIC is Schwarz information criterion, ARMA is the autoregressive moving average. AIC is Akaike information criterion, and χ^2 is chi-square.

null hypothesis (H_0) is that there is no impact on LRN by constant and LEN (–1) ARMA (1, 1). Among the estimated regression models, LRN-ARMA (–1, 1, 1) has the lowest AIC (–5.718), SIC (–5.686), and HQC (–5.705). The AIC, SIC, and HQC are used for fitting an appropriate model for forecasting the Nifty (the lowest is the best model). Even though LRN-ARMA (–1, 1, 1) model is identified as the best-fitted regression model, it still suffers from the ARCH effect. In order to confirm the volatility clustering, the ARCH test is applied to the regressed model LRN C LEN (–1) ARMA (1, 1). The ARCH-LM test result is clear that the *p*-value is 0.00, which is less than 1%. It shows the existence of the ARCH effect. It means the presence of volatility clustering in the return series of Nifty can be confirmed, and ARCH family models like GARCH models can be implemented in the present study.

Figure 2. *Residual Distribution of LRN-ARMA (–1, 1, 1) Model*

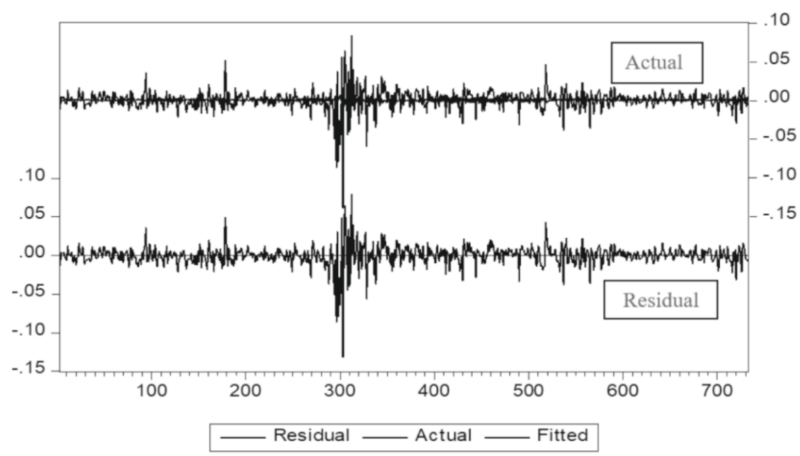

Table 4. ***Results of ARCH (1) and GARCH (1, 1) Models***

Coefficients	ARCH (1)	GARCH (1, 1)
Mean		
μ (constant)	0.001*	0.000*
LRN (–1)	–0.657*	–0.0904
AR (1)	0.175*	–0.0835
MA (1)	0.565*	0.1863
Variance		
ω (constant)	0.000*	–0.000*
α (ARCH effect)	0.171*	0.149*
β (GARCH effect)	–	0.599*
α + β	0.171	0.748
Log-likelihood	2179.99	2276.655
AIC	–5.956	–6.218
SIC	–5.918	–6.174
ARCH-LM test for heteroscedasticity		
ARCH-LM test stat.	2.559	0.001
Probability χ^2 (1) Chi-square	0.110	0.964

Source : Constructed value from Eviews 9. The above numerical value has been considered after analyzing the daily return of Nifty 50 (LRN). Data extracted from www.nseindia.com.

Note. ***, **, & * denotes 10%, 5%, & 1% significance levels.

Figure 2 shows the plotted residual distribution of fitted model regression equation LRN C LEN (–1) ARMA (1, 1) from January 1, 2019 to December 15, 2021, a total of 732 observations. Clustering volatility is a sequence of low or high volatility following low or high.

The results of ARCH (1) and GARCH (1, 1) for the fitted model are shown in Table 4. The second column reveals the parameter of ARCH (1) is statistically significant at a 1% level. The coefficients of the equation constant (ω), ARCH term (α) 0.171 are significant at a 1% level. The ARCH term in the variance equation reveals the information absorption in the market, which is the information about the news or an event prevailing in the market. The mean equation parameter LRN (–1) is negative, and AR (1) and MA (1) are positive and significant at a 1% level; this output shows that there is a positive impact in the long run.

ARCH (1) Variance equation of LRN C LEN (–1) ARMA (1, 1).

$$\sigma_t^2 = \omega + \alpha\varepsilon^2_{t-1} \qquad \ldots\ldots\ (1)$$

The third column reveals GARCH (1, 1) model is statistically significant at a 1% level. To put it simply, the coefficients viz., GARCH term (β), ARCH term (α), and constant (ω) are significant at a 1% level. Moreover, conditional variance equation (GARCH), the estimated β (0.599) coefficient is greater than the α (0.149) coefficient, revealing market has persistent memory. Therefore, existing information prevails and influences the market more than new, recent, or sensitive market information.

The sum of coefficients of the parameter in the GARCH (1, 1) model is α + β, and its value is 0.748. The sum is close to one (1), which means conditional variance shocks are highly persistent, and the negative impact is stronger. Even if the positive information floods, the market remains in a bearish trend. The mean equation parameters LRN (–1), AR (1), and MA (1) have no significant impact.

ARCH-LM test has been used to check the ARCH effect in residuals on ARCH (1) and GARCH (1, 1) models. The results are less than the probability value (0.05), which guides the conclusion that the null hypothesis of "no ARCH effect" is acknowledged for both the ARCH (1) model and the GARCH (1, 1) model. With respect to this, the test statistics also do not support any additional ARCH effect remaining in the residuals of the ARCH (1) and GARCH (1,1) models. This implies the variance equation is well specified for the Nifty return series. Hence, both models are free from the ARCH effect, but the GARCH (1, 1) model is the most desirable fit model compared to the ARCH (1) model. The adequacy of the best model fit can be identified through the AIC and SIC. Therefore, the model should have the least (minimum) AIC and SIC values to find the most desirable model.

GARCH (1, 1) Variance equation of LRN C LEN (–1) ARMA (1, 1) :

$$\sigma_t^2 = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \qquad \ldots\ldots \ (2)$$

Conclusion and Implications

The instability of an economy can be measured using the Nifty 50, which has been accelerated by trade shocks and other anticipated and unanticipated anomalies. The trade-in secondary equity market continues to make a wide range of speculation despite investors, either institutional investors or retail, raising their concerns during times of volatility because of shocks. However, putting a ceiling on market volatility may be counterproductive to keep the market stable. Such protected market volatility has a greater positive effect on investors. Volatile markets have always been a cause of concern among market participants. The Nifty 50 index acts as a barometer for investors. Therefore, a long-term understanding of trends in Nifty 50's return and measuring volatility is vital as the results offer investors insights into the market's fluctuation. Hence, the study focused on identifying the existence of volatility in the Nifty 50's daily return.

In view of this, volatility clustering has been found by employing the GARCH (1,1) equation corresponding to the daily value of Nifty. The study's findings reveal that the shock is persistent and strong over the study period. It is also found that even when new or positive information arrives, the existing negative information has a stronger hold over the market movement. Therefore, measuring the persistence of volatility in NIFTY, a sensitive index of NSE, helps market participants in the secondary market to decide whether there is good or bad news. This research article implies that the stock market and volatility are conjoint twins. Negative volatility is more persistent than positive volatility. In the stock market, volatility is inevitable, and it is the one that makes the market lively.

Limitations of the Study and Scope for Further Research

The following are the limitations of the study :

(1) This study is limited to 732 observations of the Nifty 50 index.

(2) This study is confined only to the GARCH model of the GARCH family.

The following are the scope for further research :

(1) This study can be extended to different indices.

(2) The research can be extended by identifying the factors causing the clustering volatility.

Authors' Contribution

Mr. S. Vevek developed the idea for this paper and framed the research design for it. Dr. S. Sivaprakkash extracted the relevant research papers and prepared the review of literature. Dr. M. Selvam verified the analytical methods and supervised the study. The data were extracted from relevant sources by Mr. S. Vevek, which Dr. M. Selvam approved. The analyses and interpretations of the data were made by Mr. S. Vevek using EViews 9. Finally, Dr. S. Sivaprakkash wrote the entire manuscript in consultation with both authors.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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