VOLATILITY OF INDIA’S STOCK INDEX FUTURES MARKET:
AN EMPIRICAL ANALYSIS

Manmohan Mall, B. B. Pradhan,
Siksha O Anusandhan University, Bhubaneswar, Odisha, India

P. K. Mishra,
Siksha O Anusandhan University, Bhubaneswar, Odisha, India

ABSTRACT

In recent years, the increasing importance of the futures market in the Indian financial markets has received considerable attention from researchers, academicians and financial analysts. This paper is an attempt to examine the time varying properties of volatility of India’s stock index futures market. The application of GARCH class models provides the evidence of the persistence of time varying volatility, and its asymmetric effect. It is also inferred that in India’s stock index futures market, bad news increases the volatility substantially. This volatility behavior of Indian capital market may be due to recent global financial meltdown that originated from US sub-prime crisis. Such empirical evidence keeps much relevance to policy makers and regulators of India in devising prudential norms and implementing warranted policy reforms.

Keywords: Futures Market, India, Volatility, GARCH Models
Introduction:

Introduced in 2000, financial derivatives market in India has shown a remarkable growth both in terms of volumes and numbers of contracts traded. National Stock Exchange (NSE) alone accounts for 99 percent of the derivatives trading in Indian markets. The introduction of derivatives has been well received by stock market players. Trading in derivatives gained popularity soon after its introduction. In due course, the turnover of the NSE derivatives market exceeded the turnover of the NSE cash market. For example, in 2010-11, the value of the NSE derivatives markets was Rs. 2, 92, 48,221.09 Cr. whereas the value of the NSE cash markets was only Rs. 35, 77,412 Cr. Among all the products traded on NSE in F&O segment, single stock futures also known as equity futures, are most popular in terms of volumes and number of contract traded, followed by index futures with turnover shares of 52 percent and 31 percent, respectively. Despite the encouraging growth and developments, financial analysts feel that the derivatives market in India has not yet realized its full potential in terms of growth and trading. The reason might be the relatively high level of volatility.

Thus, it is important to examine the dynamics of volatility of India’s stock index futures market. Volatility is often described as the rate and magnitude of changes in prices and in finance often referred to as risk. In the finance literature there exist voluminous research studies addressing to the issue of capital market volatility (For example, Danthine, 1978; Harris, 1989; Min and Najand, 1999; Gulen and Mayhew, 2000; Thenmozhi, 2002; Nath, 2003; Kanas, 2009; Gannon, 2010; Mishra, 2010). However, the literature is scrawny regarding the studies addressing the volatility of index futures market in emerging market economies like India.

It is with this backdrop, this paper is an attempt to examine the time varying volatility of India’s index futures market over the period June 2000 to May 2011. The rest of the paper is summarized as follows: section II describes the data and methodology of the study; Section III makes the analysis; and Section IV concludes.

Literature Review

The volatility of stock futures market has been studied by a number of researchers from different angles. Despite a disagreement of the researchers regarding the kind of influence that the market of derivatives has on the underlying market, most of them agree that it is beneficial even if the volatility is increased or decreased because the derivatives’ market acts as a catalyst for the dissemination of information. Particularly, Danthine (1978) concluded that the derivatives’ market increases the depth of a market and consequently reduces its volatility.

The destabilization theory argues that the introduction of futures trading increases spot volatility. For example, Harris (1989) documents marginal increases in the variances of S&P 500 stocks after trading in S&P 500 index futures began. Lockwood and Linn (1990) report similar variance increases when index futures began trading in 1982. Brorsen (1991) finds that futures trading tend to reduce autocorrelations and increase the volatility of index stock returns. Lee and Ohk (1992) document that the volatility of stock returns in Australia, Hong Kong, Japan, the U.K., and the U.S. rose significantly, following the introduction of index futures. On the other hand, Antoniou and Holmes (1995), and Antoniou, Holmes, and Priestly (1997) also document increases in spot volatilities after the introduction of index futures, however this increase is attributed to an increase in the rate of flow of information to spot markets.

On the other side Edwards (1988a, b), Grossman (1988), and Bechetti and Roberts (1990) find that S&P 500 index futures have an insignificant impact on cash market volatility. Schwert (1990) maintains that the growth in stock index futures and options trading has not caused increases in volatility. Similar conclusions are reached by Beckett and Roberts (1990), Kamara, Miller and Siegel (1992), Pericli and Koutmos (1997), Galloway and Miller (1997), and Darat, Rahman and Zhong
(2002), who document that introduction of stock index futures has either decreased or not significantly increased the volatility in spot markets, confirming the stabilization theory.

Min and Najand (1999) investigated lead and lag relationship in returns and volatilities between cash market and KOSPI 200 futures interactions. This study depended on some ten-minute's price data belonging to the periods of 3 May 1996 and 16 October 1996 when futures transactions were introduced over KOSPI 200. Granger causality analysis was used in the study. As for the analysis results; futures market leads the cash market by as long as 30 minutes. The trading volume has significant explanatory power for volatility changes in both spot and futures markets. Futures transactions have stronger influence than cash transactions and the futures transactions have stronger influence over cash market volatility.

Gulen and Mayhew (2000) find that spot volatility is independent of changes in futures trading in eighteen countries and that informationless futures volume has a negative impact on spot volatility in Austria and the UK.

Thenmozhi (2002) showed that the inception of futures trading has reduced the volatility of spot index returns due to increased information flow. According to Shenbagaraman (2003) the introduction of derivative products did not have any significant impact on market volatility in India. Raju and Karande (2003) also reported a decline in volatility of S&P CNX Nifty after the introduction of index futures.

Nath (2003) studied the behavior of stock market volatility after derivatives and arrived at the conclusion that the volatility of the market as measured by benchmark indices like S&P CNX Nifty and S&P CNX Nifty Junior has fallen during the post-derivatives period. The finding is in-line with the earlier findings of Thenmozhi (2002), and Raju and Karande (2003).

Bandivadekar and Ghosh (2003), and Sah and Omkarnath (2005) also investigated the behaviour of volatility in cash market in futures trading era. They also found that futures trading have led to reduction in volatility in the underlying asset market but they attributed the degree of decline in volatility in the underlying market to the trading volume in futures market. They inferred that as the trade volume in the F&O segment of BSE is very low, the volatility in BSE has not significantly declined; whereas in the case of NSE (where the trade volume is at the peak), the volatility in NIFTY has reduced significantly.

Mallikarjunappa and Afsal (2007) studied the volatility implications of the introduction of derivatives on the stock market in India using S&P CNX IT index and found that clustering and persistence of volatility in different degrees before and after derivatives and the listing in futures has increased the market volatility.

Kanas (2009), using a time-varying regime-switching vector error correction approach, finds that the NIKKEI stock index cash and futures prices are jointly characterized by regime switching, which is time-varying and dependent upon the basis, the interest rate, the volatility of the cash index, and the US futures market.

Gannon (2010) develops simultaneous volatility models that allow for simultaneous and unidirectional volatility and volume of trade effects. Intraday data from the Australian cash index and index futures markets are used to test these effects. Overnight volatility spillover effects are tested with the data from the S and P 500 index using alternative estimates of the United States volatility. It is found that the simultaneous volatility model is robust to alternative specifications of returns equations and to misspecification of the direction of volatility causality.
Data and Methodology

The very objective of this paper is to investigate the dynamics of the time varying volatility of India’s index futures market over the sample period spanning from June 2000 to May 2011. The data of daily returns based on daily closing values of near month index futures contract (FUTIDX) has been used in the study. The required data are collected for the sample period from the NSE, India database. As capital market volatility is effectively depicted with the help of GARCH class models, the estimations of the GARCH(1,1), EGARCH(1,1) and TGARCH(1,1) models have been performed so as to produce the evidence of time varying volatility which shows clustering, high persistence and predictability and responds symmetrically for positive and negative shocks.

Analysis and Discussion

In the finance literature, GARCH class models are popular in capturing the dynamics of capital market volatility. For initial volatility estimation, the GARCH (1, 1) model is used (Bollerslev, 1986). The model for return series is specified as under:

Mean Equation: \( R_t = c + \varepsilon_t \)

Variance Equation: \( \sigma_t^2 = \omega + \alpha_t \varepsilon_{t-1}^2 + \beta_t \sigma_{t-1}^2 \)

Table-1: Results of GARCH (1, 1) Model

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \omega )</td>
<td>7.84E-06</td>
<td>7.93E-07</td>
<td>9.891693</td>
</tr>
<tr>
<td>( \alpha_t )</td>
<td>0.140525</td>
<td>0.008813</td>
<td>15.94476</td>
</tr>
<tr>
<td>( \beta_t )</td>
<td>0.838001</td>
<td>0.009292</td>
<td>90.18246</td>
</tr>
</tbody>
</table>

The GARCH (1, 1) model assumes that the effect of a return shock on current volatility declines geometrically over time. This model is consistent with the volatility clustering where large changes in stock returns are likely to be followed by further large changes. The results of estimation of the GARCH (1,1) model is reported in Table-1. It is clear that the bulk of the information comes from the previous days forecast, i.e., around 83% in case of Index Futures Market. The new information changes this a little and the long run average variance has a very small effect.

Fig. 1: TS Plot of Index Futures Return and Price Series
It is very apparent from the Fig.1 that the amplitude of the daily stock returns is changing in the Index futures market. The magnitude of this change is sometimes large and sometimes small. This is the effect that GARCH is designed to measure and that we call volatility clustering. There is another interesting feature in the above graphs that the volatility is higher when prices are falling than when prices are rising. It means that the negative returns are more likely to be associated with greater volatility than positive returns. This is called asymmetric volatility effect. And, this is not captured by GARCH (1, 1) model. Hence, we will use Nelson’s Exponential GARCH (1, 1) model for stock return volatility estimation. In the EGARCH model, the mean and variance specifications are:

Mean Equation: \( R_t = c + \varepsilon_t \)

Variance Equation:

\[
\log(\sigma_t^2) = \omega + \alpha \log(\sigma_{t-1}^2) + \beta \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}
\]

Table-2: Results of EGARCH (1, 1) ESTIMATES

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \omega )</td>
<td>-0.613208</td>
<td>0.040276</td>
<td>-15.22533</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.265412</td>
<td>0.015837</td>
<td>16.75892</td>
</tr>
<tr>
<td>( \beta )</td>
<td>-0.111835</td>
<td>0.008499</td>
<td>-13.15812</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>0.950648</td>
<td>0.003835</td>
<td>247.9168</td>
</tr>
</tbody>
</table>

The results of EGARCH model are reported in Table-2. Since the value of \( \gamma \) is non-zero, the EGRACH model supports the existence of asymmetry in volatility of stock returns. But on the basis of this model we cannot say whether good news or bad news that increases volatility. This aspect of volatility modelling is captured by Threshold GRACH model developed independently by Glosten, Jaganathan, and Runkle (1993) and Zakoian (1994). The specification for conditional variance in Threshold GRACH (1, 1) model is:

\[
\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2
\]
Table-3: Results of TGARCH (1, 1) ESTIMATES

<table>
<thead>
<tr>
<th>Variance Equation</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.0000097</td>
<td>8.94E-07</td>
<td>10.93234</td>
<td>0.0000</td>
</tr>
<tr>
<td>ARCH(1)</td>
<td>0.057274</td>
<td>0.008932</td>
<td>6.411956</td>
<td>0.0000</td>
</tr>
<tr>
<td>ARCH(1)*(RESID&lt;0)</td>
<td>0.162615</td>
<td>0.015459</td>
<td>10.51914</td>
<td>0.0000</td>
</tr>
<tr>
<td>GARCH(-1)</td>
<td>0.833646</td>
<td>0.010596</td>
<td>78.67387</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

In this model, good news has an impact of $\alpha$, while bad news has an impact of $\alpha + \gamma$. If $\gamma > 0$, then bad news increases volatility, and we say that there is a leverage effect. If $\gamma \neq 0$, then the news impact is asymmetric. The results of TGARCH model are reported in Table-3. The estimated form of TGARCH model for index futures market is:

$$\sigma_i^2 = 0.0000097 + 0.0572e_{t-1}^2 + 0.8336\sigma_{t-1}^2 + 0.1626e_{t-1}^2I_{t-1}$$

It shows that the good news has an impact of 0.0572 magnitudes and the bad news has an impact of 0.0572 +0.1626= 0.2198 magnitudes in the index futures market. Thus, it is inferred that in India’s stock index futures market, bad news increases the volatility substantially. Also, this time varying stock return volatility is asymmetric. The analysis shows a better performance of the TGARCH model in estimating and predicting the market volatility. The change in the pattern of volatility and the recent irregular behaviour of the futures market came as a result of the global economic events, particularly the recent sub-prime crisis and news of probable recession.

V. Conclusion

This paper, therefore studied the volatility of India’s stock index futures market taking into account the National Stock Exchange as the role model. The study by employing GARCH, E-GARCH and T-GARCH models, provides the evidence of high persistence of time varying volatility, and its asymmetric effects. This volatility behaviour of Indian capital market may be due to recent global financial slowdown that originated from US sub-prime crisis. The results indicate that the trading volume growth of nearby-month index futures is the most influential factor for volatility in the futures market in India. Therefore, the investors are advised to predict volatility in the cash market by observing the futures volume growth as well as volatility in the index futures since volatility in the cash market is a measure of market risk.

References


