DERIVATIVE INTRODUCTION AND VOLATILITY: A STUDY IN AMERICAN CONTEXT

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ABSTRACT

Therefore the present study was done in American context to find out the volatility by the derivative introduction in the stock exchange. The objective of the study is to compare the volatility in the NASDAQ and American stock exchange (NYSE). Here researcher has estimated the volatility effect in the NYSE after the introduction of derivative trading. This study was help to understand about the investment decision in the derivative market and also in the stocks. The individual who don’t have sufficient knowledge about the market can also understand the nature of the market by studying the research.

INTRODUCTION

In the last decade, many emerging and transition economies have started introducing derivative contracts. As was the case when commodity futures were first introduced on the Chicago Board of Trade in 1865, policymakers and regulators in these markets are concerned about the impact of futures on the underlying cash market. One of the reasons for this concern is the belief that futures trading attracts speculators who then destabilize spot prices. This concern is evident in the following excerpt from an article by John Stuart Mill (1871): “The safety and cheapness of communications, which enable a deficiency in one place to be, supplied from the surplus of another render the fluctuations of prices much less extreme than formerly. This effect is much promoted by the existence of speculative merchant. Speculators, therefore, have a highly useful office in the economy of society”. Since futures encourage speculation, the debate on the impact of speculators intensified when futures contracts were first introduced for trading; beginning with commodity futures and moving on to financial futures and recently futures on weather and electricity. However, this traditional favorable view towards the economic benefits of speculative activity has not always been acceptable to regulators. For example, futures trading were blamed by some for the stock market crash of 1987 in the USA, thereby warranting more regulation. However before further regulation in introduced, it is essential to determine whether in fact there is a causal link between the introduction of futures and spot market volatility. It therefore becomes imperative that we seek answers to questions like: What is the impact of derivatives upon market efficiency and liquidity of the should these risks be addressed? Can the results from studies of developed markets be extended to emerging markets. This is the first study to examine the impact of financial derivatives introduction on cash market volatility in an emerging market, India. Further, this study improves upon the methodology used in prior studies by using a
framework that allows for generalized auto-regressive conditional it explicitly models the volatility process over time, rather than using estimated standard deviations to measure volatility. This estimation technique enables us to explore the link between information/news arrival in the market and its effect on cash market volatility. The study also looks at the linkages in ongoing trading activity in the futures market with the underlying spot market volatility by decomposing trading volume and open interest into an expected component and an unexpected (surprise) component. Finally this is the first study to our knowledge that looks at the The results of this study are crucial to investors, stock exchange officials and regulators. Derivatives play a very important role in the price discovery process and in completing the market. Their role in risk management for institutional investors and mutual fund managers need hardly be overemphasized. This role as a tool for risk management clearly assumes that derivatives trading do not increase market volatility and risk. The results of this study will throw some light on the effects of derivative introduction on the efficiency and volatility of the underlying cash markets. The study is organized as follows. Section II discusses the theoretical debate and summarizes the empirical literature on derivative listing effects, Section III details the model and the econometric methodology used in this study, Section IV outlines the data used and discusses the main results of the model and finally Section V concludes the study and presents directions for future research.

**Conceptual framework**

**Derivatives**

A derivative is a financial instrument whose value depends on underlying variables. The most common derivatives are futures, options, and swaps but may also include other trade-able assets such as a stock or commodity or non tradeable items such as the temperature .in the case of weather derivatives, the unemployment rate, or any kind of (economic) index. A derivative is essentially a contract whose payoff depends on the behavior of a benchmark. One of the oldest derivatives is rice futures, which have been traded on the Dojima Rice Exchange since the eighteenth century. Derivatives are broadly categorized by the relationship between the underlying asset and the derivative (e.g., forward, option, swap); the type of underlying asset (e.g., equity derivatives, foreign exchange derivatives, interest rate derivatives, commodity derivatives or credit derivatives); the market in which they trade (e.g., exchange-traded or over-the-counter); and their pay-off profile. Derivatives can be used for speculating purposes ("bets") or to hedge ("insurance"). For example, a speculator may sell deep in-the-money naked calls on a stock, expecting the stock price to plummet, but exposing himself to potentially unlimited losses. Very commonly, companies buy currency forwards in order to limit losses due to fluctuations in the exchange rate of two currencies.

**Volatility**

It is a statistical measure of the dispersion of returns for a given security or market index. Volatility can either be measured by using the standard deviation or variance between returns from that same security or market index. Commonly, the higher the volatility, the riskier the security.

A variable in option pricing formulas showing the extent to which the return of the underlying asset will fluctuate between now and the options expiration. Volatility, as expressed as a percentage coefficient within option-pricing formulas, arises from daily trading activities. How
volatility is measured will affect the value of the coefficient used. In other words, volatility refers to the amount of uncertainty or risk about the size of changes in a security’s value. A higher volatility means that a security’s value can potentially be spread out over a larger range of values. This means that the price of the security can change dramatically over a short time period in either direction. A lower volatility means that a security’s value does not fluctuate dramatically, but changes in value at a steady pace over a period of time. One measure of the relative volatility of a particular stock to the market is its beta. A beta approximates the overall volatility of a security’s returns against the returns of a relevant benchmark (usually the S&P 500 is used). For example, a stock with a beta value of 1.1 has historically moved 110% for every 100% move in the benchmark, based on price level. Conversely, a stock with a beta of .9 has historically moved 90% for every 100% move in the underlying index.

### NASDAQ

The NASDAQ (National Association of Securities Dealers Automated Quotations) is actually an exchange system that prices and trades stocks, but many investors use it like an index, to measure how tech stocks are doing. NASDAQ is the second largest electronic screen-based equity market in the United States with approximately 3300 companies. NASDAQ records more companies and, on regular, trades more shares each day than any other markets in United States. NASDAQ relies on a computerized system to price and exchange stocks. It provides instant quotes for securities because it does not rely on a trading floor, the usual practice of other stock exchanges. NASDAQ is concerned with the over-the-counter (OTC) stock market, and when you buy or sell on the NASDAQ, your broker only needs to enter the stock quotes and stock information for the security in question on a computer. The computer will find the best price on the stock in question and the transaction will be completed. NASDAQ allows transactions to be completed by teletype, telephone or from company inventory. Companies that wish to be listed on the NASDAQ need to have at least 100 000 publicly held shares, and usually at least a minimum of $1 million in assets. At first, the company in question must also have at least 500 shareholders to qualify for a listing. Once the company is listed on NASDAQ, the company must have at least 300 shareholders to avoid losing their position on the NASDAQ. The NASDAQ 100 Index is a composite of the biggest companies (all non-financial institutions) which are listed on the NASDAQ stock market. This index, which has been published since 1985, helps investors and finance professionals make market and investment decisions. The index includes all key industry groups and is evaluated four times a year to ensure that it does not need to be rebalanced.

### REVIEW OF LITERATURE

#### Research in the Indian context

Froot and Perold(1991) found that market depth is increased by more rapid dissemination of market-wide information and the presence of makers in the futures market in addition to the cashmarket.

Ross (1989) assumes that there exists an economy that is devoid of arbitrage and proceeds to provide a condition under which the no-arbitrage situation will be sustained. It implies that the variance of the price change will be equal to the rate of information flow. The implication of this
is that the volatility of the asset price will increase as the rate of information flow increases. Thus, if futures increase the flow of information, than in the absence of arbitrage opportunity, the volatility of the spot price must change. Overall, the theoretical work on futures listing effects offer no consensus on the size and the direction of the change in volatility. We therefore need to turn to the empirical literature on evidence relating to the volatility effects of listing index futures and options. 

Gulen and Mayhew (2000) find that futures trading is associated with increased volatility in the United States and Japan. In some countries, there is no robust, significant effect, and in many others, volatility is lower after futures have been introduced. Nathan Associates (1974) was the first to study the impact of listing options on the Chicago Board of Exchange. He reported that the introduction of options seemed to have helped stabilize trading in the underlying stocks. 

McCann and Webb (1994) and Bollen (1998) found that the direction of the volatility effect is not consistent over time. After 1987, the residual variance of both optioned stocks and stocks in a matched control group increased at the time of the option listing. This might be interpreted in two ways; viz, perhaps the listing has no true impact on volatility and there is some common unknown factor that is driving the magnitude of the idiosyncratic risk for different stocks. Or perhaps, there are spill over effects associated with listing options for some stocks, such that the dynamics of other stocks also changes. 

Sarin and Shastri (1995) found that the volume in the underlying stock does increase after the introduction of stock options. Studies have also found that after the introduction of options, prices tend to reflect new information more quickly, bid-ask spreads narrow, and the adverse selection component of the spread becomes smaller. Relatively few authors have studied the impact of stock index options listing on volatility in the cash market. Poon and Zee (1997 was found that increase in volatility for options on OTC stocks in the USA. However no consensus result emerges, which probably a result of different data and time-periods studied, as also the inherent endogenously of the option listing decision. 

**Research in American context**

Huang and Stoll (1998) analyzed the dollar contract value, trade size, and tick size of the CME’s S&P 500 index futures contract over time and relative to the dollar value of equity index futures traded on non-United States exchanges. Their analysis suggested that it would be appropriate for the CME to split the size of the S&P 500 futures contract, because the dollar value of a single contract had increased to such an extent that it had become too large for smaller investors to trade efficiently. 

Karagozoglu and Martell (1999) found that the impact of futures contract splits on market liquidity, by examining the experience of two futures contracts traded on the Sydney Futures Exchange (SFE). They found that changes in contract size were inversely related to market liquidity. 

Smith, and Whaley (2003) found that the futures contract split is conceptually akin to a stock split in the equity markets. Accordingly, we also reviewed the academic literature regarding the effects of stock splits on market quality issues. A principal purpose of stock splits is to reduce stock prices to a desirable level in order to attract additional investors and thereby enhance trading liquidity.
Maloney and Mulherin (1992) examined 384 Nasdaq equities that split between 1985 and 1989, and found that the number of shareholders of all types increased by 23.4 percent following the stock splits. They also found that the percentage of institutional shareholders increased as well. Copland (1979) examined the impact of stock splits on liquidity. He found that trading volume, after adjusting the level to account for the stock split, decreases following a stock split. Lamoureux and Poon’s (1987) study of stock splits and reverse splits for 215 stocks traded on the New York Stock Exchange and the American Stock Exchange, during the period 1968-1976, found that a stock split increased volatility, and a reverse split decreased volatility. They also found that split-adjusted trading volume decreased following a stock split. The literature on the effects of equity market fragmentation (trading the same equity on two or more exchanges) has been inconclusive.

Objective of the study is to compare the volatility in the NASDAQ and American stock exchange.

Research Methodology

The study was Descriptive. Daily data of NASDAQ was used for a period of April 2000 to March 2011. Along with this the data of American stock exchange on which derivative product are introduced is also collected, therefore the sample size is of two stock indices. Each index was act as a sample element. Non probability judgmental sampling technique was used. For Data Analysis ADF and P-P test was used for the testing unit root test in the series, JARQUE-BERA test for checking normality and GARCH (1,1) model for forecasting the time series.

The GARCH(1,1) model is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

where $\alpha_0$ is the mean, $\varepsilon_{t-1}^2$ is the ARCH term and $\sigma_{t-1}^2$ is the GARCH term.

RESULT & DISCUSSION

To fulfill the objectives of the research, the two variate GARCH-in mean model is estimated for two indexes. They index used in the study are the following – NASDAQ and the American stock index. For each index the variables collected include the daily closing price of different index. The data frequency is daily, insuring a sufficient high number of observations. The sample period varies depending upon data availability for two indexes; it goes from 01.04.2000 to 31.03.2011. The daily value of the index closing price on the 10 years and the daily price of derivative in the NASDAQ index of 10 years from 01.04.2000 to 31.03.2011 are used for the empirical tests. For the study purpose, the NASDAQ closing price data is divided into two categories: BNASDAQ: It represents closing values from time period of year 2000 to
2011 (values before the inception of NYSE) and ANASDAQ: It represents closing price data of NASDAQ after the inception of NYSE.

To estimate the volatility effect in the NYSE after the introduction of derivative trading, GARCH parameters needed to be estimated. Before proceeding for GARCH, the data was checked for normality and stationarity. Along with this, certain characteristics of data were also found using the below given statistic.

**Descriptive Statistics**

Below given table shows the values for mean, median, maximum, minimum, standard deviation, skewness, kurtosis, probability, and observation for the data under consideration. The Standard Deviation for the NASDAQ data series comes out to be maximum. The NASDAQ series is rightly skewed and NYSE series is negatively skewed.

<table>
<thead>
<tr>
<th></th>
<th>BNASDAQ</th>
<th>NYSE</th>
<th>ANASDAQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.000363</td>
<td>0.000127</td>
<td>6.25e-06</td>
</tr>
<tr>
<td>Median</td>
<td>0.000000</td>
<td>0.000462</td>
<td>0.000423</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.077685</td>
<td>0.028780</td>
<td>0.071201</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.060861</td>
<td>-0.032920</td>
<td>-0.049920</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.013532</td>
<td>0.007658</td>
<td>0.011101</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.214937</td>
<td>-0.445386</td>
<td>0.136164</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>5.705801</td>
<td>5.195883</td>
<td>0.195883</td>
</tr>
<tr>
<td>Probability</td>
<td>0.000000</td>
<td>0.000000</td>
<td>0.000000</td>
</tr>
<tr>
<td>Observations</td>
<td>1024</td>
<td>1024</td>
<td>1024</td>
</tr>
</tbody>
</table>

**Normality Test**

Jarque-Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as with 2 degrees of freedom. The reported Probability is the probability that a Jarque-Bera statistic exceeds (in absolute value) the observed value under the null hypothesis—a small probability value leads to the rejection of the null hypothesis of a normal distribution.
Below given chart displays a view containing a histogram and descriptive statistics for BNASDAQ

Here the value of Jarque Bera- statistic is 325.8920 at 0% probability. Hence we reject the null hypothesis of normal distribution at 5% level of significance.

Below given chart displays a view containing a histogram and descriptive statistics for NYSE
Here the value of Jarque Bera-statistic is 243.8009 at 0% probability. Hence we reject the null hypothesis of normal distribution at 5% level of significance.

Below given chart displays a view containing a histogram and descriptive statistics for ANASDAQ
Here the value of Jarque Bera statistic is 846.4355 at 0% probability. Hence we reject the null hypothesis of normal distribution at 5% level of significance.

Unit Root Test

1. ADF Test
In statistics and econometrics, an augmented Dickey–Fuller test (ADF) is a test for a unit root in a time series sample. It is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models. The augmented Dickey–Fuller (ADF) statistic, used in the test, is a negative number. The more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of confidence.

Null Hypothesis: $D\log(\text{BNASDAQ})$ has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic based on SIC, MAXLAG=21)

<table>
<thead>
<tr>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augmented Dickey-Fuller test statistic</td>
<td>-33.03901</td>
</tr>
</tbody>
</table>

Test critical values:
- 1% level: -3.436413
- 5% level: -2.864106
- 10% level: -2.568188


The ADF statistic value is -33.03901 and the associated one-sided p-value (for a test with 221 observations) is -2.864106. Here the statistic value is lesser than the critical values so that we reject the null at conventional test sizes. This shows that the series has no unit root.

Null Hypothesis: $D\log(\text{NYSE})$ has a unit root
Exogenous: Constant
Bandwidth: 19 (Newly-West using Bartlett kernel)

<table>
<thead>
<tr>
<th>Adj. t-Stat</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phillips-Perron test statistic</td>
<td>-36.01722</td>
</tr>
</tbody>
</table>

Test critical values:
- 1% level: -3.436413
- 5% level: -2.864106
- 10% level: -2.568188
The ADF statistic value is -36.01722 and the associated one-sided p-value (for a test with 221 observations) is -2.864106. Here the statistic value is lesser than the critical values so that we reject the null at conventional test sizes. This shows that the series has no unit root.

### Null Hypothesis: DLOG(ANASDAQ) has a unit root

**Exogenous:** Constant  
**Lag Length:** 0 (Automatic based on SIC, MAXLAG=21)

<table>
<thead>
<tr>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augmented Dickey-Fuller test statistic</td>
<td>-35.82291</td>
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### 2. Phillips Perron TEST

The unit root for serial correlation and stationary tests are performed Phillips and Perron (P-P) unit root tests. For P-P test Newey-West Bandwidth is preferred.

**PP Test** - It is a generalization of the proceedings of the DF, but unlike this, allows for autocorrelation and heteroskedasticity in the error term, which consists of three data generating processes: model without deterministic component, model and model intercept and trend, however it is not the augmented, so this test is a nonparametric solution, i.e. not follow any known distribution.

\[ \Delta Y_t = \Delta \beta + p Y_{t-1} + \Delta t \]
The hypothesis is prepared to check out whether the dependent variable (returns of stock indices) is stationary or not and whether it has any unit root or not.

- **Null Hypothesis, Ho:** The dependent variable (closing price of index) is not stationary and it has a unit root.
- **Alternative Hypothesis, Ha:** The dependent variable (closing price of index) is stationary and it has no unit root.

**Null Hypothesis: DLOG(BNASDAQ) has a unit root**

**Exogenous: Constant**

Bandwidth: 13 (Newey-West using Bartlett kernel)

<table>
<thead>
<tr>
<th>Phillips-Perron test statistic</th>
<th>Adj. t-Stat</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>-33.50231</td>
<td>0.0000</td>
<td></td>
</tr>
</tbody>
</table>

Test critical values:

<table>
<thead>
<tr>
<th>Level</th>
<th>Phillips-Perron test statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>-3.436413</td>
</tr>
<tr>
<td>5%</td>
<td>-2.864106</td>
</tr>
<tr>
<td>10%</td>
<td>-2.568188</td>
</tr>
</tbody>
</table>


Residual variance (no correction) 0.000182
HAC corrected variance (Bartlett kernel) 0.000137

As with the ADF test, we reject the null hypothesis of a unit root in the series at conventional significance levels. The series is stationary.

**Null Hypothesis: DLOG(NYSE) has a unit root**

**Exogenous: Constant**

Bandwidth: 19 (Newey-West using Bartlett kernel)

<table>
<thead>
<tr>
<th>Phillips-Perron test statistic</th>
<th>Adj. t-Stat</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>-36.01722</td>
<td>0.0000</td>
<td></td>
</tr>
</tbody>
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Test critical values:

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<tr>
<td>10%</td>
<td>-2.568188</td>
</tr>
</tbody>
</table>

As with the ADF test, we reject the null hypothesis of a unit root in the series at conventional significance levels.

**Null Hypothesis: DLOG(ANASDAQ) has a unit root**
Exogenous: Constant
Bandwidth: 20 (Newey-West using Bartlett kernel)

<table>
<thead>
<tr>
<th>Phillips-Perron test statistic</th>
<th>Adj. t-Stat</th>
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</tr>
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<td></td>
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<td></td>
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<td>-2.568188</td>
<td></td>
</tr>
</tbody>
</table>


As with the ADF test, we reject the null hypothesis of a unit root in the series at conventional significance levels.

**Summary of Results:**
The summary of result of test is shows in the form of table below-

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Test</th>
<th>CRITICAL VALUE</th>
<th>P-P Test</th>
<th>CRITICAL VALUE</th>
<th>P-P Test results</th>
</tr>
</thead>
<tbody>
<tr>
<td>BNASDAQ</td>
<td>-2.864106</td>
<td>-33.03901</td>
<td>-2.864106</td>
<td>-33.50231</td>
<td>Null hypothesis is rejected. Series is Stationery.</td>
</tr>
<tr>
<td>ANASDAQ</td>
<td>-2.864106</td>
<td>-35.82291</td>
<td>-2.864106</td>
<td>-37.77390</td>
<td>Null hypothesis is rejected. Series is Stationery.</td>
</tr>
</tbody>
</table>

**GARCH**
Autoregressive Conditional Heteroskedasticity (ARCH) models are specifically designed to model and forecast conditional variances. The variance of the dependent variable is modeled as a function of past values of the dependent variable and independent or exogenous variables. ARCH models were introduced by Engle (1982) and generalized as GARCH (Generalized ARCH) by Bollerslev (1986) and Taylor (1986). These models are widely used in various branches of econometrics, especially in financial time series analysis. See Bollerslev, Chou, and Kroner (1992) and Bollerslev, Engle, and Nelson (1994) for recent surveys.

The GARCH (1, 1) Model

We begin with the simplest GARCH (1.1) in which the mean equation is written as a function of exogenous variables with an error term. Since is the one-period ahead forecast variance based on past information, it is called the conditional variance. The conditional variance equation is a function of three terms:

- A constant term:
- News about volatility from the previous period, measured as the lag of the squared residual from the mean equation: (the ARCH term).
- Last period’s forecast variance: (the GARCH term).

The GARCH(1,1) model is given by

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \]

where \( \alpha_0 \) is the mean, \( \varepsilon_{t-1}^2 \) is the ARCH term and \( \sigma_{t-1}^2 \) is the GARCH term.

The results of the Garch estimation are discussed below in the table. The dependent variable is closing series data of NASDAQ.
The main output from ARCH estimation is divided into two sections—the upper part provides the standard output for the mean equation, while the lower part, labeled “Variance Equation”, contains the coefficients, standard errors, z-statistics and p-values for the coefficients of the variance equation. The ARCH parameters correspond to alpha and the GARCH parameters to beta in the equation the sum of the ARCH and GARCH coefficients (.075149+.901655) and are very close to one, indicating that volatility shocks are quite persistent. This result is often observed in volatility. There are many studies supporting the results like Singh and Mehta(2010).

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.000763</td>
<td>0.000357</td>
<td>2.140798</td>
</tr>
<tr>
<td>DLOG(NYSE)</td>
<td>0.019942</td>
<td>0.044433</td>
<td>0.448810</td>
</tr>
</tbody>
</table>

**Variance Equation**

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>3.99E-06</td>
<td>1.01E-06</td>
<td>3.938753</td>
</tr>
<tr>
<td>RESID(-1)^2</td>
<td>0.075149</td>
<td>0.009694</td>
<td>7.752532</td>
</tr>
<tr>
<td>GARCH(-1)</td>
<td>0.901655</td>
<td>0.010679</td>
<td>84.43355</td>
</tr>
</tbody>
</table>

- R-squared: -0.001089, Mean dependent var: 0.000363
- Adjusted R-squared: -0.004951, S.D. dependent var: 0.013532
- S.E. of regression: 0.013565, Akaike info criterion: -5.914509
- Sum squared resid: 0.190828, Schwarz criterion: -5.890762
- Log likelihood: 3086.459, Durbin-Watson stat: 2.034060
found the same volatility results for Asian stock market, Singh et.al (2010) for Japanese and Indian Market.

**FORECASTING:**

Forecast uses the estimated ARCH model to compute static and dynamic forecasts of the mean, its forecast standard error, and the conditional variance. The results of forecasting shows for BNASDAQ (i.e. time period before the formation of NYSE) show high volatility in forecast. The forecast for ANASDAQ (Series data after 2004, trading of derivatives shows that volatility in series will rise.
Similarly, the results of forecasting shows for ANASDAQ (i.e. time period before the formation of NYSE) show high volatility in forecast. The forecast for ANASDAQ (Series data after 2004, trading of derivatives shows that volatility in series will rise.

![Forecast: ANASDAQF
Actual: DLOG(ANASDAQ)
Forecast sample: 1/03/2000 12/31/2003
Adjusted sample: 1/04/2000 12/31/2003
Included observations: 1042
Root Mean Squared Error 0.011108
Mean Absolute Error 0.007898
Mean Abs. Percent Error 103.8886
Theil Inequality Coefficient 0.966305
Bias Proportion 0.000692
Variance Proportion 0.950804
Covariance Proportion 0.048504

![Forecast of Variance]

**CONCLUSION**

This study examines the transmission of volatility in derivative price on stock index of NASDAQ and NYSE and also looks about the effect of interest rate on returns of stock markets. In this study, we have studied the effect of volatility of derivative on the stock market with the help of GARCH (1,1) model. For applying this research some assumptions are taken into consideration like normality check and stationery check. Our whole data is found to be normally distributed (by Jarque-Bera test) and the time series proven as stationery. For stationery check
Augmented Dickey-Fuller (ADF) and Phillips and Perron (P-P) unit root test were used and the result shows that the dependent variable series at 5% is stationary and therefore has no unit root.

GARCH was used to check causality-in-variance running from the derivative price volatility to the stock market index volatility of the selected indices for the study. The study evaluated the impact of introduction of derivative products on spot market volatility in US stock markets. We found that the volatility in both NYSE and NASDAQ has risen in the period after index future was introduced. Tests of no causality in mean effect is used to check out whether there is any impact of independent variable (NYSE) on dependent variable (NASDAQ). In close, the empirical results of this study indicate that there has been a change in the market environment since the year 2004, which is reflected in the increase in volatility in all the NYSE and NASDAQ. The impact of a derivative product, however, on the spot market depends crucially on the liquidity characterizing the underlying market. Thus, while NASDAQ incorporates only the market effects, the increase in volatility due to “future’s effect” plays a significant role in the case of NYSE.

Reference


• Shastri (1995),” The Case of Equity Index Futures” *Journal of Finance*, 50, 1767-1774.
