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THE IMPACT OF DERIVATIVES ON STOCK MARKET VOLATILITY: A STUDY OF THE NIFTY INDEX

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ABSTRACT

This paper studies the volatility implications of the introduction of derivatives on stock market volatility in India using the S&P CNX Nifty Index as a benchmark. To account for non-constant error variance in the return series, a GARCH model is fitted by incorporating futures and options dummy variables in the conditional variance equation. We find clustering and persistence of volatility before and after derivatives, while listing seems to have no stabilisation or destabilisation effects on market volatility. The post-derivatives period shows that the sensitivity of the index returns to market returns and any day-of-the-week effects have disappeared. That is, the nature of the volatility patterns has altered during the post-derivatives period.

Keywords: conditional volatility, heteroscedasticity, volatility clustering, market efficiency

INTRODUCTION

The modelling of asset returns volatility continues to be one of the key areas of financial research as it provides substantial information on the risk patterns involved in investment and transaction processes. A number of works have been undertaken in this area. Given the fact that stock markets normally exhibit high levels of price volatility, which lead to unpredictable outcomes, it is important to examine the dynamics of volatility. With the introduction of derivatives in the equity markets in the late nineties in the major world markets, the volatility behaviour of the stock market has become further complicated as derivatives open new avenues for hedging and speculation. The derivatives market was launched mainly with the twin objectives to transfer risk and to increase liquidity, thereby ensuring better market efficiency. The examination of how far these objectives have materialised is important both theoretically and practically.

In India, trading in derivatives started in June 2000 with the launch of futures contracts in the BSE Sensex and the S&P CNX Nifty Index on the Bombay Stock Exchange (BSE) and National Stock Exchange (NSE), respectively. Options trading commenced in June 2001 in the Indian market. Since then, the futures and options (F&O) segment has been growing continuously in terms of new products, contracts, traded volume and value. At present, the NSE has established itself as the market leader in this segment in India, with more than 99.5 percent market share (NSE Fact Book, 2006, p. 85). The F&O segment of the NSE outperformed the cash market segment with an average daily turnover of Rs291.91 billion, as compared to Rs114.79 billion in the cash segment from 2006 to 2007 (Derivatives Updates on NSE website, www.nseindia.com, 2007). This shows the importance of derivatives in the capital market sector of the economy. Previous studies on the volatility effects of derivatives listing provide mixed results, suggesting case-based biases. In addition, in India, there is a lack of robust examination of the impact of derivatives on market volatility. In India, trading in derivatives contracts has existed for the last six years, which is an adequate time period to evaluate its major pros and cons. Against this backdrop, it is important to empirically examine the impact of derivatives on the stock market.

In this paper, we attempt to study the volatility implications of the introduction of derivatives on the cash market. Through this study, we seek evidence regarding whether the listing of futures and options lead to any significant change in the volatility of the cash market in India. In contrast to a sectoral index studied in previous research from Mallikarjunappa and Afsal (2007), we select a general index called the S&P CNX Nifty Index to which the first derivatives contract was introduced by the NSE in India. The previous study noted the peculiar characteristics of IT stocks and arrived at the conclusion that stock-specific characteristics must be studied for any general conclusion. As a benchmark index, the Nifty Index is expected to show wider, more balanced and more applicable results and thus can be treated as a true replica of the Indian derivatives market. Most of the Indian studies, such as Thenmozhi (2002), Sibani and Uma (2007) and Mallikarjunappa and Afsal (2007), did not consider options contract, but this study examines the introduction of options while also analysing volatility. The period under analysis spans from October 1995 through June 2006. Furthermore, to allow for a non-constant error variance in the return series, we applied a GARCH model that was more appropriate to describe the data collected. Therefore, the present work offers a valuable addition to the existing literature and should prove to be useful to investors as well as regulators, as this is a broader index than the one studied by Mallikarjunappa and Afsal (2007).

The remainder of this paper is organised as follows. Recent literature is briefly reviewed in Part 2, and Part 3 presents the econometric model, data and methodology. The empirical results of our work are discussed in Part 4, and Part 5 presents our conclusion.

RECENT LITERATURE

Various studies on the effects of futures and options listings on the volatility of an underlying cash market have been carried out across the world. Overall, the empirical evidence is mixed, and most studies suggest that the introduction of derivatives does not destabilise the underlying market. These studies also show that the introduction of derivatives contracts improves liquidity and reduces informational asymmetries in the market. However, some evidence exists in support of increased volatility with the onset of derivatives trading. Thus, the volatility implications of derivatives are still debatable. In this section, we consider the important and recent literature in this area.

Rahman (2001) examined the impact of index futures trading on the volatility of component stocks for the Dow Jones Industrial Average (DJIA). The study used a simple GARCH (1, 1) model to estimate the conditional volatility of intra-day returns. The empirical results confirm that there is no change in conditional volatility from pre- to post-futures periods. Figuerola-Ferretti and Gilbert (2001) used error-correction models and the GARCH (1, 1) regression model to study the effect of futures trading on volatility. In addition, they reported the results of a VAR model and presented an impulse response analysis to track the effects of a shock to each of the volatilities. The results show that volatility decreases in the post-futures period. Bologna and Cavallo (2002) examined the effect of the introduction of stock index futures for the Italian market. Their empirical results show that the introduction of stock index futures affects the volatility of the spot market. In addition, the results from various GARCH (1, 1) models for pre-futures and post-futures sub-periods suggest that the index futures market reduces volatility.

Chiang and Wang (2002) examined the impact of futures trading on Taiwan spot index volatility. Their study also discussed the macroeconomic and asymmetric effects of futures trading on spot price volatility behaviour. They used an asymmetric time-varying GJR volatility model. Their empirical results showed that the trading of futures on the Taiwan Index has stabilising impacts on spot price volatility, while the trading of MSCI Taiwan futures has no effects, except asymmetric response behaviour. Thenmozhi (2002) examined whether there was any change in the volatility of the S&P CNX Nifty Index in India due to the introduction of Nifty futures and whether movements in futures prices provided predictive information regarding subsequent movements in index prices. The study shows that the inception of futures trading has reduced the volatility of spot index returns.

Pilar and Rafael (2002) analysed the effect of the introduction of derivatives on the Ibex-35 Index using a dummy variable and a GJR model to test the impact of the introduction of derivative markets on the conditional volatility of the underlying asset. They found that although the asymmetry coefficient increased, the conditional volatility of the underlying index declined after derivatives were introduced. Robert and Michael (2002) investigated the impact of the introduction of stock index futures trading on the seasonality of daily returns of the underlying index for seven national markets. The results indicate reduced seasonality with respect to mean returns, thus leading to more efficiency in these markets.

Shembagaraman (2003) explored the impact of the introduction of derivative trading on cash market volatility using data on stock index futures and options contracts traded on the Nifty Index. The results suggest that futures and options trading has not led to a change in the volatility of the underlying stock index, but the nature of volatility seems to have changed in the post-futures market. The study also examined whether greater futures trading activity in terms of volume and open interest was associated with greater spot market volatility. It found no evidence of any link between trading activity variables in the futures market and spot market volatility.

Sung, Taek and Park (2004) studied the effect of the introduction of index futures trading in the Korean markets on spot price volatility and market efficiency of the underlying KOSPI 200 stocks relative to the carefully matched non-KOSPI 200 stocks; they found evidence that market volatility was not affected by futures trading, while market efficiency was improved. Taylor (2004) tried to uncover the determinants of trading intensity in futures markets. In particular, the time between adjacent transactions on the FTSE 100 index futures market was modelled using various augmentations of the basic autoregressive conditional duration (ACD). As predicted by various market microstructure theories, he found that the bid-ask spread and transaction volume have a significant impact on subsequent trading intensity. However, there was evidence that a large (small) difference between the market price and the theoretical price of the futures contract, which is known as pricing error, leads to high (low) levels of trading intensity in the subsequent period.

Boyer and Popiela (2004) looked into whether the introduction of futures to the S&P500 Index altered the effect of addition to, or removal from, the S&P500 Index. This study used the S&P500 price effect to show that overall price volatility did not show any significant increase for added stocks after trading began on the S&P500 Index futures.

Calado, Garcia and Pereira (2005) used data for eight derivative products to study the volatility effect of the initial exchange listing of options and futures on the Portuguese capital market. They did not find significant differences in the unadjusted and adjusted variance and beta for the underlying stocks after the listing of derivatives. However, some of the underlying stocks taken individually have experienced significant increases or decreases in variance after derivatives listing. Finally, they concluded that the introduction of a derivatives market in the Portuguese case has not had the average stabilisation effect on risk as detected in other markets. Gannon (2005) tested contemporaneous transmission effects across volatilities of the Hong Kong stock and index futures markets and futures volume of trade by employing a structural systems approach. Competing measures of volatility spillover, constructed from the overnight S&P500 Index futures, were tested and found to impact asset return volatility and volume of trade patterns in Hong Kong. Antoniou, Koutmos and Pericli (2005) tested the hypothesis that the introduction of index futures has increased positive feedback trading on the spot markets of six industrialised nations. Their findings support the view that futures markets help stabilise underlying spot markets by reducing the impact of feedback traders and attracting a greater number of rational investors.

Floros and Vougas (2006) examined the effect of futures trading on the volatility of the underlying spot market taking the FTSE/ASE-20 and FTSE/ASE Mid 40 Indices in Greece. The results for the FTSE/ASE-20 Index suggest that futures trading has led to decreased stock market volatility, but the results for the FTSE/ASE Mid 40 Index indicate that the introduction of stock index futures has led to increased volatility, while the estimations of the unconditional variances indicate a lower market volatility after the introduction of stock index futures.

Sibani and Uma (2007) used OLS and GARCH techniques to capture the time-varying nature of volatility and volatility clustering phenomenon of the Nifty Index due to the introduction of futures trading. The results suggest that there are no significant changes in the volatility of the spot market of the Nifty Index, but the structure of volatility changes to some extent. The study also reported that new information is assimilated into prices more rapidly than before, and there is a decline in the persistence of volatility since the introduction of futures trading.

Drimbetas, Nikolaos and Porfiris (2007) explored the effects of the introduction of futures and options into the FTSE/ASE 20 Index on the volatility of the underlying index using an EGARCH model. It is shown that the introduction of derivatives induces a reduction of conditional volatility in the FTSE/ASE20 Index and consequently increases its efficiency. Mallikarjunappa and Afsal (2007) studied the volatility behaviour of the Indian market by focusing on the CNX IT Index, which is a sectoral index, and found that underlying volatility increases with the onset of futures trading. Their result contradict many other studies carried out in India, and it is reasoned that the sectoral index showed different behaviour in terms of returns and volatility, especially during the 2001 period of market scam in India. They attributed these results to a sharp decrease in the prices of IT stocks after the stock market scam broke out in 2001. Since the sectoral index showed different results than those of earlier studies, these results must be examined as to whether they hold for the Indian market when a broader market index is studied. Their study also pointed out that results depend on the time period as well as the country studied. These results indicate the needed scope for further research as well as suggest the relevance of different samples and methodologies.

DATA AND METHODOLOGY

Data

As reported in the introduction section, in India, futures trading on the S&P CNX Nifty Index of the NSE and the BSE Sensex Index of the BSE started in June 2000. NSE accounts for about 99.5 percent of the total trading volume in the derivatives segment; therefore, we use the S&P CNX Nifty Index to study the volatility behaviour of the market. This study uses the daily closing prices of the Spot Nifty Index, the Nifty Index Futures, the Nifty Junior Index and the spot S&P500 Index from October 5, 1995, through June 30, 2006. For the Nifty futures, the data from June 12, 2000, onwards is used as the futures trading commenced from this day. The S&P CNX Nifty spot and futures and the Nifty Junior Index price data were collected from the NSE website (www.nseindia.com). The S&P500 Index price series was collected from Yahoo! Finance (www.yahoofinance.com). The closing price data were converted to daily compounded returns by taking the first log difference. Return R_t at time t is given by $R_t = \ln(P_t / P_{t-1}) * 100$, where P_t is the closing price for day t.

The S&P CNX Nifty Index is a well-diversified index of 50 stocks comprising 25 sectors of the Indian economy. The average total traded value for the six months ending in June 2006 for all Nifty stocks was approximately 49.8 percent of the traded value of all stocks on the NSE. The Nifty stocks represent about 56.5 percent of total market capitalisation as of March 31, 2006. The next most liquid security after the S&P CNX Nifty Index is the CNX Nifty Junior

Index. The maintenance of the S&P CNX Nifty and the CNX Nifty Junior Indices are synchronised so that the two will always be disjoint sets; that is, a stock will never appear in both indices at the same time. The CNX Nifty Junior Index represents about 9.77 percent of the total market capitalisation as of March 31, 2006. The S&P500 Index is an index consisting of 500 stocks. It is one of the most commonly-used benchmarks for overall US equities and is meant to reflect the risk/return characteristics of large-cap stocks.

Econometrics Techniques

Assuming a constant error variance throughout the time period (that is, a homoscedasticity model), volatility measures like estimated standard deviation, rolling standard deviation and so on were developed to study the behaviour of stock market volatility (Hodgson & Nicholls*,* 1991; Herbst & Meberly*,* 1990). These studies implicitly assume that price changes in spot markets are serially uncorrelated and homoscedastic. However, the findings on heteroscedasticity in stock returns are well documented (Mandelbrot, 1963; Fama, 1965; Bollerslev, 1986; Shembagaraman, 2003; Nath, 2003). In the presence of heteroscedasticity, the usual OLS estimates do not render the best linear unbiased estimator (BLUE) (Gujarati, 2005, p. 387).

Stock market returns assume conditional and unconditional variances; the former relates to contemporaneous or short-term shocks and is unlikely to be constant over time. The latter is assumed to be constant. Thus, the disturbance or error term in the stock return series normally exhibits 'varying' variance and hence requires heteroscedasticity as a treatment. In a seminal work, Engle (1982) proposed the Auto Regressive Conditional Heteroscedasticity (ARCH) process to model conditional variance. In an ARCH framework, the error variance is a function of the squared error variance in the previous term. To avoid the long lag lengths on the disturbance term, Bollerslev (1986) suggested the generalised ARCH, known as GARCH (*p, q*), in which the lags of the variance terms are also included in the variance equation. In this model, q refers to the lag on ε_{t-1}^2 (that is, the squared disturbance term), and p refers to the lag on h_t (that is, the variance). The GARCH model assumes that the conditional variance exhibits heteroscedasticity with homoscedastic unconditional error variance. That is, the model assumes that the change in variance is a function of the realisations of preceding errors and that these changes represent temporary and random departures from constant, unconditional variance. It takes into account excess kurtosis (that is, fat tail behaviour) and volatility clustering, which are two important characteristics of financial time series. Since the GARCH model captures the tendency in financial data for volatility clustering, it is possible to relate information to volatility explicitly, as any change in the rate at which information arrives on the market will change the volatility in that market. Thus, unless information remains constant, which is hardly the case, volatility must be time-varying, even on a daily basis. A model with errors that follow a GARCH (*p, q*) process is represented as follows:

$$Y_t = a_0 + a_1 X_t + \varepsilon_t, \quad \varepsilon / \psi_{t-1} \sim N(0, h_t) \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{2}$$

with $\alpha_0 > 0, \quad \sum_{i=1}^{q} \alpha_i, \quad \sum_{j=1}^{p} \beta_j \geq 0$

Note that equation 1 is the conditional mean equation, and 2 is the conditional variance equation. In the GARCH (*p, q*) model, the conditional variance is a function of *p*-lagged conditional variance and *q*-lagged squared disturbance terms.

Since the ARCH and GARCH processes involve iterative procedures, it is advisable to test whether it is appropriate to use the model before estimation. The Lagrange multiplier (LM) test is ideal for this purpose (Engle, 1982). The null hypothesis of "no ARCH effect" is tested using the LM test statistic TR^2, which is asymptotically distributed as $\chi^2(q)$ when the null is true. The individual lags are tested using a *t*-statistic.

Method

We subject each time series to a check for stationarity. The Dickey-Fuller test was employed to separately analyse the price and return series of the spot CNX S&P Nifty Index, Nifty Junior Index, Nifty futures and S&P500 Index. The unit root hypothesis (i.e., that the series is non-stationary) is found true in the closing price series of all four cases, whereas all the return series are stationary. Table 1 reports the result of the unit root tests.

This paper focuses mainly on two aspects. We first ask, has the very introduction of futures or options altered the volatility of the spot market? To examine this issue, we introduce a dummy variable into the conditional variance equation that measures volatility. Equation 2 becomes:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \gamma D \tag{3}$$

Table 1
Dickey-Fuller test.

		Nifty Spot	t-stat	Nifty Futures	t-stat	Nifty Junior	t-stat	S&P500	t-stat
Return Series	B_1	0.04	1.23	0.05	1.24	0.05	1.28	0.03	1.59
	δ	–0.92*	–49.04	–0.96*	–37.25	–0.85*	–44.55	–1.01*	–53.98
Closing Price Series	B_1	7.06	2.23	–0.12	–0.06	1.71	0.83	3.42	1.56
	δ	–0.01	–2.54	0.00	0.67	0.00	–0.12	–0.00	–1.69

Notes: *Significant at the one percent level.
Dickey-Fuller statistic at 1% = –3.34 and at 5% = –2.86.

$\Delta Y_t = \beta_1 + \delta Y_{T-1} + \varepsilon_T$, where $\Delta Y_t = Y_t - Y_{t-1}$.

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$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} + \gamma D \tag{3}$$

Note that D is a dummy variable taking a value zero if the time is prior to futures or options introduction and one, otherwise. If γ, the coefficient of this dummy variable, is statistically significant, then the introduction of futures or options contracts has an impact on spot market volatility. The sign of the coefficient is also important, as a negative (positive) value implies a fall (rise) in spot market volatility with the introduction of futures/options trading.

It is to be noted that any change in market behaviour, including volatility, is almost always a result of a mixture of factors. The introduction of futures or options contracts may also have a role in volatility dynamics. However, we are interested in the individual effect of futures or options introduction on spot market volatility. We want to control for market-wide factors that have the potential to influence the return volatility of the spot Nifty Index. Antoniou and Holmes (1995), Kamara, Miller and Siegel (1992), and Gregory and Michael (1996) have tried to filter out the factors that lead to market-wide volatility by regressing spot market returns against a proxy variable for which there was no related futures contract. In this study, we use the Nifty Junior Index returns as the proxy variable, which essentially captures market-wide volatility and thus serves as a perfect control factor. Furthermore, in order to isolate the unique impact of the introduction of futures or options on spot market volatility, we must remove any predictability associated with world returns and day-of-the-week effects (Pagan & Schwert, 1990; Engle & Ng, 1993). Therefore, we incorporate the lagged returns of the S&P500 Index and day-of-the-week dummy variables in the model. Earlier studies have also reported day-of-the-week effect on returns. Therefore, we examine whether these effects exist even today. The day-of-the-week effect is examined, particularly because we have to evaluate the effect of rolling settlements as opposed to the earlier practice of accounting period settlements. The seasonal dummies thus serve as a perfect controlling factor. The following conditional mean equation is estimated.

$$R_t = \alpha + \beta R_{t,N.Jun} + \gamma R_{t-1,S\&P500} + \delta \sum_{i=1}^{5} D_i + \varepsilon_t \tag{4}$$

Note that R_t is the daily return on the S&P CNX Nifty Index calculated as the first difference of the log of the index; $R_{t,N.Jun}$ is the return on the Nifty Junior index; $R_{t-1,S\&P500}$ is the lagged S&P500 index return; and D_i are day-of-the-week dummy variables from Monday through Friday. The error term or residual ε_t is expected to follow $N(0, h_t)$, where h_t is the conditional variance.

The second aspect of interest is whether the nature of volatility has changed after the introduction of futures contracts. For this, we divide the sample period into two sub-periods (namely, pre-futures and post-futures periods), using the cut-off date of 12 June 2000. We separately fit a GARCH model for each period. The same model is applied to options by using the cut-off date of 4 June 2001. A formal test to check for parameter stability in the models of the two sub-samples is also conducted. This allows us to compare the nature of volatility before and after the introduction of futures.

Testing for ARCH/GARCH effects

Before moving further, it is essential to determine the ARCH/GARCH effects in the time series under study. The Lagrange multiplier (LM) Test is used to check for ARCH/GARCH effects in the series under analysis. We start with the residual term in the mean equation for lag four using the following model; the results obtained are shown in Table 2.

$$\varepsilon_t^2 = \alpha_0 + \sum_{i=1}^{4} \alpha_i \varepsilon_{t-i}^2 \tag{5}$$

The regression test reveals that the coefficient for lag one is significant at the one percent level. The observed F value exceeds the LM test statistic value of $F(4, 2681) = 2.37$, as TR^2 is 2681*0.1173 = 314.41, which does not asymptotically follow the $\chi^2(4)$ value of 9.4877 at the five percent significance level. Therefore, we overwhelmingly reject the hypothesis that all α_is are zero and conclude that there are sufficient ARCH effects.

Table 2
Test for ARCH/GARCH.

	Coefficients	Standard Error	t-stat	P-value
Intercept	1.5505*	0.1377	11.2558	0.0000
α_1	0.3308*	0.0193	17.0995	0.0000
α_2	0.0121	0.0203	0.5961	0.5512
α_3	0.0162	0.0203	0.7975	0.4252
α_4	0.0339	0.0193	1.7541	0.0795

Notes: $R^2 = 0.1173$, Adjusted $R^2 = 0.1159$, Standard Error = 6.0879, Observations = 2681, $F = 88.8807$, Significance $F = 0$.

Having seen the presence of substantial ARCH/GARCH effects in the residuals, we must use a suitable ARCH/GARCH process to model volatility. However, given the fact that the GARCH family of models alone has nearly three dozen members (Bauer, 2005), it is an empirical question as to which model best fits the data. The evidence from the previous studies on Indian market suggests that GARCH (1, 1), EGARCH (Shembagaraman, 2003), and IGARCH (Nath, 2003) should fit the data well. Since we are not concerned with asymmetric effects in this particular study, we use the GARCH (1, 1) model in this study. Thus, the following GARCH (1, 1) conditional variance model is used.

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-i}^2 + \beta_1 h_{t-1} + \lambda D \tag{6}$$

In this paper, we ultimately compare our results with those obtained from a constructed volatility technique using the standard deviation as the measure of volatility. The use of constructed volatility analysis compares with and strengthens the result of GARCH process, though Mallikarjunappa and Afsal (2007) have not used this measure. The following model is used to empirically measure the impact of futures trading on the volatility of the spot market.

$$VS_t = \beta_0 + \beta_1 VM_t + \beta_2 D_t + \varepsilon_t \tag{7}$$

Note that VS_t is a constructed measure of volatility in the spot market during period t; VM_t is a proxy measure of market-wide volatility during period t; D_t is a dummy variable taking a value of one if t is a post-futures time period and zero for pre-futures periods; and β_0, β_1 and β_2 are regression parameters. Here VS_t is the standard deviation of log returns of the spot Nifty Index, and VM_t is the standard deviation of the log returns of the Nifty Junior Index. The dummy coefficient is assumed to capture the direction of volatility in a fashion so that a positive significant value implies an increase in volatility and a negative significant value is an indication of a decrease in volatility with the introduction of futures. If the value is not significant, it shows that futures trading did not affect volatility. The result of this analysis is presented in the next section.

RESULTS AND ANALYSIS

Analysis of Descriptive Statistics

Table 3 provides the descriptive statistics of the daily returns for the Nifty and Nifty Junior Indices. There are 2,685 daily time series observations. The Nifty Index has a mean return of 0.0409 percent with a standard deviation of 1.6180 percent. If we divide the period under study into pre-futures and post-futures periods using 12 June 2000, as the cut-off date, the daily return is 0.0294 percent in former period and 0.0497 percent in the latter period. Standard deviation, as a measure of volatility, decreases from 1.7977 percent to 1.4667 percent from the pre-futures period to the post-futures period. A similar result is shown with respect to the pre-options and post-options periods in which 4 June 2001 is the cut-off date. This result shows that there is a decrease in spread with the introduction of futures and options trading. We examine the returns of the Nifty Junior Index, which has a daily mean return of 0.0523 percent with a standard deviation of 1.8799 percent. Even though the Nifty Junior Index has no derivative contracts traded on it, it is sensible to examine the risk-return pattern before and after the introduction of derivatives. Prior to futures introduction, the return is 0.0639 percent, with a standard deviation of 2.0340 percent, whereas both of these figures decrease to 0.0434 and 1.7538 percent, respectively, after futures introduction. The analysis shows that the volatility of the market has reduced during the post-futures period. Also, the return series shows different patterns for two different general indices during the pre-derivatives and post-derivatives periods. As noted by Mallikarjunappa and Afsal (2007), the stock market scam of 2001 caused the Indian market to lose its credibility, with the market taking some time to regain its normality. It is obvious from the analysis that the stocks constituting the Nifty Index, which are highly traded and visible in the market, performed relatively well during the post-derivatives period, thereby yielding better returns, whereas the Nifty Junior stocks on average showed reduced returns and volatility after the introduction of derivatives trading. The Nifty and Nifty Junior returns show evidence of fat tails, since the kurtosis exceeds three, which is the normal value; these returns also show evidence of negative skewness, which means that the negative tail is particularly extreme. These results are similar to those of Mallikarjunappa and Afsal (2007).

Table 3
Descriptive statistics.

Period	Index	Mean return	Std. deviation	Skewness	Kurtosis
5/10/1995–30/06/2006	Nifty	0.0409	1.6180	–0.3061 (0.0472)	4.6759 (0.0945)
	Nifty.Jun	0.0523	1.8799	–0.5851 (0.0472)	4.1913 (0.0945)
Pre-futures (up to 12/06/2000)	Nifty	0.0294	1.7977	0.1211 (0.0718)	3.0293 (0.1434)
	Nifty.Jun	0.0639	2.0340	–0.1638 (0.0718)	2.3635 (0.1434)
Post-futures (after 12/06/2000)	Nifty	0.0497	1.4667	–0.8861 (0.0627)	6.7292 (0.1253)
	Nifty.Jun	0.0434	1.7538	–1.0817 (0.0627)	6.3496 (0.1253)
Pre-options (up to 4/06/2001)	Nifty	0.0081	1.7822	0.0407 (0.0652)	2.8024 (0.1304)
	Nifty.Jun	0.0193	2.0831	–0.2695 (0.0652)	1.9697 (0.1304)
Post-options (after 4/6/2001)	Nifty	0.0800	1.4144	–1.0127 (0.0685)	8.6962 (0.1369)
	Nifty.Jun	0.0887	1.6280	–1.2325 (0.0685)	9.3232 (0.1369)

Note: *Figures in the parentheses are standard errors.

The GARCH Analysis

As we have stated, in order to measure the impact of the introduction of futures and options, we introduce a dummy variable into the conditional variance equation. A significantly positive (negative) coefficient is an indication of an increase (decrease) in volatility as a result of the introduction of futures and options contracts. The results of the GARCH (1, 1) estimation with futures dummy are reported in Table 4. It is clear that market-wide factors (as measured by the Nifty Junior return) explain the return series of the Nifty Index, whereas worldwide factors (as ascertained by the lagged returns of the S&P500 Index) do not offer any predictable information about the returns of the Nifty Index. The day-of-the-week effect is also present on all weekdays except Wednesday. Notably, the coefficient of the futures dummy λ, which equals 0.0504 with a t ratio of 0.8955, is not significantly different from zero, suggesting that the introduction of futures does not appear to have had any stabilisation or destabilisation impact on spot market volatility. This is a major result that suggests that the market is not destabilised with the launch of futures trading. This finding confirms the findings of Shembagaraman (2003), who studied a sample period from October 1995 to December 2002. Our finding that no significant difference in volatility is observed with futures listing also supports the empirical results obtained by others (Chamberlain, Cheung & Kwan, 1993; Kabir, 1999; Ma & Rao, 1988; Calado et al., 2005). These results differ from those of Mallikarjunappa and Afsal (2007). However, the listing of futures has not reduced the volatility of the cash market in India, though volatility has been reduced in the major markets as reported in the empirical literature (Conrad, 1989; Fedenia & Grammatikos, 1992; Harris, 1989). The coefficients of the GARCH constant α_0, ARCH constant α_1 and GARCH constant β_1 are significantly different from zero at the one percent significance level and are within the parametric restrictions, thus implying a greater impact of shocks (or news) on volatility. A significant ARCH coefficient α_1 indicates a large shock on day $t - 1$ leads to a large (conditional) variance on day t. α_1 is the "news" component that explains that recent news has a greater impact on price changes. Specifically, it relates to the impact of yesterday's news on today's volatility. The GARCH coefficient β_1 measures the impact of "old news". A relatively higher value of β_1 in this context implies a large memory for shocks in this model. The sum of the coefficients α_1 and β_1 is near unity, indicating a large degree of persistence. Note that the conditional volatility of the Nifty Index (the middle figure) predicted by the GARCH estimation, along with residuals and returns for the period from October 1995 to June 2006, is plotted in Figure 1. The model captures volatility clustering, which occurs at different intervals as is seen in the plot.

Table 4
GARCH (1, 1) estimates with futures dummy.

		Coefficient	t-value
Α	Intercept	0.6038*	2.7988
Β	Nifty Jun.	0.04269*	2.5985
Γ	Lagged S&P500	–0.0098	–0.4287
δ_1	Dummy-Mon	–0.6244*	–2.7474
δ_2	Dummy-Tue	–0.655*	–2.9297
δ_3	Dummy-Wed	–0.3452	–1.5707
δ_4	Dummy-Thu	–0.5377#	–2.5077
δ_5	Dummy-Fri	–0.5666#	–2.5316
Λ	Dummy Futures	0.0504	0.8955
α_0	ARCH(0)	0.10618*	8.151
β_1	GARCH(1)	0.83941*	111.4766
α_1	ARCH(1)	0.12519*	14.7207

Note: *Significant at the one percent level.
Critical at the five percent level. Observations = 2685

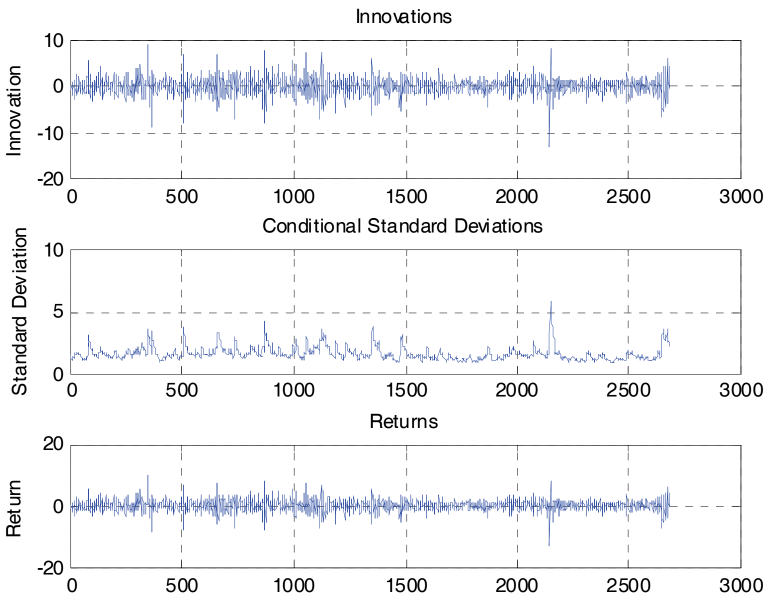

Figure 1. GARCH plots with futures dummy.

The result of the GARCH estimation that employs the options dummy variable is presented in Table 5. The dummy variable assumes a value of zero before 4 June 2001, and a value of one for the rest of the period under analysis. The model parameters indicate that the coefficient of the options dummy is insignificant at 0.0582 with a *t* value of 1.0633 given conventional critical levels, and therefore, we are unable to reject the hypothesis that options trading has no impact on cash market volatility. The result using the futures dummy is identical. In this case as well, the ARCH and GARCH coefficients describe the same functions as explained in the case of the futures dummy. Figure 2 plots the GARCH conditional variance of the Nifty Index returns over the sample period.

Most of the results on the Nifty Index confirm our results that market volatility is unaffected by the introduction of derivatives. However, these results are in contrast to those of Mallikarjunappa and Afsal (2007), who studied the CNX IT Index using similar models and sample periods but found an increase in volatility with the introduction of futures. The possible explanations for the difference are as follows. First, Mallikarjunappa and Afsal (2007) studied one sectoral index (namely, the CNX IT Index), while the present study is on a broader general index, the Nifty Index. While their study of a sector-based index was first of its type in India, a sectoral index nevertheless shows a pattern different from a general or popular index. Second, the 2001 stock market scam

Table 5
GARCH (1, 1) estimates with options dummy.

		Coefficient	t-value
α	Intercept	0.6002*	2.7878
β	Nifty Jun.	0.0424*	2.5757
γ	Lagged S&P500	–0.0098	–0.4268
δ_1	Dummy-Mon	–0.6220*	–2.7411
δ_2	Dummy-Tue	–0.6531*	–2.9268
δ_3	Dummy-Wed	–0.3418	–1.5582
δ_4	Dummy-Thu	–0.5355#	–2.4994
δ_5	Dummy-Fri	–0.5635#	–2.5254
λ	Dummy Options	0.0582	1.0633
α_0	ARCH(0)	0.1056*	8.1415
β_1	GARCH(1)	0.8402*	111.6115
α_1	ARCH(1)	0.1246*	14.6670

Note: *Significant at the one percent level.
Critical at the five percent level. Observations = 2685.

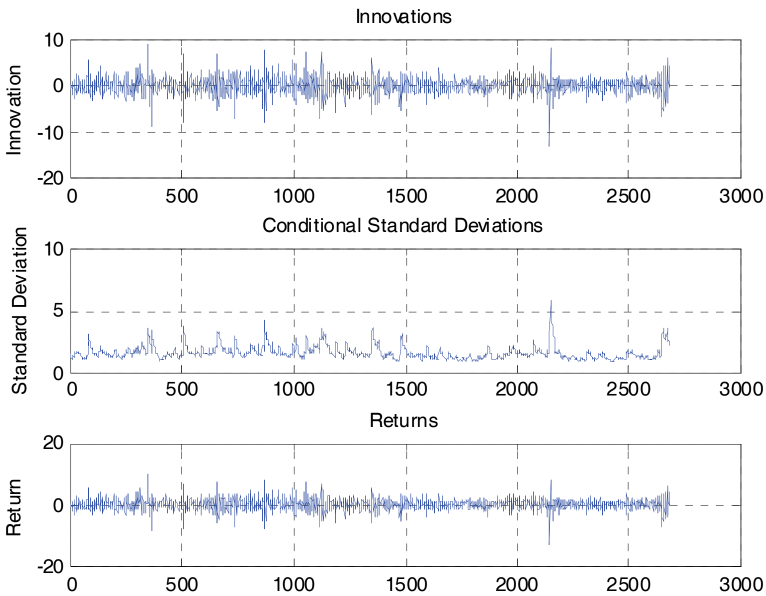

Figure 2. GARCH plots with options dummy.

affected different stocks in different ways. Because of the IT boom in India, IT stocks were high in demand and especially volatile during the period analysed by Mallikarjunappa and Afsal (2007). But other stocks did not experience such rapid rises in prices. Finally, the data period for this study is also different from that of

Mallikarjunappa and Afsal (2007) with respect to both pre-futures and post-futures periods, as they focused on data from period 2 January 2000 to 29 December 2006. Therefore, we infer that different indices may not necessarily follow the same pattern. Finally, we concur with Ma and Rao's (1988) inference that the introduction of derivatives does not have a uniform impact on the volatility of underlying stocks. The findings of this study and that of Mallikarjunappa and Afsal (2007) comprise the empirical evidence for this argument. Stock-specific characteristics are equally important in determining the volatility of the underlying market.

Constructed Volatility Measurement Analysis

The results obtained in the GARCH estimates that used both futures and options dummy variables suggest that the introduction of futures and options trading has had no statistically significant impact on the volatility of the underlying spot market. However, as was observed from the descriptive statistics, there exist two distinct volatilities, as measured by the standard deviation in the pre-futures, post-futures, pre-options and post-options sub-periods. Recognising standard deviation as a measure of volatility, we observe a reduction in the volatility of Nifty Index returns from 1.7822 percent to 1.4667 percent after the introduction of futures and from 1.7805 percent to 1.4144 percent after the introduction of options. The Nifty Junior Index, which does not have any futures or options contracts traded on its underlying market, also reported a similar fall in volatility after the introduction of futures and options. It is essential to check the statistical significance of these different volatilities; this analysis is carried out by using the constructed volatility measurement model described in equation (7). This additional measure is used to analyse whether the GARCH results regarding volatility differ from the constructed volatility measures, which test for the standard deviations before and after the introduction of derivatives as denoted by equation (7). The results presented in Table 6 reveal that the value of β_1, which is the coefficient of the Nifty Junior volatility with and without futures dummy, is not significant at the five percent level. Hence, the change in volatility in the Nifty Index is not explained by that of Nifty Junior Index. Also, the futures dummy β_2 is not statistically significant, which shows that the introduction of futures has not changed underlying market volatility. Similar results are obtained for options. This result corresponds to the result obtained in the GARCH (1, 1) estimation.

Table 6
Constructed volatility measurement analysis.

$VS_t = \beta_0 + \beta_1 VM_t + \beta_2 D_t + \varepsilon_t$

Futures	With dummy		Without dummy	
	Coefficients	t-stat	Coefficients	t-stat
Intercept	–0.0111	–0.2342	0.0000	0.0000
β_1	0.0205	1.2371	0.0205	1.2355
β_2	0.0196	0.3111	N.A.	N.A.
Options	With dummy		Without dummy	
	Coefficients	t-stat	Coefficients	t-stat
Intercept	–0.0113	–0.2542	0.0000	0.0000
β_1	0.0218	1.2344	0.0213	1.2354
β_2	0.0193	0.3123	N.A.	N.A.

The Nature of Volatility Patterns

To examine whether the nature of volatility remains the same after the introduction of futures, we divide the sample period into pre-futures and post-futures periods and then separately run the GARCH estimation for each period. The model estimates are presented in Table 7. In the pre-futures and post-futures estimates, the coefficients of ARCH and GARCH are statistically significant at the one percent level. A higher GARCH coefficient in the pre-futures period shows that the prices respond to old news more effectively before futures than afterwards. With the introduction of futures, market volatility is determined by recent innovations as evidenced by a higher ARCH value during the post-futures period. The presence of significant GARCH and ARCH coefficients in both sub-periods shows that the effect of information is persistent over time, that is, a shock to today's volatility due to some information that arrived in the market today has an effect on tomorrow's volatility as well as volatility in subsequent period. The volatility is still time-varying and conditional on innovations. In addition, during the pre-futures period, there appears to be a significant day-of-the-week effect except for Wednesday, which may be due to the NSE's earlier practice of starting their accounting settlement period on Wednesday and ending on the following Tuesday. After the introduction of futures, this effect is no longer statistically significant. The disappearance of the day-of-the-week effect may also be due to the introduction of rolling settlement. Table 8 shows the estimates for options. It is evident that the market reacts more effectively to old news than to recent news in the pre-options as well as the post-options periods. The day-of-the-week effect is same as the one reported for futures.

Table 7
GARCH estimates for Nifty Index before and after the introduction of futures.

		BEFORE		AFTER	
		Coefficient	t-value	Coefficient	t-value
α	Intercept	0.92427*	3.4914	0.3468	0.3262
β	Nifty Jun. Return	0.04265	1.4957	0.0371	1.8770
γ	Lagged S&P500	–0.01462	–0.3658	–0.0054	–0.1998
δ_1	Dummy-Mon	–1.1502*	–4.045	–0.2132	–0.1995
δ_2	Dummy-Tue	–1.2471*	–4.1032	–0.2252	–0.2123
δ_3	Dummy-Wed	–0.13665	–0.4748	–0.2692	–0.2529
δ_4	Dummy-Thu	–0.9395*	–3.4597	–0.1934	–0.1815
δ_5	Dummy-Fri	–0.95927*	–3.2658	–0.2387	–0.2241
α_0	ARCH(0)	0.22948*	4.269	0.1571*	5.8793
α_1	GARCH(1)	0.85093*	40.505	0.7374*	26.7037
β_1	ARCH(1)	0.07586*	6.0591	0.1875*	9.1159

Note: * significant at the one percent level.

Table 8
GARCH estimates for Nifty Index before and after the introduction of options.

		BEFORE		AFTER	
		Coefficient	t-value	Coefficient	t-value
α	Intercept	0.7183*	7.8527	0.3380	0.3285
β	Nifty Jun. Return	0.0545*	2.1910	0.0398	1.7804
γ	Lagged S&P500	0.0070	0.1969	–0.0160	–0.5337
δ_1	Dummy-Mon	–0.9743*	–7.8553	–0.1664	–0.1607
δ_2	Dummy-Tue	–1.2740*	–3.2198	–0.2488	–0.2424
δ_3	Dummy-Wed	0.3476	0.9201	–0.3001	–0.2913
δ_4	Dummy-Thu	–0.7007*	–5.4536	–0.2024	–0.1963
δ_5	Dummy-Fri	–0.8379*	–5.9491	–0.1750	–0.1697
α_0	ARCH(0)	0.2891*	4.7141	0.1372	5.14
α_1	GARCH(1)	0.8162*	33.7518	0.7600*	25.7395
β_1	ARCH(1)	0.0896*	6.9583	0.1658*	8.3730

Note: * significant at the one percent level.

Chow Test for Parameter Stability

In order to check for parameter stability in the regression models for pre-futures and post-futures and assuming constant error variance, we conduct a Chow test for structural change. In this test, a comparison is made between the regression coefficients of the pre-futures and post-futures models under the null hypothesis that both model coefficients are statistically the same. The Chow test statistic follows the F distribution with degrees of freedom (k, $n_1 + n_2 - 2k$), where k is the number of parameters and n_1 and n_2 are the number of observations in the pre-futures and post-futures regression models, respectively. The null hypothesis of parameter stability (i.e., no structural change) cannot be rejected if the computed F value in an application does not exceed the critical F value given d.f. (k, n_1 +

$n_2 - 2k$) at the chosen level of significance. The computed F value (7,2851) is 5.16, which exceeds the value of 2.64, and therefore, we reject the hypothesis of parameter stability. This suggests that the regression coefficients are statistically different before and after futures listing. The GARCH-estimated volatility of the Nifty Index before and after futures listing is depicted in Figures 3 and 4. From the above discussion and the comparison of Figures 3 and 4, it is evident that the nature of the volatility patterns has changed after the introduction of derivatives.

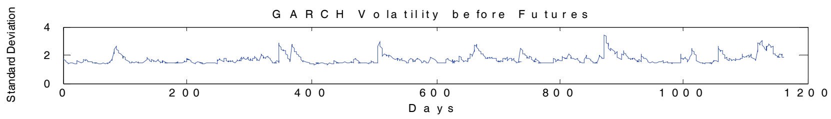

Figure 3. GARCH volatility before futures.

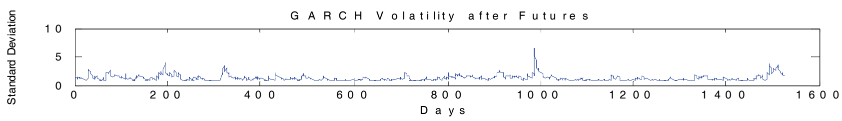

Figure 4. GARCH volatility after futures.

CONCLUSION

With the objective of analysing the impact of the introduction of derivatives on spot market volatility, we have examined the volatility behaviour of the S&P CNX Nifty Index using the GARCH model. The results suggest that the introduction of derivatives does not have any stabilising (or destabilising) effect in terms of decreasing (or increasing) volatility as has been detected in other markets, for example, by Trennepohl and Dukes (1979), Bansal, Pruitt and Wei (1989), and Pilar and Rafael (2002). Our result is similar to the majority of results obtained throughout the world. However, our results do not concur with those of Mallikarjunappa and Afsal (2007).

The separate estimates for pre-derivatives and post-derivatives reveal that the sensitivity of the Nifty return to the Nifty Junior Index and the day-of-the-week effect disappears after the introduction of derivatives contracts. The price sensitivity to old news is higher during pre-futures than post-futures periods, and with the introduction of futures, market volatility is determined by recent innovations, as also evidenced by a higher ARCH value. The appearance of large ARCH and GARCH coefficients in the post-derivatives model points to the fact that returns still predominantly depend on past innovations, and volatility is time-varying. We observe the persistence of shocks and long-term memory processes in the post-derivatives period as well, and therefore, we conclude that the introduction of derivatives has not brought the desired outcome of decline in volatility. However, the result of the Chow test for parameter stability clearly indicates structural change in the coefficients of pre-futures and post-futures periods, suggesting a change in the nature of volatility patterns during the post-futures period. Based on our results, we infer that any change in the volatility process is not due to the introduction of derivatives, but may be due to many other factors, including better information dissemination and more transparency. The speed of information flow must have increased so that the response level of stocks is more sensitive to recent innovations in the post-derivatives period. Further research is recommended to measure the changes in information flow due to the introduction of derivatives.

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