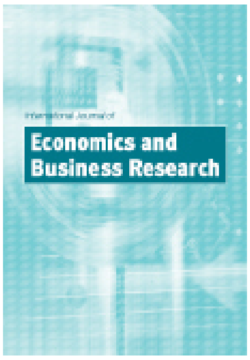

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Dynamic volatility spillover across stock markets of India and its trading partners - an empirical investigation

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Dynamic volatility spillover across stock markets of India and its trading partners – an empirical investigation

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Abstract: This study investigates the nature of volatility transmissions between India and its 14 major trading partners based on their benchmark stock market indices covering time period from January 2013 to May 2020. The results of EGARCH model provide that significant bi-directional volatility spillover exists between India and four of its trading partners; unidirectional volatility spillover exists from six of its trading partners towards India; unidirectional volatility spillover exists from India towards three of its trading partners; and volatility spillover between India and one trading partner is not found significant. The results of DCC-GARCH model reveal that time-varying/dynamic nature of the conditional correlation exists for all the pairs of stock market indices. The findings of the study have useful implications for portfolio managers, international investors and regulators for devising diversification strategies and for policy arrangements to bring stability of an economy from international financial shocks and crisis.

Keywords: volatility spillover; financial markets; DCC-GARCH model; India; EGARCH model.

JEL codes: G15, C32, C58.

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1 Introduction

Studying inter-linkages and volatility spillover across financial markets is the topic of immense importance for researchers, investors and regulators. Integration of stock markets is widely studied by the stakeholders for different purposes. Firstly, the modern investors and international portfolio managers having the objective of maximising portfolio returns while minimising the risk, have the quest to study the integration of the stock markets of different countries. According to the modern theory of portfolio given by Markowitz (1952), benefit of portfolio diversification can be obtained if the investment of funds is made in non-correlated assets. This is because if there is low or no correlation between the assets, the shock arising in one asset will have less possibility of being transmitted to other assets. The investors willing to diversify their portfolio by investing in different countries need to study their financial integration. The crisis arising in one country will be transmitted to other countries, if they are integrated in terms of volatility spillover (Baele, 2002). The investors look to invest in the non-integrated markets for maximising portfolio returns and minimising the risk. Foreign portfolio investors can better avail the diversification opportunities in different countries, when their financial market indices do not pursue similar movements (Gupta and Guidi, 2012). To add further, emerging markets are commonly targeted by foreign portfolio investors seeking to get benefits of diversification (Vo and Ellis, 2018). Secondly, market regulators and policy makers are also concerned with market integration owing to its impact on the country's macroeconomic policies. Growing integrations between the nations put an influence on their foreign trade and balance of payment position by affecting the foreign exchange reserves and the exchange rate. Because an economy is susceptible to external disturbances and troubles, policy makers can make superior decisions by acquainting them with this field (Tripathi and Sethi, 2010). To shield the country from international shocks and crisis, it is imperative for the policy makers to look at the returns patterns and volatility transmission. Thus, it becomes very important for the policy makers to understand these integrations for improved decision arrangements. Thirdly, for portfolio managers and hedgers, it is significant to look at the stock market inter-linkages over time to forecast the market behaviour and capture the other market information. Understanding of the past information about the integrations and volatility spillover between the markets will help them to know about the market behaviour enabling them to predict any future financial shock. Thus, it is imperative for governments, financial institutions and investors to investigate and comprehend the linkages and connectivity that may exist between different financial markets (Zhou et al., 2012).

The booming globalisation, liberalisation and advancement of technologies around the globe have intensified the economic trade with other countries with no trouble. Integration of global stock markets becomes inescapable, as the economies are opening up and becoming liberalised (Bekaert et al., 2002). One of the major repercussions of this magnified international trade across the borders is that any change in one country spills over to other countries thus, bringing ups and downs in their stock markets as well. Swift growth of global trading in merchandise, services and monetary assets are resulting in greater integration in the economic and financial structure of the nations (Kearney and Lucey, 2004). The amount of co-movement of the markets will be high, provided that the countries have superior bilateral trade relationships between them (Pretorius, 2002).

It is universally accepted that international trade has a prominent role in the development of an economy. Export trade boosts the overall increase in the production in the country leading to rise in its GDP. Trade promotes a shift of resources from agriculture or other traditional activities to modern economic activities leading to efficient management, better labour training, latest technology and access to foreign markets. Foreign trade also reduces the unemployment rate in the country leading to rise in wage rate, reduction of poverty, equality of income distribution and thus, promotion of overall social welfare. Efficiency of the production firms also increases due to economies of large-scale production. Due to global trading, the country can buy capital goods from foreign countries resulting in to technological advancement of the country.

Table 1 Top 10 export and import destinations of India

Export destinations				*Import destinations*			
Rank	*Country*	*Apr.–Mar. 2019 (value in USD billion)*	*Share (%)*	*Rank*	*Country*	*Apr.–Mar. 2019 (value in USD billion)*	*Share (%)*
1	USA	52.43	15.88	1	China	70.32	13.68
2	United Arab Emirates	30.13	9.13	2	USA	35.55	6.92
3	China	16.75	5.08	3	United Arab Emirates	29.78	5.79
4	Hong Kong, China	13	3.94	4	Saudi Arab	28.48	5.54
5	Singapore	11.57	3.51	5	Iraq	22.37	4.35
6	UK	9.33	2.83	6	Switzerland	18.09	3.52
7	Bangladesh	9.21	2.79	7	Hong Kong	17.99	3.5
8	Germany	8.9	2.7	8	Korea Rp.	16.76	3.26
9	Netherlands	8.81	2.67	9	Singapore	16.28	3.17
10	Nepal	7.77	2.35	10	Indonesia	15.85	3.08

Source: Annual Report 2019–2020, Department of Commerce, Ministry of Commerce & Industry, Government of India

India has prominent and strong trade relations with various nations in the world. Particularly, after the early '90s economic reforms, various kinds of trade restrictions were uplifted resulting in to opening up doors for bilateral trade relations with other countries thereby, leading to expansion of foreign trade. As per the Annual Report 2018–2019 of Ministry of Commerce and Industry, Government of India, total exports of goods and services in India has been mounting regularly since 2016–2017 and has reached at USD535.9 billion in 2018–2019. Also, as per a projection in the same report, India is on the verge of an unrelenting growth path and is expected to reach at

USD5 trillion GDP by 2025. And, a significant driver for India to achieve this stated GDP mark would be a continued elevated export growth rate. As per the annual report of the year 2019–2020 of Department of Commerce, Ministry of Commerce and Industry, Government of India, the top 10 export and import destinations of Indian economic trade are given in Table 1.

Foreign trade has been attributed as an important reason contributing to the integration of financial markets of the trading nations (Baur, 2010). The trading relations of a country with other countries lead to economic integration and causes co-movement of their stock market returns. Greater the magnitude of economic integration between the nations, greater may be the volatility spillovers between their stock markets. Given this background, this study attempts to provide empirical evidence on the relationship of the Indian stock market in terms of dynamic volatility linkages with its major economic trade partners. To be specific, the primary objective of this research paper is to estimate the nature of volatility transmissions between India and its major trading partners. The stock markets forming part of this research pursuit are the USA, UAE, China, Hong Kong, Singapore, the UK, Bangladesh, Germany, Netherlands, Saudi Arabia, Iraq, Switzerland, South Korea and Indonesia owing to their significance in economic terms as the trade partners as highlighted in Table 1.

This study makes contribution to the existing financial literature in three ways. First, the studies relating to exploring integration of Indian stock market with its major trading partners are very rare. This is the novel work which seeks to find the dynamic volatility transmissions across India and its 14 major economic trading partners. It is believed that the results of this empirical work will methodically enhance the understanding about the volatility relationships of India with its trading partners. Also, it will greatly benefit the prospective international investors in decisions concerned with portfolio diversification in developing country like India. Second, this study has applied two alternative generalised autoregressive conditional heteroscedastic (GARCH) models namely, exponential generalised autoregressive conditional heteroskedasticity (EGARCH) and dynamic conditional correlation specification of multivariate generalised autoregressive conditional heteroskedasticity (DCC-GARCH) to capture rich aspects of volatility dynamics across these markets. Third, the study is based on comparatively longer and latest data for the time period from Jan. 2013 to May 2020, thus, allowing generalisations possible from the results. In this pursuit, this study seeks to fill the gap in literature by offering empirical validations of Indian stock market integration with its major economic trading partners by adopting latest data sample and advanced econometric methodologies like EGARCH and DCC-GARCH.

1.1 Theoretical framework

Studying and forecasting stock market volatility has gained interest of researchers since few decades. Volatility is understood as a measure of surprising variations in the asset price series. To be more precise, this term was used by Markowitz (1952) as a risk measure. A data series is considered volatile when it is showing heteroscedastic behaviour which means that some error-terms are greater than others or it is having fluctuating standard deviation/variance over time. Also, volatility of a series is observed to be auto-correlated, i.e., volatility of today depends up on the volatility of previous time period. Further, volatility of a series is generally of clustering nature, i.e., small changes are followed by small changes and large changes are followed by large ones over a period. Financial markets have the predominant feature of volatility spillover where the instability or price change occurrence is transmitted from one market to the others causing a lagged effect on the price change in that market beyond the local volatility impacts. The need for accurate volatility forecasts is mounting recurrently to provide systematic and logical solution in financial modelling, hedging, asset and risk management, portfolio optimisation and various other financial decisions.

Considering the complex heteroscedastic behaviour of volatility which is not directly observable, there is need for good models which help to predict/forecast the volatility of a price series. Engle (1982) proposed popular nonlinear model, i.e., autoregressive conditional heteroscedastic (ARCH) model which was later generalised by Bollerslev (1986) in the form of GARCH model. GARCH model is believed to be common and more effective than ARCH model in capturing volatility behaviour of a price series as well as in volatility forecasting. In ARCH model, the variance of current period is modelled as weighted average of the past period's squared residuals, but in GARCH model, conditional variance is taken as a linear function of its own lags and decreasing weights for the squared residuals are estimated by the model. The economists have brought in different variants of ARCH/GARCH models to satisfy the need to understand the complex nature of volatility aspects. These models have been successfully used by the researchers to capture stylised evidences of volatility, volatility spillover, volatility clustering, etc. But, GARCH model fails to detect the asymmetric patterns or leverage effects of time series. The leverage effect signifies that a sudden price fall causes an increase in volatility more than an equivalent sudden price rise. Therefore, GARCH model was extended by Nelson (1991) in the form of EGARCH model which considers the positivity/negativity of shocks along with its magnitude. The capability of EGARCH model to capture the presence of symmetric effects among the data series led to its extensive use in determining the extent of volatility spillover between the data series.

To understand the multi-facets characteristics of volatility across assets/markets and to consider the dependence in the co-movements of asset returns stimulated the need to extend the univariate GARCH family models to multivariate ones. Estimating the covariance matrix between the assets/markets using the multivariate generalised autoregressive conditional heteroscedastic (MGARCH) models has improvised the decision-making in the field of financial modelling. These MGARCH models help to study the inter-relationship and transmission of the volatilities and co-volatilities across the assets/markets. Various MGARCH models are presently in existence catering to the needs of the time but an important requirement is to make the model parsimonious enough and yet maintaining sufficient flexibility. The first model to consider decomposition of conditional covariance matrix in to conditional correlation matrix and conditional standard deviations was introduced by Bollerslev (1990) and named as constant conditional correlation (CCC)-GARCH model. In CCC-GARCH model, the conditional standard deviation varies, but conditional correlation is supposed to be constant. The extension of CCC-GARCH model was introduced by Engle and Sheppard (2001) by the name of DCC-GARCH model. DCC-GARCH model is a generalised version of CCC-GARCH model in which the conditional correlation matrix is assumed to be dynamic, i.e., varying over time. DCC-GARCH model allows estimation of very large correlation matrices as the parameters to be estimated in the correlation process does not depend on the series to be correlated.

The current study therefore, uses advanced econometric models, i.e., EGARCH and DCC-GARCH to achieve its objective of capturing the rich aspects of volatility and estimating the dynamic nature of volatility transmissions between India and its major trading partners.

The remaining paper is organised as follows: Section 2 deals with the related past literature on the subject, Section 3 addresses the empirical methodology used in the study, Section 4 presents data along with preliminary data analysis, Section 5 reports estimation results and their interpretations, and Section 6 concludes and puts forth implications of study.

2 Review of literature

There exist extensive empirical research studies on investigation of linkages and volatility spillovers for different financial markets across the world. These studies suggest that the results of different studies in this area have not been consistent especially, when the investigations are in connection with the emerging countries. Bhar and Nikolova (2009) did extensive work on exploring the dynamic linkages and integration level of the BRIC countries with their regional counterparts as well as the world. Employing EGARCH model with dynamic correlation, the authors documented that amongst the four countries, India had topmost regional and world integration, followed by Brazil, Russia and then China. Also, a negative association was shown between India's conditional volatility and Asia-Pacific region and also between China and the world. Singh et al. (2010) in their study on popular stock indices of 15 countries belonging to North America, Europe and Asia applied VAR and AR-GARCH to test the return and volatility spillover effects. The study propounded that there were more regional impacts among Asian and European stock market than the US counterparts. Japan was affected most by the USA and Europe but in turn affected majority of Asian countries under study. Nath Mukherjee and Mishra (2010) investigated using GARCH model the linkages among India and 12 developed and developing countries. The authors reported that two ways simultaneous and positively significant intraday return spillover was present between India and other nations. While, Hong Kong, Singapore, Korea and Thailand exerted noteworthy impacts on Indian stock market; Sri Lanka and Pakistan were the countries which were impacted by Indian actions. Tripathi and Sethi (2010) in their work investigated whether there existed stock market linkages between India and four other countries, i.e., the USA, the UK, Japan and China. The authors applied co-integration and Granger causality tests and provided evidence that stock market of India was integrated with the stock market of only one country, i.e., the USA. Also, there existed causal relations in single direction only. While the USA and the UK Granger caused Indian stock market, Indian stock market also Granger caused the stock markets of China and Japan. Gupta and Guidi (2012) also checked the linkages of Indian stock market with Japan, Hong Kong and Singapore using DCC-GARCH model and confirmed the presence of time-varying conditional correlations between the markets. The authors reported that during the crisis times, the conditional correlation augmented considerably which came back to its original levels after the crisis times. Negi et al. (2012) investigated the global stock market links of the USA with 11 big emerging countries (including India, China, Brazil, Russia, etc.) covering the periods of before, during and after the 2007 financial crisis. The study employed VAR model and Granger causality tests and the results revealed that during the crisis, the long-term co-integration between the countries became stronger and after-crisis integration was more than the before-crisis integration. The authors exclaimed that the extent of the impact of the USA on emerging economies changed over time, particularly nearing the financial crisis periods. Sakthivel et al. (2012) tested the correlation and transmission of volatility across the stock market indices of five important countries, namely, the USA, India, the UK, Japan and Australia using weekly data. The authors applied Johansen co-integration test, vector error correction model and bivariate GARCH model. The results provided the presence of long-term co-integration across all the studied indices. Also, the USA and Japan stock markets were leading in terms of new information arrival and thereafter, the impact was going towards the other markets. The study reported two-directional volatility transmission between India and the USA owing to strong foreign trade and investment connections between them. Positive volatility transmissions were also reported between India and Japan. Allen et al. (2013) employed GARCH, VARMA-GARCH and VARMA-AGARCH models to capture the volatility spillover effects from China to its trading neighbours namely, the USA, Australia, Singapore, Hong Kong and Japan dividing the study period of Aug. 1991 to Nov. 2010 into four parts. The study reported that there existed spillovers from China to the studied economies prior to global financial crisis period as compared to little spillovers during the crisis period as the crisis originated in the USA and not in China. The three GARCH models used by the authors produced almost similar results. Particularly, the VARMA-AGARCH results indicated that even though the volatility spillover from China to other countries was there, but its magnitude was comparatively low. The spillover from China to Australia was the highest because it was China's main trading partner. Todorov and Bidarkota (2013) examined the extent of impact between the returns and conditional volatility of stock markets of 21 frontier markets and that of the stock market of the USA using bivariate Schwarz-Bayesian criterion (SBC). The study reported weak positive return spillover from the USA to 17 studied markets whereas, weak negative return spillover was reported in case of four markets (Jordan, Lebanon, Nigeria and Kenya) from the USA, suggesting probable diversification prospects. It was propounded in the study that most of the frontier markets are impacted more by the local information as compared to the information from the USA. Mohammadi and Tan (2015) employed VAR model to find out the short-term causal relation among the returns and three MGARCH models, namely, BEKK, CCC and dynamic conditional correlation (DCC) to find out the volatility spillover effects in context of the stock markets of the USA, China (both Shanghai and Shenzhen) and Hong Kong. The study confirmed that there were unidirectional return spillovers as well as unidirectional ARCH and GARCH effects from the USA to other three markets under study. The DCC-GARCH results put forward the fact that correlation between China and other studied nations bettered since the 2007 financial crisis. Li and Giles (2015) attempted to study the stock market linkages across the USA, Japan and emerging Asian nations namely, India, Indonesia, China, Thailand, the Philippines and Malaysia. The study employed an asymmetric MGARCH model to examine the spillover effects. The results provided confirmations of substantial one-way shock and volatility transmission from the USA to Japan as well as the emerging Asian countries' stock markets. During the span of Asian financial crisis, the spillover effects between the USA and Asian nations under study was reported bidirectional and even stronger. During the span of last five years of the study, the Japanese and Asian developing nations were found to be noticeably associated. Jebran and Iqbal (2016) in their study on Asian countries' stock markets also confirmed that there existed significant two-way return and volatility transmission between Japan and China. The volatility spillover between the stock markets of Sri Lanka and Hong Kong and Sri Lanka and China was two directional. On the other hand, one-way transmissions of volatility were concluded in case of Sri Lanka to Japan, Pakistan to Sri Lanka, India to China and Hong Kong to India and Japan. Bala and Takimoto (2017) employed MGARCH models to study the volatility spillovers in case of emerging and developed countries' stock markets and also investigated the impact of global financial crisis in this context. The authors showed in their study that developed markets were better co-integrated than the emerging markets even in the time of the crisis. Confirmations of volatility spillovers were given with the fact that emerging markets are more affected by their own volatility spillovers compared to the spillovers from other countries. Also, in case of developed countries asymmetric behaviour was significant whereas it was weak in case of emerging countries. Bakry and Almohamad (2018) researched to find the evidence of integration between the stock markets of Middle East and North Africa (MENA) countries and the USA. The authors used Zivot and Andrews (2002) and Bai and Perron (2003) methods along with autoregressive distributed lag (ARDL) and Granger causality methods to examine the structural breaks in the markets and to find out the short-term and long-term market interactions. The study stated that global financial crisis was the noteworthy incident resulting in to structural break in these markets. Co-integration was found between these MENA markets as well as with the USA. Other global shocks also had a noted impact on the studied financial markets just as the impact of the regional and local shocks on these markets. Umer et al. (2018) applied DCC and BEKK GARCH models to examine the spillover across EAGLEs stock markets, i.e., China, Russia, Brazil, India, Indonesia, Mexico and Turkey. Using the data from 2002 to 2017 and dividing it into three categories based on global financial crisis, the study put forth that the spillover effects among these countries' stock markets was positive and significant in the pre as well as post-crisis periods. The authors suggested that the returns and volatility spillovers changes with time and the shocks happening in the USA markets had powerful impact on the stock markets of other countries. Hung (2019) examined the effects of volatility spillover and daily returns between Chinese stock market and four Southeast Asian countries using bivariate GARCH BEKK model on the data of pre and post-2008 financial crisis. The study brought to light that there was unidirectional volatility spillover from China to the studied stock markets of Vietnam, Thailand, Singapore and Malaysia during the sub-prime crisis. These different stock markets were found to be significantly integrated during the crisis. Tripathi and Seth (2019) tested the stock market efficiency, linkages and spillover of volatility across the USA, the UK, Japan, India and China on data of 25 years. The study proved the existence of short-term causality from the USA and the UK towards Asian countries and also that long-term co-integration was there among all the countries under study. Using ARCH-GARCH model, the authors reported that volatility in one country's stock market had impacted the other countries' stock market volatility. Vo and Tran (2020) intended to study the volatility transmissions from advanced economy, i.e., the USA to emerging economies' stock markets, i.e., ASEAN countries. By using augmented EGARCH model along with the ICSS algorithm on a dataset covering the period of almost 15 years, the study put forth that the transmission of volatility from the USA to ASEAN stock markets was noteworthy.

Also, there are various other studies which have empirically tested the co-movements and volatility linkages of international financial markets. Studies such as Baele (2002), Baur (2010), Xiao and Dhesi (2010), Yilmaz (2010), Graham et al. (2012), Zhou et al. (2012), Balli et al. (2015), Rejeb and Boughrara (2015) and Kumar (2019) have empirically examined the volatility linkages across international stock markets and have found that volatility spillover existed from one stock market to the other.

Thus, there exists a wealth of literature studying the stock market integrations and their results are also not standardised and uniform. The period of the study, the stock markets studied, empirical methodology used, variable specification, etc. are the reasons for results variations. So, it is difficult to make generalisations in this regard. The present study makes an endeavour to contribute to the literature by the strengthening the knowledge in respect of time varying spillover of volatility existing between India and its key trade partners in a methodical manner.

3 Empirical modelling

The present study employs two empirical models to explore the volatility spillover linkages of Indian stock market with the stock markets of its trading partners. Firstly, it uses exponential GARCH proposed by Nelson (1991) to explore the asymmetric volatility spillover effects between the stock markets. Secondly, it applies DCC-GARCH model proposed by Engle (2002) on the stock returns of the sample countries to investigate the time-varying volatility dynamics between these markets.

3.1 EGARCH model

Exponential generalised autoregressive conditional heteroskedasticity model abbreviated as EGARCH model given by Nelson (1991) is an extension of the classic GARCH model. This model facilitates measuring of the asymmetric influence of innovation or shock on the estimated conditional variance, thus allowing the testing of long-term and short-term volatility spillover impacts. The superiority of EGARCH model over GARCH model lies in its ability to ascertain the positive or negative impact of shock on the volatilities along with measuring the shock's magnitude. The conditional variance equation specification of EGARCH model (see Brooks, 2014) is:

$$\ln\left(\sigma_t^2\right) = \omega + \beta \ln\left(\sigma_{t-1}^2\right) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{1}$$

where $\ln(\sigma_t^2)$ is the log of conditional variance, which itself restricts the volatility to be positive in spite of the negative parameters. ω is the constant level of volatility. The coefficient β measures the volatility consistence which is one of the functions of volatility. Larger β implies that volatility takes a prolonged time to die away following a market shock (Alexander, 2008). The coefficient γ quantifies the asymmetries or leverage impact of volatility, i.e., impact of positive or negative news on the volatility. If $\gamma = 0$, it denotes symmetric model, its positive value shows that positive (good) innovations create more volatility than negative innovations and its negative value shows that positive news create less volatility than negative news. If γ is negative and significant, it is the evidence of asymmetric or leverage effects in the model. The coefficient α shows the model's symmetric effect, i.e., it measures the 'GARCH' effect of the model. This coefficient shows the volatility reaction in response to positive news only as this term uses modulus in its calculation.

3.2 DCC-GARCH model

For the purpose of examining the dynamic association between the volatilities of two stock market returns, DCC-GARCH model developed by Engle (2002) has been used. This technique directly models the variance and covariance thus, allowing to find direct association between two or more series. DCC-GARCH involves an estimation process with two stages. First of all, conditional variance is estimated with univariate GARCH for all series. In the second stage, the DCC matrix parameters are estimated using the standardised residuals obtained. This specification includes conditions allowing the covariance matrix to be always positive and the covariance to be stationary. Multivariate DCC-GARCH is modelled as: $X_t = \mu_t + H_t^{1/2}\varepsilon_t$, where X_t is a vector of previous observations, H_t is a multi-variate conditional variance, μ_t is a vector of conditional returns and ε_t is a vector of standardised returns. The GARCH component of DCC-GARCH model can be explained by the variance-covariance matrix as: $H_t = D_tR_tD_t$, where $D_t = diag\{\sqrt{h_{it}}\}$ is a 2 × 2 diagonal matrix of conditional time-varying standard deviation from the univariate GARCH models, and $R_t = \rho_{ijt}$ for i, j = 1 and 2 is a conditional correlation matrix, which is dynamic. D_t element in DCC-GARCH follows the simple GARCH(p, q) models expressed as:

$$h_{it} = \alpha_i + \sum\nolimits_{q=1}^{Q_i} \gamma_{iq}\varepsilon_{i,t-q}^2 + \sum\nolimits_{p=1}^{P_i} \delta_{ip}h_{i,t-p} \tag{2}$$

The matrix D_t is always positive as its parameters are always positive. Also, R_t elements are ≤ 1 as these represent correlations. To ensure that R_t is positive, this matrix is decomposed into two matrices. DCC-GARCH structure includes DCC(m, n) structure specification as the second stage, which is expressed as:

$$R_t = Q_t^{*-1}Q_1Q_t^{*-1} \tag{3}$$

where

$$Q_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\bar{Q} + \sum_{m=1}^{M} a_m\left(\varepsilon_{t-m}\varepsilon_{t-m}^T\right) + \sum_{n=1}^{N} b_nQ_{t-n}$$

Q_1 $\quad q_{ijt}$ is a conditional variance-covariance matrix of standardised residuals

$\bar{Q}$ $\quad$ unconditional covariance matrix of the standardised errors ε_t found through estimation of equation [equation (2)]

Q_t^{*-1} $\quad$ diagonal matrix with the square root of the diagonal elements of Q_t at the diagonal.

This study focuses on R_t which is $\rho_{ijt} = q_{ij,t} / \sqrt{q_{ii,t}} q_{jj,t}$ and attempts to highlight the conditional correlation between the two stock market returns.

4 Data and preliminaries

4.1 Data sample

The empirical work in the study is based on daily prices of stock indices of India and its major trading partners, namely, the USA, UAE, China, Hong Kong, Singapore, the UK, Bangladesh, Germany, Netherlands, Saudi Arabia, Iraq, Switzerland, South Korea and Indonesia. The study has used commonly accepted benchmark indices for the all these 14 countries which represent the overall equity market in that country. The list of the stock indices used along with the name of the stock exchange where these indices are traded is given in Table 2. The closing prices of all these indices are collected from two sources, Bloomberg and investing.com. The data collected covers fairly longer time period from January 2013 till May 2020. The data of all indices is sourced in domestic currency to avoid transformation problems due to fluctuations in exchange rates.

4.2 Data preliminaries

First of all, the descriptive statistics of returns all the stock indices are computed. The returns are calculated as the difference of natural log of closing prices at day x and day $x - 1$. The summary of the descriptive statistics is presented in Table 3.

Table 2 Countries, leading stock exchanges, benchmark stock indices

Sr. no.	*Country*	*Stock exchange*	*Stock index*
1	India	National Stock Exchange (NSE)	Nifty 50
2	USA	New York Stock Exchange (NYSE) and the NASDAQ	Dow Jones IA
3	UAE	Abu Dhabi Securities Exchange (ADX)	ADX General
4	China	Shanghai Stock Exchange (SSE)	SSE Composite (SSEC)
5	Hong Kong	Stock Exchange of Hong Kong (SEHK)	HANG SENG
6	Singapore	Singapore Exchange (SGX)	FTSE Singapore
7	UK	London Stock Exchange (LSE)	FTSE 100
8	Bangladesh	Dhaka Stock Exchange (DSE)	DSE 30
9	Germany	Frankfurt Stock Exchange (FWB)	DAX
10	Netherlands	Euronext Amsterdam	AEX
11	Saudi Arabia	The Saudi Stock Exchange	MSCI TADAWUL 30
12	Iraq	Iraq Stock Exchange (ISX)	ISX 60
13	Switzerland	SIX Swiss Exchange	SMI
14	South Korea	Korea Exchange (KRX)	KOSPI
15	Indonesia	Indonesia Stock Exchange (IDX)	IDX Composite (JKSE)

Table 3 Descriptive statistics of stock returns

Countries	*Mean*	*Median*	*Maximum*	*Minimum*	*Std. dev.*	*Skewness*	*Kurtosis*	*Jarque-Bera*	*Prob.*
India (NIFTY 50)	0.0003	0.0005	0.0840	–0.1390	0.0112	–1.4187	24.0230	33,301.2700	0.0000
USA (DJ IA)	0.0004	0.0007	0.1076	–0.1384	0.0111	–1.0996	33.3265	68,030.1800	0.0000
UAE (ADI)	0.0003	0.0006	0.0808	–0.1392	0.0131	–1.1530	19.8741	17,149.3300	0.0000
China (SSEC)	0.0001	0.0006	0.0604	–0.0887	0.0146	–1.0536	9.7744	3,571.5250	0.0000
Hong Kong (HANG SENG)	0.0000	0.0005	0.0493	–0.0602	0.0116	–0.2979	5.7320	564.9027	0.0000
Singapore (FTSE)	–0.0001	0.0001	0.0755	–0.0748	0.0089	–0.2271	15.6731	12,148.2100	0.0000
UK (FTSE 100)	0.0000	0.0005	0.0867	–0.1151	0.0103	–1.0075	18.8108	18,799.0100	0.0000
Bangladesh (DSE 30)	–0.0001	0.0001	0.5246	–0.5242	0.0231	0.0192	400.0587	8,822,147.0000	0.0000
Germany (DAX)	0.0002	0.0008	0.1041	–0.1305	0.0126	–0.6194	15.3925	11,510.3800	0.0000
Netherlands	0.0002	0.0007	0.0859	–0.1138	0.0111	–0.8657	14.9207	10,882.4800	0.0000
Saudi Arabia (MSCI TADAWUL 30)	0.0003	0.0006	0.0808	–0.1392	0.0131	–1.1530	19.8741	17,149.3300	0.0000
Iraq (ISX 60)	–0.0008	–0.0010	0.2147	–0.2878	0.0178	–2.2981	94.8676	358,525.8000	0.0000
Switzerland (SMI)	0.0002	0.0006	0.0678	–0.1013	0.0103	–1.2079	15.2922	11,521.5500	0.0000
South Korea (KOSPI)	0.0000	0.0003	0.0825	–0.0877	0.0095	–0.2693	15.9165	12,040.0800	0.0000
Indonesia (JKSE)	0.0001	0.0007	0.0970	–0.0681	0.0109	–0.1287	11.0135	4,596.1430	0.0000

Source: Authors' computations

Table 4 Results of ADF unit root test and ARCH-LM test

Countries	*ADF test (levels)*		*ADF test (1st difference)*		*ARCH-LM test*			
	t-statistic	*Prob.*	*t-statistic*	*Prob.*	*F-statistic*	*Prob. F*	*Obs. * R-squared*	*Prob. chi-square*
India	–2.2995	(0.4334)	–14.6831	(0.0000)**	60.3989	(0.0000)**	58.4751	(0.0000)**
USA	–3.2367	(0.0776)	–24.7639	(0.0000)**	334.6064	(0.0000)**	281.5496	(0.0000)**
UAE	–3.3722	(0.0555)	–37.0797	(0.0000)**	188.4119	(0.0000)**	166.5209	(0.0000)**
China	–1.6743	(0.7624)	–39.1944	(0.0000)**	76.7888	(0.0000)**	73.5566	(0.0000)**
Hong Kong	–2.1667	(0.5074)	–41.6248	(0.0000)**	43.9807	(0.0000)**	42.9405	(0.0000)**
Singapore	–2.4530	(0.3518)	–14.1165	(0.0000)**	335.9788	(0.0000)**	283.6904	(0.0000)**
UK	–2.7490	(0.2169)	–42.5982	(0.0000)**	54.3922	(0.0000)**	52.8328	(0.0000)**
Bangladesh	–0.6896	(0.9729)	–35.6153	(0.0000)**	443.2985	(0.0000)**	333.5990	(0.0000)**
Germany	–2.8994	(0.1629)	–27.7352	(0.0000)**	5.7933	(0.0162)**	5.7810	(0.0162)**
Netherlands	–3.3373	(0.0606)	–40.9603	(0.0000)**	27.1456	(0.0000)**	26.7714	(0.0000)**
Saudi Arabia	–3.3722	(0.0555)	–37.0797	(0.0000)**	188.4119	(0.0000)**	166.5209	(0.0000)**
Iraq	–1.6639	(0.7666)	–23.1101	(0.0000)**	219.5510	(0.0000)**	180.8306	(0.0000)**
Switzerland	–4.0722	(0.0070)**	–40.9557	(0.0000)**	112.7239	(0.0000)**	106.0556	(0.0000)**
South Korea	–2.9035	(0.1615)	–26.2274	(0.0000)**	911.2462	(0.0000)**	597.0749	(0.0000)**
Indonesia	–1.9039	(0.6520)	–38.7319	(0.0000)**	85.1136	(0.0000)**	81.1795	(0.0000)**

Note: Figures in parentheses indicate probability values and **indicates 5% level of significance.

Source: Authors' computations

Table 3 indicates that the USA has highest mean returns (0.0004), whereas Iraq has lowest mean return (–0.0008). The average daily returns of most of the stock market indices are positive. Indices of three countries namely, Singapore, Bangladesh and Iraq are showing negative average daily returns. Bangladesh stock market has highest daily standard deviation of 0.0231 and Singapore stock market has lowest daily standard deviation of 0.0089 followed by South Korea stock market having standard deviation of 0.0095. It shows that Bangladesh stock market is most volatile and Singapore stock market is least volatile. The skewness value for all stock returns except Bangladesh is negative indicating that large negative returns are present. The kurtosis values for all indices returns is very high indicating that sharp peaks and fat tails are present in returns distributions. The Jarque-Bera statistic for all returns series shows that these series do not follow normal distribution.

To check the stationarity of the stock indices and their order of integration, augmented Dickey-Fuller (ADF) test of unit root is used both with trend and intercept. The results of the ADF test as exhibited in Table 4 show that the null hypothesis of unit root is rejected for all the indices at their return or first difference. Thus, it can be concluded that all stock indices under study are stationary and integrated of order 1, i.e., $I(1)$. Also, we test for the presence of ARCH effects in the return series as by ignoring this preliminary test, there may be loss of efficiency. The study applies ARCH Lagrange multiplier (LM) test on the residuals after running the LS regression. This test takes the null hypothesis that no ARCH effects are present in the data. From the results presented in Table 4, it can be inferred that the null hypothesis is strongly rejected in case of all the return series under study. It shows that significant ARCH effects are present in all indices thereby, providing evidence that the residuals are heteroskedastic and time varying volatility clustering is accepted for the data. Prima facie, it establishes a valid reason to use the GARCH family models.

5 Data analysis and results

This section deals with data analysis and detailed discussion of the empirical results.

5.1 Results of EGARCH model

After testing the preliminaries of the data, the asymmetric volatility spillover has been tested by employing bivariate EGARCH model. This model is applied on the pairs of return series of the stock market of India and its trading partners taken one at a time. The volatility spillover is studied in the direction of India to trading partner as well as trading partner to India with the help of the following EGARCH equations:

$$\ln\left(\sigma_{India\,t}^2\right) = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta\ln\left(\sigma_{t-1}^2\right) + \psi\left(\varepsilon_{Partner\,t-1}^2\right) \tag{4}$$

$$\ln\left(\sigma_{Partner\,t}^2\right) = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta\ln\left(\sigma_{t-1}^2\right) + \psi\left(\varepsilon_{India\,t-1}^2\right) \tag{5}$$

Bivariate EGARCH model helps to inspect the impact of the lagged square error term of one country's stock market returns on the conditional volatility of the other country. The lagged squared error term of one country is estimated with the help of mean equation applied on the other country's equation. This squared error term is included in the EGARCH model as an exogenous regressors. The coefficient of the fifth term, i.e., ψ in the above equations captures the cross-market volatility spillover, i.e., the significance of volatility spillover across the two stock markets. The results of bivariate EGARCH model are exhibited in Table 5.

Table 5 presents the estimation results of EGARCH model. The bivariate EGARCH tests for volatility spillover are conducted for Indian stock market returns by taking each trading partner's stock market returns one by one. Panel A, i.e., left side of Table 5 presents the results of volatility spillover from trading partners to India and Panel B, i.e., right side of Table 5 presents the volatility spillover from India to its trading partners. The results indicate value of the coefficients, standard error and the probability value of all the regression coefficients in the EGARCH model. The results provide the evidence that significant bi-directional volatility spillover exists between India and four of its trading partners namely, the USA, the UK, Germany and South Korea. It confirms that any external shock in these countries will impact the volatility of Indian stock market the next day. Similarly, if any sudden shock comes in India, it will also impact the volatility of these countries' stock markets the next day. This may be because of the strong interrelation of these economies through international trade. It also suggests that India is both the transmitter and the receiver of volatility for these countries. There exists unidirectional volatility spillover from six of its trading partners namely, UAE, Singapore, Netherlands, Saudi Arabia, Switzerland and Indonesia towards India indicating that any sudden news or shock in these countries will bring fluctuation in the Indian stock market on the following day. It is suggestive of the fact that India is the net receiver of volatility from these countries. Further, there exists unidirectional volatility spillover from India towards three of its trading partners, i.e., China, Bangladesh and Iraq showing that stock market returns of these countries are sensitive to the volatility of Indian stock market. It is indicative of the fact that India is the net transmitter of volatility for these countries. The results highlight that volatility spillover between India and Hong Kong is not significant.

The results reveal that there are positive volatility transmissions from all trading partners except Iraq towards India as the value of the spillover coefficient ψ is positive. Also, there are positive volatility transmissions from India to all its trading partners except China and Iraq. The spillover coefficient from India to six of its trading partners namely, the USA, China, Hong Kong, Bangladesh, Iraq and South Korea is greater in magnitude than the spillover coefficient from these trading partners to India. And, the spillover coefficient from eight of its trading partners, namely, UAE, Singapore, the UK, Germany, Netherlands, Saudi Arabia, Switzerland and Indonesia to India is greater in magnitude than the spillover coefficient from India to these countries. Overall, the results highlight that UAE, Singapore, the UK, Germany, Netherlands, Saudi Arabia, Switzerland and Indonesia are exporting their volatility to India with India exporting its volatility to the USA, China, Hong Kong, Bangladesh, Iraq and South Korea.

With reference to the parameter γ, we found a negative and significant coefficient in case of all trading partners to India showing that volatility spillover mechanism is asymmetric. Similarly, leverage effect is accepted for EGARCH model applied from India to all its trading partners except China and Bangladesh. These results bring to light the fact that negative news creates more volatility than the positive news for these countries. The volatility persistence parameter β is close to one and significant for all test pairs except spillover from India to Bangladesh. It indicates that there exists high volatility persistence with slow fading away of volatility shocks. Therefore, it may be stated that present innovations retain their significance for all future forecasts of conditional variances.

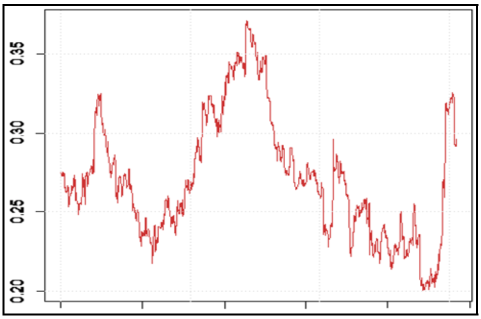
5.2 Results of DCC-GARCH model

The volatility spillover is also examined with the help of MGARCH model, i.e., DCC-GARCH proposed by Engle (2002). The DCC-GARCH helps to measure time-varying correlation between the conditional variances of the returns of stock market indices of India and its trading partners. The parameter estimates of DCC-GARCH model are reported in Table 6.

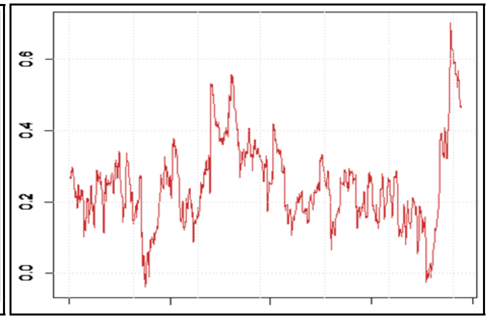
Table 6 presents the results of DCC-GARCH model for all 14 pairs of stock indices returns. The Ω, $\alpha 1$ and $\beta 1$ indicates the intercept term, the ARCH term and the GARCH term of the GARCH (1, 1) model. The joint DCCα indicates the volatility spillover as a result of unexpected shocks as captured by errors of the mean equation whereas DCCβ indicates volatility spillover between the conditional variance of the two markets estimated with the help of GARCH model. The results of univariate GARCH model show that the sum of the coefficients of ARCH ($\alpha 1$) and GARCH terms ($\beta 1$) is approaching to 1 indicating the presence of high persistence (decaying at a lower rate) in conditional variances. The DCC parameter DCCα are having positive and small values compared to DCCβ with the sums of both coefficients approaching to unity showing that conditional volatility exhibits a highly persistent nature for all market pairs used in study. In the DCC estimation, the probability value of DCCα is found to be significant in case of nine countries namely, UAE, Singapore, the UK, Bangladesh, Germany, Netherlands, Saudi Arabia, South Korea and Indonesia. These results suggest the significant volatility spillover as a result of unexpected shock in case of these nine country pairs. When some sudden market shock comes in these countries, these markets become more volatile and also export some of their volatility to the counter market. However, the p-value is not found significant in case of other five countries namely, the USA, China, Hong Kong, Iraq and Switzerland. From the perspective of volatility transmissions, the results provide interesting insights that the coefficients of DCCβ are positive and statistically significant in case of the all country pairs used in the study. This can be concluded from the results that time-varying or dynamic nature of the conditional correlation exists for all the pairs of stock indices on which tests have been conducted. Therefore, it can be concluded that significant volatility transmissions are present across all the country pairs and their stock markets maintain co-movement equilibrium. To put in other words, the volatility in one market leads to disturbance in other market.

Finally, we investigate the patterns of pairwise time-varying correlations across all the markets. The DCCs obtained from DCC-GARCH model are plotted in Figure 1.

Figure 1 Time varying correlations between stock markets returns of India with each of the trading partner, (a) DCC between India and the USA (b) DCC between India and UAE (c) DCC between India and China (d) DCC between India and Hong Kong (e) DCC between India and Singapore (f) DCC between India and the UK (g) DCC between India and Bangladesh (h) DCC between India and Germany (i) DCC between India and Netherlands (j) DCC between India and Saudi Arabia (k) DCC between India and Iraq (l) DCC between India and Switzerland (m) DCC between India and South Korea (n) DCC between India and Indonesia (see online version for colours)



(a)



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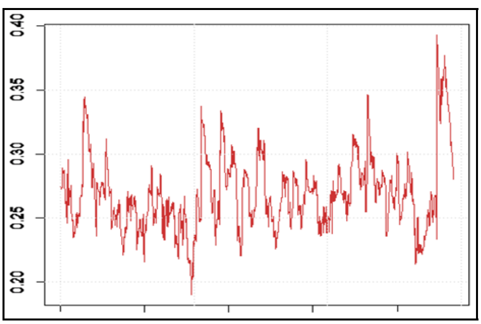

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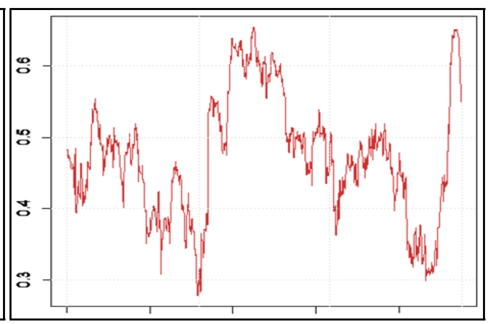

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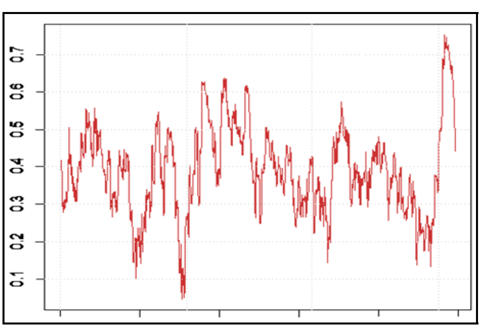

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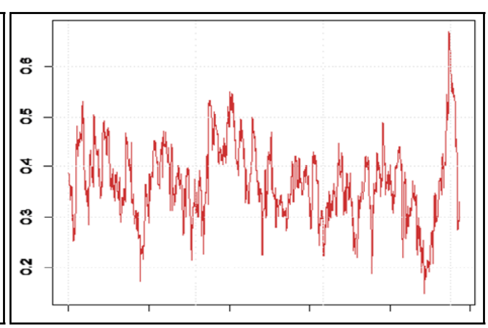
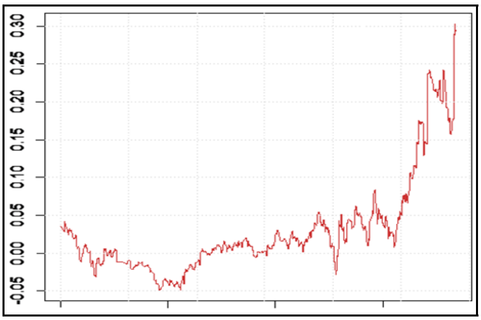
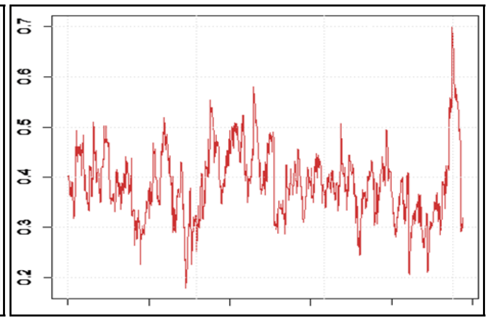


(f)

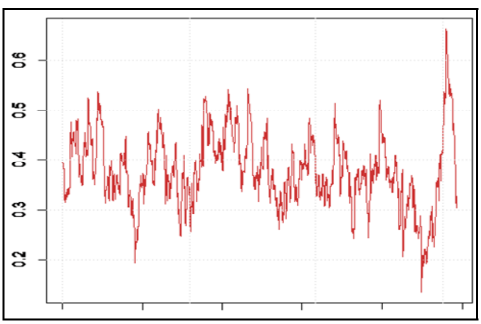
Figure 1 Time varying correlations between stock markets returns of India with each of the trading partner, (a) DCC between India and the USA (b) DCC between India and UAE (c) DCC between India and China (d) DCC between India and Hong Kong (e) DCC between India and Singapore (f) DCC between India and the UK (g) DCC between India and Bangladesh (h) DCC between India and Germany (i) DCC between India and Netherlands (j) DCC between India and Saudi Arabia (k) DCC between India and Iraq (l) DCC between India and Switzerland (m) DCC between India and South Korea (n) DCC between India and Indonesia (continued) (see online version for colours)



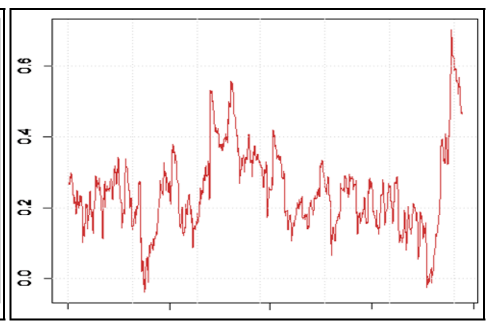
(g)



(h)



(i)



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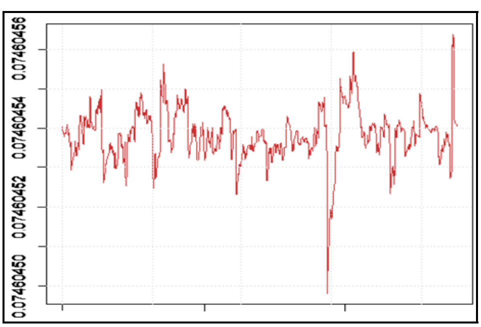

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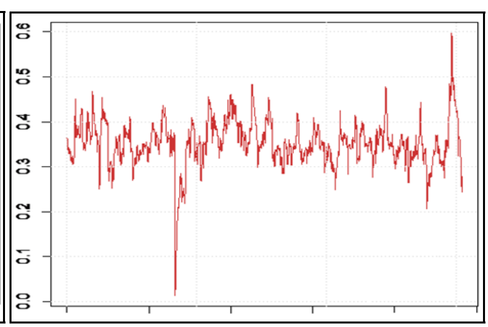
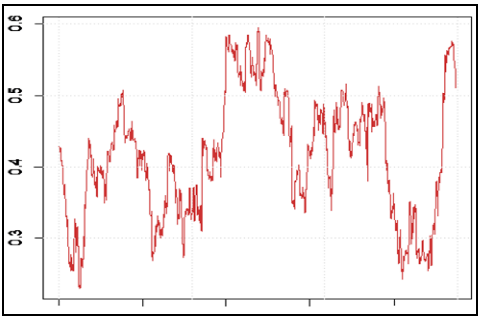


(l)

Figure 1 Time varying correlations between stock markets returns of India with each of the trading partner, (a) DCC between India and the USA (b) DCC between India and UAE (c) DCC between India and China (d) DCC between India and Hong Kong (e) DCC between India and Singapore (f) DCC between India and the UK (g) DCC between India and Bangladesh (h) DCC between India and Germany (i) DCC between India and Netherlands (j) DCC between India and Saudi Arabia (k) DCC between India and Iraq (l) DCC between India and Switzerland (m) DCC between India and South Korea (n) DCC between India and Indonesia (see online version for colours)



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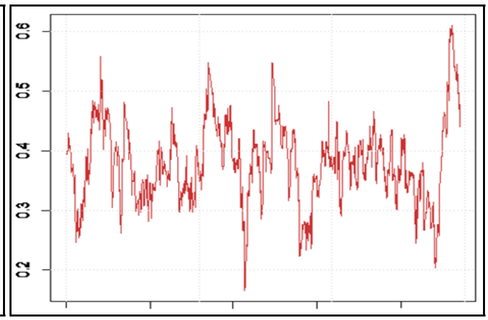

(n)

Figure 1 reveals that varying patterns of correlation dynamic path are existing which warrants the application of DCC-GARCH modelling techniques. The dynamic correlations exhibit that moderate level of conditional correlation is found across Indian stock market and the stock markets of UAE, Hong Kong, Singapore, the UK, Germany, Netherlands, Saudi Arabia, Switzerland, South Korea and Indonesia. Low level of conditional correlation is observed across Indian stock market and the stock markets of the USA, China and Bangladesh and very low level of conditional correlation is observed across Indian and Iraq stock markets. Overall, DCC is found to be positive for all market pairs implying that increase in volatility in one market will lead to increase in volatility in the other market as well and *vice versa*. This clearly indicates significant volatility transmission and interdependence among the market pairs during the period of study.

6 Conclusions and implications

This paper explores the nature of volatility transmissions between India and its 14 major trading partners, the USA, UAE, China, Hong Kong, Singapore, the UK, Bangladesh, Germany, Netherlands, Saudi Arabia, Iraq, Switzerland, South Korea and Indonesia. The study is based on the data of the benchmark stock market indices of these countries covering time period from January 2013 to May 2020. After preliminary data analysis, the study has applied two advanced econometric models EGARCH and DCC-GARCH to gather the information relating to dynamic volatility transmission across India and its trading partners. The results of volatility modelling are interesting.

Table 5 Results of EGARCH model for stock returns

Countries	*(A) Volatility spillover from trading partners to India*					*(B) Volatility spillover from India to trading partners*				
	ω	α	γ	β	ψ	ω	α	γ	β	ψ
India-USA	–0.446	0.086	–0.125	0.960	50.074	–0.798	0.195	–0.216	0.934	52.452
	(0.049)	(0.019)	(0.010)	(0.005)	(10.739)	(0.071)	(0.021)	(0.013)	(0.007)	(21.918)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.017]**
India-UAE	–0.428	0.032	–0.151	0.956	42.071	–0.921	0.274	–0.122	0.921	40.184
	(0.054)	(0.013)	(0.010)	(0.006)	(9.654)	(0.126)	(0.023)	(0.012)	(0.013)	(32.027)
	[0.000]**	[0.012]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.210]
India-China	–0.386	0.124	–0.150	0.969	8.884	–0.181	0.166	–0.006	0.993	–27.807
	(0.040)	(0.019)	(0.010)	(0.003)	(6.868)	(0.017)	(0.010)	(0.007)	(0.002)	(9.476)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.196]	[0.000]**	[0.000]**	[0.359]	[0.000]**	[0.003]**
India-Hong Kong	–0.402	0.135	–0.138	0.968	19.722	–0.451	0.084	–0.084	0.957	23.486
	(0.055)	(0.019)	(0.012)	(0.005)	(27.193)	(0.062)	(0.013)	(0.010)	(0.007)	(12.682)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.468]	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.064]
India-Singapore	–0.419	0.120	–0.136	0.966	54.420	–0.327	0.096	–0.098	0.974	14.838
	(0.047)	(0.019)	(0.010)	(0.005)	(20.384)	(0.048)	(0.015)	(0.010)	(0.004)	(9.640)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.008]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.124]
India-UK	–0.488	0.120	–0.133	0.959	75.784	–0.775	0.153	–0.164	0.932	49.238
	(0.055)	(0.021)	(0.012)	(0.005)	(16.785)	(0.083)	(0.021)	(0.012)	(0.008)	(21.468)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.022]**
India-Bangladesh	–0.437	0.093	–0.175	0.959	0.617	–9.569	0.876	0.459	–0.006	354.760
	(0.079)	(0.018)	(0.014)	(0.008)	(1.401)	(0.287)	(0.021)	(0.021)	(0.032)	(45.763)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.659]	[0.000]**	[0.000]**	[0.000]**	[0.841]	[0.000]**

Notes: Figures in parentheses ( ) indicate standard error.
Figures in brackets [ ] indicate probability values.
**Indicates 5% level of significance.

Source: Authors' computations

Table 5 Results of EGARCH model for stock returns (continued)

Countries	*(A) Volatility spillover from trading partners to India*					*(B) Volatility spillover from India to trading partners*				
	ω	α	γ	β	ψ	ω	α	γ	β	ψ
India-Germany	–0.491	0.112	–0.138	0.958	64.412	–0.318	0.094	–0.145	0.972	15.148
	(0.052)	(0.019)	(0.011)	(0.005)	(13.144)	(0.047)	(0.015)	(0.011)	(0.004)	(7.643)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.048]**
India-Netherlands	–0.489	0.113	–0.130	0.958	83.694	–0.566	0.159	–0.190	0.953	24.240
	(0.051)	(0.020)	(0.011)	(0.005)	(16.209)	(0.059)	(0.020)	(0.012)	(0.005)	(13.796)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.079]
India-Saudi Arabia	–0.428	0.032	–0.151	0.956	42.071	–0.921	0.274	–0.122	0.921	40.184
	(0.054)	(0.013)	(0.010)	(0.006)	(9.654)	(0.126)	(0.023)	(0.012)	(0.013)	(32.027)
	[0.000]**	[0.012]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.210]
India-Iraq	–0.525	0.052	–0.181	0.946	–2.306	–3.870	0.975	–0.236	0.619	–613.925
	(0.130)	(0.018)	(0.016)	(0.014)	(3.588)	(0.246)	(0.040)	(0.027)	(0.026)	(12.353)
	[0.000]**	[0.004]**	[0.000]**	[0.000]**	[0.521]	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**
India-Switzerland	–0.446	0.117	–0.132	0.963	74.069	–1.040	0.244	–0.181	0.910	33.461
	(0.045)	(0.019)	(0.011)	(0.004)	(19.449)	(0.111)	(0.021)	(0.017)	(0.011)	(29.569)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.258]
India-South Korea	–0.459	0.120	–0.165	0.961	41.781	–0.689	0.083	–0.127	0.936	52.860
	(0.071)	(0.021)	(0.013)	(0.007)	(17.734)	(0.097)	(0.017)	(0.013)	(0.010)	(17.868)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.019]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.003]**
India-Indonesia	–0.517	0.103	–0.139	0.955	105.146	–0.499	0.158	–0.104	0.960	16.509
	(0.053)	(0.019)	(0.011)	(0.005)	(21.804)	(0.069)	(0.019)	(0.013)	(0.007)	(15.599)
	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.290]

Notes: Figures in parentheses ( ) indicate standard error.
Figures in brackets [ ] indicate probability values.
**Indicates 5% level of significance.

Source: Authors' computations

Table 6 Results of DCC-GARCH model of stock returns of India with its trading partners

Country pairs	*Ω (India_r)*	*α1 (India_r)*	*β1 (India_r)*	*Ω (Partner_r)*	*α1 (Partner_r)*	*β1 (Partner_r)*	*DCCα (joint)*	*DCCβ (joint)*
India-USA	0.000	0.099	0.880	0.000	0.191	0.771	0.003	0.992
	(0.000)	(0.023)	(0.022)	(0.000)	(0.028)	(0.057)	(0.002)	(0.005)
	[0.062]	[0.000]**	[0.000]**	[0.382]	[0.000]**	[0.000]**	[0.135]	[0.000]**
India-UAE	0.000	0.076	0.893	0.000	0.219	0.716	0.022	0.954
	(0.000)	(0.007)	(0.013)	(0.000)	(0.033)	(0.040)	(0.010)	(0.025)
	[0.003]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.030]**	[0.000]**
India-China	0.000	0.100	0.878	0.000	0.078	0.920	0.007	0.952
	(0.000)	(0.020)	(0.016)	(0.000)	(0.066)	(0.060)	(0.006)	(0.025)
	[0.083]	[0.000]**	[0.000]**	[0.786]	[0.237]	[0.000]**	[0.239]	[0.000]**
India-Hong Kong	0.000	0.117	0.863	0.000	0.053	0.929	0.013	0.982
	(0.000)	(0.024)	(0.020)	(0.000)	(0.013)	(0.017)	(0.008)	(0.018)
	[0.062]	[0.000]**	[0.000]**	[0.205]	[0.000]**	[0.000]**	[0.108]	[0.000]**
India-Singapore	0.000	0.105	0.873	0.000	0.084	0.896	0.028	0.947
	(0.000)	(0.023)	(0.021)	(0.000)	(0.022)	(0.023)	(0.007)	(0.012)
	[0.052]	[0.000]**	[0.000]**	[0.178]	[0.000]**	[0.000]**	[0.000]**	[0.000]**
India-UK	0.000	0.108	0.869	0.000	0.171	0.775	0.024	0.931
	(0.000)	(0.022)	(0.019)	(0.000)	(0.020)	(0.028)	(0.008)	(0.025)
	[0.051]	[0.000]**	[0.000]**	[0.001]**	[0.000]**	[0.000]**	[0.003]**	[0.000]**
India-Bangladesh	0.000	0.078	0.894	0.000	0.173	0.821	0.005	0.995
	(0.000)	(0.009)	(0.015)	(0.000)	(0.092)	(0.108)	(0.003)	(0.008)
	[0.017]**	[0.000]**	[0.000]**	[0.727]	[0.061]	[0.000]**	[0.034]**	[0.000]**

Notes: Figures in parentheses ( ) indicate standard error.
Figures in brackets [ ] indicate probability values.
**Indicates 5% level of significance.

Source: Authors' computations

Table 6 Results of DCC-GARCH model of stock returns of India with its trading partners (continued)

Country pairs	*Ω (India_r)*	*α1 (India_r)*	*β1 (India_r)*	*Ω (Partner_r)*	*α1 (Partner_r)*	*β1 (Partner_r)*	*DCCα (joint)*	*DCCβ (joint)*
India-Germany	0.000	0.109	0.867	0.000	0.094	0.887	0.022	0.933
	(0.000)	(0.021)	(0.018)	(0.000)	(0.026)	(0.042)	(0.010)	(0.037)
	[0.083]	[0.000]**	[0.000]**	[0.517]	[0.000]**	[0.000]**	[0.030]**	[0.000]**
India-Netherlands	0.000	0.108	0.869	0.000	0.165	0.806	0.022	0.940
	(0.000)	(0.022)	(0.020)	(0.000)	(0.251)	(1.379)	(0.008)	(0.052)
	[0.052]	[0.000]**	[0.000]**	[0.981]	[0.511]	[0.559]	[0.004]**	[0.000]**
India-Saudi Arabia	0.000	0.076	0.893	0.000	0.219	0.716	0.022	0.954
	(0.000)	(0.007)	(0.013)	(0.000)	(0.033)	(0.040)	(0.010)	(0.025)
	[0.003]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.030]**	[0.000]**
India-Iraq	0.000	0.073	0.881	0.000	0.432	0.567	0.000	0.920
	(0.000)	(0.005)	(0.013)	(0.000)	(0.361)	(0.143)	(0.000)	(0.104)
	[0.000]**	[0.000]**	[0.000]**	[0.362]	[0.231]	[0.000]**	[1.000]	[0.000]**
India-Switzerland	0.000	0.109	0.865	0.000	0.185	0.767	0.018	0.904
	(0.000)	(0.020)	(0.018)	(0.000)	(0.022)	(0.032)	(0.010)	(0.037)
	[0.184]	[0.000]**	[0.000]**	[0.010]**	[0.000]**	[0.000]**	[0.068]	[0.000]**
India-South Korea	0.000	0.117	0.860	0.000	0.083	0.871	0.013	0.982
	(0.000)	(0.024)	(0.020)	(0.000)	(0.008)	(0.012)	(0.004)	(0.008)
	[0.219]	[0.000]**	[0.000]**	[0.003]**	[0.000]**	[0.000]**	[0.004]**	[0.000]**
India-Indonesia	0.000	0.109	0.865	0.000	0.127	0.839	0.019	0.945
	(0.000)	(0.021)	(0.022)	(0.000)	(0.019)	(0.070)	(0.007)	(0.021)
	[0.291]	[0.000]**	[0.000]**	[0.632]	[0.000]**	[0.000]**	[0.007]**	[0.000]**

Notes: Figures in parentheses ( ) indicate standard error.
Figures in brackets [ ] indicate probability values.
**Indicates 5% level of significance.

Source: Authors' computations

The results of EGARCH model provide the evidence that significant bi-directional volatility spillover exists between India and four of its trading partners namely, the USA, the UK, Germany and South Korea; unidirectional volatility spillover exists from six of its trading partners namely, UAE, Singapore, Netherlands, Saudi Arabia, Switzerland and Indonesia towards India; unidirectional volatility spillover exists from India towards three of its trading partners, i.e., China, Bangladesh and Iraq and volatility spillover between India and Hong Kong is found not significant. The results reveal that UAE, Singapore, the UK, Germany, Netherlands, Saudi Arabia, Switzerland and Indonesia are exporting their volatility to India with India exporting volatility to the USA, China, Hong Kong, Bangladesh, Iraq and South Korea. Further, the volatility spillover mechanism is asymmetric, i.e., negative news creates more volatility than the positive news for these market pairs. Also, there exists high volatility persistence with slow fading away of volatility shocks.

The results of DCC-GARCH model reveal that time-varying or dynamic nature of the conditional correlation exists for all the pairs of stock indices, thus, providing evidence that significant volatility transmissions are present across all the country pairs and their stock markets maintain co-movement equilibrium. Also, conditional volatility exhibits a highly persistent nature for all market pairs used in study. In case of nine country pairs, UAE, Singapore, the UK, Bangladesh, Germany, Netherlands, Saudi Arabia, South Korea and Indonesia, significant volatility spillover as a result of unexpected shock is present suggesting that a sudden market shock in these countries makes the counter market more volatile.

The findings of the study have relevant and useful implications for academicians, portfolio managers, international investors and hedgers for devising exploitable trading and diversification strategies to maximise their return keeping the risk at minimum. They might be able to predict the impact of the trading partners' financial fluctuations on the stock market of an emerging country like India and an accurate forecast of the spillover relationships existing between international financial markets is vital for risk management and mitigation. The study has strong practical implications for government, regulators and policy makers in policy arrangements as the insight of global volatility linkages are crucial for stability of an economy from international financial shocks and crisis. Especially, gauging the depth of the volatility transmission relationships between two trading partners will enable the policy makers to understand the impact of any policy they make on other financial markets, thereby achieving policy effectiveness.

For this study, the country specific benchmark stock market indices have been used which are having varying number of constituents. The study did not consider global market composite indices for analysis. This may be taken as future research endeavour. The study offers scope for future research in the area of volatility spillovers across more stock markets of different regions, spillovers between other markets (commodity, currency, etc.) of different countries, spillovers between financial markets and macro economy, spillovers using weekly, monthly or high-frequency data.

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