Stock Market Volatility Due to Cross-Listing of Tradable Assets

Aditya Keshari [1]
Amit Gautam [2]

Abstract

Purpose : The study analyzed the return and volatility spillover among the Indian and overseas stock markets, namely Luxembourg, the United States, and the United Kingdom, where the assets are cross-listed. The increased worry of investors, regulators, and dealers about stock market volatility produced by worldwide integrated stock trading has focused on the symmetric and asymmetric volatility caused by the cross-listing of tradable assets that has damaged the domestic stock market.

Methodology : The analysis for the study incorporated the longitudinal time series of daily closing prices from January 01, 2011, to December 31, 2021, of the sample indices taken from the Bloomberg terminal. The study used GARCH, EGARCH, and PARCH models to analyze the return and volatility spillover among the Indian and cross-listed stock markets.

Findings : The findings indicated that prior index return volatility was significant and impacted current index return volatility. The findings also suggested that volatility exhibited asymmetric behavior, with positive shocks to volatility having different impacts than adverse shocks. The Luxembourg Stock Exchange was negligible in all models, implying it is exogenous.

Practical Implications : It was suggested that investors use information from another market to forecast the behavior of one market. The current analysis supported this assumption by demonstrating the market dominance of the United States. By focusing on market activity in the United States, preventative measures could be taken to minimize worldwide shocks.

Originality : The present study incorporated the impact of cross-listing of tradable assets and volatility, which was yet to be investigated earlier despite cross-listing being an essential aspect of the spillover effect.

Keywords : cross-listing, spillover effect, stock market volatility, tradable assets

JEL Classification : C32, C58, D53, F36

Paper Submission Date : October 5, 2022 ; Paper sent back for Revision : June 26, 2023 ; Paper Acceptance Date : July 10, 2023 ; Paper Published Online : September 15, 2023

The growing integration of the world market in the last two decades became crucial in terms of technological exchange, better political relations, and increased flow of capital across borders. It also promoted the Indian multinational firms to raise capital from foreign markets in the form of American depository receipts (ADR) and Global depositary receipts (GDR) to decrease their cost of equity (El Hedi Arouri et al., 2013; Errunza & Miller, 2000). As the stock market of developed countries is saturated, it helps companies raise capital at less cost and gives them an alternate market for raising capital (Dikshita & Singh, 2019). ADR and GDR are crucial factors in the volatility spillover effect (Upadhyay, 2016). These cross-listed assets provide an opportunity for domestic companies to raise capital from the developed foreign market, which helps reduce their

[1] *Doctoral Fellow (Corresponding Author),* Institute of Management Studies, Banaras Hindu University, Lanka, Varanasi - 221 005, Uttar Pradesh. (Email : adityakeshari@fmsbhu.ac.in)

[2] *Professor,* Institute of Management Studies, Banaras Hindu University, Lanka, Varanasi - 221 005, Uttar Pradesh. (Email : amitgautam@fmsbhu.ac.in)

DOI : https://doi.org/10.17010/ijf/2023/v17i9/173184

cost of capital and gives investors benefits for portfolio diversification in the form of more options for investing. Cross-listing assets result in the spillover effect over the domestic markets from the foreign markets (Alpanda & Kabaca, 2020; Li, 2019). As a result, it becomes vital to assess the impact of volatility spillover on the Indian market arising from cross-listed assets to foreign exchanges formally known as ADRs and GDRs. These tradable assets pose a spillover effect on the nations from where the assets are being cross-listed to foreign stock markets (Dou & Verdelhan, 2015). Investors, policymakers, traders, and marketers expressed concern about the stock market's volatility, a consequence of the onset of global integrated stock trading. Earlier research provides, by far, the most alternatives for solving the issue. However, the evidence to date is inconclusive as to whether the trading of cross-listed assets is accompanied by volatility spillover; however, managing it can aid in reducing volatility spillover. So far, the evidence suggests that the volatility of return rates on the NASDAQ, London Stock Exchange, and Nifty indices have yet to be investigated in terms of cross-listing and addressing the issue will aid in adequately managing the investors' portfolios, and the present study will assist in managing the factors responsible for global portfolios.

Justification of the Study

The volatility spillover effect is a widely accepted phenomenon in financial dynamics and has received special attention from researchers in recent years due to a succession of international events that have caused turmoil in the system (Chun et al., 2020). Several studies have focused on the issue of the COVID-19 impact (Baek et al., 2020; Bakry et al., 2022; Gherghina et al., 2021; Kusumahadi & Permana, 2021; Li et al., 2022; Onali, 2020; Uddin et al., 2021), rising crude oil prices (Liu et al., 2023; Tang et al., 2021), economic and political unpredictability (Chun et al., 2020; Li et al., 2020; Liang et al., 2020), and the governments' shifting emphasis on climate risk and climate policies (Haritha & Rishad, 2020; Lv & Li, 2023). Researchers consider volatility management a measure to mitigate risk while making investment and trading decisions. In the asset pricing literature, returns and volatility are the primary components that characterize the fundamental aspects of cross-listed assets, and better management of volatility will result in more accurate asset valuation (Khanna & Kumar, 2020; Singh & Kaur, 2015). Since volatility dynamics are related to risk diversification and hedging, market practitioners and investors treat it carefully (Mishra, 2019; Slivka et al., 2015). Cross-listing of tradable assets and volatility is yet to be investigated despite cross-listing being an essential aspect of financial research. Consequently, the study emphasizes the symmetric and asymmetric volatility caused by cross-listing tradable assets that affect the domestic stock market. Thus, the following objectives were formed for further investigation:

- ***RO1 :*** To investigate the volatility effect of cross-listed foreign markets on the domestic stock exchange.
- ***RO2 :*** To examine the modeling of asymmetric volatility spillover using the GARCH, EGARCH, and PARCH models.

Literature Review

Stock Market Volatility

In the literature, Su (2010) studied the differences in market return volatility between the stock exchange of China and other stock exchanges using daily data spanning 10 years. According to the GARCH and EGARCH models, the EGARCH model outperforms the GARCH model in simulating volatility during the sample period. Idrees et al. (2019) investigated the volatility of stock trends and developed an innovative approach to predict the stocks that give higher returns. Nandy and Chattopadhyay (2019) estimated the spillover effect on the United States, Indian, and Japanese markets by applying the DCC-MV-TARCH for 16 years. They found significant differential spillovers seen between the Indian stock market and international stock markets. Also, they aimed to maximize the investors' return by minimizing the associated returns.

Forecasting in financial dynamics is considered cumbersome work, so they tried to incorporate the ARIMA model for forecasting the nonlinear stochastic pattern of significant stock market indices like Sensex and Nifty. Haritha and Rishad (2020) in their study investigated the significance of irrational investor attitudes in determining stock market volatility by examining the link between investors' attitudes with volatility in the stock market. They used the GARCH and Granger causality frameworks on monthly market-related indices data. According to their findings, asymmetrical characteristics of investor sentiment contributed to the excess volatility and returns of the market indices. Onali (2020) examined the return volatility among the six Asian countries and found a significant implied volatility impact among these nations. Gherghina et al. (2021) evaluated the volatility of the Romanian stock market utilizing daily data from January 2020 to April 2021 in their study. To simulate volatility, they employed a GARCH MIDAS regime-switching model. They used a regime-switching model of GARCH MIDAS to simulate the volatility. Their findings indicated that conditional volatility of daily return showed evidence of volatility shifting, which increased over the period due to the COVID-19 impact. Nammouri et al. (2022) investigated the contagion impact across the nations and how they may be recovered from shocks. They recommended that forecasting price fluctuations using the GARCH model will enhance portfolio diversification. As a result, the available literature review is used to develop the following null hypothesis:

➭ **H01 :** There is no asymmetric volatility arising from cross-listed stock markets on the Indian stock market.

Indian Stock Market

Mukherjee and Mishra (2010) investigated the dynamic links between the stock markets of India and other Asian countries and discovered a significant and reciprocal spillover impact between the countries. Yilmaz (2010) examined the contagion and interdependence among India's stock market and other East Asian countries, where a substantial difference between volatility spillover occurred among the indices over time. Several researchers, including the study, have established the spillover impact consistent with the Indian stock market with other international markets. Joshi (2011) used the GARCH-BEKK model to study the bidirectional shock and volatility spillover across Asian stock markets and discovered evidence of spillover effect phenomena. Jebran and Iqbal (2016a) examined volatility spillover among India, Japan, Pakistan, Sri Lanka, China, and Hong Kong by applying the EGARCH model. They found the bidirectional asymmetric volatility spillover effect between India and other foreign exchange markets.

Kumar et al. (2019) applied the MGARCH model to analyze the spillover effect of the energy stocks and hedging ratios procedure on the Indian stock market. It was discovered that the energy stocks and hedging ratios were interconnected and had a bidirectional volatility spillover impact with the Indian stock market.

By employing the GARCH model, this paper examines the volatility spillover between the Nifty stock market in India and the NASDAQ, FTSE, and LUXX stock markets in the UK, United States, and Luxembourg, where the assets are being listed. The present research is distinct from earlier studies, emphasizing cross-listing, a crucial factor in volatility spillover. The study was expanded to include the EGARCH and PARCH models to offer a comprehensive overview and comparative analysis of the asymmetric volatility spillover among nations. As a result, it leads to the creation of the following hypothesis:

➭ **H02 :** There is no volatility spillover effect from the cross-listed foreign stock markets on the Indian stock market.

Methodology

The present study employs a descriptive research design to investigate the volatility relationship. This design allows us to describe, analyze, and interpret the concerned phenomenon, including the stock market volatility due to the cross-listing of stocks (Myers et al., 2010). Using the GARCH family model, a well-known econometric framework for quantifying and predicting volatility is intended to evaluate the relationship between cross-listing activities and market volatility. The GARCH model enables us to analyze the time-varying character of volatility, incorporating both the short- and long-term effects of cross-listing on the stock market's volatility (Kumar & Khanna, 2018; Varughese & Mathew, 2017). By integrating descriptive research with quantitative analysis, the study aims to provide an extensive overview of the volatility patterns associated with cross-listing tradable assets. It resulted in answering the following research questions related to the study:

(1) Is there any volatility spillover effect of the selected financial market over the Indian market due to cross-listing?

(2) Which among the GARCH, EGARCH, and PGARCH models does the asymmetric volatility spillover in a better way?

Data

The analysis for the study has incorporated the longitudinal time series of daily closing prices of the sample indices, spanning from January 01, 2011, to December 31, 2021. The extended duration of 10 years or more has been chosen as it aligns with previous studies that have established it as a suitable period for capturing the genuine depiction of volatility spillover in the sample (Nandy & Chattopadhyay, 2019). Thus, a specific period has been diligently included in the study. The stock market indices NIFTY50, NASDAQ, FTSE_AIM100, and LUXX100 are taken as a proxy of the included countries, i.e., India, the US, the UK, and Luxembourg, respectively, and their daily closing prices were retrieved from the Bloomberg database. All price indices were transformed into return series to circumvent the currency exchange dilemma. EViews 12 has been used for the analysis. The returns were calculated using the formula:

$$R_t = \log(P_0/P(-1))*100 \tag{1}$$

It is estimated that the stock market series must adhere to stationarity to maintain their long-term relationship. Augmented Dickey–Fuller (ADF) and Phillip and Perron (PP) tests are being used to check the stationarity of the data for estimating the long-run relationship among the time series.

ADF test:

$$Dx_t = a_0 + a_1 x_{t-1} + \sum\nolimits_{j=1}^{m} b_j\ Dx_{t-j} + v_t \tag{2}$$

PP test:

$$y_t = b_0 + b_1 y_{t-1} + u_t \tag{3}$$

The GARCH (1, 1) Model

The GARCH model permits the conditional variance to be dependent on its antecedent latencies, like as whether the basic GARCH (1,1) formulation is employed to initiate the conditional deviations.

$$Y_t = X'_t \theta + \varepsilon_t \quad (4)$$

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \quad (5)$$

The mean $\alpha\varepsilon^2_{t-1}$ in equation (5) is written as a function of exogenous variables and contains an error term. Based on previous evidence, the one-period forward forecasting variation is termed as conditional deviations, and the notation σ^2_t represents it.

It may be easier to understand the model if one of these two possible formulations of a variance equation is being used:

The conditional variance may be defined as the weights assigned to the summation of the lagged values of their residual square if we iteratively replace its lags on the right-hand side.

$$\sigma^2_t = \frac{\omega}{(1-\beta)} + \alpha \sum\nolimits_{j=1}^{\infty} \beta^{j-1} \varepsilon^2_{t-j} \quad (6)$$

It can be observed that the variance occurring in the equation for the sample period is equivalent to the GARCH (1,1) variance formulation, which down-weights more significant proximal latent squared errors. The model is then defined in the error components via changing its variances in the given variance equation and re-arranging variables to get the error in the squared returns:

$$\varepsilon^2_t = \omega + (\alpha + \beta)\,\varepsilon^2_{t-1} + v_t - \beta v_{t-1} \quad (7)$$

Exponential GARCH Model

Nelson proposed the EGARCH model in 1991. Using the conditional variance framework, it is presented as follows:

$$\log(\sigma^2_t) = \omega + \sum\nolimits_{j=1}^{\rho} \beta_j \log(\sigma^2_{t-j}) + \sum\nolimits_{i=1}^{\rho} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum\nolimits_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \quad (8)$$

Taking into account the conditional variance's log on the left-hand side gives conditional variance predictions, which are sure to be nonnegative, and the leveraging impact is exponential rather than quadratic. The assumption that $yi < 0$ may be used to assess if leverage effects are present. If $yi > 0$, the influence is asymmetric.

PARCH

The conditional variance equation comprises PARCH (a,b,c). It reflects the linear formula: Generalized GARCH variance sequence for PARCH model provides the order to ARCH term a, GARCH term b, and asymmetry c.

$$(\sigma_t)\ \dot{\theta} = \omega + \sum\nolimits_{j=1}^{b} \alpha_i |\varepsilon_{t-i}| \theta + \sum\nolimits_{l=1}^{K} \lambda\, 1X_{l,t} \quad (9)$$

Data Analysis and Results

Descriptive Statistics

Table 1 presents the descriptive statistics of stock returns from different indices, including mean, median, skewness, kurtosis, Jarque–Bera statistics, and probability value. Kurtosis analyses whether the data peaks or is

Table 1. ***Summary Statistics for Stock Returns***

	RNIFTY	*RNASDAQ*	*RLUXX*	*RFTSE*
Mean	0.0380	0.0641	0.0032	0.0257
Median	0.5960	0.1114	0.0000	0.0069
Maximum	8.4002	8.9349	7.5381	8.0387
Minimum	–13.9037	–13.1492	–9.7440	–9.8201
Std. Dev.	1.1000	1.2211	1.3275	1.0145
Skewness	–1.0195	–0.8164	–0.3626	–0.8616
Kurtosis	18.1793	14.3103	7.0188	14.6781
Jarque–Bera	266623.73	14822.06	1892.857	15816.1
Probability	(0.000)	(0.000)	(0.000)	(0.000)
Sum	103.6139	174.7387	8.7273	70.0214
Sum Sq. Dev.	3295.063	4060.638	4798.892	2803.029
Observations	2,724	2,724	2,724	2,724

flat concerning the normal distribution. In contrast, skewness quantifies the probability distribution's divergence on either side of the mean, as it is clear from the skewness value that the return from these indices is negatively skewed, which indicates that these countries have longer and fatter tails on the left side of the probability density function (Singh & Gautam, 2022). Furthermore, the kurtosis value exhibits that returns from these indices follow the leptokurtic distribution. One of the reasons for leptokurtic distribution is the presence of extreme importance in a series. So, the tails are flatter and have a more extended distribution. With these properties, it is confirmed that the series does not follow the normal distribution, which is also confirmed by the Jarque–Bera statistics for normal distribution as the p-value is less than 0.005 at the 1% level. So, the null hypothesis cannot be accepted, and the rejection means that the series does not follow the normal distribution. Thus, it shows the inefficiency of the stock market.

Application of the GARCH model is the subject of fulfilling the two criteria, namely:

- Series must follow the stationarity of the same order.
- Series should show the sign of volatility clustering, i.e., small shocks follow small shocks, and big shocks follow big ones.

Figure 1 shows the volatility clustering of these stock indices, which shows the occurrence of shocks in order and follows the pattern of small shocks in continuation with small shocks, and big shocks follow the big shocks by these indices.

Unit Root Test

The next step of our study is to assess whether or not our data exhibits stationarity. It is crucial to ensure that our variables remain stationary. Ensuring the stationarity of a series is necessary because the nonstationary series will give inaccurate results.

The findings in Table 2 imply that all indices reflecting various indicators are nonstationary at the level. The ADF and PP tests show that the data set is asymmetric at the intercept and trend levels. Table 3 shows that the series reached a standstill following the first set of deviations. As a result, the selected stock market data are integrated into the first order, often known as the $I(1)$ process.

Figure 1. ***Volatility Clustering of Stock Markets***

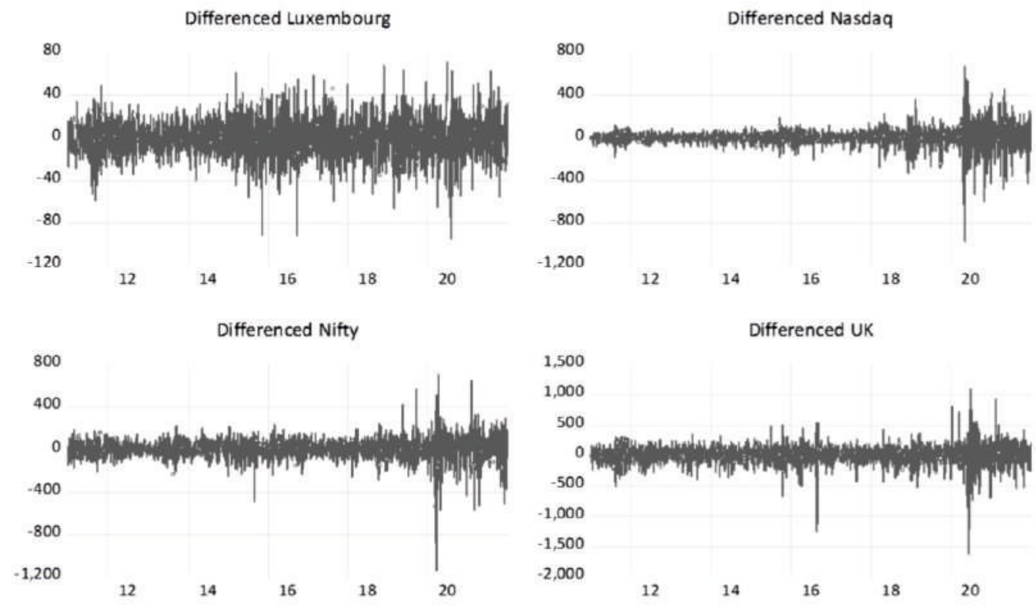

Table 2. ***Level Series***

Hypothesis : Time Series has a unit root.		
Index	**Augmented Dickey–Fuller**	**Phillip and Perron**
Nifty	1.054476(0.9972)	0.971228(0.9964)
Nasdaq	2.035384(0.999)	2.343980(1.00)
Luxembourg	–2.050123(0.2654)	–2.045536(0.2674)
UK	–1.046792(0.7384)	–1.027045(0.7456)

Table 3. ***Series at First Difference***

Index	**Augmented Dickey–Fuller**	**Phillip and Perron**
Nifty	–18.62645(0.0000)	–51.03980(0.0001
Nasdaq	–16.57(0.000)	–60.28092(0.0001)
Luxembourg	–51.90420(0.0001)	–51.9067(0.0001)
UK	–46.72204(0.0001)	–46.71602(0.0001)

EGARCH : $\mathrm{Log}(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6) * RESID(-1)/@SQRT(GARCH(-1))) + C(7) * \mathrm{Log}(GARCH(-1))) + C(8) * RLUXX + C(9) * RFTSE + C(10)*RNASDAQ$ ……………… (10)

PARCH : $@SQRT(GARCH)\ \hat{}\ C(11) = C(4) + C(5) * (ABS(RESID(-1))) - C(6)*RESID(-1))\ \hat{}\ C(11) + C(7) * @SQRT(GARCH(-1))\hat{}C(11) + C(8)*RLUXX + C(9)*RFTSE + C(10)*RNASDAQ$ ……………… (11)

The comparison of the GARCH, EGARCH, and PARCH models is shown in Table 4. The constant in the mean equation in EGARCH is not significant. However, all of the coefficient components of the variance equation

Table 4. *Comparison of GARCH, EGARCH, and PARCH Models*

Method : ML-ARCH- Normal Distribution (BFGS/Marquardt steps).

It included observations : 2,723 after adjustments.

Convergence was achieved after 64 iterations.

	Variable	Variance Equation Coefficient	Standard Error	*Z*-Statistics	*p*-value
GARCH	*C*	0.021327	0.004497	4.742961	0.0000
	ARCH (1)	0.082569	0.007157	11.53677	0.0000
	GARCH (1)	0.899024	0.009739	92.31616	0.0000
	RLUXX	–0.010197	0.006164	–1.541886	0.1231
	RFTSE	0.009066	0.009171	6.345823	0.0034
	RNASDAQ	–0.010042	0.009806	8.457634	0.0002
EGARCH	*C*	0.032199	0.017265	1.864970	0.0622
	C(4)	–0.092110	0.011015	–8.362188	0.0000
	C(5)	0.113813	0.013743	8.281196	0.0000
	C(6)	–0.111784	0.007263	–15.39033	0.0000
	C(7)	0.978316	0.002937	333.1158	0.0000
	C(8)	0.003713	0.006970	0.532662	0.5943
	C(9)	0.010190	0.009238	1.102994	0.2700
	C(10)	0.024908	0.009021	2.761027	0.0058
PARCH	*C*	0.030437	0.017764	1.713399	0.0866
	C(4)	0.024111	0.003415	7.060971	0.0000
	C(5)	0.050119	0.004220	14.00803	0.0000
	C(6)	0.999967	2.1E–104	4.8E+103	0.0000
	C(7)	0.919497	0.006715	136.9356	0.0000
	C(8)	0.000232	0.004353	0.005322	0.9576
	C(9)	0.006805	0.005748	1.183901	0.2365
	C(10)	0.012337	0.005698	2.165117	0.0304
	C(11)	1.234130	0.100227	12.31334	0.0000

(eq. 10) in the EGARCH model, *ABS* (*RESID* (–1)/@*SQRT*(*GARCH* (–1), *RESID*(–1)) ^ *C*(11) + *C*(7) * @*SQRT* (*GARCH*(–1)) are significant at 1% in the EGACRH model, which reflects the behavior of indices in the present as well due to the influence of past volatility in the indices returns. Thus, the null hypothesis (H01) is rejected, which means that significant asymmetric volatility arises from the cross-listed markets on the Indian stock market. Additionally, the equation shows that volatility has asymmetric behavior. It implies that positive shocks of volatility have different impacts than adverse shocks. RFTSE and RLUXX are not substantial. However, the volatility spillover from RNASDAQ is strong at 1%, demonstrating that it will affect the movements in these indices (RFTSE and RLUXX), which will finally impact the fluctuation in stock returns of the Indian stock market. For the PARCH model, the constant for the mean equation is not significant at 1%, but for the variance equation, it is significant. Also, the variance equation (eq. 11) of the PARCH model shows that (*ABS*(*RESID*(–1))), *RESID*(–1))@*SQRT*(*GARCH*(–1)) are statistically significant, which means that the present-day movement in returns is being influenced by the past volatility. Thus, the second hypothesis (H02), i.e., no volatility spillover effect from the cross-listed foreign stock market on the Indian stock market is rejected, which means that the past volatility influences the current movement in returns in the Indian stock market. Also, the coefficient of RNASDAQ and RFTSE are significant, which shows the asymmetric volatility spillover effect of the US stock market on India due to the major cross-listing of assets. Still, it is insignificant in the case of RLUXX, showing no volatility effect.

Discussion

Researchers widely use the GARCH family of models to compute the volatility in the stock market caused by tradable assets. The GARCH/EGARCH/PARCH model is typically used to calculate or predict volatility. The optimal outcome is obtained when all model parameters have *p*-values of zero or are incredibly close to zero. In our study, we apply the GARCH (1,1) model with spillover variables on the closing price index data from January 2011 to December 2021 and capture the volatility effect arising from the stock exchanges where Indian assets are cross-listed in the form of ADR/GDR. Also, a comparative analysis is conducted by applying the GARCH/EGARCH and PARCH models to validate the study findings. The results suggest that past volatility of indices returns is significant and influences the current volatility among its return, which aligns with recent research (Baek et al., 2020; Hanif et al., 2021). Furthermore, the Indian stock market is highly volatile in response to the US market due to cross-listing, which is aligned with the previous literature (Jebran & Iqbal, 2016b; Joshi, 2011). However, in the case of GDR, the results are not much consistent for the UK and Luxembourg markets, which is demonstrated in the equations 10 and 11. Also, it is clear from the EGACRH and PARCH models that the UK market poses a spillover effect on the Indian market up to some extent, but it is absent in the case of the Luxembourg market.

EGARCH and PGARCH models also show that the series' past volatility is consistent and influences the present movement of the index return. In the variance equation, all the coefficient terms are significant at 1% in EGACRH, which means that positive shocks affect differently than negative shocks on volatility. Volatility spillover of the US market is significant at 1%, which shows that the changes in these indices will affect the movement in the stock return of the Indian stock market. In contrast, the UK and Luxembourg markets are not significant. The PARCH model also confirms the same results obtained from the EGARCH model. The analysis reveals the dominance of the US market due to its size and many cross-listed tradable assets (Curto & Serrasqueiro, 2022).

Managerial and Theoretical Implications

The globalization of capital markets enables the movement of money across borders, resulting in foreign institutional and retail investments. As the markets of developed countries are saturated, individual investors can diversify their portfolios if they go beyond these traditional channels of investment into the emerging financial markets, which provide competitive returns in the medium to long run. It would allow them to explore new investment possibilities, provided the stock markets of other nations are only partially integrated due to the irregular price spillover effect. So, the present study helps to find the exogenous market where the spillover effect is limited, as the Luxembourg market is somewhat isolated and has less impact on the Indian market. It will act as an opportunity for investors to invest in the global stocks listed on the Luxembourg market. The revelation shows that a considerable spillover effect occurred across the markets, which provides evidence of a transfer of information between markets, and the two markets are integrated. Based on these findings, individuals may forecast the movement in one market based on the results of another market. Supporting this notion, the present study shows that the US market is dominant. Therefore, substantial efforts may be made to avert worldwide shocks by concentrating on trends in the US market.

This study enriches the previous research in two ways. First, it contributes to the literature on volatility spillover, ignoring the crucial aspect of cross-listing, which is a significant factor in causing long-term disruption. Second, the study focuses on tradable assets, an essential aspect of empirical finance to which previous research has not paid much attention. By combining these two concepts, the present study contributes to a comprehensive understanding of the spillover effect caused by tradable assets.

Conclusion

The present study has focused on the volatility spillover among stock markets due to the cross-listing of tradable assets. The indices of the stock markets in the United States, the United Kingdom, and Luxembourg are used as proxies for their respective stock markets. The GARCH (1,1) model is adopted to predict the volatility spillover, which implies that the previous return affects the market's return at present. The US and UK stock markets also greatly influence the returns of the Indian stock market. After that, the EGARCH and PARCH models are applied to confirm the GARCH(1,1) results, which show a significant role of ADRs in the volatility spillover.

On the other hand, the EGARCH and PARCH models stated that no significant spillover effect arises from the cross-listing of GDRs. Since the Luxembourg market does not appear relevant to any of the models that lead to this conclusion, it can be said that the cross-listed ADRs significantly affect the volatility of the Indian market and put the United States market in the lead on the world financial market. Each case shows that the one-way connection between the framework and the United States market proved very important. The United Kingdom market also demonstrates some influence over the Indian market, but the PARCH model found this relationship inconsistent.

Limitations of the Study and Scope for Further Research

Identifying the right investment opportunity is critical for investors. While doing so, they must consider factors other than the volatility spillover effect arising from the foreign stock markets, such as macroeconomic variables impacting stock returns. This paves the way for further research into countries where macroeconomic factors like foreign exchange, bond, and currency market fluctuations can be investigated. Furthermore, the study is limited to Indian cross-listed assets and indices where they are primarily listed; significant Asian stock exchanges such as Japan, China, and Hong Kong cannot be included. Therefore, further studies can incorporate these stock exchanges to capture a global perspective.

Authors' Contribution

Prof. Amit Gautam conceived the idea and developed a quantitative design for the empirical study. Aditya Keshari extracted research papers with a high reputation, filtered these based on keywords, and generated concepts and codes relevant to the study design. Amit Gautam verified the analytical methods and supervised the study. Aditya Keshari gathered the study's data. He performed the numerical computations while using the EViews 12 version. He collaborated with and was supervised by Prof. Amit Gautam while writing the study.

Conflict of Interest

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

Funding Acknowledgment

The authors received no financial support for the research, authorship, and/or for publication of this article.

References

Alpanda, S., & Kabaca, S. (2020). International spillovers of large-scale asset purchases. *Journal of the European Economic Association, 18*(1), 342–391. https://doi.org/10.1093/jeea/jvy053

Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters, 37*, 101748. https://doi.org/10.1016/j.frl.2020.101748

Bakry, W., Kavalmthara, P. J., Saverimuttu, V., Liu, Y., & Cyril, S. (2022). Response of stock market volatility to COVID-19 announcements and stringency measures: A comparison of developed and emerging markets. *Finance Research Letters, 46*(Part A), 102350. https://doi.org/10.1016/j.frl.2021.102350

Chun, D., Cho, H., & Ryu, D. (2020). Economic indicators and stock market volatility in an emerging economy. *Economic Systems, 44*(2), 100788. https://doi.org/10.1016/j.ecosys.2020.100788

Curto, J. D., & Serrasqueiro, P. (2022). The impact of COVID-19 on S&P500 sector indices and FATANG stocks volatility: An expanded APARCH model. *Finance Research Letters, 46*(Part A), 102247. https://doi.org/10.1016/j.frl.2021.102247

Dikshita, & Singh, H. (2019). Estimating and forecasting volatility using ARIMA model: A study on NSE, India. *Indian Journal of Finance, 13*(5), 37–51. https://doi.org/10.17010/ijf/2019/v13i5/144184

Dou, W. W., & Verdelhan, A. (2015). *The volatility of international capital flows and foreign assets.* September. http://web.mit.edu/adrienv/www/.Theauthorsthank

El Hedi Arouri, M., Rault, C., Sova, A., Sova, R., & Teulon, F. (2013). Market structure and the cost of capital. *Economic Modelling, 31*, 664–671. https://doi.org/10.1016/j.econmod.2013.01.004

Errunza, V. R., & Miller, D. P. (2000). Market segmentation and the cost of the capital in international equity markets. *Journal of Financial and Quantitative Analysis, 35*(4), 577–600. https://doi.org/10.2307/2676256

Gherghina, Ș. C., Armeanu, D. Ș., & Joldeș, C. C. (2021). COVID-19 pandemic and Romanian stock market volatility: A GARCH approach. *Journal of Risk and Financial Management, 14*(8), 341. https://doi.org/10.3390/jrfm14080341

Hanif, W., Mensi, W., & Vo, X. V. (2021). Impacts of COVID-19 outbreak on the spillovers between US and Chinese stock sectors. *Finance Research Letters, 40*, 101922. https://doi.org/10.1016/j.frl.2021.101922

Haritha, P. H., & Rishad, A. (2020). An empirical examination of investor sentiment and stock market volatility: Evidence from India. *Financial Innovation, 6*(1), Article 34. https://doi.org/10.1186/s40854-020-00198-x

Idrees, S. M., Alam, M. A., & Agarwal, P. (2019). A prediction approach for stock market volatility based on time series data. *IEEE Access, 7*, 17287–17298. https://doi.org/10.1109/ACCESS.2019.2895252

Jebran, K., & Iqbal, A. (2016a). Dynamics of volatility spillover between stock market and foreign exchange market: Evidence from Asian countries. *Financial Innovation, 2*(1), Article 3. https://doi.org/10.1186/s40854-016-0021-1

Jebran, K., & Iqbal, A. (2016b). Examining volatility spillover between Asian countries' stock markets. *China Finance and Economic Review, 4*(1), Article 6. https://doi.org/10.1186/s40589-016-0031-1

Joshi, P. (2011). Return and volatility spillovers among Asian stock markets. *SAGE Open, 1*(1). https://doi.org/10.1177/2158244011413474

Khanna, S., & Kumar, A. (2020). GARCH and TGARCH approach to information linkages. *Indian Journal of Finance, 14*(8–9), 35–51. https://doi.org/10.17010/ijf/2020/v14i8-9/154947

Kumar, A., & Khanna, S. (2018). GARCH - BEKK approach to volatility behavior and spillover : Evidence from India, China, Hong Kong, and Japan. *Indian Journal of Finance, 12*(4), 7–19. https://doi.org/10.17010/ijf/2018/v12i4/122791

Kumar, S., Pradhan, A. K., Tiwari, A. K., & Kang, S. H. (2019). Correlations and volatility spillovers between oil, natural gas, and stock prices in India. *Resources Policy, 62*, 282–291. https://doi.org/10.1016/j.resourpol.2019.04.004

Kusumahadi, T. A., & Permana, F. C. (2021). Impact of COVID-19 on global stock market volatility. *Journal of Economic Integration, 36*(1), 20–45. https://doi.org/10.11130/jei.2021.36.1.20

Li, H. (2019). Direct overseas listing versus cross-listing: A multivalued treatment effects analysis of Chinese listed firms. *International Review of Financial Analysis, 66*, 101391. https://doi.org/10.1016/j.irfa.2019.101391

Li, T., Ma, F., Zhang, X., & Zhang, Y. (2020). Economic policy uncertainty and the Chinese stock market volatility: Novel evidence. *Economic Modelling, 87*, 24–33. https://doi.org/10.1016/j.econmod.2019.07.002

Li, W., Chien, F., Kamran, H. W., Aldeehani, T. M., Sadiq, M., Nguyen, V. C., & Taghizadeh-Hesary, F. (2022). The nexus between COVID-19 fear and stock market volatility. *Economic Research-Ekonomska Istraživanja, 35*(1), 1765–1785. https://doi.org/10.1080/1331677X.2021.1914125

Liang, C., Tang, L., Li, Y., & Wei, Y. (2020). Which sentiment index is more informative to forecast stock market volatility? Evidence from China. *International Review of Financial Analysis, 71*, 101552. https://doi.org/10.1016/j.irfa.2020.101552

Liu, F., Umair, M., & Gao, J. (2023). Assessing oil price volatility co-movement with stock market volatility through quantile regression approach. *Resources Policy, 81*, 103375. https://doi.org/10.1016/j.resourpol.2023.103375

Lv, W., & Li, B. (2023). Climate policy uncertainty and stock market volatility: Evidence from different sectors. *Finance Research Letters, 51*, 103506. https://doi.org/10.1016/j.frl.2022.103506

Mishra, A. (2019). Foreign exchange, gold, and real estate markets in India: An analysis of return volatility and transmission. *Indian Journal of Finance, 13*(7), 50–64. https://doi.org/10.17010/ijf/2019/v13i7/145535

Mukherjee, K. N., & Mishra, R. K. (2010). Stock market integration and volatility spillover: India and its major Asian counterparts. *Research in International Business and Finance, 24*(2), 235–251. https://doi.org/10.1016/j.ribaf.2009.12.004

Myers, J. L., Well, A. D., & Lorch Jr., R. F. (2010). *Research design and statistical analysis* (3rd). Routledge.

Nammouri, H., Chlibi, S., & Labidi, O. (2022). Co-movements in sector price indexes during the COVID-19 crisis: Evidence from the US. *Finance Research Letters, 46*(Part A), 102295. https://doi.org/10.1016/j.frl.2021.102295

Nandy, S., & Chattopadhyay, A. K. (2019). 'Indian stock market volatility': A study of inter-linkages and spillover effects. *Journal of Emerging Market Finance, 18*(2_suppl), S183–S212. https://doi.org/10.1177/0972652719846321

Onali, E. (2020). COVID-19 and stock market volatility. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3571453

Singh, A., & Kaur, P. (2015). Modelling dynamic volatility spillovers from the U.S. to the BRIC countries' stock markets during the subprime crisis. *Indian Journal of Finance, 9*(8), 45–55. https://doi.org/10.17010/ijf/2015/v9i8/74562

Singh, V. K., & Gautam, A. (2022). Structural investigation of export assistance and performance of handloom exporters. *Metamorphosis, 21*(1), 7–18. https://doi.org/10.1177/09726225211066160

Slivka, R. T., Gao, S., & Ren, J. (2015). An empirical model of India's Nifty VIX Index. *Indian Journal of Finance, 9*(8), 7–18. https://doi.org/10.17010/ijf/2015/v9i8/74559

Su, C. (2010). *Application of EGARCH model to estimate financial volatility of daily returns : The empirical case of China* (Master Degree Project No. 2010: 142). http://hdl.handle.net/2077/22593

Tang, Y., Xiao, X., Wahab, M. I., & Ma, F. (2021). The role of oil futures intraday information on predicting US stock market volatility. *Journal of Management Science and Engineering, 6*(1), 64–74. https://doi.org/10.1016/j.jmse.2020.10.004

Uddin, M., Chowdhury, A., Anderson, K., & Chaudhuri, K. (2021). The effect of COVID – 19 pandemic on global stock market volatility: Can economic strength help to manage the uncertainty? *Journal of Business Research, 128,* 31–44. https://doi.org/10.1016/j.jbusres.2021.01.061

Upadhyay, A. (2016). Foreign direct investment and Indian economy. *SSRN Electronic Journal.* https://doi.org/10.2139/ssrn.2710148

Varughese, A., & Mathew, T. (2017). Asymmetric volatility of the Indian stock market and foreign portfolio investments : An empirical study. *Indian Journal of Finance, 11*(6), 36–49. https://doi.org/10.17010/ijf/2017/v11i6/115595

Yilmaz, K. (2010). Return and volatility spillovers among the East Asian equity markets. *Journal of Asian Economics, 21*(3), 304–313. https://doi.org/10.1016/j.asieco.2009.09.001

About the Authors

Aditya Keshari is pursuing his Ph.D. in International Finance from the Institute of Management Studies, Banaras Hindu University. He has published papers in national and international journals of repute and has also presented several research papers at various conferences. He has also published a book on *International Financial Management* from PHI Learning.

Amit Gautam is a Professor at Banaras Hindu University with more than 23 years of expertise. In New Delhi, he has published 10 books by PHI Learning, Himalaya Publishers, Excel Publishers, and ABC Publishing House. He has completed various research projects financed by IOE, AICTE, UGC, IOCL, and other organizations. He has also mentored eight Ph.D. students. He has over 80 research publications and has traveled worldwide, including the United States, the United Kingdom, and Russia.