

Return and volatility spillover between India and leading Asian and global equity markets: an empirical analysis

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Abstract

Purpose – The study uses the multivariate GARCH-BEKK model (which was first proposed by Baba *et al.* (1990) and then further developed by Engle and Kroner (1995)) to examine the return and volatility spillover between India and four leading Asian (namely, China, Japan, Singapore and Hong Kong) and two global (namely, the United Kingdom and the United States) equity markets.

Design/methodology/approach – The study employs a multivariate GARCH-BEKK model to quantify return correlation and volatility transmission across the pre- and post-2008 global financial crisis periods (apart from other conventional time series modelling like cointegration, Granger causality using vector error correction model (VECM)).

Findings – The results show a tendency of the Indian stock market index to move along with the US and Hong Kong market indices. The decrease in the value of the co-integration coefficient during the recession was explained by reduced investor confidence in developing countries. The result further shows a clear distinction in terms of volatility spillover between the Asian market vis-a-vis US and UK markets. Volatility transmission from India to Asian markets was found to be significantly higher as compared to the US and UK. So also, the study's results show a puzzling result giving us comparable co-integration ranks for phase 2 (expansion) and phase 3 (slow-down) of the business cycle in most cases.

Research limitations/implications – In Granger causality testing, the results were unable to ascertain the difference between phase 2 (expansion) and phase 3 (slowdown). However, the multivariate GARCH (MGARCH)-BEKK model showed a clear reduction in volatility transmission to NIFTY50 (is the flagship index on the National Stock Exchange of India Ltd. (NSE)) as India entered slow-down. This shows that the Indian economy does go through different business cycles, and the changes in parameters hence prove hypothesis 3 to be true with respect to volatility transmission to India from International markets.

Originality/value – The results show that for all countries, the volatility transmitted to India increases significantly going from phase 1 (recession) to phase 2 (expansion) and reduces again once the countries enter slow-down in phase 3 (slowdown). This shows that during expansion shocks and impulses in international markets affect the Indian markets significantly, supporting the increase in co-integration in phase 2 (expansion). During expansion, developing markets like India become profitable for investors, due to the high

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growth rate when compared to developed countries. This implies that a significant amount of capital enters Indian markets, which is susceptible to the volatility of international markets. The volatility transmission from India to the US and UK was insignificant in phase 1 (recession and recovery) and phase 3 (slow-down) showing a weak linkage between the markets during volatile time periods.

Keywords Equity markets, Return spillover, Volatility spillover, GARCH-BEKK model, Business cycle, Investor behaviour

Paper type Research paper

1. Introduction

The globalization of financial markets is becoming a visible trend all across the globe. Domestic stock markets are becoming increasingly globalized as a result of greater international investor participation, technological advancement and the elimination of cross-border capital movement barriers in most nations. Emerging stock markets have been a popular destination for international portfolio investors seeking diversity. Furthermore, investors are looking for better rates of return in these economies due to low-interest rates in their own nations since the global crisis. This increasing international financial integration emphasizes the significance of understanding and forecasting the stock return connection and volatility transmission among stock markets across the globe. Investors are particularly interested in volatility transmission across foreign markets because they must continuously monitor and evaluate changes in stock market connections in order to enjoy the advantages of portfolio diversification and risk-sharing (Jung and Maderitsch, 2014; Kocaarslan *et al.*, 2017).

With increasing global financial integration, investors and regulators are more interested in information transmissions (return and volatility) across stock markets. For instance, if asset volatility is transferred from one market to another during times of turbulence or crisis, portfolio managers must adjust their asset allocations (Bouri, 2013; Syriopoulos *et al.*, 2015; Vo and Ellis, 2018; Hung, 2019; Yousaf *et al.*, 2020) and financial policymakers must alter their policies to mitigate the risk of contagion (Yang and Zhou, 2017). The interdependence of stock markets, particularly during times of crisis, may have significant consequences for asset allocation, portfolio diversification, asset valuation, hedging and risk management.

In the last two decades, as the significance of emerging markets has grown, financial economists have been drawn to the interplay between developing and established markets for their implications for global integration and financial deregulation. Numerous studies have examined the co-movement of stock prices across foreign financial markets experimentally, including Bekaert and Harvey (1997), Ng (2000), Jebran *et al.* (2017), Jin and An (2016), Gupta and Guidi (2012), Al Nasser and Hajilee (2016), and Balli *et al.* (2015).

Against this backdrop, this paper envisages an understanding of differences in the reaction of equity markets between India, leading Asian countries (namely, Singapore, Hong Kong, China and Japan), and two developed regions countries (namely, the US and the UK). The equity indices being used for these countries are NIFTY50 (India), S&P 500 (the US), FTSE 100 (the UK), Straits Times (Singapore), Shanghai Composite (Hong Kong), Hang Seng (China) and Nikkei 225 (Japan). All these indices were chosen based on their volatility and market depth, and in their respective countries, these exchanges track the largest firms based on their revenue and profitability. A few studies have started the discussion on inter-country analysis with an econometric analysis of cross-country currency rates (Grubel, 1968). Traders that usually operate with high capital often tend to have a diversified portfolio containing stocks from multiple countries. Market investors have a certain holding time for their portfolios which allows them to gain profits by exploiting the differences in the market. However, if markets co-move then the arbitrage opportunity vanishes after they catch up

with each other. Thus, an analysis of co-integration and volatility among markets is required to find the period of opportunity for investors, although absolute co-integration among markets cannot exist as was proven in research (Granger, 1969). This can be reinforced further by applying volatility models which show how shocks in markets are transmitted cross-country over time (Engle and Kroner, 1995).

The objective of the paper is to analyse the following seven specific research questions: (1) Is the volatility of a stock market leading to the volatility of other markets? (2) Is the volatility of an asset transmitted to another asset directly (through its conditional variance) or indirectly (through its conditional covariances)? (3) Does a shock on a stock market increase the volatility on another market, and by how much? (4) Is the impact the same for negative and positive shocks of the same amplitude? (5) Whether the correlations between asset returns change over time. (6) Are they higher during periods of higher volatility (sometimes associated with financial crises)? (7) Are they increasing in the long run, perhaps because of the globalization of financial markets?

In this paper, we use an advanced multivariate GARCH (MGARCH-BEKK) model, named after Baba *et al.* (1990) to gather information, which can quantify market reactions and provide a more precise view of linkages between Nifty50 and other international markets in US, UK, Singapore, Hong Kong, China and Japan. Finding such linkages is also important to policymakers with globalization picking up in recent years.

Econometric analysis of the MGARCH-BEKK model and its usability that has been carried out in the past decade shows the usability of the model when a diagonal restriction is applied (Chang and McAleer, 2018). The same model has also found applications in cryptocurrency analysis (Katsiampa *et al.*, 2019), alternative energy input prices (Katircioğlu *et al.*, 2019) and several other economic analyses. Within these studies, the order of the model was always fixed to (1, 1) because the BEKK model does not calibrate well with high order GARCH (Ng and Lam, 2006).

A major analysis is performed by following the co-integration theory. Co-integration rank for each section of data is calculated to measure the time it takes for markets to catch up with each other. Markets have a certain set of trends with their data, and often due to several external factors, a lot of these are common among them. The co-integration theory helps us quantify these trends in a manner that allows us to draw conclusions from it. We will analyse these results across the timeframe chosen with daily market data to introduce an element of evolving time over the analysis.

This paper is organized as follows. Section 2 briefly discusses the relevant literature and presents the testable hypotheses of the study. Following this, Section 3 presents the data and discusses the MGARCH-BEKK methodology. Section 4 presents the empirical results, followed by a discussion of the same in Section 5, and finally, Section 6 concludes.

2. Literature review

The literature defines volatility spillover as follows: bidirectional volatility spillover among stock markets; unidirectional volatility flow from one stock market to another stock market; and non-persistence of volatility spillover among them (Hung, 2018). Primarily developed-country financial markets were studied initially. Hamao *et al.* (1990) detected price volatility transmissions from New York to London and Tokyo (1990). Like Koutmos and Booth (1995), negative innovations in established markets (New York, Tokyo and London) increase volatility in the next market to trade.

A few studies look at the stock market interactions between India and the US, China and the US. They deploy a fractionally integrated vector error correction model (FIVECM) to assess cross-market co-integration. The research also evaluates first and second-moment

spillover effects concurrently by adding a multivariate GARCH component to FIVECM. Their findings show that the US stock market dominates the other two, although the Indian and Chinese stock markets interact (Lobo *et al.*, 2016).

According to research conducted on the Indian stock market, it has grown more interconnected with global counterparts such as Tokyo, South Korea, Hong Kong and Russia, and its reflexes are in sync. American Depository Receipts (ADRs) and Global Depository Receipts (GDRs) have become a popular way for Indian firms to transmit information across exchanges, enhancing the sensitivity of the home country's stock market to other exchange movements (Mukherjee, 2007).

Several publications claim that short-term returns from global stock markets are unsuitable for long-term investors. This model incorporates both the long-term and short-term relationships among financial markets, as well as their interaction. Determining co-integration started in 1990, showing that G7 economic cooperation had a role in the links (Georgoutsos and Kouretas, 2001). Studies have also explored India's stock market's financial integration with global and regional markets since 1991. To mirror the investment style of international investors, the Indian stock market is globally interconnected, with values judged in US dollars rather than local currency. Price co-integration between the US dollar and local currency shows the inefficiencies of national stock markets (Dhal, 2009).

Emerging economies like India are highly linked and contagious. The US shocks deepen interdependence, whereas developing market shocks intensify contagion (Samarakoon, 2011). From January 1999 to August 2004, the Nasdaq, Nikkei, NIFTY50 and BSE Sensex were evaluated using end of day (EOD) prices. The Indian stock market has no long-term link to the US (or Japanese) equities markets. The Nasdaq moves independently of the Indian indices. Stock markets are segmented when long-term correlations are low and short-term causal effects are minimal (Ahmad *et al.*, 2005). From March 2005 to November 2010, the impact of the global financial crisis on the degree of financial integration between the US and Indian stock markets was analysed. They explore the dynamic relationship between the two indices using Johansen co-integration and the vector auto regression (VAR) model. All four periods (Gangadharan and Yoonus, 2012) found no link. The Indian stock market returns show a lot of US–India feedback, but the US stock market returns show a little reaction.

Moreover, studies show that the BSE and Nasdaq moving in lockstep has been seen as an indication of Indian financial market integration, from Nasdaq to the BSE/NSE. Hansda and Ray (2002) found a unidirectional causality from Nasdaq to the BSE/NSE. The studies use intraday data to estimate returns during trading hours and aftermarket hours between 1999 and 2001, the correlation and volatility transmission between the US and Indian stock markets (Kotha and Mukhopadhyay, 2002).

The study focuses on the economic aspects of the volatility transmission between seven developed and developing nations. For this purpose, several statistical surveys were considered (Soriano Felipe and Climent Diranzo, 2005; Oliveira *et al.*, 2018; Doryab and Salehi, 2018; Hung, 2019; Bouteska and Regaieg, 2020; Mishra *et al.*, 2022; Mishra and Ghate, 2022) which ultimately led to the choice of MGARCH-BEKK model. Unlike other studies, the analysis here has a more economic angle and also tries to show how MGARCH-BEKK can be advantageous for other studies as well.

2.1 Testable hypotheses

- H1. A better affinity of stock markets between India and the Asian region can be noticeable as compared to the interactions between India and developed Western countries, post-globalization, i.e. after 2008.

Method of testing: The task of quantifying cross-region interactions is done by analysing volatility spillover between the regions. Academically, one of the most common models used for the task is MGARCH-BEKK since it allows for an objective analysis of market linkages (Cardona *et al.*, 2017). Basic data properties are calculated like mean median and maximum value calculation. Autocorrelation of the dataset is calculated by using the Durbin–Watson test on a scale of 0–4, for the indices and daily returns to see if any form of autocorrelation exists in the data. Jarque–Bera test (Jarque and Bera, 1987) will explain the skewness and heteroskedasticity of the datasets, which will be compared for analysis.

H2. Markets under consideration have significantly different trends and cross-interactions during a recession as compared to different sections of the business cycle e.g. expansion and slow-down.

Method of testing: To perform testing for this hypothesis, four different categories of the dataset will be made, each category will have a fixed set of values, equal for both markets creating a multivariate system with two variables. Each category will be tested for co-integration as proposed in Johansen (1988), the VECM model is applied, and each coefficient is analysed to draw results. Granger causality tests (Granger, 1969) are performed to test the causation effect between the two markets. All four categories are tested, and results are compared to draw results for this hypothesis.

3. Method

3.1 Data

Data collected is the daily EOD value for the time period of January 2008 to December 2019. NIFTY50 data are published every day by the National Stock Exchange on Alpha Vantage, using their Application Programming Interface (API) data pipelines for data collection. Stock index data are published at EOD by the exchanges, and these data were collected directly using respective data pipelines. Daily volume data from datasets was discarded due to inaccuracy and time gaps. The data can be visualized in Figure 1.

After the data review, it was found that there is a difference in market holidays in the seven stock indices. In the 12-year frame, there were 74 such instances among 3,102 data points. Seeing as the mismatch was less than 5% of the full data, all mismatches were filled with the nearest values in the dataset after the date (see Table 1).

The raw data are converted to log daily returns for the MGARCH-BEKK model, which can be mathematically represented as:

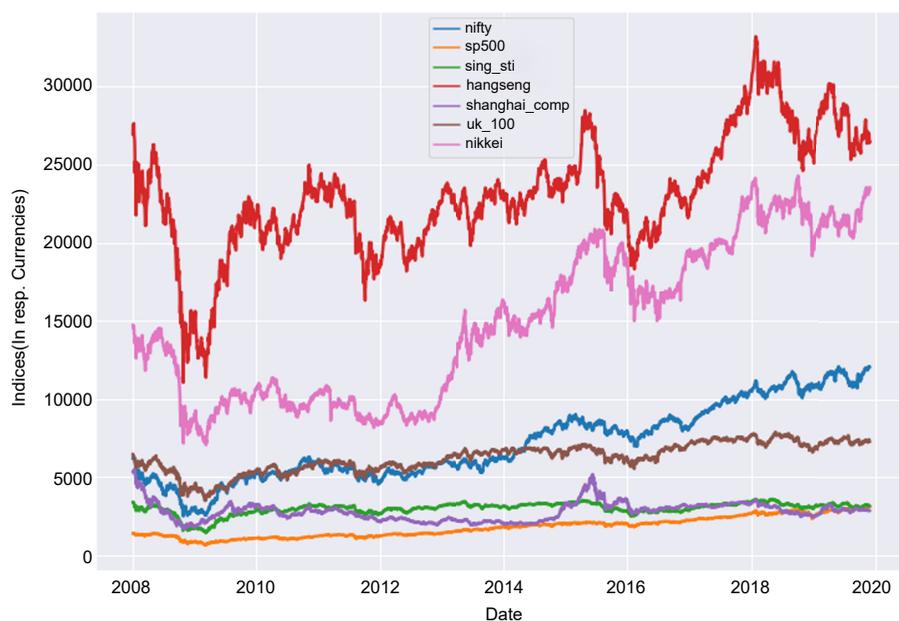
$$P_{\log\text{-returns}} = \log\Delta(P) \quad (1)$$

where $\Delta()$ function provides the percent change of current price from the previous value.

Data analysis and manipulation are done using Python 3.7, without any graphical processing, due to the linear nature of data. Libraries used included pandas, NumPy, Matplotlib and BEKK [1]. To ensure reproducibility, a common seed was set for all “random” functions in NumPy.

3.2 Methodology

Econometrics explains how markets respond in long-term equilibrium. However, unpredictable price shocks and impulses pose a serious problem. These may occur for a variety of causes that are difficult to anticipate. Quantifying these shocks may help us anticipate or explain market responses if they occur. Various studies have attempted to quantify volatility spillovers using the MGARCH-BEKK model (Engle and Kroner, 1995; Cardona *et al.*, 2017; Mohammadi and Tan, 2015). Since 2008, many studies have published



Source(s): Own elaboration

Figure 1. Evolution of the stock market index for India and six international markets, Jan 2008–Dec 2019

findings showing significant evidence of market indices co-integration (Dhal, 2009). This research looks at the volatility spillover from developed markets in the US and Europe to regional Asian markets, and vice versa. This research tries to anticipate or explain market responses owing to abrupt impulses during recessions using advanced indices analysis.

A VECM is a restricted VAR designed for use with non-stationary series that are known to be cointegrated (Chougala and Srivatsa, 2016; Ahmad *et al.*, 2005; Agrawal *et al.*, 2010). First, we will use the Durbin–Watson test (Durbin and Watson, 1992) to see whether the indices are autocorrelated with their lagged values. To evaluate data stationarity, the Augmented Dickey–Fuller test (Dickey and Fuller, 1981) is used to look for a unit root within the data trends. The Jarque–Bera test (Jarque and Bera, 1987) predicts data distribution and calculates the third and fourth moments of the data, skewness and kurtosis.

3.2.1 Phase-wise split. Keynes presented the business cycle in many notions, demonstrating that “History repeats itself.” The trade cycle theory shows that the economy passes through cycles of recession and growth in a set time. Even while economic cycles have been studied for years, there is still a considerable question about whether they are absolute (Lucas, 1980). The article assumes that although business cycles are not absolute, their intermediate states may be visualized. We divided the dataset into three stages. Phase 1 (crisis and recovery) covers the period January 2008 to December 2011, when economies started to recover from the 2007–08 recession. This shows that the global economy was growing from December 2011 to December 2015, but it will be difficult to pinpoint the era of “Boom” as described in business cycles. Phase 3 (Slow-down) spans from December 2015 through December 2019. Since 2017, the gross domestic product (GDP) growth of India started slowing below estimates [2], a trend which was continuing till the end of 2019. This phase-wise split helps visualize the progression of trade cycles. The analysis of

Table 1.
Stock returns – Daily
data description

	NIFTY50	S&P 500	Hang Seng	Singapore STI	Shanghai co	FTSE 100	Nikkei 225
Datapoint count				3,102			
Mean	7258.18	1846.62	23117.34	3006.84	2811.08	6247.81	14891.79
Std	2484.50	656.35	3721.45	376.43	581.79	920.54	4917.77
Min	2524.20	676.53	11015.80	1456.95	1706.70	3512.09	7054.98
50%	6338.95	1845.16	22921.63	3096.37	2844.30	6338.01	14599.14
Max	12362.30	3386.15	33154.12	3615.28	5497.89	7877.45	24270.62
Daily Data: 02-01-2008 to 16-12-2011							
Phase 1: Recession and Recovery							
Datapoint count				1,051			
Mean	4804.97	1143.05	20473.80	2724.42	2824.72	5270.60	10248.66
Std	920.41	171.12	3328.46	465.37	588.67	646.49	1687.80
Min	2524.20	676.53	11015.80	1456.95	1706.70	3512.09	7054.98
50%	5034.90	1165.28	21149.02	2847.26	2790.12	5384.07	9859.20
Max	6301.55	1447.16	27615.80	3437.79	5497.89	6479.39	14691.41
Daily Data: 20-12-2011 to 10-12-2015							
Phase 2: Expansion							
Datapoint count				1,051			
Mean	6703.32	1746.59	22638.31	3160.70	2573.74	6369.69	14241.77
Std	1261.25	275.74	1976.16	184.17	711.56	436.57	3781.28
Min	4544.20	1241.30	18185.59	2646.35	1950.01	5260.19	8295.63
50%	6175.35	1795.50	22677.71	3191.94	2268.61	6490.66	14594.52
Max	8996.25	2130.82	28442.75	3539.95	5166.35	7103.98	20868.03
Daily Data: 14-12-2015 to 03-12-2019							
Phase 3: Slow-down							
Datapoint count				1,000			
Mean	9901.53	2532.15	25946.20	3142.09	3035.13	7106.06	20198.12
Std	1348.87	327.01	3386.09	237.09	236.26	477.85	2296.66
Min	6970.60	1829.08	18319.58	2532.70	2464.36	5536.97	14952.02
50%	10234.55	2583.62	26456.68	3190.40	3048.14	7250.48	20638.78
Max	12100.70	3153.63	33154.12	3615.28	3651.77	7877.45	24270.62

Source(s): Resp. Stock Exchanges

the phases will show if different trade cycles do affect the co-integration of stock exchange indices.

3.2.2 Correlation testing. The standard correlation matrix is created by using the well-known Pearson coefficient of correlation to calculate cross-correlation between the two datasets.

$$r = \frac{\sum (X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum (X - \bar{X})^2} \sqrt{\sum (Y - \bar{Y})^2}} \quad (2)$$

Here “r” is the correlation of datasets containing X and Y .

Autocorrelation tests were performed by using the Durbin–Watson test (Durbin and Watson, 1992).

$$\sum_{t=2}^T (e_t - e_{t-1})^2 \bigg/ \sum_{t=1}^T e_t^2 \quad (3)$$

The value e_t is the value of the index at time t . The result comes out in the range 0–4, where a result of 2 means no autocorrelation, a result closer to 4 gives positive correlation, and a result closer to 0 gives negative correlation.

3.2.3 Unit-root testing. Unit-root stationarity is tested by using the Augmented Dickey–Fuller test (Dickey and Fuller, 1981) is used to determine if the series is stationary by checking for unit root.

$$\Delta x_t = \mu + \delta T + \alpha x_{t-1} + \sum_{i=1}^m \gamma_i \Delta x_{t-i} + \varepsilon_t \quad (4)$$

3.2.4 Vector error correction model. VECM model can be represented as:

$$\Delta X_t = \sum_{i=1}^n A_i \Delta X_{t-i} + \sum_{i=1}^r \xi_i \Theta_{t-1} + v_t \quad (5)$$

Here, X_t is the stock indices series vector with a dimension of $N \times 1$, A is a vector of estimable parameters, v_t at the end of the equation represents the impulses, i.e. unexpected movements from the stock index. Θ_{t-1} represents the MLE coefficients calculated using the Johansen method (Johansen, 1988) and provides the co-integration rank used for analysis further on.

3.2.5 Granger causality test. Granger causality is used as an auxiliary test in the analysis. Studies show that a no-causality test is no longer required if results can be drawn from co-integration as well as if co-integration is high or significant then the Granger causality test is not performed (Granger, 1969). We have performed this test to show the usability of the statistic obtained from this test as a way to check co-integration between stock indices.

Granger causality is a great tool to measure short-run co-integration which we will be doing, VECM models on the other hand work well with long-run results. Since our analysis includes both short-run and long-run data, we perform the Granger causality test.

3.2.6 MGARCH-BEKK model. The model used during the study was a BEKK (1,1) model (Engle and Kroner, 1995), where the first number represents the order of the ARCH component of the model, and the second number represents the order of the GARCH component of the model. Data are first passed on into a bivariate VAR(p) model:

$$Y_t = v + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + u_t \quad (6)$$

where u_t represents the model residuals:

$$u_t \sim Normal(0, \Sigma_u)$$

The conditional variance is then modelled using the residuals as:

$$H_t = CC' + Au_{t-1}u'_{t-1}A' + BH_{t-1}B' \quad (7)$$

where A represents the ARCH component parameters of the model, and B represents the GARCH component parameters. The equation is calculated recursively using starting parameters defined by default. A restriction is placed on the parameter matrices calculated, making them diagonal. Squared values of the diagonal parameters provide us with perturbation and volatility spillover between the markets.

The order of the model, i.e. (1,1), is chosen based on the number of data points. Studies done with GARCH models suggest that higher-order models have more bias as the number of data points reduce. [Ng and Lam \(2006\)](#) experimentally show that ~1000 data points are optimal for a first-order model, which meets our requirements (refer to [Table 1](#)). A direct conclusion drawn in the study is that, as the order of the model increases, the number of data points grow as well.

4. Results

4.1 Initial tests: autocorrelations, normality and Augmented Dicky–Fuller test

[Table 2](#) shows an absence of autocorrelation within the VAR model residuals used to construct the BEKK model, whereas, in [Table 3](#), it is observed that none of these stock indexes show the case of normal distribution. ADF test, on the other hand, clearly shows that for all datasets and phases, the data are not stationary ([Table 4](#)). The McKinnon statistic ([Dickey and Fuller, 1981](#)) for 5 and 10% levels of significance are 3.3 and 3.9, respectively. However, in the first returns form or the log daily returns form, the data were found to be stationary, which was used for volatility models since models with inherent trends often fail with such data.

4.2 Co-integration and Granger causality

Co-integration results of the indices present a significant finding ([Table 5](#)). For the full timeframe of 2008–2019, if there is a 1% movement in the S&P 500 index, a 3.9% movement can be expected by NIFTY50 in the same direction, this result however is not replicated in other indices. In the long run, across the timeline, the Indian market did not show significant movements due to the movement of a few Asian markets. Along with this, Hang Seng had a co-integration relation but NIFTY50 did not move more than 0.2% in either direction due to a 1% change in Hang Seng.

The lack of co-integration between India and Singapore ([Table 6](#)) is explained by Singapore's market competition. It represents bigger and more established enterprises in Singapore's emerging markets. Investors often divide their cash between the two nations rather than risk-sharing. The co-integration loss between India and the UK may be explained by their trading activity. Compared to US or Asian markets, the UK–India goods trade route is poor. Due to this mismatch, pricing changes in the UK and India seem to be unrelated. Granger causality, however, paints a different picture. In the near term, there is a direct causation from Singapore and the UK to the Indian markets. It may be described using the VECM model's error-correction terms.

The VECM model's error correcting terms monitored the short-run dynamics. A poor short-run relationship between India and the S&P 500 ([Table 7](#)). Contrary to long-run equilibrium, Hang Seng was highly cointegrated with Indian markets. Similarly, UK and Japanese markets were cointegrated only during recessions. From an economic perspective, it

illustrates that during recessions, investors want to shift money out of India towards more stable economies like Japan and the UK.

4.3 Cross-country volatility transmission

The cross-country volatility transmission is measured using a combination of the VAR(ρ) process along with the MGARCH-BEKK volatility model (Baba *et al.*, 1990). A bivariate VAR model is fitted on the “log daily returns” and its residuals are tested for heteroskedasticity for robustness. It is to be noted that since daily data were non-stationary, first differenced returns data were used for the model to ensure precision in the model. The residuals are then modelled as innovation variables in the BEKK (1,1) model. The conditional variance of the model is then represented by a recursive equation, whose coefficients are determined using the residuals.

Perturbation of the model specifies the amount of deviation caused in a market due to shock in the independent variable. The variables have been tested at a 5% level of significance and very few insignificant variables were found. Parameter values have been scaled to higher powers of ten for easy analysis.

The data show a clear distinction in the behaviour of Asian markets with respect to India (Table 8). The Asian markets have a significant level of volatility transmitted from Indian markets as compared to the US and the UK.

5. Discussion

As a closed economy, China receives and invests less money than other nations. However, given the enormous amount of commerce between India and China, the link between NIFTY50 and Hang Seng will need to be examined further. The Indian markets had little impact on the Nikkei 225, owing to the minimal amount of trading between the two nations. Investors frequently see Japanese markets as a shelter. Thus, the long-run equilibrium between Japan and India is unlikely.

However, the co-integration of the Indian and Hong Kong markets was notable. Hong Kong’s free economy attracts money from all around the world, including India. Because Shanghai Composite is an established market, investors have similar beliefs. Decoupling occurs during recessions when investors lose faith in emerging countries like India. The co-integration between NIFTY50 and S&P 500 is considerable over time, maybe because investors generally watch India’s economic position by comparing it to the US. During the recession, Indian markets went in the other way. During recessions, investors frequently do not want to maintain money in uncertain emerging countries, which explains the capital flight from India to the US.

For each market, we divided the dataset into stages. Phase 1 co-integration rank is greater than the overall rank. This means that during recessions and recovery, the movement of

	Full data
NIFTY50	2.00
S&P 500	2.00
STI Singapore	2.01
Hang Seng	2.01
FTSE 100	2.00
Nikkei 225	1.99
Shanghai Co	2.00

Source(s): Own elaboration

Table 2.
Autocorrelations in
model residuals
(Durbin–Watson test)

	NIFTY50	S&P 500	STI Singapore	Hang Seng	Nikkei 225	FTSE 100	Shanghai Co
<i>2008–2019</i>							
JB statistic	2E+02***	2E+02***	3E+03***	4E+01***	3E+02***	1E+02***	1E+03***
<i>p</i> -value	2E–39	9E–42	0E+00	2E–10	2E–57	3E–33	1E–244
Skewness	3E–01	3E–01	–2E+00	–2E–01	1E–01	–5E–01	1E+00
Kurtosis	2E+00	2E+00	7E+00	3E+00	2E+00	3E+00	5E+00
<i>Jan 2008–Dec 2011</i>							
JB statistic	1E+02***	6E+01***	2E+02***	1E+02***	1E+02***	9E+01***	1E+03***
<i>p</i> -value	1E–31	1E–13	1E–50	2E–26	5E–31	3E–21	2E–240
Skewness	–9E–01	–5E–01	–1E+00	–8E–01	9E–01	–7E–01	1E+00
Kurtosis	3E+00	2E+00	3E+00	3E+00	3E+00	3E+00	7E+00
<i>Dec 2011–Dec 2015</i>							
JB statistic	1E+02***	9E+01***	4E+01***	4E+01***	5E+01***	8E+01***	6E+02***
<i>p</i> -value	1E–22	1E–20	1E–08	2E–08	4E–12	1E–18	2E–124
Skewness	3E–01	–2E–01	–4E–01	4E–01	–5E–02	–6E–01	2E+00
Kurtosis	2E+00	2E+00	3E+00	4E+00	2E+00	2E+00	5E+00
<i>Dec 2015–Dec 2019</i>							
JB statistic	7E+01***	6E+01***	3E+01***	4E+01***	7E+01***	2E+02***	1E+01***
<i>p</i> -value	8E–16	5E–14	1E–07	6E–10	5E–16	4E–47	2E–03
Skewness	–4E–01	–2E–01	–3E–01	–3E–01	–5E–01	–1E+00	–1E–01
Kurtosis	2E+00	2E+00	2E+00	2E+00	2E+00	3E+00	3E+00
<i>(Jarque–Bera test of VAR Model Residuals) 2008–2019</i>							
JB statistic	7E+03***	2E+03***	2E+03***	9E+03***	2E+04***	7E+02***	5E+03***
<i>p</i> -value	0.00	0.00	0.00	0.00	0.00	3E–172	0.00
Skewness	–3E–02	–6E–01	–2E–01	–3E–01	–9E–01	–2E–01	–4E–01
Kurtosis	1E+01	7E+00	7E+00	1E+01	2E+01	5E+00	9E+00

Table 3. Normality test (Jarque–Bera test of closing prices)

Note(s): * means significant at the 10% level, ** means significant at the 5% level and *** means significant at the 1% level
Source(s): Own elaboration

developed markets has a higher impact than in other periods. One explanation is that during recessions, market volatility is greater than normal. International investors will lose faith in India's economy. So, they would rather sell their interests in India. The Indian market has fallen quicker than other markets.

The empirical findings allow Asian stock market investors to forecast market returns up to 5 days in advance. For example, a Singaporean investor has exposure to the Indian market hedged by a Singaporean investment. Assuming an exchange rate-balanced investment in India, a 1% shock to returns in the Indian market may cause an equivalent shock in the Singapore market with a probability of 35%. This may be used to update risk models and calibrate investments.

In the long term, the difference between phase 2 and phase 3 co-integration rank is negligible. Business cycles are a controversial topic (Lucas, 1980). The results may have been biased in the short-term owing to noise. Alternatively, the slowdown began later or sooner than the time range selected for phases 2 and 3.

All Asian regional markets are linked to India by commerce, both financial and products. As a result, political or otherwise, shocks in the Indian system tend to disrupt critical supply lines, affecting Asian nations rapidly and dramatically. The only markets that are not volatile are the Hang Seng and Singapore STI. So, the long-term separation of the Chinese and

			Full data	Phase 1	Phase 2	Phase 3
NIFTY50		ADF test statistic	-1.00	-1.83	-1.43	-1.04
		<i>p</i> -value	0.75	0.36	0.57	0.74
S&P 500		ADF test statistic	-0.15	-1.85	-1.37	-0.65
		<i>p</i> -value	0.94	0.35	0.60	0.86
Singapore STI		ADF test statistic	-2.39	-1.50	-2.63	-2.00
		<i>p</i> -value	0.15	0.53	0.09	0.29
Hang Seng	Indices (in corresponding currencies)	ADF test statistic	-2.24	-2.44	-2.58	-1.57
		<i>p</i> -value	0.19	0.13	0.10	0.50
Shanghai Co		ADF test statistic	-3.71***	-4.48***	-1.24	-3.35*
		<i>p</i> -value	0.00	0.00	0.66	0.01
FTSE 100		ADF test statistic	-1.92	-1.97	-2.59	-2.34
		<i>p</i> -value	0.32	0.30	0.10	0.16
Nikkei 225		ADF test statistic	-0.99	-2.42	-0.97	-1.31
		<i>p</i> -value	0.76	0.14	0.77	0.63

Source(s): Own elaboration

Table 4.
Augmented Dickey–Fuller test

Singaporean markets has been confirmed. Over time, volatility transmission varies. Phase 1 (recession) to phase 2 (growth) and then drops to phase 3 (growth) (slowdown). To promote deeper co-integration in phase 2, global market shocks and impulses impact Indian markets. Emerging countries like India attract investors due to their high growth rate compared to developed ones. This implies a lot of money enters fragile Indian markets. There was a weak correlation between the markets in phase 1 (crisis and recovery) and phase 3 (slowdown). These findings support [hypothesis 2](#).

Granger causality tests failed to distinguish between phase 2 and phase 3. As India's economy slowed, the MGARCH-BEKK model revealed a drop in volatility transmission to NIFTY50. This shows that the Indian economy has various economic cycles, proving premise 1 about volatility transmission from international markets to India.

6. Conclusions

This study's major aim was to analyse and compare Indian market linkages with Asian (Singapore, China, Hong Kong and Japan) and developed Western markets (US and UK). We studied the volatility transmission from the international markets to Indian markets using the MGARCH-BEKK model. The model showed a clear distinction between the Asian markets and the US and the UK. Volatility transmission from India to Asian markets was found to be significantly higher as compared to US and UK.

An analysis across time showed a clear drop in volatility transmission from international markets to India, from phase 2 to phase 3, statistically confirming a reduction in market linkage as India entered a slow-down. The model also confirmed the inference of reduction in linkage during a recession as compared to expansion. The results show that for all countries, the volatility transmitted to India increases significantly going from phase 1 (recession) to phase 2 (expansion) and reduces again once the countries enter slow-down in phase 3

Table 5.
Long-run dynamics
w.r.t. NIFTY50 (co-
integration relation of
indices, in respective
currencies)

	Full data	Phase 1	Phase 2	Phase 3
NIFTY50	CoInt. Coefficient 1.000*** <i>p</i> -value 0.000	1.000*** 0.000	1.000*** 0.000	1.000*** 0.000
S&P 500	CoInt. Coefficient -3.913*** <i>p</i> -value 0.000	2.479*** 0.000	-6.401*** 0.000	10.209*** 0.000
Hang Seng	CoInt. Coefficient -0.199*** <i>p</i> -value 0.000	0.037 0.215	-0.227*** 0.000	-0.141 0.117
Singapore STI	CoInt. Coefficient 0.348 <i>p</i> -value 0.471	-2.254*** 0.000	-3.036*** 0.000	0.267 0.852
Shanghai Co	CoInt. Coefficient -0.957*** <i>p</i> -value 0.000	-0.009 0.913	0.693*** 0.000	-1.638 0.012
FTSE 100 (UK)	CoInt. Coefficient -0.117 <i>p</i> -value 0.696	-0.151 0.335	3.353*** 0.000	0.454 0.169
Nikkei 225	CoInt. Coefficient 0.196*** <i>p</i> -value 0.000	-0.092 0.076	-0.130 0.063	-0.248 0.089
Intercept	Coefficient 3997.870*** <i>p</i> -value 0.000	32.842 0.934	-2423.917* 0.023	-19180.000*** 0.000
Trend	Coefficient -0.070 <i>p</i> -value 0.837	-1.019*** 0.000	0.241 0.759	-13.471*** 0.000

Note(s): * means significant at the 10% level, ** means significant at the 5% level and *** means significant at the 1% level

Source(s): Own elaboration

		Full data	Phase 1	Phase 2	Phase 3
S&P 500	<i>F</i> -value	3.57	2.66	3.342	2.4
	Conclusion	S&P 500 does Granger-cause NIFTY50	S&P 500 does Granger-cause NIFTY50	S&P 500 does Granger-cause NIFTY50	S&P 500 does Granger-cause NIFTY50
Hang Seng	<i>F</i> -value	1.416	0.8655	2.435	1.312
	Conclusion	Hang Seng does Granger-cause NIFTY50	Hang Seng does not Granger-cause NIFTY50	Hang Seng does Granger-cause NIFTY50	Hang Seng does not Granger-cause NIFTY50
Singapore STI	<i>F</i> -value	1.273	1.819	2.179	1.901
	Conclusion	Singapore STI does not Granger-cause NIFTY50	Singapore STI does Granger-cause NIFTY50	Singapore STI does Granger-cause NIFTY50	Singapore STI does Granger-cause NIFTY50
Shanghai Co	<i>F</i> -value	2.098	1.969	2.997	1.945
	Conclusion	Shanghai comp does Granger-cause NIFTY50	Shanghai comp does Granger-cause NIFTY50	Shanghai comp does Granger-cause NIFTY50	Shanghai comp does Granger-cause NIFTY50
FTSE 100	<i>F</i> -value	1.525	1.711	2.498	1.672
	Conclusion	FTSE 100 does Granger-cause NIFTY50	FTSE 100 does Granger-cause NIFTY50	FTSE 100 does Granger-cause NIFTY50	FTSE 100 does Granger-cause NIFTY50
Nikkei 225	<i>F</i> -value	1.329*	2.037	1.721	1.764
	Conclusion	Nikkei does Granger-cause NIFTY50	Nikkei does Granger-cause NIFTY50	Nikkei does Granger-cause NIFTY50	Nikkei does Granger-cause NIFTY50

Source(s): Own elaboration

Table 6.
Granger causality using VECM model w.r.t NIFTY50

		Full data	Phase 1	Phase 2	Phase 3
S&P 500	Coint. Coefficient	0.001	0.009	-0.004*	-0.006***
	<i>p</i> -value	0.267	0.064	0.049	0.000
Hang Seng	Coint. Coefficient	0.037**	0.311***	0.102**	0.025
	<i>p</i> -value	0.001	0.000	0.002	0.089
Indices Singapore STI	Coint. Coefficient	0.003*	0.038***	0.008**	-0.002
	<i>p</i> -value	0.019	0.000	0.004	0.113
Shanghai Co	Coint. Coefficient	0.012***	0.056***	0.002	0.0001
	<i>p</i> -value	0.000	0.000	0.736	0.931
FTSE 100 (UK)	Coint. Coefficient	0.006*	0.075***	-0.013	-0.006
	<i>p</i> -value	0.037	0.000	0.080	0.056
Nikkei 225	Coint. Coefficient	-0.012	0.156***	-0.030	0.012
	<i>p</i> -value	0.112	0.000	0.259	0.281

Note(s): * means significant at the 10% level, ** means significant at the 5% level and *** means significant at the 1% level

Source(s): Own elaboration

Table 7.
Short-run dynamics w.r.t. NIFTY50 (co-integration relation of indices, in currencies)

(slowdown). This shows that during expansion shocks and impulses in international markets affect the Indian markets significantly, supporting the increase in co-integration in phase 2 (expansion). During expansion, developing markets like India become profitable for investors, due to the high growth rate when compared to developed countries. This

Data used: Log-returns of daily prices			Complete timeline	Phase 1	Phase 2	Phase 3
S&P 500	From NIFTY50	Perturbance	0.1463**	0.1332**	0.1435**	0.1737
		Volatility	0.0307**	0.0286**	0.0164**	0.1571
		Transmission	0.1308**	0.2057	0.1327**	0.0609**
	To NIFTY50	Perturbance	0.2296**	0.1504**	0.4389*	0.0634**
		Volatility				
		Transmission				
Hang Seng	From NIFTY50	Perturbance	0.1813**	0.2140	0.1908**	0.2779
		Volatility	0.3975**	0.5698**	0.2052**	0.0127***
		Transmission	0.1594**	0.2881*	0.1320*	0.0968**
	To NIFTY50	Perturbance	0.0460**	0.0255**	0.3835**	0.0985***
		Volatility				
		Transmission				
Singapore STI	From NIFTY50	Perturbance	0.1690**	0.1652**	0.1980**	0.1136**
		Volatility	0.3747**	0.3577*	0.2009**	0.6609***
		Transmission	0.1555**	0.2178	0.1739**	0.1294**
	To NIFTY50	Perturbance	0.0306**	0.1800	0.2447	0.0959**
		Volatility				
		Transmission				
Shanghai Co	From NIFTY50	Perturbance	0.2072**	0.2216	0.1552**	0.1790**
		Volatility	0.1713**	0.2348**	0.3120**	0.1500**
		Transmission	0.1285**	0.1831	0.1324**	0.0967*
	To NIFTY50	Perturbance	0.1749**	0.1448**	0.4397	0.0953***
		Volatility				
		Transmission				
FTSE 100	From NIFTY50	Perturbance	0.2000*	0.0787**	0.2491**	0.1145**
		Volatility	0.0023**	0.8181	0.0009**	0.1389**
		Transmission	0.1111**	0.2288**	0.1087**	0.1027**
	To NIFTY50	Perturbance	0.2792**	0.0607**	0.5184**	0.0628**
		Volatility				
		Transmission				
Nikkei 225	From NIFTY50	Perturbance	0.1288**	0.1069	0.1293**	0.1064**
		Volatility	0.3193**	0.2692**	0.3136**	0.5856
		Transmission	0.1354**	0.2242**	0.1371	0.0791
	To NIFTY50	Perturbance	0.1338**	0.1525**	0.3112	0.0346**
		Volatility				
		Transmission				

Table 8.
Volatility transmission
(MGARCH-BEKK
coefficients for
BEKK (1,1))

Note(s): * means significant at the 10% level, ** means significant at the 5% level and *** means significant at the 1% level
Source(s): Own elaboration

implies that a significant amount of capital enters Indian markets, which are susceptible to the volatility of international markets. The volatility transmission from India to the US and UK was insignificant in phase 1 (recession and recovery) and phase 3 (slow-down) showing a weak linkage between the markets during volatile time periods.

The study presented a puzzling result, showing comparable co-integration ranks for phase 2 (expansion) and phase 3 (slow-down) in most cases. This could be attributed to

issues within the business cycle theory, but to investigate further we used a short-run test called the Granger causality test (Granger, 1969). The test showed a clear distinction between phase 2 and phase 3. This implies that our time frame was skewed in some manner. The Granger causality test showed a reduction in linkage from phase 2 to phase 3; however, such an inference could be flawed since VECM models tend to fail at low data.

Investors often prefer strong economies and hence are always quick to withdraw positions from developing countries at the first sign of slowdown. Market linkage is existent because of the capital flow generated by these international investors, and they try to match their moves in both countries. The future of this research will focus on a more event-based impact analysis, measuring the actual effects of economic policy changes as compared to the expected effects, in India and other developing Asian countries.

Notes

1. Translated from R package “MGARCH” for python users. Original R package can be referred to as MGARCH. Python package can be found at BEKK.
2. Data sourced from the Ministry of Statistics and Program Implementation (India).

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