5.1 INTRODUCTION

Financial markets exhibit dramatic movements, and stock prices may appear too volatile to be justified by changes in fundamentals. Such observable facts have been under scrutiny over the years and are still being studied vigorously (LeRoy and Porter, 1981; Shiller, 1981; Zhong et al., 2003).

Volatility as a phenomenon as well as a concept remains central to modern financial markets and academic research. The link between volatility and risk has been to some extent elusive, but stock market volatility is not necessarily a bad thing. In fact, fundamentally justified volatility can form the basis for efficient price discovery. In this context volatility dependence that implies predictability is welcomed by traders and medium-term investors. The importance of volatility is widespread in the area of financial economics. Equilibrium prices, obtained from asset pricing models, are affected by changes in volatility, investment management lies upon the mean-variance theory, while derivatives valuation hinges upon reliable volatility forecasts. Portfolio managers, risk arbitrageurs, and corporate treasurers closely watch volatility trends, as changes in prices could have a major impact on their investment and risk management decisions.

Volatility may be defined as the degree to which asset prices tend to fluctuate. Volatility is the variability or randomness of asset prices. Volatility is often described as the rate and magnitude of changes in prices and in finance often referred to as risk. The Nobel laureate Merton Miller writes “by volatility public seems to mean days when large market movements, particularly down moves, occur. These precipitous market wide price drops cannot always be traced to a specific news event. Nor should this lack of smoking gun be seen as in any way anomalous in market for assets like common stock whose value depends on subjective judgment about cash flow and resale prices in highly uncertain future.
The public takes a more deterministic view of stock prices; if the market crashes, there must be a specific reason.”

There are two schools of thought that have divergent views on the reasons of volatility. The economists in their fundamentalist approach argue that these market movements can be explained entirely by the information that is provided to the market. They have tried to put forward theories to explain this phenomenon and more still have tried to use these theories to predict future changes in prices. They go on to say that since the efficient market hypothesis holds, the information changes affect the prices. Market volatility keeps changing as new information flows into the market. Others have argued that the volatility has nothing to do with economic or external factors. It is the investor reactions, due to psychological or social beliefs, which exert a greater influence on the markets. The Popular Models Theory\(^1\) proposes that people act inappropriately to information that they receive. Thus, freely available information is not necessarily already incorporated into a stock market price as the efficient market hypothesis would have proved.

The issue of changes in volatility of stock returns in emerging markets has received considerable attention in recent years. The reason for this enormous interest is that volatility is used as a measure of risk. The market participants also need this measure for several reasons. It is needed as an input in portfolio management. It is indispensable in the pricing of options.

Furthermore, in the process of predicting asset return series and forecasting confidence intervals, the use of volatility measure is crucial. The current chapter provides an overarching review of the equity market volatility, covering areas that have caught the attention of researchers and practitioners alike. It aims to enlighten financiers and anyone interested in equity markets about the theories underlying stock market volatility, the historical trends and debates in the field, as well as the empirical findings at the forefront of academic research.

### 5.2 SPECULATION AND VOLATILITY

\(^1\) Popular Models are a qualitative explanation of prices.
Speculators are usually seen with some sort of resentment by the wider community. From the early days, scholars have either supported that speculators stabilize prices (Smith, 1776; Mill, 1871; Friedman, 1953) or argued that speculators make money at the expense of others, which in turn produces a net loss and results in unnecessary price fluctuations (Kaldor, 1960; Stein, 1961; Hart, 1977). In any event, large institutional investors should be able to insure against excess fluctuations (at least in the short run), while small agents may have to bear the consequences.

Analysts often argue that there is a link between speculation and volatility, while some even commit themselves to the post hoc ergo propter hoc fallacy. It is crucial, however, to distinguish between the order of events and the factors that rule out any connection between the two episodes, i.e., understand the concept of coincidental correlation, or more formally separate the notion of correlation and causation. In essence, a case could be made that speculators act as momentum traders by identifying peaks and troughs in retrospect, which in turn accelerates upward/downward movements or even increases the amplitude and frequency of fluctuations. What determines the level of disruption in the cash market is the speculators’ (poor) forecasting ability and lack of information (Baumol, 1957; Seiders, 1981). But from a practical point of view, how do speculators inject excess volatility (if any) in financial markets?

Volatility is an inevitable market experience mirroring (1) fundamentals, (2) information, and (3) market expectations. Interestingly, these three elements are closely associated and interact with each other. Adjustments in equity prices (should) echo changes in various aspects of our society such as economic, political, monetary, and so forth. That is, corporate profitability, product quality, business strategy, political stability, interest rates, etc., should have a role to play in shaping the intensity of price fluctuations, as the market moves from one equilibrium to another. At the same time, information about changes in fundamentals should spark market activity changing the landscape of future prices. In fact, the process can be viewed as a “game” where the sequence becomes one of changes in fundamentals,
information arrival, and new expectations (hence new trading positions), which in turn results in an endless cycle where these events embrace each other in a series of lagged responses. The point here is what kind of information speculators possess, which raises a few interesting questions. First, do speculators have superior access to information? Speculators devote more resources to follow the markets and, because of their size, are able to reduce any associated expenses. Second, do speculators, by means of expertise/knowledge, better interpret the same set of information than others? Theoretically, sophisticated speculators should be one step ahead. On the other hand, historical cases do not endorse such a claim, which places more emphasis on the roots of excessive volatility and market instability. Third, on the basis of information received/interpreted, do speculators behave in a proactive rather than inactive way? This actually leads us, indirectly, to the concept of herding behavior. Market analysts sometimes pin down the origins of volatility to either uninformed trading or collective irrationality—possibly resulting from herding behavior. Such an approach reinforces the view that speculation can lead to unjustified price variability.

The debate over speculation and excess volatility has become more of a two-handed lawyer problem. If speculators indeed lead the market, then we shall observe faster price adjustments on the basis of their actions. It would also be hard to blame them for acting quicker than others, or hold them responsible for long-term excess volatility. Besides, such volatility should fade away rather quickly in an efficient market. On the other hand, if speculators simply follow the market or possess the same information set interpreted in the same way as by the rest of the market, then their actions would lack the material information required to justify price changes or even excess volatility.

The professional market players measure their performance against their peers’ (Lakonishok et al., 1992a), while some tend to “rationally” herd (Lakonishok et al, 1992b; Wermers, 1999; Grinblatt et al., 1995; Welch, 2000). The argument advocated by the second group of studies preserves reputation since the failure/loss is shared with the market peers. This issue has been the subject of
analysis (Devenow and Welch, 1996; Calvo and Mendoza, 2000), but bear in mind that markets closely watch those who tend to lose as a result of taking decisions different from heir peer group. Finally, note that the approaches discussed are based on the fact that legitimate information (about future demand) governs the actions of speculators. Yet, price manipulation is a market reality. It is certainly possible that through price manipulation excess profits can be earned (Allen and Gorton, 1992; Allen and Gale, 1992; Jarrow, 1992, 1994; Cooper and Donaldson, 1998), but all largely depends upon the underlying model assumptions, such as risk aversion, information, etc.

5.3 INFORMATION, LIQUIDITY AND VOLATILITY

Volatility is a natural consequence of trading, which occurs through the news arrival and the ensuing response of traders. The chain reaction of market participants will force equity prices to reach a post information equilibrium level. Revision of expectations and subsequent actions will be reflected in the liquidity of the particular market and specifically on the amount of stocks traded. If we place the above process in a continuous time of revising expectations, and since the underlying prime mover is common, i.e., flow of information, then it is expected that information, liquidity, and volatility are related.

The relation among information, volume (liquidity), and volatility is consistent with four competing propositions: the mixture of distributions hypothesis (MDH) (Clark, 1973; Epps and Epps, 1976; Harris, 1986, 1987), the sequential information hypothesis (Copeland, 1976; Morse, 1980; Jennings et al., 1981; Jennings and Barry, 1983), the dispersion of beliefs approach (Harris and Raviv, 1993; Shalen, 1993), and the information trading volume model of Blume et al. (1994). The motivation behind the MDH is drawn by the apparent leptokurtosis exhibited in daily price changes attributed to the random events of importance to the pricing of stocks. The MDH postulates that volume and volatility are contemporaneously and positively correlated, while jointly driven by a stochastic variable defined as the information low. The question of how non-correlated news can change these variables in a simultaneous fashion, prompted Andersen (1996) to
argue for a modified version of MDH, where information is serially correlated implying that current volume and volatilities are affected by their past values. The MDH is subject to one limitation: It fails to consider the precision or quality of information.

Under the sequential information hypothesis, information is absorbed by traders on a group-by-group basis who then trade upon the arrival of news. The implication of this model is that the volume-volatility relation is sequential, not contemporaneous. A number of incomplete equilibrium are observed before a final equilibrium is attained—when all traders observe the same information set. The sequential response to the arrival of information implies that price volatility can be forecasted, based on the knowledge of trading volume. Yet, the model is not flawless as (1) it does not account for the fact that traders learn from the market price as other traders become informed, and (2) it implies that volume is greatest when all investors agree on the meaning of the information.

The dispersion of beliefs model holds that the greater the dispersion of beliefs among traders, the higher the volatility/volume relative to their equilibrium values. The approach engulfs both informed and uninformed segments of financial markets, with uninformed traders reacting to changes in volume/prices as if these changes reflect new information. On the other hand, knowledgeable investors make their trades on price reflecting fair values, as they possess homogeneous beliefs. It is therefore expected that uninformed investors will shake prices and increase price volatility.

Finally, the information trading volume approach is based on the notion that volume plays an informationally important role in an environment where traders receive pricing signals of different quality. The assumption that the equilibrium price is not revealing given that pricing signals alone do not provide sufficient information to ascertain the underlying value. Trading volume is treated as containing information regarding the quality of signals received by traders, whereas prices alone do not. This in turn leads to the formulation of a link among trading
volume, the quality of information flow, and volatility. It is also argued that traders who use information contained in market statistics do better than those who do not.

Over the recent years, scholars have made noteworthy advances in equity volatility modeling by taking into account features of returns not previously considered. One of the assumptions underlying time-series models is that time intervals over which price variations are observed are fixed. Price changes and news arrival, however, can take place in irregular time intervals. Empirical evidence using high-frequency data indicates that adjusting volume and volatility for the duration between trades provides time-consistent parameter estimators in microstructure models, while allowing for proper integration of the information proxied by trade intensity—into the regression model (Engle and Russell, 1998; Dufour and Engle, 2000; Engle, 2000). Recent research shows that volatility and volume are persistent and highly auto-correlated, while shorter time duration between trades implies higher probability of news arrival and higher volatility (Xu et al., 2006). The findings suggest that there is an inverse relation between price impact of trades and duration between trades. A similar relationship is documented for the speed of price adjustment to trade-related information and the time interval between transactions.

The issue of information asymmetry is also important. Agents with different information sets take different trade positions, while their actions lag signals and cause a persistent impact on equity prices. As trading actions spread, news is conveyed into the market and stock prices adjust to reflect expectations based on previous trades and all available information. Empirical research (Glosten and Harris, 1988; Hasbrouck, 1988, 1991a, 1991b) has put forward models to understand the equity pricing function by integrating the news arrival process into equity prices. The results suggest that past price changes as well as signed trades have a persistent impact on current price changes, thereby being important in determining the intrinsic value of stocks.

Within noisy rational expectations framework Wang (1994) and Blume et al. (1994) unveil a positive association between volume and price changes. McKenzie
and Faff (2003) take into account liquidity disparities for equities, as they exert a significant impact on individual stocks but not on indices. They show that conditional autocorrelation in equity returns is highly dependent on trading volume for individual stocks but not for indices. Elsewhere, Li and Wu (2006) find that by controlling for the effect of informed trading, return volatility is negatively correlated with volume. This is consistent with the contention that liquidity increases market depth and reduces price volatility.

The empirical research in general supports a positive correlation between equity price changes and volume. However, the difficulty in evaluating such a relationship stems from the ambiguity regarding the information content of volume. It might be suggested that volume provides insights on the dispersion and quality of information signals, rather than representing the information signal per se.

5.4 DERIVATIVES TRADING AND VOLATILITY

The general belief that futures trading triggers excess speculation, and possible price instability, has been a fertile research terrain for many scholars (Damodaran and Subrahmanyam, 1992). The implications for policy makers and those responsible for regulating futures trading have also been noted. The debate became more vivid after “Black Monday,” which has led to much interest in examining volatility in modern financial markets. It is not yet clearly established whether derivatives induce excess volatility in the cash market and thus destabilize equity prices. Financial bubbles along with the existence of speculators have been addressed (Edwards, 1988a, 1988b; Harris, 1989; Stein, 1987, 1989) as other potential sources of excess price variability. It is also true that closer to the expiration day, traders attempt to settle their contracts, close their trading positions, and aggressively arbitrage on price differences. Miller (1993) finds that futures trading have raised volatility in the Japanese market, possibly attributed to low-cost speculative opportunities. These arguments along with the discussion in Section 4.1 underline the role of derivatives trading in destabilizing financial markets.
On the other hand, there is a consensus among another school of thought that derivatives trading contribute to stabilizing the underlying equity market. The very nature of derivatives is risk reducing, being a platform for competitive price discovery, and acting as a hedging device for buyers and sellers. Derivatives also increase market liquidity and expand the investment opportunity set at lower transaction costs and margin requirements. Exchange traded derivatives are more centralized, enabling participants to trade and communicate their information more effectively. Assuming that derivatives do attract rational traders, then equity prices should move closer to their fundamentals and markets should become less volatile. Based on intraday data, Schwert (1990) shows that the equity cash market is 40% less volatile than its counterpart futures market, while Merton (1995) argues that the volatility’s asymmetric response to the arrival of news is reduced in the presence of futures markets.

Yet, anecdotal evidence both supports and refutes the aforesaid hypotheses. Moreover, tightening any regulatory framework in the derivatives market is not empirically endorsed. With the lack of a clear-cut theoretical background that justifies market realities, the question becomes an empirical one. At times, when fluctuations are large, they can easily call into question the collective rationality of the market. The issue is whether volatility is a sign of collective irrationality or is consistent with the kind of fluctuations expected to arise naturally from the actions of less informed investors.

Early evidence (Bessembinder and Seguin, 1992) points out that futures trading improve liquidity and depth in the cash equity market, which is corroborated by more recent studies (Board et al., 2001). Analysis of the FTSE100, S&P500, and DJIA indices (Robinson, 1994; Pericli and Koutmos, 1997; Rahman, 2001) reveals either a volatility reduction in the post futures phase or no change in the conditional volatility over the two periods. Elsewhere, findings indicate that twenty-three international stock indices exhibit either a reduction or no change in volatility during the post-futures period, while the opposite applies for the U.S. and Japanese equity markets (Gulen and Mayhew, 2000). Recently, Dawson and
Staikouras (2008) investigated whether the newly cultivated platform of derivatives volatility trading has altered the variability of the S&P500 index. They documented that the onset of the CBOE volatility futures trading has lowered the equity cash market volatility, and reduced the impact of shocks to volatility. The results also indicate that volatility is mean reverting, while market data support the impact of information asymmetries on conditional volatility. Finally, comparisons with the UK and Japanese indices, which have no volatility derivatives listed, show that these indices exhibit higher variability than the S&P500.

The dynamic interaction between derivatives and cash equity markets engulfs the issue of volatility asymmetric response to the arrival of news (Engle and Ng, 1993). In other words, the market participants react differently upon the arrival of bad and good news. The information transmission mechanism, from futures to spot market, is yet unclear. The role of asymmetries in the futures market will have implications for the effectiveness of policy frameworks at both an institutional and a state level. Early evidence unveils that bad news in the futures market increases volatility in the cash markets more than good news (Koutmos and Tucker, 1996; Antoniou et al., 1998), while post futures asymmetries are significantly lower for major economies, except the United States and United Kingdom. When both spot and futures markets are examined, it seems that asymmetries run from the spot to the futures market. The leverage hypothesis is not the only force behind asymmetries, as market interactions, noise trading, and irrational behavior may well contribute to the rise of asymmetries.

Analysts and traders use techniques such as portfolio insurance, sentiment, and other technical indicators, as well as extrapolative expectations that are in line with the positive feedback trading approach. The latter calls for tracking market movements in retrospect of a trend change. On that basis, as futures do attract a diverse number of participants, then some form of market destabilization may take place. Recent evidence (Antoniou et al., 2005; Chau et al., 2008) indicates that feedback trading is either reduced or not attributed, at least in large part, to the existence of futures markets. When feedback trading does take place, both rational
and any other investors/speculators tend to join the trading game, which in the short run may drive prices away from fundamentals. On the other hand, in efficient markets and under rational expectations, the effect of feedback trading might be limited as speculators will ultimately start liquidating their positions, driving equity prices closer to their intrinsic values.

Finally, research has concentrated on stock indices rather than individual shares. It is a fact, however, that individual share futures (ISFs) are traded in modern markets, and their analysis sheds light on financial markets’ behavior (McKenzie et al., 2001; Chau et al., 2008). It is true that equity indices capture wide-market forces, but when it comes to identifying the origins of a phenomenon, the large number of constituent stocks poses an obstacle. Liquidity is another motive behind such an analysis, as indices are more liquid than individual stocks, amplifying any possible impact of stock index futures on the underlying asset. At the same time, the underlying asset on stock index futures is not traded as opposed to Individual Stock Futures (ISFs), making the latter an apt alternative for investigation. In a multi aspect examination, McKenzie et al. (2001) study the systematic risk, asymmetries, and volatility of ISFs. Their stock-specific empirical findings add to the mixed results of the ongoing literature. They detect a clear reduction in beta risk and unconditional volatility, during the post-IFS listing, and offer some mixed evidence regarding the change in conditional volatility, while asymmetric response is not consistent across all stocks.

5.5 STYLIZED FACTS OF VOLATILITY MODELING

It is well established by now that equity volatility is time varying and tends to display patterns, thereby rendering the stock returns’ empirical distribution abnormal. Several historical time-series models have been proposed to account for such features. The simplest class of historical volatility models lies on the premise that past standard deviations of returns can be estimated. The most naive historical volatility model is the Random Walk, where the best forecast of today’s volatility is yesterday’s realized value, i.e. $\sigma_t^2 = \sigma_{t-1}^2$. Another approach is the Historical Average (HA), which amounts to a long-term average of past standard deviations.
Whereas the HA uses all past standard deviations, the Moving Average (MA) discards older information by deploying a rolling window of fixed length (N), typically 20 to 60 trading days. The MA volatility forecast can be described by the below equation:

$$\hat{\sigma}_t^2 = \left(\frac{1}{N}\right) \sum_{i=1}^{N} \hat{\sigma}_{t-i}^2 = \left(\frac{1}{N}\right) \sum_{i=1}^{N} r_{t-i}^2$$

Where $r_t$ is the observed return on day $t$, with squared returns typically used as an estimate of the ex-post daily variance. The drawback of MA is that all past observations carry the same weight, while the so-called ghosting feature\(^2\) should be ignored.

A more refined approach is the Risk Metrics model (JP Morgan, 1996), which uses an Exponentially Weighted Moving Average (EWMA) to forecast volatility and gives greater importance to more recent volatility estimates. The EWMA variance forecast is formulated as follows:

$$\hat{\sigma}_t^2 = (1 - \lambda) \sum_{i=1}^{N} \lambda^{t-i} r_{t-i}^2$$

Where the decay parameter is set at $\lambda = 0.94$ for daily and $\lambda = 0.97$ for monthly forecasts, and a window of $N=75$ days is typically used. The EWMA posits geometrically declining weights on past observations, giving greater emphasis to new information. The smaller the $L$, the higher the impact of recent news and the faster the decay in weights for old news.

Volatility clustering is a characteristic of equity returns and mirrors the leptokurtosis (fat tails) in the returns’ distribution. Volatility clustering refers to large/small price changes being followed by large/small changes in either direction. It has been attributed to the quality of information reaching the market in clusters (Gallant et al., 1991), as well as to the time-varying rate of information arrival and

\(^2\)The volatility forecast increases as a direct result of including a particular high observation. After $N$ days this observation is dropped out of the estimation window, causing a sudden fall in volatility, ceteris paribus.
news processing by the market (Engle et al., 1990). One of the major breakthroughs in financial economics is the modeling of non constant variances (Conditional Heteroskedasticity) and volatility clustering in equity returns. The GARCH class models build on the notion of volatility dependence to measure the impact of last period’s forecast error and volatility in determining current volatility. In this backdrop the current work has used the GARCH class models in determining volatility in the cash market.

5.6 TESTING OF VOLATILITY

The very objective of this chapter is to investigate the dynamics of the time varying volatility of India’s spot and 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 nifty and nifty based 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.

5.6.1 Volatility in Spot Market

For volatility estimation, the GARCH (1, 1) model is used Bollerslev (1986). The model for daily stock return is specified as under:

Mean Equation: $R_i = c + \varepsilon_i$

Variance Equation: $\sigma_i^2 = \omega + \alpha_i \varepsilon_{i-1}^2 + \beta_i \sigma_{i-1}^2$

Since $\sigma_i^2$ is the one-period ahead forecast variance based on past information, it is called the conditional variance. The above specified conditional variance equation is a function of three terms: a constant term ($\omega$), news about volatility from the previous period, measured as the lag of the squared residual
from the mean equation \( \varepsilon_{t-1}^2 \), and the last period’s forecast variance \( \sigma_{t-1}^2 \). 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.

**TABLE 5.1: GARCH (1, 1) ESTIMATES FOR SPOT MARKET**

<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>9.67E-06</td>
<td>9.65E-07</td>
<td>10.01642</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.130904</td>
<td>0.009673</td>
<td>13.53327</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.835658</td>
<td>0.011385</td>
<td>73.40047</td>
</tr>
</tbody>
</table>

It is clear that the bulk of the information comes from the previous days forecast, around 83% in case of NSE. The new information changes this a little and the long run average variance has a very small effect.

It is very apparent from the Fig.5.1 that the amplitude of the daily stock returns is changing in both the stock markets. 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.

**Figure 5.1 Daily Stock Returns and Stock Prices in India**
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:**

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

The left hand side of above variance equation is the logarithm of the conditional variance. This implies that the leverage effect is exponential and that the forecasts of the conditional variance are guaranteed to be non-negative. In this model, \( \alpha \) is the GARCH term that measures the impact of last period’s forecast variance. A positive \( \alpha \) indicates volatility clustering implying that positive stock price changes are associated with further positive changes and the other way around. \( \beta \) is the ARCH term that measures the effect of news about volatility from the previous period on current period volatility. \( \gamma \) is the measure of leverage effect. The presence of leverage effect may be tested by the null hypothesis that the coefficient of the last term in the regression is negative \( (\gamma < 0) \). Thus, for a leverage effect, we would see \( \gamma > 0 \). The impact is asymmetric if this coefficient is different from zero \( (\gamma \neq 0) \). Ideally \( \gamma \) is expected to be negative implying that bad

---

3It has been practically observed that volatility reacts differently to a big price increase or a big price drop. This phenomenon is referred to as leverage effect.
news has a bigger impact on volatility than good news of the same magnitude. The sum of the ARCH and GARCH coefficients, that is, $\alpha + \beta$ indicates the extent to which a volatility shock is persistent over time\(^4\). The stationary condition is $\alpha + \beta < 1$.

**TABLE 5.2: EGARCH (1, 1) ESTIMATES FOR SPOT MARKET**

<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>-0.722863</td>
<td>0.052977</td>
<td>-13.64497</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.238685</td>
<td>0.015251</td>
<td>15.65089</td>
</tr>
<tr>
<td>$\beta$</td>
<td>-0.123225</td>
<td>0.009183</td>
<td>-13.41843</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.935178</td>
<td>0.005165</td>
<td>181.0489</td>
</tr>
</tbody>
</table>

Since the value of $\gamma$ is non-zero, the EGARCH 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:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

Here, the dummy variable $I_{t-1}$ is an indicator for negative innovations and is defined by: $I_{t-1}=1$, if $\varepsilon_{t-1}<0$ and $I_{t-1}=0$ if $\varepsilon_{t-1} \geq 0$. In this model, good news, $\varepsilon_{t-1} > 0$, and bad news, $\varepsilon_{t-1} < 0$, have differential effects on the conditional variance; 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 $\gamma \neq 0$, the news impact is asymmetric.

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\(^4\) A persistent volatility shock raises the asset price volatility.
TABLE 5.3: TGARCH (1, 1) ESTIMATES FOR SPOT MARKET

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance Equation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>1.33E-05</td>
<td>1.13E-06</td>
<td>11.76987</td>
<td>0.0000</td>
</tr>
<tr>
<td>ARCH(1)</td>
<td>0.049081</td>
<td>0.009306</td>
<td>5.274312</td>
<td>0.0000</td>
</tr>
<tr>
<td>ARCH(1)*(RESID&lt;0)</td>
<td>0.192885</td>
<td>0.018825</td>
<td>10.24626</td>
<td>0.0000</td>
</tr>
<tr>
<td>GARCH(-1)</td>
<td>0.810239</td>
<td>0.013772</td>
<td>58.83184</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

The estimated form of TGARCH model for NSE is:

$$\sigma_i^2 = 0.0000102 + 0.0772\varepsilon_{i-1}^2 + 0.8416\sigma_{i-1}^2 + 0.1057\varepsilon_{i-1}^2 I_{i-1}$$

It shows that the good news has an impact of 0.0772 magnitudes and the bad news has an impact of 0.0772 +0.1057= 0.1829 magnitudes in the NSE.

Thus, it is inferred that in the Indian spot markets, the bad news increases the volatility substantially. Also, the 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 stock market came as a result of the global economic events, particularly the recent sub-prime crisis and news of probable recession.

5.6.2 Volatility in Index Futures Market

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: $$R_i = c + \varepsilon_i$$

Variance Equation: $$\sigma_i^2 = \omega + \alpha_i \varepsilon_{i-1}^2 + \beta_i \sigma_{i-1}^2$$

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-5.4.
TABLE 5.4: GARCH (1, 1) MODEL FOR FUTURES MARKET

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance Equation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\omega$</td>
<td>7.84E-06</td>
<td>7.93E-07</td>
<td>9.891693</td>
</tr>
<tr>
<td>$\alpha_i$</td>
<td>0.140525</td>
<td>0.008813</td>
<td>15.94476</td>
</tr>
<tr>
<td>$\beta_i$</td>
<td>0.838001</td>
<td>0.009292</td>
<td>90.18246</td>
</tr>
</tbody>
</table>

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.

It is very apparent from the Fig.5.3 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.

**Fig. 5.3: TS Plot of Index Futures Return and Price Series**
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:** \( \log(\sigma_t^2) = \omega + \alpha \log(\sigma_{t-1}^2) + \beta \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \)

**Table-5.5: EGARCH (1, 1) ESTIMATES FOR FUTURES MARKET**

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variance Equation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \omega )</td>
<td>-0.613208</td>
<td>0.040276</td>
<td>-15.22533</td>
<td>0.0000</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>0.265412</td>
<td>0.015837</td>
<td>16.75892</td>
<td>0.0000</td>
</tr>
<tr>
<td>( \beta )</td>
<td>-0.111835</td>
<td>0.008499</td>
<td>-13.15812</td>
<td>0.0000</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>0.950648</td>
<td>0.003835</td>
<td>247.9168</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

The results of EGARCH model are reported in Table-5.5. 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: 

$$\sigma_i^2 = \omega + (\alpha + \gamma I_{\varepsilon_{i-1}}) \varepsilon_{i-1}^2 + \beta \sigma_{i-1}^2$$

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-5.6.

<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>

The estimated form of TGARCH model for index futures market is:

$$\sigma_i^2 = 0.0000097 + 0.0572 \varepsilon_{i-1}^2 + 0.1626 \varepsilon_{i-1}^2 I_{\varepsilon_{i-1}}$$

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.
The volatility test of Nifty and its derivative for the sample period has exhibited groundbreaking results. Three GARCH family models are used such as the GARCH(1,1), the EGARCH(1,1) and the T-GARCH(1,1) (GJR model). To begin with, we apply the basic GARCH (1,1) model. For the post-introduction period, we have the ARCH parameter equal to $\alpha_1 = 0.140525$ and the GARCH coefficient, $\beta_1 = 0.838001$ with the standard errors being 0.008813 and 0.009292 respectively. Thus, the sum of $\alpha_1$ and $\beta_1$ equals 0.978526 which approach unity. This implies that shocks to the conditional variance will be highly persistent. Both ARCH and GARCH parameters are statistically significant at the 5% significance level which means that the “news” parameter and the persistence coefficient are significant. Thus, the volatility of the Nifty index will change after the introduction of futures trading significantly.

Another way to capture the volatility of the Nifty index is by applying the EGARCH model. We applied the E-GARCH (1,1) model for the post-introduction period in the same way as in the GARCH(1,1) analysis above.

All the parameters of the EGARCH model are highly significant. Thus, the news parameter and the persistence coefficient are significant in the post-introduction period. The leverage effect coefficient, $\gamma$ is also significant, different from zero and negative which means that there is leverage in the returns for our sample-period and the news impact is asymmetric. Negative shocks imply a higher conditional variance for the post-introduction period than positive shocks of the same magnitude do.

Comparing the results from Tables 5.4 and 5.5, we can conclude that for the EGARCH(1,1), both ARCH and GARCH parameters have increased in the post-introduction period and their sum too. Thus, the news is reflected in prices more rapidly and old news has higher impact on today’s prices. Thus, the introduction of futures trading has a significant positive impact on the spot market volatility of the Nifty index. The leverage effect coefficient $\gamma$ is positive for the EGARCH(1,1). Thus, the leverage effect is significant in the post-introduction period with the EGARCH(1,1) analysis.
The final step is to examine the volatility of the underlying spot index with the GJR model. By following the same procedure, we have the following results for the TGARCH(1,1): ARCH and GARCH parameters are highly significant indicating that there is a significant positive change in the volatility of the Nifty spot index after the introduction of futures. The leverage effect is insignificant indicating the absence of asymmetric effects in the post-introduction period.

The increase in the ARCH parameter implies that there is a greater impact of the good news on the volatility and that the rate at which news is reflected in prices is higher. An increase in the GARCH coefficient suggests that old news has a higher persistent effect. The leverage effect is lower as in the TGARCH(1,1) analysis and insignificant, indicating no asymmetric effects. In TGARCH(1,1) model, the GARCH coefficient is higher in the post-introduction period indicating that old news has a greater persistent effect on prices with TGARCH models.

4.7 TO SUM UP

One of the most recurring themes in empirical financial research is studying the effect of Derivatives trading on the underlying asset. As exchange-traded stock index futures and other derivatives become more pervasive in the world’s financial markets. The previous literature on the effects of stock index futures trading has focused primarily on developed markets, and it is unclear to what extent these results are applicable to less-developed markets. Moreover, the existing research has come to conflicting conclusions regarding the effect of futures trading on volatility. While some authors have found that volatility appears to increase with the introduction of futures, others have found no significant effect, and still others have found that volatility decreases. Thus, Special interest has to be devoted in analysing whether Derivatives markets stabilize or destabilize the underlying markets in developing countries like India. Many theories have been advanced on how the introduction of Derivatives market might impact the volatility of an underlying asset. The traditional view against the Derivatives markets is that, by encouraging or facilitating speculation, they give rise to price instability and thus amplify the spot volatility. This is called the Destabilization hypothesis. This has led to call for greater regulation to
minimize any detrimental effect. An alternative explanation for the rise in volatility is that Derivatives markets provide an additional route by which information can be transmitted, and therefore, increase in spot volatility may simply be a consequence of the more frequent arrival, and more rapid processing of information. Thus Derivatives trading may be fully consistent with efficient functioning of the markets. This topic has been the focus of attention for both academicians and practitioners alike. In empirical terms, practitioners and regulators are both concerned with different experiences of how the introduction of trading new financial instruments are associated with price volatility.

Thus despite the long debate about the issue of stock market volatility, an agreement seems to be difficult to reach, when it concerns the identification of the sources of stock market volatility, including futures transactions. An increase in volatility of the stock market can simply reflect a change in the underlying economic context, and thus it must not be considered, ex-ante, a market-destabilizing factor. Stock index futures, because of operational and institutional properties, are traditionally more volatile than spot markets. The close relationship between the two markets induces the possibility of transferring volatility from futures markets to the underlying spot markets. There are numerous studies that have approached the effect of the introduction of Index Futures trading from an empirical perspective. Majority of the studies compare the volatility of the spot index or individual component stocks in an index before and after the introduction of the futures contract using different methodologies ranging from simple comparison of variances, to linear regression to more complex GARCH models with different underlying assumptions and parameters in the models.

This chapter studied the volatility of spot and index futures market of India 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. The futures market is showing high level of volatility from that of the spot market. The result also exhibits that bad news have more role in the volatility in the futures as well as in the
spot market. Thus, when an information is released it will first adjusted in the prices in the futures market and after that it passes to the spot market leading lower level of volatility as compared to the index futures market. This effect is popularly called as volatility spillover. In the present study there is a volatility spillover effect from index futures market to the spot market. This volatility behaviour of futures market may be due to recent global financial slowdown that originated from US sub-prime crisis. Therefore, the investors are advised to predict volatility in the cash market by observing volatility in the index futures since volatility in the cash market is a measure of market risk.
REFERENCES


