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Volatility Interactions Across Indian and Chinese Stock Markets

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Abstract

Volatility is an important component in risk return analysis of financial assets. It imparts liquidity to the financial system and also serves as an information source for rational decision making. Since the latter half of the 20th century, volatility in stock returns has been found to be time varying and exhibiting patterns and therefore, various models have been developed to capture such dynamic properties of volatility. The introduction of Autoregressive Conditional Heteroscedasticity (ARCH) models by Engle in 1982 has led to a better understanding of the behaviour of stock market volatility than the traditional measures including standard deviation.The present study attempts to model various aspects including clustering, leverage effect and spillover effect of stock market volatility in Indian and Chinese stock markets during 2001-2016 using daily time-series data with Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models. Volatility has been seen to be highly persistent in both the markets. The T-GARCH model has been applied in order to assess the presence of information asymmetry that bad news impacts volatility more than good news. Our results reveal that both Indian and Chinese stock markets' volatility shows time varying behaviour.The theoretical reasoning of the asymmetric impact of news that bad news affects volatility more than good news has been confirmed in both markets. Furthermore, the spillover effect of volatility across the two markets has been tested using the T-GARCH-X model. The results show unidirectional spillover effect of volatility from Chinese stock market to the Indian stock market. This implies that shocks from Chinese stock market impact conditional volatility in the Indian stock markets only but not vice-versa.

Keyword: T-GARCH, Leverage Effect, Spillover, Volatility Clustering

JEL Classification: G12, G15.

1. Introduction

Volatility as a measure of risk, which measures variability of returns, has gained attention over the past few decades. Some level of volatility is essential for the functioning of the stock market as it helps to impart liquidity to the market. As Goudarzi and Ramanarayanan (2011) have stated that the fluctuation of stock prices is a sign of market efficiency. Excessive volatility can be detrimental to the smooth functioning of the financial system, sometimes putting an economy into crisis. There has been a continuous debate in academics that whether volatility is constant over time or time varying. Many researches including Sood and Saluja (2006), Demetrescu (2007), Bhar and Nikolova (2007), Mukherjee and Mishra (2010), Gupta (2014), and Banumathy and Azhagaiah (2015) have established the time varying nature of volatility and some of the stylised facts including volatility clustering, leptokurtic distribution of returns, leverage effect. The common measure of risk is the standard deviation or variance. However, the introduction of the Autoregressive Conditional Heteroscedasticity (ARCH) model by Engle in 1982 led to the modelling of time varying conditional volatility in financial time series. A generalised version of ARCH was introduced by Bollerslev in 1986 which apart from explaining the volatility with past shocks also incorporates the impact of previous volatility. The GARCH model also helps in explaining the persistence

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of volatility. The symmetric GARCH does not show differential impact of news on conditional volatility. A number of asymmetric GARCH models constituting a family of GARCH models have been introduced to incorporate the impact of the nature of the shock while estimating the conditional volatility.

Much of the work on volatility modelling has been done in the context of developed markets. However, there is a lack of comprehensive research on the issue for developing markets in general and the fastest growing economies like India and China in particular. The present study aims to model the conditional volatility in the Indian and Chinese stock market and also assess the presence differential impact of news on the time varying conditional volatility. In the process, we have aimed to examine certain stylised facts about volatility including volatility clustering, leptokurtosis, and leverage effect in the two major emerging markets of the world. Finally, we have analysed the presence of spillover effect of volatility across the two markets. The rest of the paper is organised as follows. Second section reviews the existing literature. The research design including period of study, sample and methodology is provided in third section. The empirical analysis is presented in fourth section. Finally, the paper concludes in fifth section.

2. Review of Literature

2.1. Volatility Clustering

The phenomenon of volatility clustering that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes" was first documented by Mandelbrot (1963). The same was further elaborated by Engle (1982) and Bollerslev (1986) with introduction of Autoregressive Conditional Heteroscedasticity (ARCH) and Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models. Cont (2007) while using a simple agent-based model has explained the phenomenon of volatility clustering through the activity of market participants on the basis of news arrival process. The agent-based models explain the behaviour of prices in terms of the trading rules adopted. The authors have found that significant autocorrelation function of absolute returns over several lags decaying slowly to zero is the typical manifestation of the volatility clustering phenomenon. Demetrescu (2007) has argued that market participants perceive risk, often proxied by volatility, associated with a stock differently leading to a less forceful correction of price when speculators are risk loving and a more forceful correction when speculators are risk averse. These being individual perceptions, may thus vary. However, the general perception of all the market participants about risk of a stock is the perceived market risk. Thus, when there is a perception of high market risk, the scatter of limit orders in terms of price will also be higher. The market orders which are matched against these limit orders will have a higher price impact and thus realised volatility will also be high. On the other hand, since volatility is assumed to be time varying, modeling the same on the basis of historic data would lead to a higher expectation of current volatility and thus a higher perception of market risk. The contrary is also true. Gaunersdorfer and Hommes (2007) have found that even though price changes are unpredictable, absolute changes or squared returns are predictable, implying that small changes are followed by small changes and large changes are followed by large changes. Banumathy and Azhagaiah (2015) have found that since the mean returns on the NIFTY index were found to be positive, the stocks have positive average returns. They have used the Autoregressive Conditional Heteroscedasticity Lagrange Multiplier (ARCH-LM) test check whether volatility exhibits patterns of clustering. Their results show that low volatility is followed by periods of low volatility and high volatility is followed by periods of high volatility, thus confirming presence of volatility clustering in the the Indian stock market. Schmitt and Westerhoff (2016) have attributed the volatility clustering phenomenon associated with stock returns to the herding behaviour of speculators. During periods of high uncertainty, the market trading rules becomes less heterogeneous as speculators observe other speculators on trading rules. The result is high volatility since prices are adjusted strongly by the market maker who faces a less balanced excess demand. However, during periods of low volatility in the stock market, the trading rules adopted by speculators are relatively more heterogeneous, since speculators trade independent of each other. The market maker facing a balanced excess demand eventually adjusts prices less forcefully and as such volatility remains low (Schmitt & Westerhoff, 2016, pp. 3-4).

2.2. Asymmetric Volatility

The asymmetric property of volatility that bad news has a greater impact on volatility than good news was first of all documented by Black (1976). The empirical support to the asymmetric effect found by the author was the presence of a negative correlation between stock returns volatility with higher statistical significance in case of negative returns. Dutta (2014) has stated that for volatility modelling the model should be such in which the asymmetric impact of news is taken care of. However, the traditional GARCH model does not take into account the differential impacts of good and bad news on stock return volatility. The asymmetric property of volatility has been often described in research as the leverage effect. The reason behind the leverage effect as mentioned by Christie (1982) is that with a decline in price the value of market equity reduces compared to the market value of debt as such increasing the financial leverage of the firm. This implies that the risk of the firm increases as such increasing the volatility of the firm. Schwert (1990) has argued that in an all equity firm the volatility of equity returns equals to the volatility of its asset returns. However, if the firm finances half of its assets with debt the risk of the equity holders will increase thereby increasing the volatility of the returns. Similarly, firms having high operating leverage will incur huge losses during economic downturns and thus will be facing high volatility of returns. Mishra and Rahman (2010) have found that while the Japanese stock market is impacted more by negative news, in the Indian stock market the influence of positive news is more. Goudarzi and Ramanarayanan (2011) have stated that negative returns are generally associated with upward revisions of conditional volatility. The market participants generally being risk-averse respond more to bad news. Gogia (2012) has pointed out that the leverage effect hypothesis is a down market effect since the effect is much stronger when the market is falling. However, the argument placed is that the phenomenon is more pronounced for indices that for individual stocks. Gupta (2014) and Sood and Saluja (2006) separately have established the presence of leverage effect in the Indian stock market using threshold (T-GARCH) and exponential (E-GARCH) models.

2.3. Volatility Spillover

The process of globalisation and liberalisation has led to the flow of information across stock markets at a greater pace than that in the pre-globalisation and pre-liberalisation era. Thus, the transmission of stock market volatility (volatility spillover) which contains most of the stock market information across countries has become inevitable. Bhar and Nikolova (2007) have shown evidence of a positive return spillover from world index to all the BRIC countries, a positive volatility spillover effect from world index to Russia, Brazil, and India and a negative volatility spillover effect from world index to China. Singh, Kumar, and Pandey (2008) have analysed the spillover across India and most of the major world economies including United States, China, Japan and Germany. The results of the multivariate GARCH (BEKK) show that Asian markets are more integrated than European or US markets and that returns and volatility influences are prevalent more in the former than in the latter two markets. They have also found evidence of the impact of Japanese volatility on the Asian markets which itself is influenced by the volatility from US and European markets. Overall, their results support the presence of positive volatility spillover from developed markets to the Indian market. On the basis of these results, the authors have suggested for the existence of opportunities of diversification for international investors. Mukherjee and Mishra (2010) have used the basic GARCH (1,1) model to test the intraday and overnight return as well as volatility spillovers across India and 12 Asian countries. Their results have shown bi-directional spillovers across India and most of the trading partners. However, intraday volatility spillover has been found to be significant from most of the foreign trading partners to India and not the other way. Jebran and Iqbal (2016) have studied the stock market integration and volatility spillover effect for the major Asian economies. The results of GARCH (1,1) model with an autoregressive AR(1) process in the mean equation has revealed absence of any spillover effect of volatility across Indian and Chinese stock markets. However, bidirectional and unidirectional spillover effects have been established across other Asian markets.

Based on the above review of existing literature, we have developed the following research hypotheses regarding stock market volatility in the Indian and Chinese stock markets:

1. Volatility exhibits time varying characteristics manifested through the phenomenon of clustering.
2. There is a differential impact of bad news on the stock market volatility.
3. There is a spillover effect of volatility across the Indian and Chinese stock markets.

3. Research Design

3.1. Period of Study and sample

The data for the study comprises 3835 daily closing prices of S&P BSE SENSEX and SSE Composite Index representing stock market activities for India and China respectively from 2nd January 2001 to 30th December 2016. The dates on which the stock market remained closed for either of the country has been excluded from the sample. This has a major implication for analysing the spill over effects across the two countries as the impact of a shock in one market will not be identified in the other market contemporaneously. The reason for including China in the study is its importance as being the second largest economy in terms of nominal GDP after USA as well as second largest growing economy after India.

3.2. Methodology

We have calculated daily log returns of both S&P BSE SENSEX and SSE Composite index by taking the log differences of the daily closing prices as follows:

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right)$$

First of all, we have analysed the descriptive statistics including mean, standard deviation, skewness, kurtosis and normality of the returns of SENSEX and SSE Index. These will provide inputs regarding properties of the sample and the insights regarding the use of appropriate volatility models. The Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests have been used to check the stationarity of the return series. The null hypothesis for both these tests is that data is non-stationary.

Before modelling the conditional volatility, it is important to test for the presence of ARCH effect in the residuals in order to examine whether or not the residuals are heteroscedastic. We have tested the presence of ARCH effect at 1 and 5 lags by using the ARCH-LM test. The residuals should also be autocorrelated for which we have used the Ljung-Box Q^2 statistics at 12 lags. These tests give insights about volatility clustering.

The Generalised Autoregressive conditional heteroscedasticity (GARCH) model given by Bollerslev in 1986 has been used to model the conditional volatility for Indian and Chinese Stock returns. The GARCH (1, 1) model allows the conditional volatility to be a function of last period's squared forecast error and its own lag. The model consists of two parts, the mean equation and the variance equation and can be expressed as:

$$\text{mean equation: } r_t + \mu + \varepsilon_t \text{ and}$$

$$\text{variance equation: } h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

$$\varepsilon_t = z_t\sqrt{h_t} \ \ where\ z_t \approx N(0, \sigma_t^2)$$

Here, r_t is the return of stock index at time t, μ is the average return, ε_t is the error term, h_t is the conditional variance at time t, and h_{t-1} is the lagged volatility. Also, $\omega > 0$, $\alpha \geq 0$ and β ≥, since volatility cannot be negative. The GARCH (1, 1) model contains two terms. The ARCH (α) term represents the impact of previous period shock on error variance while as the GARCH (β) term represents the effect of yesterday's volatility viz-a-viz past shocks on today's volatility Brooks (2008). The (α+β) parameter shows the persistence of volatility that is the rate at which volatility decays over time. For the GARCH model to be meaningful, the (α+β) should be ≤ 1. If α+β = 1, it is said to be an explosive process which means the impact of shock will never die down and thus volatility is highly persistent. The value of (α+β) > 1 is meaningless in practice as it implies that the impact of news will never decay rather will amplify with time. Hence, the condition (α+β) < 1 is strictly imposed in GARCH modelling of volatility (Brooks, 2008, p. 394).

Further, to examine whether the Indian and Chinese stock markets respond differently to the nature of shock we have used the T-GARCH proposed by Zakoin in 1994. The conventional GARCH model suffers from the drawback that it lacks the ability to model asymmetric impact of news on volatility. The T-GARCH variance model can be expressed in simple form as:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 D_{t-1} + \beta h_{t-1}$$

where, $$D_{t-1} = \begin{Bmatrix} 1 \ \text{if} \ \varepsilon_{t-1} < 0 \\ 0 \ \text{if} \ \varepsilon_{t-1} > 0 \end{Bmatrix}$$

The γ parameter measures the asymmetric impact on volatility. It is also known as the leverage effect. The non-negativity constraint as in the symmetric GARCH model holds in the T-GARCH model as well. The dummy takes the value of 1 when ($\varepsilon_{t-1} < 0$) representing bad news and 0 when ($\varepsilon_{t-1} > 0$) defining good news. The parameter γ represents the impact of bad news and its significance confirms the presence of asymmetric impact on volatility that is, negative shocks have differential impact on the conditional variance. The parameter α measures the differential impact of good news on conditional volatility (Brooks, 2008, p. 405).

Finally, we have used the squared error estimated from the basic GARCH (1, 1) model for India (China) to see whether there is any evidence of volatility spillover to China (India). The volatility model having the lowest Akaike Information Criteria (AIC) among the symmetric and asymmetric GARCH model has been used to test for the presence of volatility spillover across the two markets. The GARCH-X model developed by Apergis in 1998 extends the conditional volatility modelling while allowing for the incorporation of exogenous regressors as independent variables determined outside the volatility model. The simple specification of the variance model is as under:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 D_{t-1} + \beta h_{t-1} + \theta\varepsilon_{i,t}^2$$

where, $\varepsilon^2_{i,t}$ is the standardised squared error of the other market the impact of whose is to be analysed in the volatility model and θ represents the contemporaneous volatility spillover effect from one market to the other. The contemporaneous impacts have been chosen to be analysed because the Indian and Chinese stock markets work in almost the same timeframe with the Chinese stock market opening before the Indian stock market.

The residuals of the volatility models for both the markets have been tested for the presence of ARCH effects. The Ljung-Box Q^2 (12 lags) and ARCH-LM test (1 and 5 lags) have been used for residual diagnostics.

4. Empirical Results

4.1. Return Characteristics

The descriptive statistics of daily returns on SENSEX and SSE Index for the sample period have been summarised in Table 1. The average returns have been found to be positive in both the markets with SENSEX providing higher average returns than SSE Composite Index. This also implies that there has been increase in stock index prices over the sample period. The negative skewness points out to the fact that there is a high probability of earning above average returns. The value of kurtosis being greater than 3 establishes that returns are leptokurtic. This is indicative of the fact that the return series are not normally distributed. The assumption of normality has been further rejected by the Jarque-Bera statistics at 1% level of significance.

Table 1: Descriptive Statistics of Daily Returns from January 2001 to December 2016

Statistic	*SENSEX*	*SSE*
Mean	0.000493	0.000101
Standard Deviation	0.015032	0.016690
Skewness	-0.186975	-0.278243
Kurtosis	11.26505	7.460626
Jarque-Bera	10935.02*	3228.046*
Q^2 (12 lags)	1145.0*	775.83*
ARCH LM (1)	167.8171*	96.35909*
ARCH LM (5)	77.49415*	60.31009*

Source: Estimation output from Eviews.

Note: ** denotes significance at 1% level of significance.*

4.2. Volatility Clustering

Fig. 1 and Fig. 2 show the daily returns of the S&P BSE SENSEX and SSE Composite Index from 2nd January 2001 to 30th December 2016. It can be clearly seen that that there exist periods of high (low) volatility followed by periods of low (high) volatility which is an indication of the phenomenon of volatility clustering. The volatility clustering property has been statistically tested by the use of Ljung-Box Q^2 statistics which presents the first order autocorrelation in squared returns. Table 1 presents the results of Ljung-Box statistics. It can be seen from the results that the squared returns are showing significant autocorrelation at 12 lags in Indian as well as Chinese index returns. This also confirms the presence of volatility clustering. Finally, we have tested the presence of ARCH effect in the residuals of the return series by using the ARCH-LM test at 1 and 5 lags. The results of the test are presented in Table 1. The null hypothesis of "no ARCH effect" can be rejected in both the cases at 1% level of significance. Thus, we can conclude that the returns of SENSEX and SSE index are heteroscedastic and exhibit volatility clustering which is a pre-requisite of modelling conditional volatility. The explanation of volatility clustering as mentioned by Demetrescu (2007) and Schmitt and Westerhoff (2016) separately can be the reduction in the heterogeneity in trading rules adopted by market participants during high uncertainty amplified by the modelling of volatility on the basis of historic data. Thus, volatility clustering can be attributed to the herding behaviour of market participants.

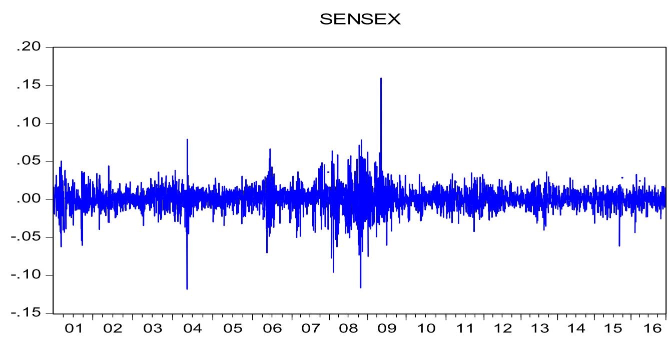

Fig. 1: Volatility Clustering of Daily Returns of SENSEX

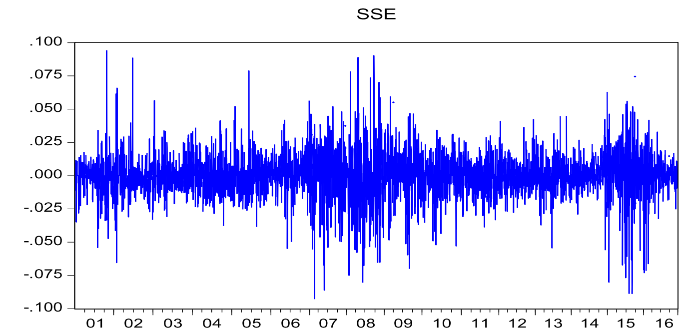

Fig. 2: Volatility Clustering of Daily Returns of SSE Index

4.3. Volatility Estimates Using Symmetric/ Simple GARCH Model

In order to proceed towards modelling of conditional volatility with GARCH models the unit root properties of the data should be checked. The results of the ADF and PP test as presented in Table 2 reveal that the index values at log levels were found to be non-stationary. The log returns of SENSEX as well as SSE index were found to be stationary at 1% level of significance. These results confirm the weak-form efficiency of the Indian and Chinese stock markets as the prices are found to follow a random walk.

Table 2: Unit Root Test of Daily Price Levels and Returns of SENSEX and SSE

Variable	*ADF Test*		*PP Test*	
	Log level	**1st difference**	**Log level**	**1st difference**
SENSEX	-0.880524	-44.71642*	-0.917891	-58.16274*
SSE	-1.428471	-15.82314*	-1.327107	-60.73539*

Source: Estimation output from Eviews.

*Note: * denotes significance at 1% level of significance.*

The results of GARCH (1,1) model for SENSEX and SSE has been presented in Table 3. From the results of the mean model, it can be seen that the average returns in both the markets are positive and statistically significant at 1% level of significance. Further, from the variance equation, all the coefficients are positive thus fulfilling the non-negativity constraint of the simple GARCH model. The ARCH term (α) has been found to be significant in both the cases. However, the ARCH coefficient has been found to be greater in case of SENSEX than SSE. This means the Indian stock market volatility is more sensitive to new surprises than the Chinese stock market volatility. The GARCH term (β) is also significant and greater that the ARCH term in both the cases implying that volatility is more sensitive to its one period lag than any new surprise in the market. However, the volatility in Chinese returns is more sensitive to its lagged values than that in the Indian market. The (α+β) parameter is also very high in both the markets and close to 1 in the Chinese stock market. These results reveal that volatility has a long memory in both the markets.

Table 3: Estimated Result for GARCH (1,1) Model

Coefficients	*SENSEX*	*SSE*
Mean equation		
μ (constant)	0.000890*	0.000200*
Variance equation		
ω (constant)	$4.72e^{-6}$*	$2.77e^{-6}$*
α (ARCH term)	0.111265*	0.068268*
β (GARCH term)	0.867604*	0.923100*
α+β	0.978869	0.991368
AIC	-5.889012	-5.601831
Diagnostics Statistics		
Q^2 (12lags)	9.0296	8.8419
ARCH LM (1 lag)	0.028554	0.407621
ARCH LM (5lags)	0.381755	0.446031

Source: Estimation output from Eviews.

*Note: * denotes significance at 1% level of significance.*

The residuals of the GARCH (1, 1) model were put to diagnostic testing using the Ljung-Box and ARCH-LM test. The results show that the squared returns were not autocorrelated at 12 lags; no ARCH effect was present in the residuals. This implies that the variance equation is well-specified for both the markets.

4.4 Asymmetric Volatility

The conventional/ symmetric GARCH does not show any asymmetric impact on volatility. The asymmetric effect occurs when bad news increases volatility more than good news. This is also commonly known as the leverage effect, since the market value of equity decreases by a price drop (bad news) raising the debt-equity ratio. Consequently, risk of the equity holders increases which leads to an increase in volatility. We have used the T-GARCH (1, 1) model to establish the presence of asymmetric impact of news on volatility. The results if the T-GARCH (1, 1) model reported in table 4 reveal that the asymmetric effect of news on volatility measured by γ is significant at 1% for both India and China. Besides this, the ARCH and GARCH terms are also significant at 1% level of significance. The persistence parameter (α+β) is also high for both the markets. As pointed out by Gogia (2012), the asymmetric volatility is a down market effect, our results are consistent with his argument, since most of the stock markets throughout the globe witnessed downward price movements after the US subprime crisis during the sample period. These results also reflect the risk characteristics of investors. According to Goudarzi and Ramanarayanan (2011), the asymmetric volatility evidence implies that the investors are risk averse, hence we may say that both the Indian and Chinese investors are risk averse.

Table 4: Estimated Result for T-GARCH (1, 1) Model

Coefficients	*SENSEX*	*SSE*
Mean equation		
μ (constant)	0.000606*	$7.06e^{-5}$
Variance equation		
ω (constant)	$5.36e^{-6}$*	$3.05e^{-6}$*
α (ARCH term)	0.052048*	0.054084*
β (GARCH term)	0.865589*	0.920744*
γ (TGARCH term)	0.111776*	0.030241*
α+β	0.917637	0.974828
AIC	-5.902943	-5.604330
Diagnostics Statistics		
Q^2 (12lags)	10.617	9.0412
ARCH LM (1 lag)	1.385130	0.526223
ARCH LM (5lags)	0.435289	0.430869

Source: Estimation output from Eviews.

*Note: * denotes significance at 1% level of significance.*

The residuals of the T-GARCH model have been checked for the presence of any ARCH effects at 1 and 5 lags. As per the ARCH-LM test the null hypothesis of "no ARCH effect" has been accepted. The Ljung-Box statistics reveals absence of any autocorrelation in the residuals. The AIC value of the T-GARCH model has been found to be less than the symmetric GARCH (1, 1) model. It can thus be said that the T-GARCH model explains the conditional volatility in a better way for both the markets.

4.5. Spillover Effect

The GARCH-X model introduced by Apergis in 1998 allows for introduction of exogenous variables in the variance equation. Since the T-GARCH (1, 1) model has been established as a better model explaining the conditional volatility in the Indian and Chinese stock market, the spillover effect has been analysed using the same model. We have used the squared error as a measure of volatility spillover from each of the market to see its impact on the conditional volatility of the other market. The results of the spillover effect have been presented in Table 5. The spillover coefficient θ is positive and significant in case of Indian stock market which implies that as the Chinese stock market volatility increases, the conditional volatility in the Indian stock market also increases. However, the converse has not been proven statistically. One of the reasons of the unidirectional volatility spillover from Chinese to India stock market can be attributed to the degree of restrictions in the two markets. The Chinese stock market is more restricted than its Indian counterpart. Over the past decade, the Indian stock market has witnessed reduction in restrictions for trading in stocks by allowing more participation of foreign investors. On the contrary, the Chinese regulators have imposed several restrictions including restrictions on selling of shares for big investors, introduction of the circuit breaker mechanism, and establishment of the national team for buying stocks on the behest of the government for stabilising the market. Apart from this, most of the Chinese stock market capitalisation is closed for foreign investing.

Table 5: Estimated Result for TGARCH -X (1, 1) Model

Coefficients	*SENSEX*	*SSE*
Mean equation		
μ (constant)	0.000616*	6.61e^{-5}
Variance equation		
ω (constant)	4.45e^{-6}*	2.95e^{-6}*
α (ARCH term)	0.054673*	0.054231*
β (GARCH term)	0.861704*	0.918175*
γ (TGARCH term)	0.106010*	0.031218*
θ (spillover effect)	1.75e^{-6}*	6.30e^{-7}
α+β	0.916377	0.972406
AIC	-5.906391	-5.604209
Diagnostics Statistics		
Q^2 (12lags)	10.687	9.3250
ARCH LM (1 lag)	1.197940	0.646855
ARCH LM (5lags)	0.365238	0.454797

Source: Estimation output from Eviews.

*Note: * denotes significance at 1% level of significance.*

The residuals of the above model have been tested for autocorrelation and ARCH effect with Ljung-Box and ARCH-LM test as presented in Table 5. The diagnostics show absence of any further autocorrelation and ARCH effects in the T-GARCH-X model.

5. Conclusion

Volatility is an important component of the risk-return trade-off analysis of financial assets. The presence of volatility makes the market liquid and also signifies the efficiency of financial markets. However, excessive volatility can be harmful for the efficient functioning of the financial system and many a time can bring the entire system into a halt. Over past stock market volatility was considered to be constant, however, the time varying nature of volatility has been established and some of the stylised facts including clustering, leptokurtic distribution of returns, leverage effect have been empirically established. With the introduction of the Autoregressive Conditional Heteroscedasticity (ARCH) and generalised ARCH (GARCH) models, the modelling of financial time series which exhibits time varying conditional volatility has been revolutionised.

The volatility in the Indian and Chinese stock markets in the present study has been estimated while using GARCH models. We have found presence of volatility clustering and asymmetric impact of news on the conditional volatility in both the markets. The persistence of volatility has also been found to be high. Finally, the spillover effect of volatility from Chinese stock market to Indian stock market has been confirmed. Thus, it has been established that Indian stock market volatility has an impact of the volatility from Chinese stock market.

Our findings have a number of policy implications for academicians, policy makers and investor community in general. Firstly, during periods of high volatility, investors tend to be drawn by the known bandwagon effect. This is true particularly when investors are risk averse. Thus, when there is a high perception of risk, the market trading rules becomes less heterogeneous as speculators observe other speculators on trading rules. This results in high volatility since the prices are adjusted strongly by the market maker who faces a less balanced excess demand. Secondly, the differential impact of news on volatility in both the markets is indicative of the fact that investors are risk averse. Thus, both the markets can be characterised by high volatility during economic downturns which is manifested through panic selling by the investors. Finally, the Indian stock market has been found to be vulnerable to events taking place in foreign stock markets, in our case from the Chinese stock market. Thus, there is a need to strengthen the Indian economy to deal with the adverse impacts of global developments.

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