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Repercussions of Global Turbulence and Market Volatility in Spot & Futures Market: India Preparedness

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Abstract: *This article examines the repercussions of global turbulence and market volatility in Indian Capital market for the period spanning from January 1, 2003 to August 31, 2013 with a total of 2654 observations and it is broken into pre-crisis and post-crisis respectively. The study employed Generalized Autoregressive Conditional Heteroskedasticity (1,1) model to measure the volatility persistence by employing dummy variables. Cointegrating Regression Augmented Dickey Fuller (CRADF) and Vector Error Correction Model (VECM) was employed to investigate the casual nexus between spot and futures market in both short and long run equilibrium. The squared residuals of VECM were applied to investigate the lead-lag relationship between the bivariate variables. Our findings indicate that there was a significant change in the post crisis period for spot and futures market volatility. Our result suggests that nothing can be learned and new regulation can only do more harm. Apart from this, nobody knows which financial instrument will be at the centre of the next crisis. Overall, the comprehensive financial sector reform like Credit Default Swap, Valuation Assumptions and Basel II Accord can create more problems and make the investors more complex to meet the global challenges environment.*

Keywords: *Emerging Market, Volatility, Price Discovery, GARCH, CRADF, VECM*

JEL Classification: *C22, C52, G13, G14*

1. INTRODUCTION

The globalization of financial systems and the acceleration of information technology have increased the risk of financial crisis, as a crisis in one country can spread to other countries and bring about worldwide crises. The Smithsonian Agreement, Mexican Peso, Asian crisis, Russian crashed and Euro Debt crisis were followed by a sequence of stock market and exchange rate crises in other markets. These finally collapses have driven researchers to ask how such shocks are transmitted internationally and

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why they have such intensity. Due to this, global turbulence the economic growth will be negative for two consecutive quarters; it signifies a fall in real GDP, lower National income and lower National output. Global turbulence has negative impact on economic growth and makes unconstructive impact on the nation. The effect of global turbulence is often characterized by following factors - impulsive rise in unemployment, rise in government borrowing, sharp decline in stock markets and share prices, lower inflation and fall in investment. Global turbulence becomes a pessimistic phase for the ruling government as it is burdened up with extra weight of borrowing.

This article examines the repercussions of global turbulence and market volatility in Indian Capital market and makes a resounding impact on share market, due to global turbulence the share markets look shaky and share-holders often face disappointment, which leads to low profitability and low dividends. Many a times shares price fall sharply, as an anticipation of predictable financial catastrophe, arising out from the fear of recession. It is not always that share prices fall as there can be any other reasons for their decline. Therefore, the turbulence will reduce the appropriate demand and correspondingly will enforce pressure on the prices and will rage out price-war in the market, this may lead to decline in rates and so it might results into lower inflation rates. In the phase of global turbulence, the investor always feels finicky and shaky to invest as the fear of acquiring substantial profits increases manifold. The investment in the market becomes more unstable and it affects the economic growth. It leads to lowering of economic growth and simultaneously other related aspects of it.

Recently, a great deal of attention is given to the wide ranging global turbulence and its impact on various sectors of the economy, which provoked the researchers, academicians and policy makers to study in-depth analysis in the existing scenario and to bring out suggestive policy guidelines to contain the down turn and withstand the ill effects of turbulence. The impact of spot market volatility, price discovery and lead-lag relationship explains how the information disseminates from one market to another. It has been argued that the lead lag relationship between spot and futures market returns can be attributed to one or more market imperfection like differences in transaction cost, liquidity differences between two market, short selling restriction, dividend uncertainties, and differences in margin requirements. Pursuing research on this controversial topic will leads to following questions; first does the global turbulence influence futures price volatility in the spot market. Second, whether there exists a long-run equilibrium between the spot and futures market variables. Third, the lead-lag relationships between spot and futures market innovations are examined. Even with a perfectly specified and estimated volatility model, the impact of global turbulence is inherited by futures market volatility, subsequently it transferred to spot market affecting the current level of volatility. The remainder of this paper is organized as follows: We present a brief review of antecedent literature in Section 2. Section 3 introduces the data and sample size conducted in this study. Section 4 describes brief discussion about Econometric methodological issues concerning to the impact of recession on futures market on the underlying spot market volatility for pre and post crisis period, while Section 5 incorporates the data used and validity of the assumptions made about the model. Finally, Section 7 summarizes and concludes.

2. REVIEW OF LITERATURE

Though there is a vast amount of literature focusing on the impact of derivative trading on spot market volatility in developed markets. Figlewski (1981) studied the impact of futures trading on Government National Mortgage Association (GNMA) by using standard deviations of the returns and concludes that the volatility of underlying asset were increased after the introduction of futures markets. The introduction of futures trading has not induced any change in spot market volatility in the long-run, but the futures markets induced short-run volatility on the expiration days of futures contracts Edwards (1988). Harris (1989) examined the volatility effects for pre-futures and post futures and suggests the increase in volatility was a common phenomenon in different markets and index futures may not be the cause. Bessembinder and Seguin (1992) examined the dynamic relationship between futures trading activity and spot market volatility for United States. Kamara *et al.* (1992) investigated the impact of futures trading on spot market and indicates the volatility of daily returns in post futures period was higher than the pre futures period. Antoniou and Holmes (1995) found that the introduction of stock index futures caused an increase in spot market volatility in the short run while there was no significant change in long run.

Butterworth (2000) found no significant change in the volatility of FTSE-250 index after onset of futures trading. Board, Sandmann and Surcliffe (2001) shows contrary to regulatory concern and the results of other papers, contemporaneous information less futures market trading has no significant effect on spot market volatility. In contrast to the above studies, Bansal, Pruitt and Wei (1989) and Skinner (1989) found that option trading reduces the volatility of underlying spot markets by employing ARIMA model and reveals that active futures market trading are associated with decreased rather than increased volatility of the spot market by enhancing the liquidity and depth of the spot markets. Similarly the studies by Chatrath, Arjun, Ramchander and Song (1995) indicate that S&P 100 options market has a stabilizing effect on the underlying index. Phil Holmes (1996) examined the relationship between futures trading activities and stock market volatility in UK stock market and observed the inception of futures trading has a beneficial impact on underlying spot market. Furthermore, the recent studies of Bologna and Cavallo (2002) for Italy. Thenmozhi (2002), Nath (2003), Raju and Karande (2003) for India and Goodfellow and Salm (2008) for Poland have found that the onset of stock index futures trading had decreased the volatility of underlying spot market. The early study by Similarly, Kawaller et al. (1987) use minute to minute data on the S&P 500 spot and futures contract and prove that futures lead the cash index by 20-45 minutes. Herbst, McCormack and West (1987) examine the lead lag relationship between the spot and futures markets for S&P 500 and VLCI indices.

They find that for S&P 500 the lead is between zero and eight minutes, while for VLCI the lead is up to sixteen minutes. Stoll and Whaley (1990) find that S&P 500 and MM index futures returns lead the stock market returns by about 5 minutes. Similarly, Cheung and Ng (1990) analyze price changes over fifteen minute periods for the S&P 500 index using a GARCH model. Chan, Chan, and Karolyi (1991) use a bivariate GARCH model and find that S&P 500 futures returns lead spot returns by about five minutes. Abhyankar (1995) observed that futures market leads spot market returns during the period of high volatility. Turkington and Walsh (1999) examine the high frequency relationship between SPI futures and AOI in Australia and evidenced bidirectional causality between the two series. Kavussanos and Nomikos (2003) investigated the casual relationship between futures and spot prices in the freight futures market and found that futures price tend to discover new information more rapidly than spot prices

Thenmozhi (2002) examined the lead-lag relationship between stock index futures and spot index returns and reveals that futures trading returns lead the spot market. On the other hand, Raju and Karande (2003) examined the price discovery between the S&P CNX Nifty and its corresponding futures during the period 2000-2002. Cointegration technique and Error Correction models were employed for examining the objectives. The analysis revealed that price discovery occurs in the both futures and the spot market. Similarly, the study of Mukherjee and Mishra (2006), Kapil Gupta and Balwinder Singh (2006) investigate the spot and futures market returns and observed there exists a bidirectional relationship between these variables. Recent study by Shalini Bhatia (2007) employed Cointegration and VECM to examine the intra day lead-lag relationship between S&P CNX nifty spot and futures market and suggested that nifty futures lead the spot index by 10 to 25 minutes. In contrast, there exists a little work on the impact of global turbulence on spot and futures volatility on Indian stock market. To shed light on this issue, we employ GARCH (1,1) model to examine the impact of global turbulence on spot market volatility for pre and post futures periods by using a dummy variables. The Engle-Granger approach is used to test the long-run equilibrium relationship between spot and futures market variables by Error Correction Models (ECMs). The uncorrelated residual series generated from Vector Error Correction Model were used to check the lead-lag relationship between the bivariate series by using Granger causality test, which may be important for the investors, academicians and researchers.

3. DATA SAMPLE AND THEIR PROPERTIES

This paper investigates the effect of global turbulence and market volatility and determines the dominant role played by spot and futures market in price discovery process. The dataset for S & P CNX Nifty spot and futures markets were obtained from NSE and the contract specifications and trading details are available from their website terminal. The returns are calculated for daily closing prices for spot and futures market between January 1, 2003 and August 31, 2013. As per Financial Stability Report of U.S, the total number of observations is divided into pre and post, respectively. The pre period prior consist from 1st January 2003 to 31st December 2006. Since most trading activities take place in the near-month contract, only near-month contract are examined. The closing price indices were converted to daily compounded return by taking the log difference as $R_t = \log (P_t / P_{t-1})$, where P_t represents the value of index at time t. S & P CNX Nifty is owned and managed by India Index Services and products Limited (IISL), which is a joint venture of NSE and CRISIL. All the observations are transformed into natural logarithms so that the price changes in returns prevent the non-stationary of the price level series approximate the price volatility.

4. METHODOLOGY

Before estimating GARCH (1,1) model, the first step in time-series data is to determine the order of integration for each return series using Augmented Dickey Fuller (1979) test and Phillips and Perron (1988) test. Since most of the time series have unit roots as many studies indicated including Nelson and Plosser (1982), Stock and Watson (1988) suggest that the time series are non-stationary, the conventional regression techniques based on non-stationary time series produce spurious regression Granger and Newbold (1974). The spot and future market return series should be examined for I (1) first.

4.1. Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

The effect of global turbulence on spot market volatility was examined by applying the methodology developed by Engle (1982) autoregressive conditional heteroskedasticity (ARCH) model, which were the most extensively used time-series models in the finance literature. The ARCH model suggests that the variance of residuals at time t depends on the squared error terms from past periods Engle (1982). The residual term ε_{it} is conditionally normally distributed and serially uncorrelated. The strength of ARCH techniques was well established and specified for economic variables, the conditional mean and conditional variance are the two main specifications.

A useful generalization of this model is the GARCH parameterization introduced by Bollerslev (1986) extended Engle's ARCH model to the GARCH model and it is based on the assumption that forecasts of time varying variance depend on the lagged variance of the asset. The GARCH model specification is found to be more appropriate than the standard statistical models because it is consistent with return distribution, which is leptokurtic and it allows long-run memory in the variance of conditional return distributions. As a result, the unexpected increase or decrease in returns at time t will generate an increase in the expected variability in the next period. The GARCH (1,1) model works well in most applied situations Bollerslev *et al.* (1992). The basic and most widespread model GARCH (1,1) can be expressed as;

$$R_t = a + bR_{t-1} + \varepsilon_t$$

$$\varepsilon_t \mid I_{t-1} \; N(0, h_t),$$

$$h_{it} = \alpha_0 + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \lambda_j u_{t-j}^2$$

Where, R_t denotes the realized return, h_{it} is the conditional variance, which is proxies by R_{t-1}, α, β and λ are the coefficients to be estimated. The sizes of β and λ parameters measure the volatility dynamics of the time series. The λ scaling parameter h_t now depends both on past values of the shocks, which captured by the lagged squared residual terms, and on past values of itself, which are captured by lagged h_t terms. The β parameter refers to the last periods forecast variance, the larger coefficients value of GARCH term characterize the shocks to conditional variance take a long time to die out. The GARCH is weekly stationery $\Sigma\beta_i + \Sigma\lambda_j < 1$, the latter two quantifying the persistence of shocks to volatility Nelson (1992). The parameter for GARCH (1,1) model indicate, the persistence of volatility shocks mainly depends on $\beta_i + \lambda_j$ Engle and Bollerslev (1986), Engle and Mustafa (1992). An increase or decrease in $\beta_i + \lambda_j$ point out the introduction of futures trading increase or decrease persistence of volatility shocks.

4.2. Cointegrating Regression Augmented Dickey Fuller (CRADF)

The existence of long-run equilibrium relationship between cash and futures market series were examined by Engle-Granger approach on the following regression equation;

$$S_t = \alpha_0 + \beta_0 f_t + z_t$$
$$F_t = \alpha_0 + \beta_0 s_t + z_t$$

Where, S_t and F_t are the logarithms of price changes on contemporaneous cash and futures prices at time t and z_t is the disequilibrium error, the deviation from long-run equilibrium.

4.3. Vector Error Correction Model (VECM)

If the non-stationary series with the same order of integration may be cointegrated for spot and futures markets, then there exist some linear combination of the series that can be tested for stationarity, the adequate method to examine the issue of causation is the Vector Error Correction Model (VECM) is expressed as follows;

$$R_{s,t} = \alpha_1 + \sum_{j=1}^{n} \beta_{1j} R_{s,t-j} + \sum_{j=1}^{n} \gamma_{1j} R_{f,t-j} + \lambda_1 z_{s,t-1} + v_{s,t}$$

$$R_{f,t} = \alpha_2 + \sum_{j=1}^{n} \beta_{2j} R_{f,t-j} + \sum_{j=1}^{n} \gamma_{2j} R_{s,t-j} + \lambda_2 z_{f,t-1} + v_{f,t}$$

Where, $R_{s,t}$ and $R_{f,t}$ represents spot and futures price returns at current period 't'. The stationary disturbance was denoted by v and Z_{t-1} was the error-correction terms.

Since Vector Error Correction Model (VECM) can capture both the short-run dynamic and the long-run equilibrium relationship between variables, we use it to estimate the relationship between cash and futures market variables. The coefficients of lagged returns γ_{1j} and γ_{2j} stand for short-run dynamics. These hypotheses can be tested by applying F-statistics for exploring the joint dynamics of the lagged estimated coefficients of $R_{s,t}$ and $R_{f,t}$. Furthermore, the error correction coefficients are used to explain the speed of adjustment towards the short-run and long-run equilibrium by correcting the changes in spot and futures markets.

4.4. Granger Causality Test

The unautocorrelated residuals of $v_{s,t}$ and $v_{f,t}$ are obtained from VECM are used for Granger (1969) causality test to estimate the lead-lag relation between the spot and futures market series. This test were used to check whether the lagged futures returns improve the accuracy of spot returns beyond the lagged spot returns alone by using the following hypothesis;

H_{0A}: $R_{f,t}$ does not Granger cause $R_{s,t}$ (that is, $\gamma_{1j} = 0$ for all j).

H_{0B}: $R_{s,t}$ does not Granger cause $R_{f,t}$ (that is, $\gamma_{2j} = 0$ for all j).

A lead lag between the spot and futures series were described by using the following models;

$$R_{s,t} = \alpha + \sum_{l=-n}^{l=+n} b_l R_{f,t+1} + \varepsilon_t$$

The coefficients with positive subscripts (b_{+1}) and negative subscripts (b_{-1}) denotes lead and lag coefficients, respectively. If the lead coefficients are significant, spot returns leads the futures returns whereas if the lag coefficients are significant the futures returns leads the spot returns. The computed raw data for estimating the lead lag relation between the variables may suffer from infrequent trading bias and leads to misleading conclusion Both Stoll and Whaley (1990) and Chan (1992). As a result, the lead lag relation was investigated by using the return innovations where the portion of spot price changes due to infrequent trading days were filtered out for the analysis.

5. RESULTS & DISCUSSION

The explosion of testing the stationary of the time series data should be kept into consideration for testing the presence of unit root in the variables, otherwise the analysis may produce spurious results. Each of the spot and futures price series was first examined for I (1), which is carried out in two step process for Pre, Post and Entire turbulence period and reported in Table 1. We conduct the unit root tests using both the Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test, on the levels and first differences for the bivariate variables. Besides, the unit root test results

Table 1
Results of Unit Root Test

Periods	*Markets*	*ADF Test*		*PP Test*	
		Intercept	*Trend & Intercept*	*Intercept*	*Trend & Intercept*
Entire Period	**Spot**	-6.480942	-6.480984	-38.86937	-37.85632
	Futures	-5.548679	-5.564528	-26.81742	-25.80402
Pre Period	**Spot**	-5.155411	-5.261888	-15.28199	-15.32630
	Futures	-6.849302	-6.932337	-22.72714	-21.75171
Post Period	**Spot**	-5.278187	-5.271532	-20.74615	-21.72875
	Futures	-4.454238	-4.451316	-24.58225	-25.56304

Note: ADF is the Augmented Dickey Fuller test and PP refers to Phillips-Perron test.

concludes that both the series are found to be stationary at first order differencing and integrated at the order of I (1).

The objective of the study is to examine the effect of global turbulence on underlying spot market volatility to news. The results of GARCH (1,1) estimation with dummy variables are reported in Table 2. The results evidence that the S & P CNX Nifty spot was found to be positively significant at 1 per cent level implying that the series financial crisis since the great depression has an impact on volatility in the stock market. In mean equation the lagged return series were found to be insignificant for pre and post period. The coefficients of β_1 were found to be significant at all the estimates, but the β_1 effects were found to be escalating in post periods at 0.1025 per cent. The large coefficients of $\hat{a}_1$ indicate that shocks to conditional variance take long time to die out and hence volatility is persistence. The α_1 for pre period and post period were observed with 0.2382 and 0.1022 respectively. It is clear, that the α_1 effect were found to be higher for pre crisis period, it is an indication that the market is less persistence and more reactive in volatility. So, the volatility position in β_1 for post period suggests that the recent information is more important than old information and the information decays very fast. The last column of Table 2 exhibits the persistence of volatility shocks depends primarily on (β_1 + α_1) is generally close to unity. The overall volatility persistence for the entire period stood at 0.9971, but there was a decrease and increase in pre and post period crisis with 0.9952 and 0.9978 respectively. Hence, the high value of β_1 + α_1 implies long memory volatility persistence in spot market for post period.

The Engle-Granger Cointegration tests for forward and reverse period regression for S & P CNX Nifty spot and futures market series are reported in Table 3. The Cointegrating Regression Augmented Dickey Fuller (CRADF) test statistics and their associated lag values are examined to test the autocorrelation function of the bivariate series. Taking into account the results from both tests, we reject the null hypothesis of non-cointegration at 1 per cent level for all the periods considered for the purpose of analysis. Therefore, we proceed with the estimation of a Vector Error Correction Model

Table 2
Generalized Autoregressive Conditional Heteroskedascity (1, 1) Model

Periods	$R_t = \alpha_0 + R_{t-1} + u_t$		$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 D_t$				
	α_0	R_{t-1}	α_0	α_1	β_1	δ_1	$\alpha_1+\beta_1$
Entire Period	0.0015[a]	0.0737[a]	0.0000[a]	0.1603[a]	0.8368[a]	0.00017[a]	0.9971
	(4.0079)	(2.4822)	(5.1563)	(9.3622)	(08.0395)	(3.8475)	
Pre Period	0.0018[a]	0.0749	0.0000[a]	0.2382[a]	0.7571[a]		0.9952
	(3.9923)	(1.8094)	(4.5321)	(7.3191)	(10.0873)		
Post Period	0.0008	0.0612	0.0000[a]	0.1022[a]	0.8956[a]		0.9978
	(1.0380)	(1.2925)	(3.3496)	(6.0181)	(09.5368)		

Note: t-statistics are in the parentheses. a denote significance at the 1 % level of significance

Table 3
Engle-Granger Cointegration tests for S&P CNX Nifty Spot and Futures Markets

Period	*Cointegration Regression*	*CRADF*	*Lag order*
Entire Period	S_t = (0.000674) + (-0.072081)	-8.247778[a]	13
	F_t = (0.000675) + (-0.083437)	-36.94534[a]	01
Pre Period	S_t = (0.001106) + (-0.137546)	-7.866065[a]	09
	F_t = (0.001081) + (-0.167799)	-7.803951[a]	09
Post Period	S_t = (0.000218) + (-0.036962)	-8.068554[a]	07
	F_t = (0.000279) + (-0.041637)	-24.69732[a]	01

Note: a denote significance at the 1 % level of significance.

(VECM). It can be concluded, that the two markets are linked in the long-run and short-run equilibrium.

The lag lengths for the two bivariate series are estimated using the Vector Error Correction Model (VECM) for entire period and two sub periods are determined on the basis of Akaike Information Criterion (AIC) and Schwatz's Bayseian Information Criterion (SIC) and the tests results are reported in Table 4. The coefficients of ECM_{t-1} for entire period and pre period are statistically significant at one per cent level, which is an indication of bidirectional error correction. Whereas, in the post period, the value of ECM_{t-1} were found to be significant at one per cent level, but the futures market were envisaged with insignificant effect. The results of spot market indicate the speed of adjustment to any disequilibrium towards a long-run at 130 per cent was corrected each year. The F statistics for all the entire, forward and reverse period indicates the rejection of hypothesis that the coefficients jointly equal to zero. Furthermore, the estimates of the VECM indicate the existence of bidirectional causality was observed for entire and pre period, but for the post period unidirectional causality running from futures to spot in the long-run.

The residuals of VECM are used to estimate the lead-lag relationships between the spot and futures markets series by tested with Wald tests of coefficient restrictions are reported in Table 5. In most of the cases, the raw returns series can cause spurious lead-lag relation because of infrequent trading of stocks within the index portfolio, the models use spot market innovations, $I_{s,t,}$ and futures market innovations, $I_{f,t}$. Initially, several ARMA(p,q) processes were estimated including the ARMA(2,3) model used by Stoll and Whaley (1996) and Fleming et al. (1996). However, all of these were less successful at eliminating autocorrelation than a simple AR(1) process. The higher-order ARMA models leads to low explanatory power and correlograms were observed with significant residual autocorrelation. Thus, the lead-lag relation is estimated with return innovations generated by an AR(1) process. The choice of five leads and lags is based on preliminary evidence from cross-correlation coefficients which are small and insignificant at longer leads and lags. The dependent and independent variable are the spot market and futures market innovations, respectively. The contemporaneous relationships between spot and futures market were observed with strong for the bivariate variables. In all periods, the estimated contemporaneous coefficients for S_t causing on F_t were significant and large. Some of the lead coefficients are significant at one per cent level and evidenced that spot market is leading the futures market. However, the relations for successive years show this lead declining. There is stronger

Table 4
Estimates of Vector Error Correction Model for S&P CNX Nifty Spot and Futures Markets

Periods	*Entire Period*		*Pre Period*		*Post Period*	
	Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*
Constant	3.52E-06	3.14E-06	-4.86E-06	-3.55E-05	-6.97E-05	4.04E-05
	(0.009)	(0.005)	(-0.012)	(-0.054)	(-0.717)	(0.038)
$\mathbf{S_{t-1}}$	0.1706[a]	-0.6103[a]	0.7418[a]	-0.5003[a]	-0.0104	-0.6323[a]
	(5.275)	(-11.634)	(9.766)	(-3.888)	(-1.584)	(-8.888)
$\mathbf{S_{t-2}}$	0.0787[b]	-0.4391[a]	0.3714[a]	-0.3051[a]	-0.0074	-0.4547[a]
	(2.570)	(-8.837)	(6.413)	(-3.109)	(-1.162)	(-6.576)
$\mathbf{S_{t-3}}$	-0.0213	-0.2833[a]	0.0877[b]	-0.2589[a]	-0.0030	-0.2625[a]
	(-0.779)	(-6.383)	(2.167)	(-3.777)	(-0.506)	(-4.048)
$\mathbf{S_{t-4}}$	0.0003	-0.2004[a]	-0.0228	-0.2131[a]	0.0018	-0.1815[a]
	(0.013)	(-5.319)	(-0.756)	(-4.170)	(0.359)	(-3.228)
$\mathbf{S_{t-5}}$	0.0269	-0.0841[a]	-0.0168	-0.0682	-0.0029	-0.0889[b]
	(1.498)	(-2.888)	(-0.700)	(-1.670)	(-0.736)	(-2.072)
$\mathbf{F_{t-1}}$	-1.1460[a]	-0.2086[a]	-2.0028[a]	-0.1699	-1.2764[a]	-0.6510
	(-27.687)	(-3.107)	(-22.080)	(-1.105)	(-35.575)	(-1.679)
$\mathbf{F_{t-2}}$	-0.9575[a]	-0.1514[b]	-1.4630[a]	-0.1359	-1.2791[a]	-0.5781
	(-23.605)	(-2.302)	(-16.565)	(-0.908)	(-35.631)	(-1.491)
$\mathbf{F_{t-3}}$	-0.8186[a]	-0.0656	-0.9542[a]	-0.1395	-1.2736[a]	-0.4857
	(-22.925)	(-1.134)	(-12.857)	(-1.109)	(-35.471)	(-1.252)
$\mathbf{F_{t-4}}$	-0.7631[a]	0.0030	-0.5747[a]	-0.0943	-1.2751[a]	-0.4287
	(-25.234)	(0.062)	(-10.568)	(-1.024)	(-35.866)	(-1.116)
$\mathbf{F_{t-5}}$	-0.0889[a]	0.0399	-0.2192[a]	-0.0620	-0.3401[a]	-0.3690
	(-3.569)	(0.988)	(-6.824)	(-1.138)	(-9.570)	(-0.961)
$\mathbf{ECM_{t-1}}$	-1.1840[a]	0.7045[a]	-2.1096[a]	0.7208[a]	-1.3084[a]	0.2525
	(-12.445)	(10.070)	(-10.478)	(9.533)	(-13.299)	(0.630)
F-Statistics	365.421[a]	103.268[a]	200.337[a]	57.294[a]	102.35 0[a]	47.594[a]

Note: t-statistics are in the parentheses. a and b denote significance at the 1% and 5% levels, respectively.

Table 5
Lead – Lag relationship between S & P CNX Nifty futures and Spot Market variables

Periods	*Entire Period*		*Pre Period*		*Post Period*	
	Spot	*Futures*	*Spot*	*Futures*	*Spot*	*Futures*
Constant	-2.14E-05	1.47E-05	-0.0001	3.17E-05	0.0001	-6.23E-05
	(-0.062)	(0.025)	(-0.455)	(0.052)	(0.970)	(-0.061)
$\mathbf{S_{t-1}}$	-0.0961[a]	0.0441	-0.4231[a]	0.1373[b]	-0.4241[a]	-0.3884
	(-3.654)	(1.023)	(-11.113)	(2.256)	(-9.522)	(-0.900)
$\mathbf{S_{t-2}}$	-0.2798[a]	0.1433[a]	-0.5487[a]	0.1220	-0.2173[a]	0.3128
	(-10.846)	(3.387)	(-13.415)	(1.865)	(-4.632)	(0.688)
$\mathbf{S_{t-3}}$	-0.3298[a]	0.0332	-0.5036[a]	-0.0188	-0.0923[b]	0.1705
	(-12.373)	(0.761)	(-11.419)	(-0.266)	(-2.109)	(0.401)
$\mathbf{S_{t-4}}$	-0.0386[b]	0.0021	-0.3416[a]	-0.0108	0.0064	-0.0040
	(-2.051)	(0.068)	(-7.761)	(-0.153)	(1.358)	(-0.086)
$\mathbf{S_{t-5}}$	-0.1259[a]	0.0272	-0.2360[a]	0.0984	-0.0436[a]	0.0051
	(-6.679)	(0.882)	(-5.646)	(1.472)	(-9.707)	(0.117)
$\mathbf{F_{t-1}}$	0.0082	0.0013	0.1042[a]	-0.0132	0.0167[a]	0.0301
	(0.493)	(0.048)	(4.352)	(-0.346)	(3.633)	(0.674)
$\mathbf{F_{t-2}}$	0.1937[a]	-0.0367	0.5913[a]	-0.0232	0.0053	-0.0249
	(11.667)	(-1.348)	(24.591)	(-0.603)	(1.146)	(-0.555)
$\mathbf{F_{t-3}}$	0.1516[a]	0.0003	0.5856[a]	-0.0418	0.0087	0.0016
	(8.773)	(0.013)	(17.793)	(-0.794)	(1.910)	(0.036)
$\mathbf{F_{t-4}}$	0.0709[a]	-0.0257	0.4841[a]	-0.0070	-0.0045	-0.0376
	(4.065)	(-0.901)	(12.437)	(-0.113)	(-1.070)	(-0.924)
$\mathbf{F_{t-5}}$	0.7162[a]	-0.0060	0.4769[a]	-0.0373	0.9344[a]	-0.0092
	(40.880)	(-0.210)	(11.589)	(-0.567)	(22.130)	(-0.226)
H_0: all lead coefficients are zero						
χ^2 (*p* - Value)	55.87 (0.000)		45.82 (0.000)		36.82 (0.000)	
F (*p* - Value)	7.45 (0.000)		5.81 (0.000)		4.24 (0.000)	
H_1: all lead coefficients are zero						
χ^2 (*p* - Value)	1028.53 (0.000)		451.16 (0.000)		367.87 (0.000)	
F (*p* - Value)	169.25 (0.000)		89.36 (0.000)		52.42 (0.000)	

Note: t-statistics are in the parentheses. a and b denote significance at the 1 % and 5 % levels, respectively.

evidence that futures lead the spot market. Even though the magnitude of the coefficients declines, the evidence suggests that futures market tend to lead price movements in the spot market. Clearly, although there is weak evidence that the spot market leads the futures market, there is stronger evidence that the stock index futures market leads the stock market.

6. CONCLUSION

This article investigates the effect of global turbulence and market volatility in spot and futures market in India. The results of GARCH (1,1) model suggest the volatility persistence in quite common phenomena in the Indian stock market, it is mainly due to the collapse in subprime mortgages ignited the crisis, but it is not the fundamental cause. At the root of the current crisis are the global imbalances and the underestimation of risk that led to excessive leverage in the years before the crisis. Apart from that, the loss of investor's confidence in various investment alternatives, credit default swap, sub-prime lending crisis and securitized mortgages, which added fuel to the fire in the developing markets and prompted a substantial injection of capital into international market. The Vector Error Correction Model (VECM) and Granger causality test for entire and pre period were observed with bidirectional causality between spot and futures market, but in post crisis period unidirectional causality running from futures to spot in the long-run. Thus, the returns in these two markets are largely contemporaneous, but with week evidence that the spot market leads the futures market and stronger evidence that the futures market leads the spot market. Therefore, the study indicates that nothing can be learned and new regulation can only do more harm to the International Market. Apart from that, nobody knows which financial instrument will be at the centre of the next crisis, because the financial markets in many advanced economies have come to function like giant casinos, where the house almost always wins and everybody else loses. In summary, it is necessary to develop a macro-prudential regulatory system based on countercyclical capital provisioning and to develop institutions for the supervision of all the different financial markets that are focusing systemic risk and nothing else.

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