Stock Market Contagion and Volatility Spillover: Evidence from an Emerging Market

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Abstract

Global economic and political shocks significantly affect financial markets in general and emerging financial markets in particular. In this paper, we attempt to identify and analyze the channels of transmission of stock market turbulence and the impact of international contagion on emerging markets. Using daily data from January to December 2016 on FTSE100 index as proxy for the UK market and Nifty50 index as proxy for Indian market, we try to quantify and analyze the price movements and volatility spillover effects between the two markets, around the Brexit period . We divide our study period into two parts : pre- and post-BREXIT referendum – to compare the statistical significance of the transmission shocks and spillover effects between the post and pre crisis period. The results show that there indeed exists short run and long run dynamic and co-integrating relationships between the two markets; the correlation being amplified in the shorter horizon during the BREXIT crisis, both by the uncertainty of the referendum results and information adjustment due to the post-crisis shocks. The quantile regression results also evidently put forth the important global& domestic variables influencing various levels of the post-BREXIT Nifty returns. This evidently indicates that the FTSE 100 index affects the Nifty index and acts as a regulating gauge for the information transmission and its dynamics across the two markets.

Keywords: Volatility spillover, Market integration, Contagion, BREXIT, Emerging markets, Financial Crisis

JEL Codes: C32, E44, F36, G10

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Introduction

This paper studies the extent of market integration and contagion spillover across two major markets, one being an emerging economy that is India and another being the UK market. We show whether increasing financial integration has increased Emerging markets' vulnerability to external global shocks, focusing primarily on the transmission through equity markets, with the benchmark indices as the 23rd June marked an important event -the referendum on Britain's membership of the European Union (EU), resulting in its exit from the EU—Brexit. The event jolted markets and economies globally. The Sensex opened lower by 635 points and went down by 1,091 points before closing the day with a decline of 605 points or 2.24%. .The debt market, reacted negatively as well, with 10-year bond yields rising next day (markets, however, recovered the same day) remained relatively calm on Brexit. The currency market took a beating and the rupee lost big the upcoming week and ended the week with a loss of 89 paisa against the US dollar. Our results suggest that there indeed exists short run and long run dynamic and co-integrating relationships between the two markets; the correlation being amplified in the shorter horizon during the BREXIT crisis, both by the uncertainty of the referendum results and information adjustment due to the post-crisis shocks. The quantile regression results also evidently put forth the important global& domestic variables influencing various levels of the post-BREXIT Nifty returns. This evidently indicates that the FTSE 100 index affects the Nifty index and acts as a regulating gauge for the information transmission and its dynamics across the two markets. These findings could enrich the literature on the growing importance of emerging economies for investors looking for international investment opportunities. With such insights, we believe, global investors should be able to understand the inter-market linkages in a better way to make right portfolio investments.

The Indian economy is the 10th largest economy in the world with a GDP of $2.04 Trillion (U.S.). The PPP indicator (roughly transforming how much that money can buy in India compared to other countries) puts the Indian economy as the third largest one (worth $7.277 trillion U.S.). With such a size, particularly among the emerging economic counterparts, it become critical how strongly financial market is associated with the rest of the world. Integration into the world economy has proven a powerful means for countries to promote economic growth, development, and poverty reduction. Policies that make an economy open to trade and investment with the rest of the world are needed for sustained economic growth. Due to openness in trade and investment, that is a corollary of globalization, national markets are interacting and increasingly becoming global (Wei et al., 1995). Rapid use of internet in the trading process has increased the speed of trading decision and operating efficiency of the market. Cross listing with different stock exchanges and the use of GDRs have enabled firms to be listed and traded with more than one stock exchange (Sabri, 2006).

While international investments help in hedging portfolios and mutual funds through international diversification, negative side effects too exist. Market turbulence or crisis in one country transmits its effects to other countries; not only the neighboring economies but also the distant ones. Spillovers across stock markets in different countries is of growing concern as, volatility and returns jolts. International financial spillovers from emerging markets have increased significantly over the last 20 years. This paper argues that growing financial integration of emerging economies and synchronization of the market is more important than their rising share in global trade network in driving this trend, and amplifying spillover effects during crisis periods from a developed market to an emerging one.

The paper first traces fluctuation in both the indices during the sudden crisis shock and tries to capture the speed of information adjustment in the NIFTY50 index. The paper also tries to create an empirical framework for assessing what drives EM equity prices - domestic/fundamental factors, and global/external condition. The paper finishes with a summary of the key results, draws some policy conclusions, and points to measures that can help make equity markets more resilient when equity prices decline. Furthermore, our study aims at building on the lines of present literature on the synchronicity between developed and emerging markets and in the process, bringing out the implications of global market liberalization and integration; most importantly the of transmission of volatility shocks during the crisis periods in developed markets. The Brexit crisis provides an opportunity to investigate the return and volatility spillover effect from the FTSE index to its NIFTY 50 index and vice versa during the recent crisis period.

The paper addresses the following key questions:

1. Is there empirical evidence of spillover from the U.K. to emerging Asian financial markets (in this case India, if possible other economies) post and pre-Brexit?
2. If so, when did the effect start spreading and for how long did it last (for this, synchronicity values on a biweekly basis for 5 months daily data pre and post-Brexit taken between FTSE and nifty 50 index) and the trend analyzed.
3. More importantly, through what channels did the spillover spread to the Indian markets?

To address these questions, we employ an array of multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models. We mainly focus on time-varying dynamic conditional correlations during the recent crisis instead of unconditional correlation coefficients. We also implement the following issues while explaining the dynamics of inter-market linkages in a turbulent global macroeconomic environment:

- Modelling any sudden acceleration of systemic risk when exogenous shocks occur;
- Variables considered for the factors that determine the time-varying conditional cross-country correlations. We consider the following three channels of spill over:
    - the factors that proxy the vulnerability of the UK. financial markets;
    - we use the oil and energy prices (or any other suitable spread) as a proxy for weakness of emerging markets;

  - numerous volatility measures ranging from 10 day to 30 day, to effectively ascertain the volatility spillover from FTSE 100 to NIFTY 50 index;
- Implement Quantile regression on eight global and domestic variables including oil prices, GBP-INR, GARCH modeled volatilities to quantify their impact on various levels of the post –Brexit NIFTY returns and try to sort out the most important variables influencing the dependent variable (post Brexit NIFTY returns).

Review of Literature

Regardless of the fact that the Indian Stock Market is the fastest growing emerging market, studies related to Indian market and application of econometric analysis in NSE have remained limited until recently. This paper also contributes to the emerging literature on financial market spillovers during global financial crisis.

Most of the existing literature on the study of inter linkages amongst markets have largely used the approach that involves testing the synchronicity and dependence on one another using simple cointegration (or VAR) techniques and these studies have been done concerning markets of developed and emerging countries. According to this approach if two or more indices are found to be cointegrated; then this implies interdependence of these stock markets.

Byers and Peel (1993) examined the interdependence between indices of the U.S., the U.K., Japan, Germany and the Netherlands using bivariate and multivariate cointegration (Johansen, 1988) techniques for the period October 1979 – October 1989.

The inter-linkages between returns and volatility in Indian market and other developed markets was carried out under a comparative analytical framework by Mukherjee (2007) against the Korean, Japanese and the US market exchange indices during various sub-periods from 1995 to 2016 to capture the effect and movement of stock exchanges with each other during different periods and economic situations. The study showed that Indian markets have started integrating into other global exchanges since

2002; and that this linkage is traced back to the South Asian crisis on the 90's (largely unaffected due to Government. policies), the influence being the strongest since the NYSE spilled over its market fluctuations after 9/11 to the Indian market.

A financial stress index was modeled to capture the estimated spillover of the Lehman shock induced global crisis (Moriyama, 2010) in the emerging market economies in the MENA region. The predicted models suggested an increased financial stress in advanced economies that could explain the drop in real GDP growth in MENA-EM countries after the Lehman shock. The global contagion effects and transmission shock due to information adjustment was carried out on the BRICS markets during the financial crisis (Bekiros, 2014) applying stepwise filtering methodology under the VAR/VECM/GARCH framework. The study sample included the after-Euro period, the financial crisis, and the Eurozone debt crisis. The empirical results proposed that BRIC economies have become more globally integrated since the US financial crisis and contagion is further substantiated.

Lee, Rui, and Wang (2004) studied the dynamic linkages between the daily returns and volatility of the NASDAQ and Asian markets using EGARCH and VAR-based methodology, and found strong evidence of volatility spillovers from the US to Asia. Bennett and Kelleher (1988), Hamao et al. (1990) and Susmel and Engle (1990) showed that US returns appear to cause the other countries and that lagged spillovers of price volatility are found between the major markets. Hong Li, Shamim Ahmed and Thanaset Chevapatrakul (2016) quantified four types of volatility spillover measures to characterize the volatility spillover dynamics of the Brexit shock across France, Germany, Switzerland and UK using intraday data. The result pointed that France and Germany were in general the net volatility transmitters to others, while Switzerland and the United Kingdom the net receivers from others during January 4, 2016 to September 30, 2016.

The present study differs from existing literature on volatility spillovers, crisis contagion and Brexit crisis shock in the following ways. The opening and closing prices of both the Indian and UK index are considered to capture the short run adjustments and various lag considerations. Secondly, the current study attempts to add to the limited volume of literature on the usefulness of cointegration and VECMs in understanding the dynamic relationship between markets, focusing on crisis periods. Quantile regression estimates are also implemented to assess the impact of various domestic as well as global factors and variables on the different quantiles of the Post Brexit NIFTY returns. The focus of the study is to scrutinize the speed of transmission of shocks from UK to India in the long-run, short-run deviations and swiftness of recovery during UK Brexit crisis.

Data Variables and Preliminary Results

Data

The dataset consists of daily stock market indices of UK and India for the period January 4, 2016 to December 5, 2016 and the data were extracted from the Bloomberg database. Brexit crises period is considered from 23rd June 2016 onwards.

Data series entails the daily index values (open and close) of the FTSE100, and NIFTY50 for the UK and India respectively. Following are the details related to the sample data:

- daily observations of stock price indices and foreign exchange rates obtained from Bloomberg
- Asset returns are calculated by taking two-day differentials of logged asset prices, multiplied by 100.
- We then study the dynamic conditional correlations between daily returns of the FTSE index and NSE index returns, as well as the foreign exchange rate returns
- GARCH Volatility estimates are also plotted for both the indexes returns and for the exchange rate returns

Preliminary Results

Stationarity : Stationarity of the time series data is checked using the ADF tests (Augmented Dickey –Fuller) tests to examine for a unit root in the equation. In our case, we have used first and second lag differences.

The unit root test results can be summarized as below .It reports the result of the standard unit root tests on the integration properties of the FTSE and NIFTY-open and close prices. Since the t statistics (-10.92097 and -11.00881) are greater than the critical values for all the confidence levels, null hypothesis of unit root in the first differences is rejected , and thus unit root is not present. In the level form, unit root tests are rejected for all the UK-India market. Hence, the time series data is stationary in the first difference and is integrated of the order I(1); hence necessitates a co integration test .

Table 1: Results of Unit-root Tests for Open and Close Prices

Variables	Deterministic	FTSE	NIFTY	inference	Significance
OPEN	Intercept	-11.00881	-10.92097	No unit root	stationary
CLOSE	Intercept	-12.05699	-10.58894	No unit root	stationary

Cointegration: We employ the Johansen's cointegration test to ascertain long term or equilibrium relationship between the two indices data. The empirical test results are tabulated below (Table 2).

Table 2: Results of co-integration tests

Markets	*Hypothesize no. of CEs*	*Eigenvalue*	*Trace statistic*	*95% CV for trace test*	*Max Eigen statistic*	*95% CV for max eigen value test*
FTSE-NIFTY	r=0	.319287	131.830	15.49471	84.61520	14.26460
	r<=1	0.193146	47.2148	3.841466	47.21485	3.841466

Trace test indicates 2 cointegrating eqn (s) at the 0.05 level; Also denotes rejection of the hypothesis at the 0.05 level.
Max-eigenvalue test indicates 2 cointegrating eqn (s) at the 0.05 level; * denotes rejection of the hypothesis at the 0.05 level.

The trace test strongly rejects the null hypothesis that there is no cointegration relationship between the variables. Even the eigenvalue test has t statistics significant enough to reject the null hypothesis .Both the tests reject the hypothesis of absence of cointegrating relations, but strongly indicate, with a 95% confidence interval, that there exists 2 cointegrating equations at the 5% significance level. Hence, it shows a long-term relationship does exist between the Indian & UK markets starting from the Brexit period. So, a long-term equilibrium phenomenon can be seen between the two indices.

Post-Brexit Johansen's Cointegration Tests : The post brexit NIFTY & FTSE indices data are statistically tested through the Johansen cointegration test; and both the trace and eigenvalues test strongly reject the null hypothesis of absence of cointegrating equations; and thus a long run relationship between the FTSE 100 and NIFTY 50 index returns can be ascertained .

Table 3: Results of co-integration tests (post-Brexit)

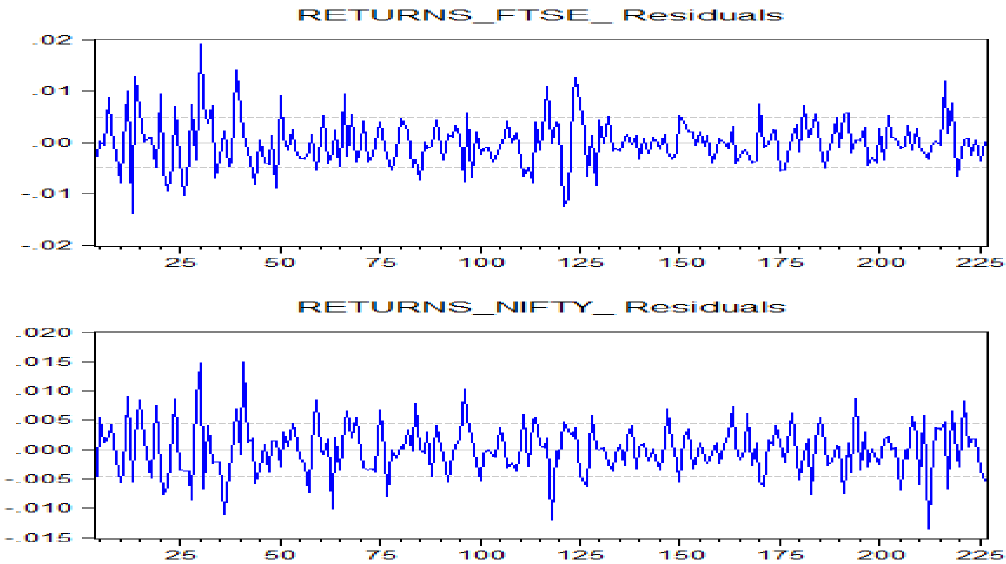
Markets	Hypothesize no. of CEs	Eigenvalue	Trace statistic	95% CV for trace test	Max Eigen statistic	95% CV for max eigen value test
FTSE-NIFTY	r=0	0.287970	53.5680	15.49471	34.64282	14.26460
	r<=1	0.169346	18.9252	3.841466	18.92525	3.841466

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level; Also denotes rejection of the hypothesis at the 0.05 level.
Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level; * denotes rejection of the hypothesis at the 0.05 level.

Empirical Results

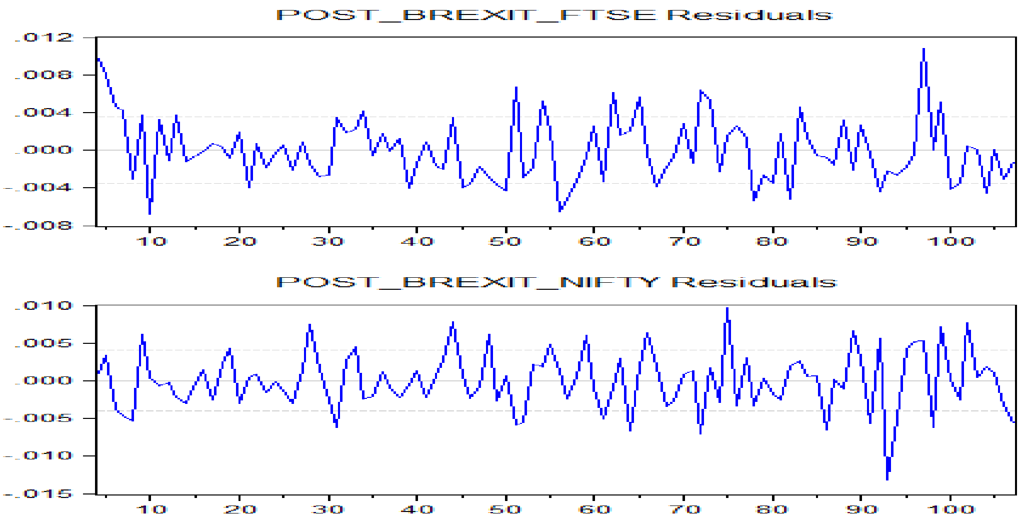
Vector Error Correction Model (VECM): The existence of cointegration between the variables suggests a long-term dynamic relationship. VECM is used next to determine the speed of adjustment due to the information shock of Brexit, in the short run among the variables. The graphs below represents the residuals of VECM for NSE-FTSE index for the entire sample (Jan –Dec 2016).

Exhibit 1



The graph below provides VECM residuals for NSE-FTSE index close just after the financial crisis (Brexit) sub sample (Jan-Dec 2016):

Exhibit 2



In the above exhibits, abscissa axis represents the time period (Unit: Daily), ordinate axis represents the range in the values of VECM residuals expressed in percentage. The results imply that in both the cases the VECM model well fits the data set as the residuals fall within the acceptable range of 0.1.

VECM Results: The results of the VECM tests for the entire study sample are tabulated below:

Error Correction:	D(RETURNS_FTSE_)	D(RETURNS_NIFTY_)

CointEq1	-0.759655	0.449790
	(0.10089)	(0.09298)
	[-7.52991]	[4.83736]
D(RETURNS_FTSE_(-1))	-0.098741	-0.354851
	(0.08400)	(0.07742)
	[-1.17549]	[-4.58346]
D(RETURNS_FTSE_(-2))	-0.154745	-0.209826
	(0.06470)	(0.05963)
	[-2.39190]	[-3.51895]
D(RETURNS_NIFTY_(-1))	-0.464279	-0.318691
	(0.08956)	(0.08254)
	[-5.18401]	[-3.86083]
D(RETURNS_NIFTY_(-2))	-0.297457	-0.247556
	(0.07278)	(0.06708)
	[-4.08725]	[-3.69069]
C	4.41E-05	4.78E-06
	(0.00033)	(0.00030)
	[0.13562]	[0.01594]

Exhibit 3: VECM estimates; Figures in [ ] are t-values associated with the respective parameters. Δ denotes first differences.

The VECM results for the (Brexit) crisis period is tabulated below

Error Correction:	D(POST_BREXIT_FTSE)	D(POST_BREXIT_NIFTY)
CointEq1	-1.022971	0.351479
	(0.12229)	(0.13902)
	[-8.36492]	[2.52832]
D(POST_BREXIT_FTSE(-1))	0.186861	-0.312230
	(0.09712)	(0.11041)
	[1.92396]	[-2.82804]
D(POST_BREXIT_FTSE(-2))	0.087812	-0.192126
	(0.08346)	(0.09487)
	[1.05216]	[-2.02511]
D(POST_BREXIT_NIFTY(-1))	-0.579084	-0.492604
	(0.09462)	(0.10756)
	[-6.11994]	[-4.57972]
D(POST_BREXIT_NIFTY(-2))	-0.356004	-0.345085
	(0.08597)	(0.09772)
	[-4.14125]	[-3.53132]
C	6.55E-05	-8.18E-05
	(0.00035)	(0.00040)
	[0.18758]	[-0.20603]

Exhibit 4: VECM estimates. Figures in [ ] are t-values associated with the respective parameters. Δ denotes first differences.

The parameter estimation of VECM with first difference for the period (Jan – Dec 2016) is presented in exhibit 4. The C1 values reflect the log-run price of instance embedded in the cointegrating vectors. C2 coefficients indicate the long run risk premiums for different series. The optimal lag length to be used in the ECM is determined using the SC criterion (Darrat et al., 1998). SC criterion dictates the lag length to be chosen as 3 and 3 cointegrating vectors are identified for the full sample period and during the financial crisis period. A sub sample study for the Brexit crisis period (June 2016-Dec 2016) is done to analyze the response of NIFTY 50 due to the crisis shock and is compared with the results from the complete sample. The long-run results are presented in equations and t-statistics are in brackets:

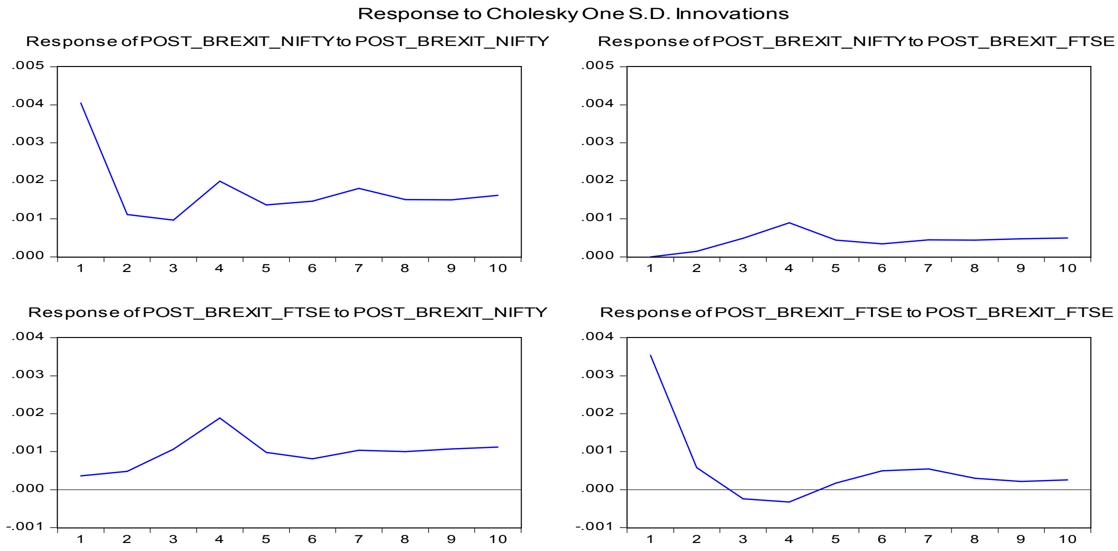
NIFTY(entire sample) = .3394* FTSE(entire sample) -.000128[-3.43992] - (1)

POST BREXIT NIFTY = .7827* POST BREXIT FTSE -.000563[-3.91694] - (2)

The results during the Brexit period can be interpreted as follows. A 1% increase in Post brexit FTSE causes Post Brexit NIFTY returns to increase by 0.78% It is thus likely that post-Bexit FTSE returns are positively related to post-Brexit NIFTY returns. The increase percentage almost doubled during the Brexit crisis period as compared with the entire sample study. The intercept term is negative. This shows that the NIFTY returns deviate much more during crisis.

According to the estimates obtained and equations, we argue that the returns of NIFTY present different levels of responses to FTSE returns during Brexit Crisis. The error correction coefficient for the explanatory variables NIFTY (full sample (ecm1, t–1) and POST Brexit NIFTY (ecm2, t–1) is about 0.84 and 0.92, with a negative sign and statistically significant. This means that both the (entire sample and crisis sample) returns deviation in period (t – 1) and its long run equilibrium value is corrected by 84% and 92 %. The ECM not only validates the long run equilibrium, but also emphasizes the effect of short-term variables fluctuations. It can be observed from the findings of VECM that the error correction coefficients have similar significant convergence parameters for the entire sample and during financial crisis.

The impulse response plots indicate that, it takes a lag of 4-5 days for the Brexit information shock to affect the NIFTY 50 index. The impulsive response of NIFTY on itself suggests that the initial information adjustment to Brexit was quick (1 day) and was not due to the FTSE index fluctuations.



The impulsive response of FTSE 100 on NIFTY 50 suggests that it takes 4 days for the FTSE index fluctuations to affect the NIFTY 50 index. Hence, the information transmission of FTSE to NIFTY due to the Brexit shock takes 4 days to adjust itself.

Granger Causality Test: One of the ways to confirm the short run causality among variables is to employ Granger causality test (Engle and Granger, 1987). This test is applied to our sample time series, namely FTSE 100 returns and NIFTY 50 returns over the entire 11 month period starting from 4 January 2016 to 5 December 2016 (full sample), and from 24 June to 5 December (sub-sample crisis period) to capture the forecasting relationship between the two over the different periods, specifically to observe the significance during the post-Brexit period. The below results present the Granger causality of both the indices over the full period and during the crisis period respectively:

Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
RETURNS_NIFTY_ does not Granger Cause RETURNS_FTSE_	222	2.09360	0.0828
RETURNS_FTSE_ does not Granger Cause RETURNS_NIFTY_		1.04748	0.3837

Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
POST_BREXIT_NIFTY does not Granger Cause POST_BREXIT_FTSE	103	2.07788	0.0898
POST_BREXIT_FTSE does not Granger Cause POST_BREXIT_NIFTY		0.64514	0.6317

According to the above tables, the pair wise Granger causality test reveals that bidirectional causality exists between NIFTY and FTSE returns. Unidirectional causality subsists from FTSE to NIFTY open and close returns. Similarly, unidirectional causality runs from NIFTY close returns to both FTSE open and close returns and from NIFTY close to NIFTY open returns. In other words from the results of granger causality it can be inferred that NIFTY (open and close) returns and FTSE market (open and close) returns influence each other in the short run for entire sample period and also during the financial crisis period. We try to capture the speed of information assimilation due to the Brexit shock in the Indian markets by applying lags of 1, 2 and 4 to check for the time take for markets to absorb and adjust to the shocks at higher lags.

Table 3: Pairwise Granger Causality Tests (Obs.: 222; lag length: 4)		
Null Hypothesis	F-Stat.	Prob.
FTSE returns does not Granger Cause Nifty Returns	1.0474	0.3837
Nifty returns does not Granger Cause FTSE returns	2.0936	0.0828

At lag length 2, we find the following results:

Table 4: Pairwise Granger Causality Tests (Obs.: 223; lag length: 2)		
Null Hypothesis	F-Stat.	Prob.
FTSE returns does not Granger Cause Nifty Returns	1.9815	0.1403
Nifty Returns does not Granger Cause FTSE returns	2.4038	0.0928

At lag length 1, we find the following results:

Table 5: Pairwise Granger Causality Tests (Obs.: 225; lag length: 1)		
Null Hypothesis	F-Stat.	Prob.
FTSE returns does not Granger Cause Nifty Returns	1.767	0.185

	2	1
Nifty Returns does not Granger Cause FTSE returns	0.160 4	0.689 1

Based on the above results, a preliminary conclusion is observed about the information lag in the index data. Since lag 2 has the highest statistic (nearly 2), the null hypothesis, i.e. the FTSE doesn't cause NIFTY can be rejected for lag 2 .Then Lag 1 can be accepted as the next best significant statistic. Hence, it can be asserted that, it takes NIFTY index 2 days to be affected (and shock adjusted) by FTSE index.

Quantile Regression Approach

Preliminary examination of sample dataset suggests that the distribution of data series is leptokurtic as are most financial time series, hence we are more interested in using different measures of central tendency and statistical dispersion in order to obtain a more comprehensive picture of the relationship between our sample variables. We, therefore, seek to employ quantile regression which captures the conditional quantile functions instead of conditional mean functions as in ordinary least square methods.

We begin with the standard quantile regression approach as follows. Let us assume the τ-th conditional quantile function of Post-Brexit NIFTY returns as,

$$\mathbf{QPostBrexit\_NFTY(\tau)} = \mathrm{PostBrexit\_FTSE} + \gamma 2(\tau)\mathrm{PostBrexit\_10day} + \gamma 3(\tau)\mathrm{PostBrexit\_30day} + \gamma 4(\tau)\mathrm{PostBrexit\_WTI} + \gamma 5(\tau)\mathrm{PostBrexit\_FX} + \gamma 6(\tau)\mathrm{PostBrexit\_FTSEGARCH} + \gamma 7(\tau)\mathrm{PostBrexit\_NIFTYGARCH} + \gamma 8(\tau)\mathrm{PreBrexit\_FTSE} + \gamma 9(\tau)\mathrm{PreBrexit\_FTSE} + x'_t\beta(\tau) \quad \text{-(3)}$$

The parameter $\gamma i(\tau)$ captures the effect of the variables (as per the following nomenclature) at the τ-th quantile of the conditional distribution of Post brexit NIFTY returns.

- Post Brexit FTSE returns- PostBrexit_FTSE

- Pre Brexit FTSE returns- PreBrexit_FTSE
- Post Brexit FTSE 10day volatility(logarithmic)- PostBrexit_10day
- Post Brexit FTSE 30 day volatility(logarithmic)- PostBrexit_30day
- Post Brexit WTI prices(logarithmic)- PostBrexit_WTI
- Post Brexit INRGBP FX rate(logarithmic)- PostBrexit_FX
- Post Brexit FTSE GARCH modeled volatility- PostBrexit_FTSEGARCH
- Pre Brexit Nifty returns - PreBrexit_FTSE
- Post Brexit NIFTY GARCH modeled volatility- PostBrexit_NIFTYGARCH

Quantile Regression Estimates

The quantile regression parameter estimates the change in a specified quantile of the response variable produced by a one-unit change in the predictor variable. In our analysis, we consider 9 variables to better capture the various quantile responses to them. This allows comparing how some percentiles of the Post Brexit Nifty returns may be more affected by certain control variables (as shown below) than other percentiles. This is reflected in the change in the size of the regression coefficient. Coefficient estimates for the tenth quantiles (from .1 to .9) and the linear regression coefficient estimates for the post-Brexit Nifty returns are presented in the following table (Table 6):

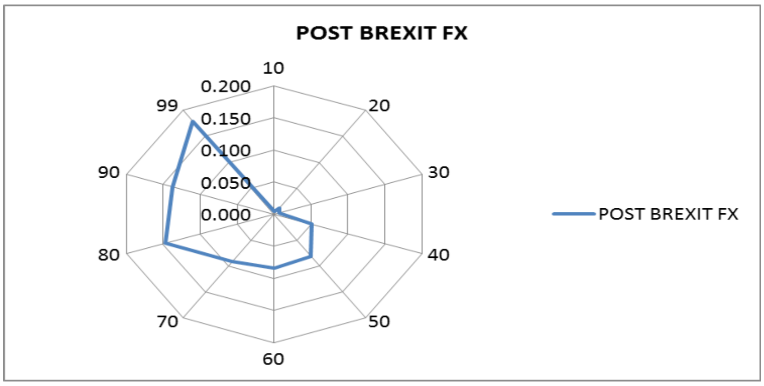
[Table 6 about here]

According to the linear regression model, the mean response of NIFTY returns post-Brexit to post-Brexit (GARCH) volatility is -0.1. The quantile regression results indicate that post-Brexit (GARCH) volatility has a larger negative impact on the upper quantiles (90%, 99%) of post-Brexit NIFTY returns. A point to note would be the post-Brexit FTSE returns having a higher positive impact on the 99% quantile of the post-Brexit Nifty returns.

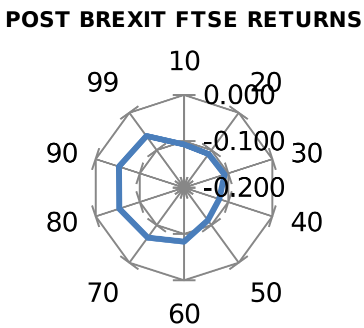
A cross-quantile analysis of each of the sample control variables support our estimates and provide robustness to our findings. Residual diagnostics correlogram in both the absolute and the squared values evidently show that the distribution is normal and that the partial and autocorrelation are within the critical values.

***Cross-quantile analysis of control variables*:**

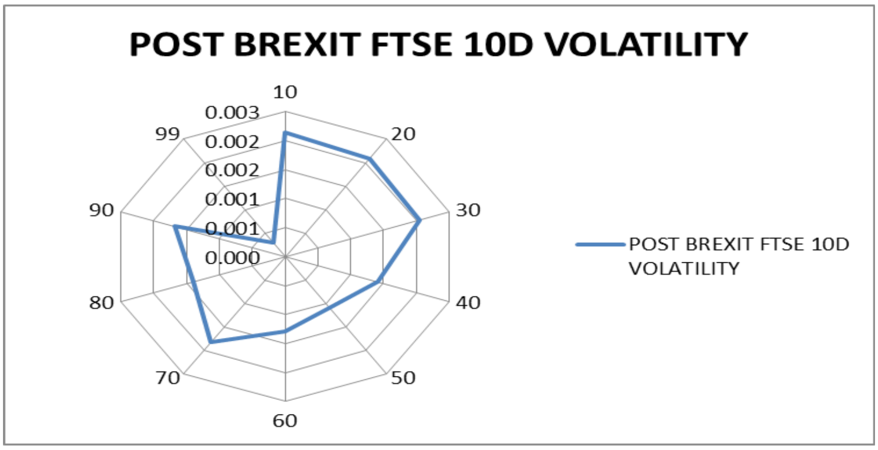
(i) POST BREXIT Foreign exchange rate: As depicted by the below radar diagram, the impact of FX rate is more pronounced on the upper quantiles(70 and above) and the effect increases gradually beyond the median point. The effect is practically negligible for the lower quantiles(40 and below) ,thus sharp upward movements in the post Brexit NIFTY returns are increasingly and adversely affected by the post Brexit GBP-INR exchange rate.



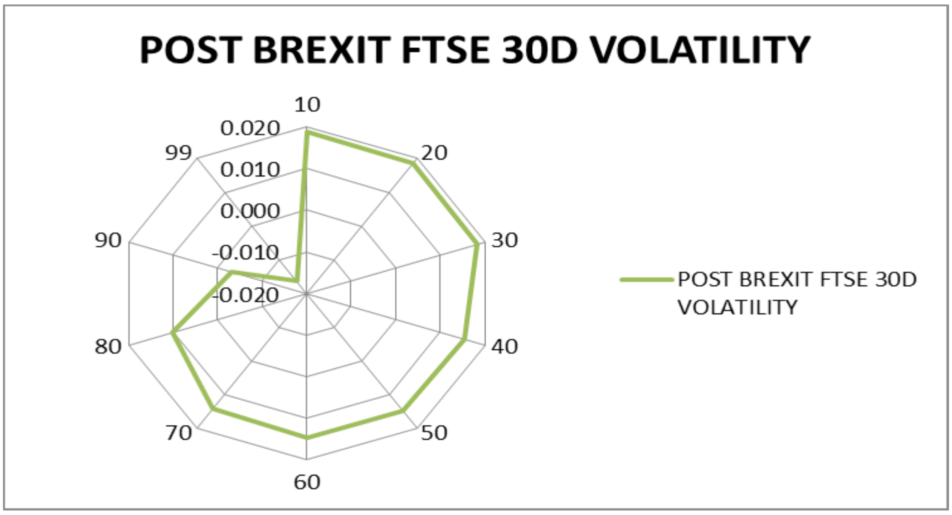
(ii) Post Brexit FTSE Returns: The below radar diagram clearly depicts the upper quantiles being more explained by the FTSE post-Brexit returns. This goes to prove that abnormal or excessive returns are attributed to the crisis information shock. The negative effect is sharper for the lower quantiles(60 and below) ,evidently showing that FTSE affects the minor jumps and the major declines in NIFTY more promptly.



(iii) Post Brexit FTSE 10-Day Volatility: As depicted below, the 10 day volatility of the FTSE index has a marginally higher impact on the lower quantiles, going to show that initial minor jumps in NIFTY returns could be explained by the short run FTSE volatility.

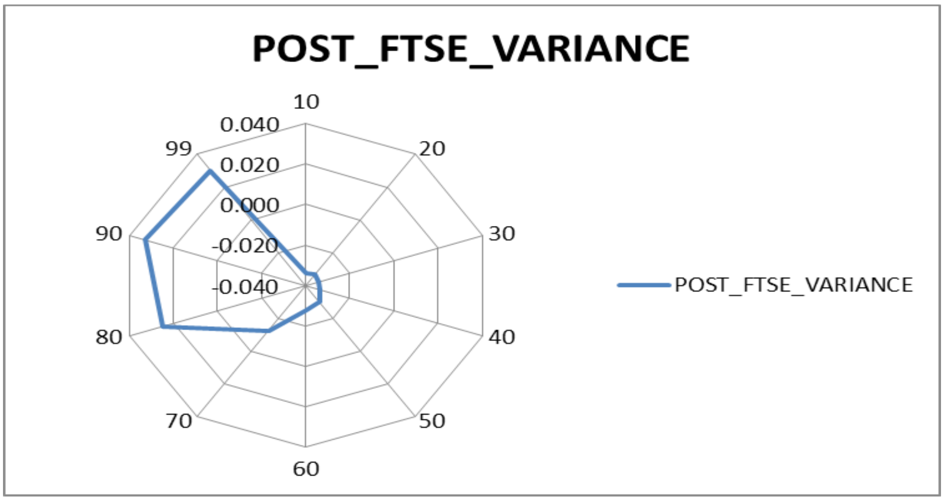


(iv) Post FTSE 30-day volatility: the long run volatility of the FTSE index has marginally higher positive impact on the lower quantiles, again indicating the fact that minor jumps in returns are better explained by short run measures of volatility of the post-Brexit FTSE index. The negative impact on the upper quantiles goes to show that higher returns in the post Brexit NIFTY index is attributed to the negative volatility in the FTSE index.

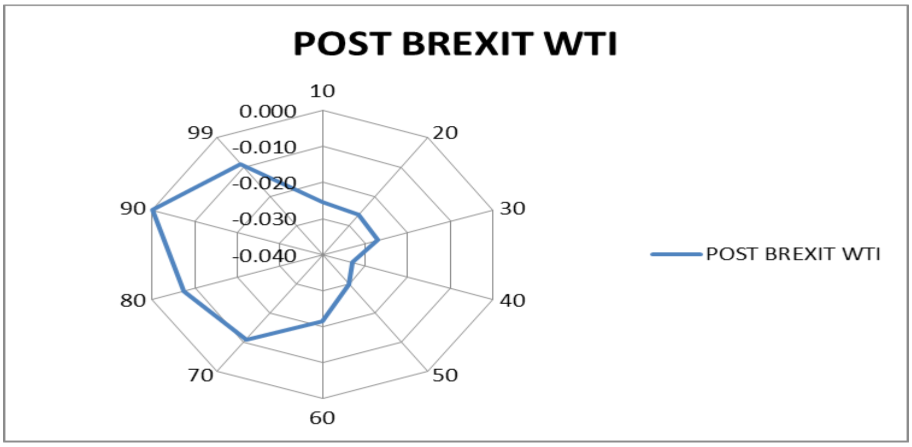


(v) Post Brexit FTSE variance (GARCH modeled): again the GARCH modeled FTSE post brexit variance has a greater positive effect on the higher quantiles, indicating that greater volatility in the

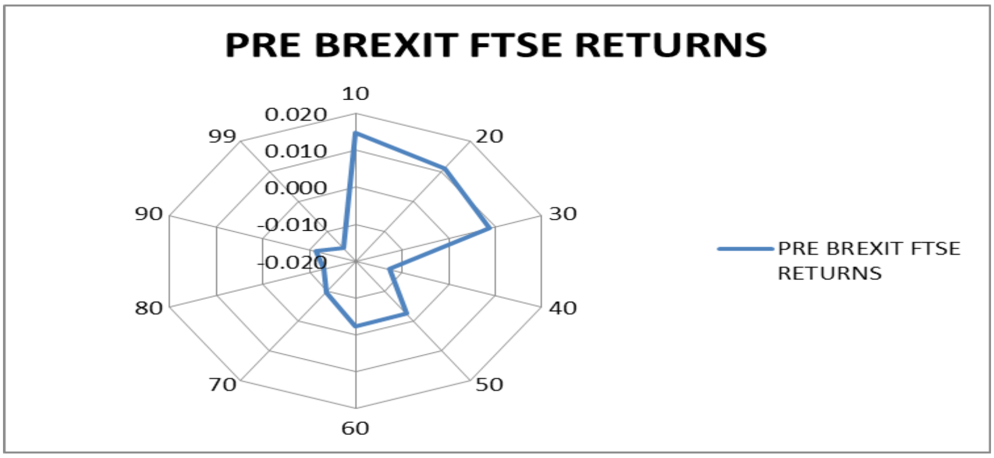
FTSE index is transmitted in the form of greater returns; establishing the known risk reward relationship, but in a cross-market context .The negative effect on the lower quantiles (60 and below) indicate that smaller gains in the NIFTY index from upward movements are adversely affected by the post Brexit FTSE variance(GARCH modeled volatility)



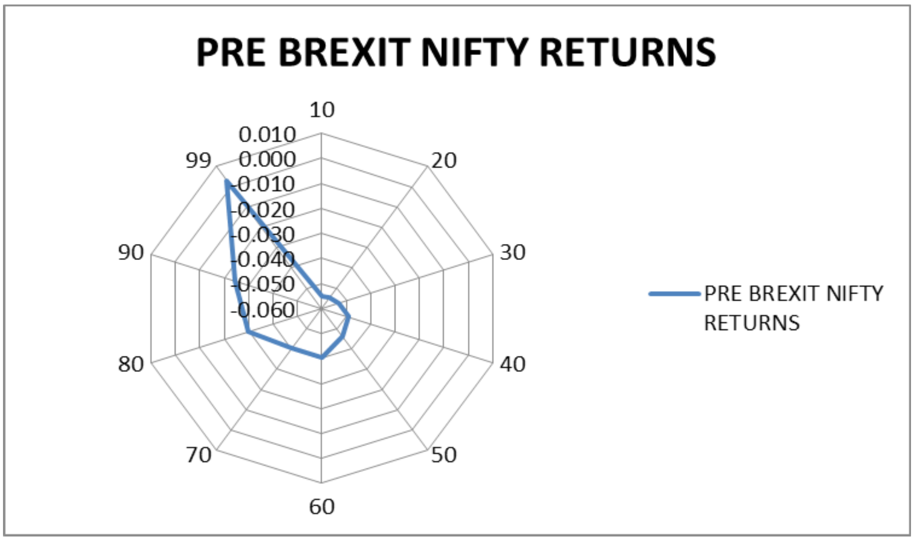
(vi) Post-Brexit WTI: Given the negative impact of the WTI on all the quantiles except the 90th quantile; it can be readily concluded that since India is a net importer of oil, decrease in oil prices helps the Indian markets due to reduced inflation; the effect more pronounced in the lower quantiles.



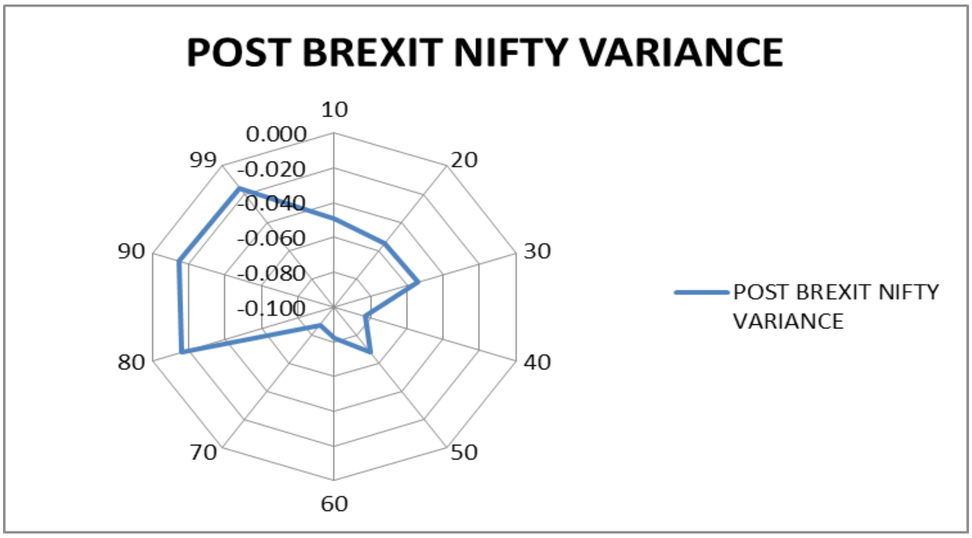
(vii) Pre-Brexit FTSE Returns: Given the greater positive impact on the lower quantiles, it can very well be conjectured that the pre-Brexit FTSE returns incorporating the Brexit certainty; has a positive impact on the minor jumps in the NIFTY returns post-Brexit.



(viii) Pre-Brexit NIFTY returns: The negative impact of the lagged NIFTY returns on its post-Brexit returns, follows a positive trend on the quantiles; showing that higher quantiles are less negatively impacted.



(ix) Post-Brexit NIFTY Variance (GARCH): establishing the variance – return relationship in the post-Brexit period; the higher quantile returns are less negatively impacted than the lower quantiles. The results imply that sharp NIFTY declines are much more significantly associated with the variance.



Summary and Concluding Remarks

We carried out our study to investigate the nature of dynamic relationship between the Indian and UK markets during the Brexit period. Brexit certainly has had an impact on markets globally, specifically emerging economies like India, which have slowly started integrating into the global economy. We employed econometric GARCH modeled tests, co-integration test, VECM, Granger causality for relative analysis and the changing patterns of short and long run dynamic relationships between the UK and Indian Markets. The empirical results establish a long run co-integrating between the NIFTY 50 and FTSE 100, supported by the Johansen's Co-integration test. The VECM test quantifies the short run adjustments to the dynamic relationship equilibrium. The error correction coefficients evidently establish that the FTSE returns influence the post-Brexit NIFTY returns more than the Pre-Brexit NIFTY returns, thus supporting our starting hypothesis of spillover of crisis shock from the UK to the Indian Market. Also, in the short run, post-Brexit FTSE returns granger cause post-Brexit NIFTY returns.

The quantile regression results clearly quantify the impact of various global as well as domestic factors/variables, emphasizing on the various levels of NIFTY returns that these variables have an influence on. The quantile regression results exhibit the greater effect of post-Brexit FTSE returns, INR-GBP FX and the GARCH modeled FTSE volatility on the higher quantiles of Post Brexit NIFTY returns. The results highlight the linkages between Indian market, an emerging economy and the UK market, a developed economy showing that positive as well as negative factors influence Indian markets, in the process quantifying the information transmission across the two markets. Increasing volatility in the markets subsequently lead to financial and macroeconomic instability. The study is of utmost importance to investors looking for international diversification of their portfolios, especially during financial crisis periods. The response of the India-NIFTY to changes in UK-FTSE returns implies investing opportunities for risk diversification of international investors.

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Table 6: Quantile Regression Estimates

	Linear	10	20	30	40	50	60	70	80	90	9
OST BREXIT FX	.067	0.004	0.011	0.008	0.050	0.081	0.084	0.091	0.147	0.137	0.17
OST BREXIT FTSE ETURNS	-.032	-0.107	-0.110	-0.108	-0.120	-0.113	-0.084	-0.067	-0.053	-0.053	0.06
OST BREXIT FTSE 10D OLATILITY	.003	0.002	0.002	0.002	0.001	0.001	0.001	0.002	0.001	0.002	0.00
OST BREXIT FTSE 30D OLATILITY	-.001	0.019	0.019	0.018	0.015	0.015	0.015	0.014	0.010	-0.003	0.01
OST_BREXIT_FTSE_VARI NCE	-.087	-0.034	-0.033	-0.034	-0.033	-0.030	-0.028	-0.012	0.025	0.033	0.03
OST BREXIT WTI	-.038	-0.026	-0.026	-0.027	-0.033	-0.030	-0.022	-0.011	-0.007	0.000	0.00
RE BREXIT FTSE ETURNS	.003	0.015	0.011	0.009	-0.013	-0.002	-0.002	-0.010	-0.013	-0.011	0.01
RE BREXIT NIFTY ETURNS	-.028	-0.055	-0.055	-0.053	-0.049	-0.046	-0.040	-0.040	-0.030	-0.024	0.00
OST BREXIT NIFTY ARIANCE	-.006	-0.049	-0.055	-0.054	-0.083	-0.068	-0.082	-0.087	-0.016	-0.014	0.01