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RETHINKING THE EXPIRATION HOUR EFFECT: A HIGH FREQUENCY GARCH ANALYSIS

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ABSTRACT

The impact of derivatives trading on the underlying stock market has been widely documented in the Finance literature. In particular, significant differences in the statistical properties of asset returns (for instance, mean and variance) during expiration and non-expiration days have been advanced as *an* evidence for the destabilization effect (or lack thereof) of derivative instruments. The earlier studies have, however, drawn their conclusions without rigorously modelling the underlying stochastic data generation process. Given that the statistical properties mentioned before are merely traits of the asset returns, this approach can lead to spurious results if analysed in isolation of the underlying process. We propose to address this crucial shortcoming by examining the expiration day effect from a GARCH framework. We use both daily and high frequency (5 minutes and 10 minutes) data on S&P CNX Nifty Index. Our central finding using intra-day data is that while there is no pressure – downward or upward - on index returns, the volatility is indeed significantly affected by the expiration of contracts. This effect, however, doesn't show up in daily data.

I. Introduction:

It is widely acknowledged today that trading in derivatives affects the underlying spot market in one of the following ways: (a) since they provide a cheap alternate conduit for dissemination of information, derivative instruments make the price discovery mechanism more efficient; (b) the trading activities of speculators, who are attracted by the excessive leverage offered by these instruments, and the unwinding operations of index arbitrageurs destabilize the underlying stock market.

One prominent strand of literature that seeks to provide evidence for the latter viewpoint examines the abnormal price and volatility movements (or lack thereof) during the expiry period of the derivative contracts. These studies essentially strive to answer a question that is of equal importance to the regulators, traders and investors: *Are there persistent pressures, upward or downward, on the returns and/or volatility at the time of expiry of the derivatives contract?* A persistent pattern of excessive returns would suggest potential profitable trading strategies for the trader; the regulator will have reasons to worry if there is a non insignificant increase in volatility during periods close to expiration.

Empirical evidence favoring increased trading volume, abnormal volatility and economically insignificant price pressures on expiration day was first documented by Stoll and Whaley (1986, 1987). Evidence from international markets, though differing in the specifics, concurs broadly with the above results: Karolyi (1996) for Japan, Bollen and Whaley (1999) for Hong Kong, Pope and Yadav for UK (1992), Schlag (1996) for Germany and Stoll and Whaley (1997) for Australia. A summary of their key findings is presented in Table 1. Oddly, most of the studies have not made an attempt to model the data generating process[1]; they have merely compared the *unconditional* mean and variance of returns on expiration days with those observed on non-expiration days. We propose to address this rather significant shortcoming. Our motivation is in the spirit of De Jong et.al. (1992)'s conclusion that effective modeling of the underlying process governing the stock returns is crucial in validating *any* inference made about the expiration day effects. Analyzing the expiration day effects while *simultaneously* modeling the data generating process using the more robust Generalized Auto Regressive Conditional Heteroskedastic (GARCH) model is our chief contribution to the literature.

Price distortions caused by trading activities around the expiration day would be transient in nature and prices should *revert* to their previous levels. This effect, usually dubbed the *price reversal,* has been examined in earlier studies by comparing the return over the expiration period with the close-open return. This approach overlooks the fact that price reversal is merely a trait of the asset return process and should not be viewed in isolation of the data generation process. We correct for this crucial oversight by extending our GARCH model.

As is obvious, the outcome of this study hinges critically on robustly modeling the underlying stochastic process. Towards this end, we use continuous high frequency data (sampled at frequencies of 5 minutes and 10 minutes) for the entire period under study.

[1] The only notable exception is the study by Hancock (1991); however, the author chooses not to model the entire sample data. Rather, he builds one GARCH model for every expiration day and every non-expiration day - a total of 28 models!

By choosing Indian markets for demonstrating our approach, we hope to fill a significant gap in the literature on this emerging market.

Before proceeding further, we would like to formally clarify our usage of the terms “expiration day” and “expiration hour”. Expiration day refers to the last Thursday, when all contracts (index futures, index options, stock futures, stock options) expire; expiration hour refers to the last *half-hour* of the expiration day. The latter definition is motivated by the fact that the last half-hour weighted average price of the underlying is used in cash-settling all open contracts. At this juncture, we would also like to briefly mention about another term that is widely used in this strand of literature, namely the “triple witching hour”. This is the last hour on expiration day when all contracts (index options, index futures, stock options) expire. In the Indian context, it would be more appropriate to call this as “quadraple witching hour” since individual stock futures also expire along with the aforementioned contracts.

Our analysis gathers some preliminary evidence on the expiration day effect using data of lower frequency – daily data. The effect of expiration day on both conditional mean and variance of the returns is found to be insignificant. However, empirical analysis on high frequency data narrates a different tale: during the expiration hour, though there is no price pressure, we *do* find significant increase in the conditional variance. Of greater import is the presence of a significant upward pressure during the first half-hour of trading on the day *after* the expiration day. This could imply one of the two possibilities: (a) the market participants demand excess returns to commensurate for a non-existent price pressure; (b) systematically, positive (or negative) news is released to market after the expiration of the spot month contract. We discuss these results and their implications in Section 5. In Section 2, we provide a quick overview of the Indian derivatives market. The data used in this study along with some useful descriptive statistics of the same is presented in Section 3. We elaborate further on our model in Section 4. We conclude with our comments on the current settlement procedure in Section 6.

II. Equity Derivatives in India

Equity Derivatives are relatively new phenomena in Indian markets. Futures on the index were first introduced by National Stock Exchange (NSE) in June 2000. This was followed by introduction of options on the index (June 2001), stock options (July 2001) and stock futures (November 2001). In the short period since inception, the derivative segment has exploded in volume; by September 2002, the average daily turnover in this segment had surpassed that of the cash segment. Figure 1 shows the trading volume of derivative contracts traded on the National Stock Exchange during the period 2001-2004. Current contract specifications are outlined in Table 2.

In this study, we propose to examine the effect of index futures on the S&P CNX Nifty. Nifty comprises of fifty liquid stocks, each stock being awarded a weight in proportion to its relative market capitalization. The constituent stocks represent a wide range of industries and their total market capitalization accounts for about 60% of the market capitalization of the Indian equity market.

The empirical evidence on Indian stock market (Thenmozhi, 2002; Gupta, 2002; Shenbagaraman, 2003; and Kiran & Mukhopadhyay, 2003) show that derivative products in general, and index futures in particular, have not destabilized the spot market volatility. The above-mentioned studies have essentially strived to detect an increase, if any, in the volatility of spot market after the derivatives introduction. However, none of these studies have attempted to examine the impact of derivative contracts on the behavior of spot market during the expiration hour.

III. Data

For our preliminary analysis, we use daily data on the index. This data is readily available in the public domain; we obtained the data from the website of National Stock Exchange (http://www.nseindia.com). We use data for the period June 2000 (corresponding to the inception of index futures) through August 2004.

We use the high frequency data on S&P CNX Nifty Index (Nifty hereafter) made available to us by the National Stock Exchange. The database provides tick-by-tick trade data for individual stocks; the index is also updated instantaneously and its value recorded. Given that the intra-day data is irregular (on a normal time scale), the interval at which the data is sampled reflects a trade-off between *not* losing valuable information about the temporal pattern in returns and avoiding spurious autocorrelation in the returns (normally attributed in literature to, among others, bid-ask bounce). We choose to sample the data at frequencies of five minutes and ten minutes; to be more specific, we use the first available price in every five- (ten) minute period.

We use data from January 2003 through June 2003 (the latest intra-day data that NSE provides) for our analysis. In this period, we have six expiration days and the remaining days are non-expiration days. The term “non-expiration days” as it is usually used in this branch of study is, unfortunately, a misnomer. For instance, if a particular derivative contract expires on last Thursday, the third Thursday or the second Thursday or some combination thereof is taken as “non-expiration days”. Though the argument that considering data from comparable periods would remove any seasonal effect (such as day of the week effect) has high merit, we believe that it is a highly constraining one[2]. In essence, by taking this approach, we distance ourselves from the underlying data generating process and this can potentially lead to spurious results.

III.A. Descriptive Statistics

We offer some basic descriptive statistics of the data in Table 3**;** the raw return series are plotted in Fig 2. It can be observed that the variance of returns on expiration days (hour) is higher than that on non-expiration days (hour). The reported F-statistic for the variance comparison suggests that the differences are significant at all frequencies. The measures for skewness and kurtosis indicate that compared with normal distributions, all return series are skewed and highly leptokurtic; this is reinforced by the highly significant Jarque-Bera statistic. Before performing further analysis, it is imperative to ensure that the return series is stationary. Returns at all frequencies are subjected to Augmented Dickey-Fuller tests and the null hypothesis of unit root is strongly rejected in all cases.

[2] A more robust approach would be to use the entire sample data and capture such effects using appropriate *day of week* dummy variables.

Fig 2 provides some preliminary evidence in favour of time-varying volatility; all return series display volatility clustering. The correlogram of returns and squared returns up to lag 16 is plotted in Fig 3 for different frequencies; the corresponding Ljung-Box statistic is also reported. The presence of significant autocorrelations in returns and squared returns suggest strong linear and nonlinear dependence, respectively. These features, significant autocorrelation among squared returns and excess kurtosis, are compatible with the volatility clustering phenomenon that has been documented in studies involving high frequency studies; for instance, Bollerslev, Chou and Kroner (1992), Pagan(1996), Goodhart & O'Hara (1997). These statistics motivate the need for GARCH type models that can easily accommodate the observed time varying and persistent patterns in return volatility.

IV. Model

This section presents the approach used in measuring the expiration day effect of derivatives trading. As mentioned earlier, the existing studies on expiration day effects contend themselves with comparing unconditional means and variances by applying classical hypothesis testing procedures like t- and F-tests; however, they do not account for stylized features of high frequency financial data such as time varying volatility, skewness and excess kurtosis. The Generalized AutoRegressive Conditional Heteroscedasticity (GARCH) model proposed by Bollerslev (1986) has been widely used in finance literature to explicitly capture these empirical features. The GARCH framework not only aids in explicitly capturing the time varying nature of volatility but also provide an avenue for verifying the presence of endogenous drivers of volatility shifts. Since this approach meets our twofold objective of robustly modeling the data generating process and verifying the impact, if any, of trading on expiration days, we choose this framework for our analysis.

In the spirit of Pagan and Schwert (1990) and Engle and Ng (1993), as the first step in GARCH modeling of high frequency return series, we remove any predictability associated with lagged returns[3] by incorporating the required number of AR and MA terms. To study the impact of expiration day on the conditional mean, we include a dummy variable for the expiration hour. Since we intend to verify the presence of price reversal, we also include another dummy for the first half-hour of trading on the day after the expiration day. For each of the return series, the conditional mean equation is specified thusly:

$$R_t = \alpha_0 + \sum_{k=1}^{r} \alpha_k R_{t-k} + \sum_{l=1}^{s} \phi_l \varepsilon_{t-l} + \lambda_1 Exp_t + \lambda_2 Next_t + \varepsilon_t \qquad (1)$$

where R_t is the logarithmic return over the sampling period (daily or 5-minute or 10-minute), Exp_t is the dummy for expiration period and $Next_t$ is the dummy for the opening half-hour of the day succeeding the expiration day. If the coefficient of dummy Exp_t turns up significant and negative (positive), then one can affirm the presence of downward (upward) pressure on the *conditional* return during the expiration period. Further, if coefficients of both Exp_t and $Next_t$ turn up significant and have different (same) sign,

[3] We have not accounted for day-of-week effects in this version. This can be and will be accounted for in the future.

presence of price reversal (price continuation) can be validated. An interesting scenario would arise if one finds Exp_t insignificant and $Next_t$ significant. As mentioned earlier, this could imply that either market participants demand excess returns to commensurate for a non-existent price pressure or systematically, positive (or negative, depending on the sign of λ_2) news is released to market after the expiration of the spot month contract.

If the residuals obtained from equation (1) exhibit autocorrelation in their squared series and excess kurtosis, then it suggestive of time-varying volatility, which would in turn motivate the need for GARCH modeling. The standard GARCH(p,q) model can be expressed as follows:

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t)$$
$$h_t = \beta_0 + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j} \tag{2}$$

where ε_t is the error in the conditional mean equation and Ω_t represents the universe of information available at time *t.* The coefficients of the moving average component of conditional variance, β_i, are typically interpreted as "news coefficients" that measure the impact of recent news on volatility; γ_j, the coefficients of the autoregressive component of conditional variance, are similarly interpreted as "persistence coefficients" that measure the impact of "less recent" or "old" news on current volatility. The abovementioned interpretation for coefficients in the conditional variance is widely employed in literature; for instance, Antoniou and Holmes (1995) and Butterworth (2000). To ensure that the conditional variance is never negative, zero, or infinite, the values of β_i and γ_j have to be between 0 and 1. Further, the model is covariance stationary if and only if $\sum_{i=1}^{q}\beta_i + \sum_{j=1}^{p}\gamma_j < 1$.

To examine the expiration day effect on conditional variance, we augment the conditional variance equation (2) with the dummies introduced in the mean equation as follows:

$$
\begin{gathered}
R_t = \alpha_0 + \sum_{k=1}^{r}\alpha_k R_{t-k} + \sum_{l=1}^{s}\phi_l \varepsilon_{t-l} + \lambda_1 Exp_t + \lambda_2 Next_t + \varepsilon_t \\
\varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t) \\
h_t = \beta_0 + \sum_{i=1}^{q}\beta_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p}\gamma_j h_{t-j} + \delta_1 Exp_t + \delta_2 Next_t
\end{gathered}
\tag{3}
$$

A positive (negative) significant value for δ_1 would suggest the presence of upward (downward) pressure on the conditional variance during the expiration period. A positive (negative) significant δ_1 coupled with a negative (positive) significant δ_2 would imply that the shift in volatility induced by trading during expiration day is transient and is reversed immediately.

The conditional mean and variance parameters in (3) can be estimated using the QML technique of Bollerslev and Wooldridge (1992); for optimization, we use the Broyden, Fletcher, Goldfarb and Shanno (BFGS) quasi-Newton algorithm. Though a standard ARMA-GARCH model with normality assumption adequately captures time-varying volatility, it might be ineffective in capturing the excess kurtosis or fat tails that are present in raw returns. If the conditional mean and conditional variance are correctly specified, the quasi-maximum likelihood estimator is consistent under the assumption that errors follow normal distribution. Though these estimators are unbiased, they are inefficient; the degree of inefficiency increasing with the degree of departure from normality (Engle et al 1991). Further, it may be expected that excess kurtosis displayed by the residuals of a standard GARCH model will be reduced when a more appropriate distribution is used. Student-t (Bollerslev 1987, Beine et al 2002) and Generalized Error Distribution (Nelson 1991, Kaizer, 1996) are two fat-tailed distributions that are widely used in empirical literature in place of normal distribution. In this study, we use Student-t distribution wherever normal distribution gives suspicious results.

V. Empirical Results

V.A. Preliminary analysis using daily data

We first estimate the conditional mean and variance as specified in equation 3 for daily return series; the corresponding results are reported in Table 4. On the basis of AIC model selection criteria, we choose the MA(1) – GARCH(1,1) model. It can be observed that the estimated GARCH model is stable as the sum of $\beta_1+\gamma_1$ is less than one. The model diagnostic graph, namely the correlogram of residuals and residual squares, is displayed in Fig 4A**.** Portmanteau Ljung-Box statistics up to lag 16 for both residual and residual squares is reported in Table 4. These diagnostics suggest that the residuals of the estimated model are reasonably well behaved and that most of the conditional dependency in returns and squared returns have been captured by the model. The insignificant LM test statistics suggests absence of further ARCH effects.

The coefficients of expiration day dummies in the mean and variance equation (as specified in equation 3) are clearly insignificant; hence we can reject the hypothesis that expiration day trading has an impact on daily returns of Nifty. The coefficients of $Next_t$ are also insignificant; hence, there is no reversal in either the mean or volatility of returns immediately after the expiration day. Finally, to examine the relationship between volume and volatility, we augment equation 3 with daily volume series variable (δ_3) and a multiplicative volume dummy variable (δ_4). We do not find any evidence to suggest any volume-volatility relationship for the period considered. In essence, using daily data we conclude that expiration of derivatives contract is a “no-event”.

V.B. Analysis of high frequency data

The conditional mean and variance for 5-minute returns is estimated by assuming error distribution to be Normal; the results are summarized in Table 5. Since the measure of persistence, $\beta_1+\gamma_1$, is more than one, the parameter estimates are not stable indicating a high persistence of volatility shocks. At such high frequencies, this is expected see Goodhart & O'Hara (1997). The Normal distribution predicts a kurtosis of 3, while the data sampled at five minutes has a leptokurtic distribution (kurtosis of 27), meaning that returns are more peaked around zero than the corresponding normal distribution. Under these circumstances, the estimators will still be unbiased but the standard errors will be understated. Thus, hypothesis-testing procedures become unreliable (for instance, Baillie and Bollerslev (1989)). Further, the model with normal distribution does not survive the Negative, Positive size bias tests and hence the conditional variance equation is incorrectly specified. It should however be noted that the model with normal distribution captures the linear and non-linear dependency in returns adequately, as suggested by the corresponding Ljung-Box statistics.

To deal with the problem of excess kurtosis, we use student-t distribution as the error distribution in the GARCH model. The density function of a student-t distribution with ν degrees of freedom is given by

$$f(\varepsilon_t \mid \Omega_{t-1}) = \frac{\Gamma\{(\nu+1)/2\}}{\sqrt{\pi(\nu-2)}\Gamma(\nu/2)}\left[1+\frac{\varepsilon_t^2}{(\nu-2)}\right]^{-(\nu+1)/2}$$

where Γ (.) is the gamma function. The conditional student-t distribution allows heavier tails than does the normal distribution; in the limit ν tends to infinity, the student's t-distribution approaches the normal distribution.

The maximum likelihood estimates of conditional mean and variance equation 3 with error distribution assumed to be student-t are reported in Table 5. On the basis of AIC model selection criteria, ARMA(1,1)-GARCH(1,1) model is chosen. LB test statistic up to lag 16 for autocorrelation in residuals and residual squares of the model are reported; Fig 4B provides information on residual and residual squares autocorrelation. The graph, along with the insignificant LB statistics, implies that the estimated model captures reasonably well the conditional dependence in returns and volatility. Further the sign, size bias and joint bias tests are not significant, suggesting that the conditional variance equation is correctly specified and that no asymmetric effects are present. Thus, the ARMA(1,1)-GARCH (1,1) model with errors conditionally following student-t distribution seems to provide a simple and parsimonious description of the time series properties.

There are several interesting points to be noted about the reported results for parameter estimates. First, the estimated degrees of freedom parameter, ν, is just 4.2078 and it is interesting to note that the implied estimate of the conditional kurtosis, $\kappa = \frac{3\nu - 6}{\nu - 4}$ is 31.87114 is in greater concordance with the raw return kurtosis of 27.10 than is the kurtosis of 3 of the normal distribution. Second, unlike the model with normal distribution, the GARCH model with student-t distribution is stable, as is reflected by the volatility persistence (β_1+γ_1) being less than one.

The coefficient estimates of expiration day dummy in conditional mean equation is insignificant; however, it is positive and significant in the conditional variance equation. This suggests that the Nifty volatility on expiration hour is significantly higher by 0.008187. Further, the coefficient of $Next_t$ in conditional variance equation is insignificant; however, it is positive and significant in the conditional mean equation suggesting the presence of an upward pressure in mean returns after the expiry hours. Moreover, the finding that the co-efficient of expiration day dummy is insignificant while that of $Next_t$ is significant means that there is no price reversal in returns following the expiration of derivative contracts.

To check for the robustness of the expiration day results, we replicated the entire analysis with 10-minute return series. For 10-minute return series, normal distribution does not pose any persistence problems and we do find any evidence suggesting misspecification in the conditional variance equation. The estimation results for 10-minute return series are juxtaposed with those for 5-minute returns in Table 5; the correlogram of residual and residual squares is plotted in Fig 4C. A cursory look at Table 5 confirms that the expiration day effects presented earlier for 5-minute returns hold true for the analysis with 10-minute returns. In essence, we conclude that the intra-day time series behavior can be approximated with a ARMA(1,1)-GARCH(1,1) model with Student-t innovations.

VI. Conclusion

Our central finding that on expiration hour, there is significant increase in volatility and insignificant pressure on returns has far-reaching implications. In the spirit of the earlier studies, we use our results to evaluate the efficiency of the settlement procedure adapted in the market. Since the derivative contracts are *not* settled to prices observed at *a single* point of time, index arbitrageurs are left with a large time window during which they can unwind their positions with *relatively* little basis risk. This, coupled with the depth of Indian capital markets, ensures that the liquidation activities do not impart *any* significant shock to the demand curve, and by extension, to the prices of underlying securities. *This is confirmed by the absence of significant pressure on returns during the expiration hour*.

However, the average settlement procedure also has a flip side: since exact settlement price is not known *a priori*, there is some basis risk associated with the unwinding operations of any index arbitrageur. Unless a trader can come up with some procedure by which the proceeds from his liquidation activities exactly replicate the settlement price, there is no way in which this basis risk can be removed. However, he can minimize his basis risk by spreading out the liquidation trades over the expiration hour; such strategies, unfortunately, have the undesirable effect of creating temporary order imbalances, thereby increasing the volatility of the spot market. *This is affirmed by the increase in conditional variance of returns during the expiration hour.*

Does this mean that we should change the settlement procedure? Given the available popular alternatives, our answer is in the negative. Settling derivatives to prices observed at a given point of time (as in the case of S&P 100 index options and S&P 500 index futures – closing price for the former and the opening price for the latter) can potentially lead to acute shocks to the demand curve. The procedure adapted by the Hong Kong Stock Exchange for settling Hang Seng Index (HSI) derivatives is the other popular alternative that we consider. HSI contracts are settled to the average of five-minute quotations of the index obtained during the *entire* trading day. While such a mechanism gives more time for the index arbitrageurs to unwind their operations, it also greatly increases the basis risk and by our earlier argument, the underlying spot volatility.

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Table 1

Brief Summary of earlier studies on expiration day effect of derivatives on spot market

Author	Market	Impact on returns	Impact on volatility
Bollen & Whaley, 1999	HIS, Hong Kong	No effect	No effect
Stoll & Whaley, 1997	AOI, Australia	No effect	Mixed
Schlag, 1996	DAX, Germany	Present	Present
Chen & Williams, 1994	NYSE and S&P 100	No effect	No effect
Hancock, 1991	S&P500 Futures	No effect	Present
Trevor & Cheung, 1989	TSE, Canada	Present	Present
Cinar & Joseph Vu, 1987	S&P 500	No effect	No effect
Karolyi, 1996	Nikkei 225, Japan	Present (marginal)	Present (marginal)
Stoll & Whaley, 1987, 1991	S&P 500	Present	Present
Pope & Yadav, 1992	FTA ASI, UK	Present	No effect

Table 2A

Selected specifications of the S&P CNX Nifty futures and option contracts traded on the National Stock Exchange

Futures on the Nifty

Contract unit	200 units and multiples thereof
Minimum tick size	INR 0.05
Contracts available	At any point of time, there are three contracts available for trading in the market – those that expire in the spot month, those that expire in the next month and those that expire in the month after.
Expiration day	Last Thursday of the expiry month
Settlement Mechanism	Cash settlement
Settlement price	Last half an hour weighted average value in the Capital Market segment of NSE, on the last trading day of the futures contracts.

Options on the Nifty: Put and Call

Contract unit	200 units and multiples thereof
Minimum tick size	INR 0.05
Contracts available	At any point of time, there are three contracts available for trading in the market – those that expire in the spot month, those that expire in the next month and those that expire in the month after.
Expiration day	Last Thursday of the expiry month
Settlement price	Last half an hour weighted average value in the Capital Market segment of NSE, on the last trading day of the futures contracts.
Exercise Type	European

Table 2B

Selected specifications of futures and option contracts on individual stocks traded on the National Stock Exchange. Currently, 55 securities are traded in the derivative segment

Futures on Individual Stocks

Contract unit	Multiples of 100; at time of initiation, the value of the contract should not be less than INR 2 lakhs
Minimum tick size	INR 0.05
Contracts available	At any point of time, there are three contracts available for trading in the market – those that expire in the spot month, those that expire in the next month and those that expire in the month after.
Expiration day	Last Thursday of the expiry month
Settlement Mechanism	Cash settlement
Settlement price	Last half an hour weighted average value in the Capital Market segment of NSE, on the last trading day of the futures contracts

Options on Individual Stocks: Put and Call

Contract unit	Multiples of 100; at time of initiation, the value of the contract should not be less than INR 2 lakhs
Minimum tick size	INR 0.05
Contracts available	At any point of time, there are three contracts available for trading in the market – those that expire in the spot month, those that expire in the next month and those that expire in the month after.
Expiration day	Last Thursday of the expiry month
Settlement price	Last half an hour weighted average value in the Capital Market segment of NSE, on the last trading day of the futures contracts.
Exercise Type	American

Table 3: Descriptive Statistics

PANEL A: Descriptive statistics for return series at different frequencies									
	Daily data			5-minute Returns			10-minute Returns		
	NonExpiration	Expiration	Full	NonExpiration	Expiration	Full	NonExpiration	Expiration	Full
Mean	0.074524	0.016834	0.009213	0.000573	-0.034742	0.000384	0.000779	-0.074155	0.000779
Variance	1.463449	2.287578	2.313867	0.013454	0.029923	0.013541	0.026943	0.065528	0.026944
Skewness	-0.625871	-0.966104	-0.950989	-0.315111	-0.568335	-0.323044	-0.267627	-0.562131	-0.267627
Kurtosis	3.87144	10.58175	10.36828	27.36208	4.074122	27.10054	13.84508	2.802581	13.84508

PANEL B: Results of Diagnostic tests						
	Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value
J-B test stat	2490.089	0.0000	201113.7	0.0000	20962.06	0.0000
LB(16)	61.698	0.0000	29.6731	0.0200	31.885	0.0100
$LB^2(16)$	349.89	0.0000	351.1662	0.0000	161.82	0.0000
F-test	1.563142	0.0166	2.224148	0.0021	2.43204	0.0165
Stationarity test	-24.09452	0.0000	-67.6570	0.0001	-69.00800	0.0001

Table 4: Results from Daily Data Analysis

$$R_t = \alpha_0 + \phi_1 \varepsilon_{t-1} + \lambda_1 Exp_t + \lambda_2 Next_t + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1} + \delta_1 Exp_t + \delta_2 Next_t + \delta_3 Volume_t + \delta_4 Volume * Exp_t$$

Results	***Daily Returns***		
	Normal Distribution		
	Estimate	*Std Error*	*p-value*
Mean Parameters			
α_0	0.063978	0.048816	0.189993
λ_1	0.175714	0.233804	0.452324
λ_2	0.061802	0.210894	0.769487
Φ_1	0.155674	0.038419	5.08E-05
Variance Parameters			
β_0	0.048428	0.103735	0.640613
β_1	0.225269	0.095198	0.017966
γ_1	0.585472	0.220155	0.007829
δ_1	0.354326	1.011835	0.726202
δ_2	0.341647	0.600662	0.569503
δ_3	9.68E-05	7.03E-05	0.168518
δ_4	-0.000151	0.000274	0.581665
Residual Diagnostics			
Skewness	-0.340760		--
Kurtosis	4.021400		--
LB(16)	17.158800		0.375393
LB^2(16)	14.802300		0.539166
LM(16)	1.101500		0.354430

Table 5 : Expiration Day Results from High Frequency Data : Jan 2003 – June 2003

$$R_t = \alpha_0 + \alpha_1 R_{t-1} + \phi_1 \varepsilon_{t-1} + \lambda_1 Exp_t + \lambda_2 Ne\bar{xt}_t + \varepsilon_t$$
$$\varepsilon_t \sim N(0, h_t) / Student - t$$
$$h_t = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1} + \delta_1 Exp_t$$

Results	***5-minute Returns***				***10-minute Returns***	
	Student-t Distribution		***Normal Distribution***		***Normal Distribution***	
	Estimate	*p-value*	*Estimate*	*p-value*	*Estimate*	*p-value*
Mean Parameters						
α_0	0.002536	0.048732	-0.002509	0.064735	-0.000614	0.799107
α_1	-0.452718	0.000000	-0.297578	0.000430	--	--
λ_1	-0.025442	0.451753	-0.061364	0.109558	-0.093595	0.106217
λ_2	0.059026	0.031274	0.070399	0.017547	0.098542	0.018074
Φ_1	0.533102	0.000000	0.425505	0.000000	-0.043517	0.015389
Variance Parameters						
β_0	0.000594	0.000000	0.000789	0.000004	0.005361	0.000005
β_1	0.100844	0.000000	0.320869	0.000000	0.209040	0.000021
γ_1	0.719991	0.000000	0.703637	0.000000	0.611791	0.000000
δ_1	0.008187	0.012059	0.012981	0.004596	0.036446	0.039203
ν	4.207820	0.000000	--	--	--	--
Residual Diagnostics						
Skewness	-0.082740	--	-0.06444	--	-0.197960	--
Kurtosis	21.720290	--	18.87616	--	14.166260	--
LB(16)	20.095900	0.215932	26.023200	0.053703	23.433800	0.102620
$LB^2(16)$	4.228000	0.998452	9.937100	0.869894	8.298700	0.939474
LM(16)	0.277100	0.997920	1.019700	0.395490	0.391600	0.814780
Sign bias	-0.332100	0.739820	-0.771500	0.440440	0.845900	0.397630
+ve size bias	-0.845700	0.397730	-2.002200	0.045290	0.294400	0.768500
-ve size bias	1.375100	0.169130	1.847000	0.064790	0.909900	0.362910
Joint bias	1.096600	0.349140	2.789800	0.039030	0.348100	0.790570

LB (k) is the portmanteau statistic testing joint significance of return autocorrelations up to lag k
LB^2 (k) is the portmanteau statistic testing joint significance of return autocorrelations up to lag k
LM (k) is the portmanteau statistic testing the presence of ARCH effects up to lag k
Sign bias, Negative size, Positive size, and Joint bias tests are asymmetric test statistics proposed by Engle and Ng (1993)

Figure 1: Growth in trading volume of derivatives traded in the National Stock Exchange

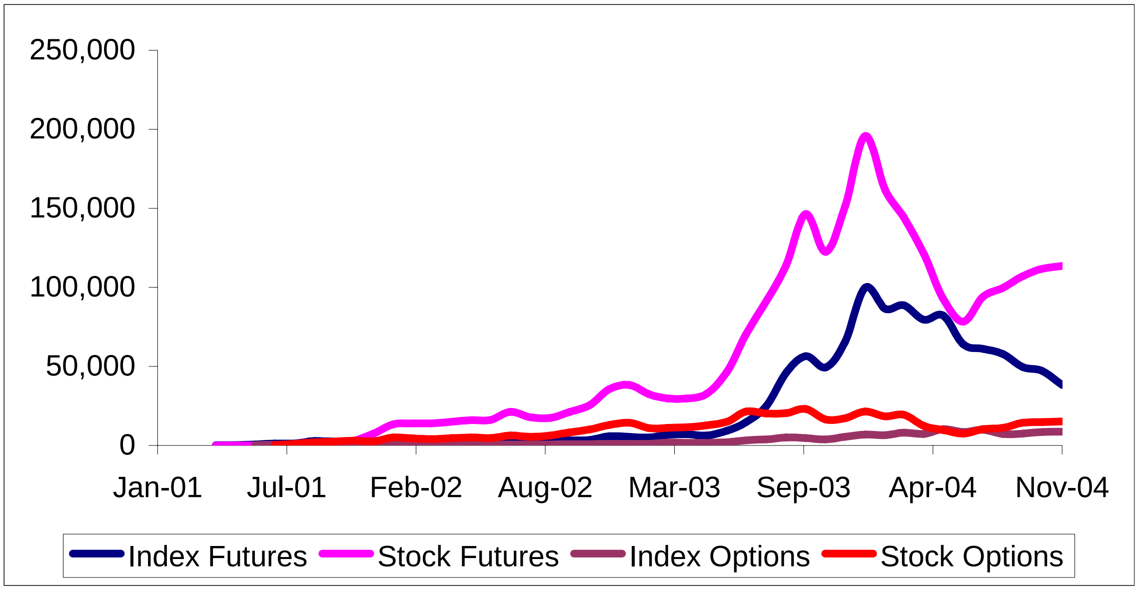

Fig 2 : Raw Return Series Plots

Fig 2A : NSE Nifty Daily Returns : June 2000 - August 2004

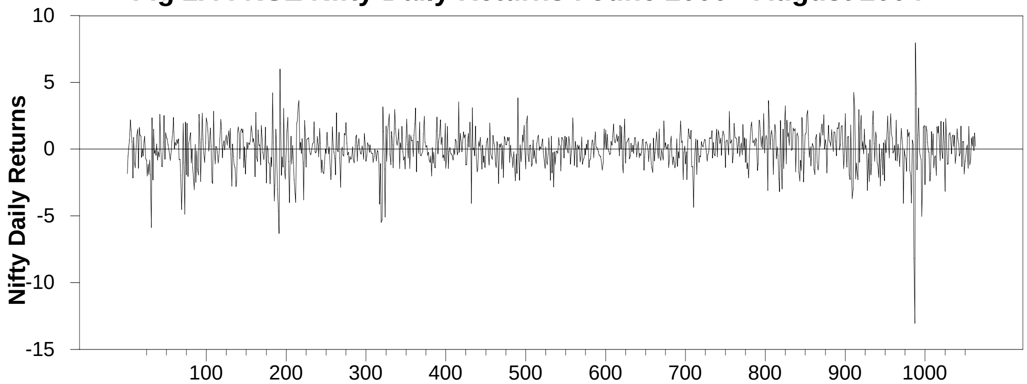

Fig 2B :NSE Nifty 5-minute Returns : Jan 2003 - June 2003

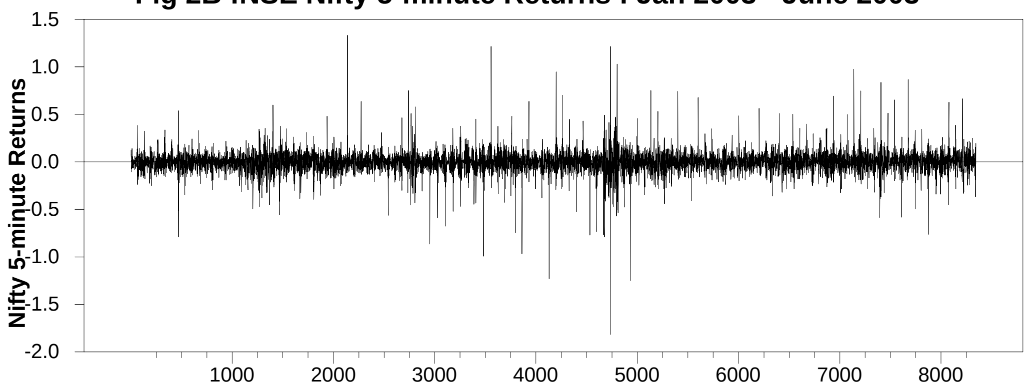

Fig 2C :NSE Nifty 10-minute Returns : Jan 2003 - June 2003

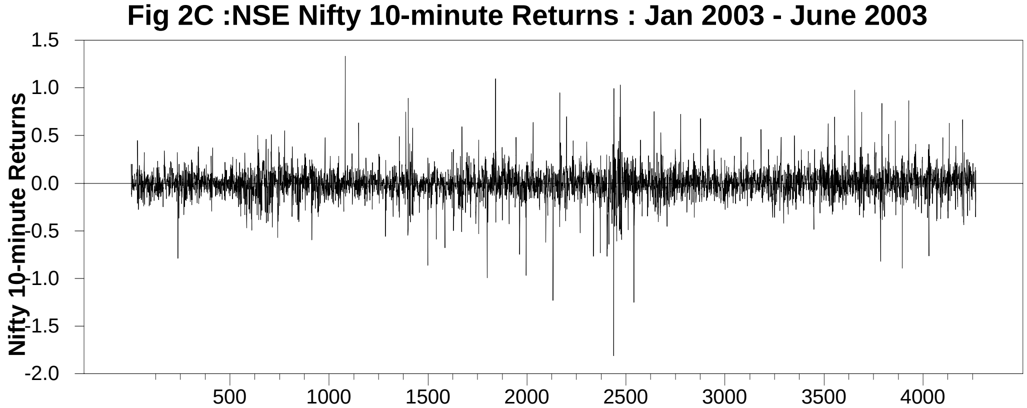

Fig 3: Correlogram of Raw Return Series

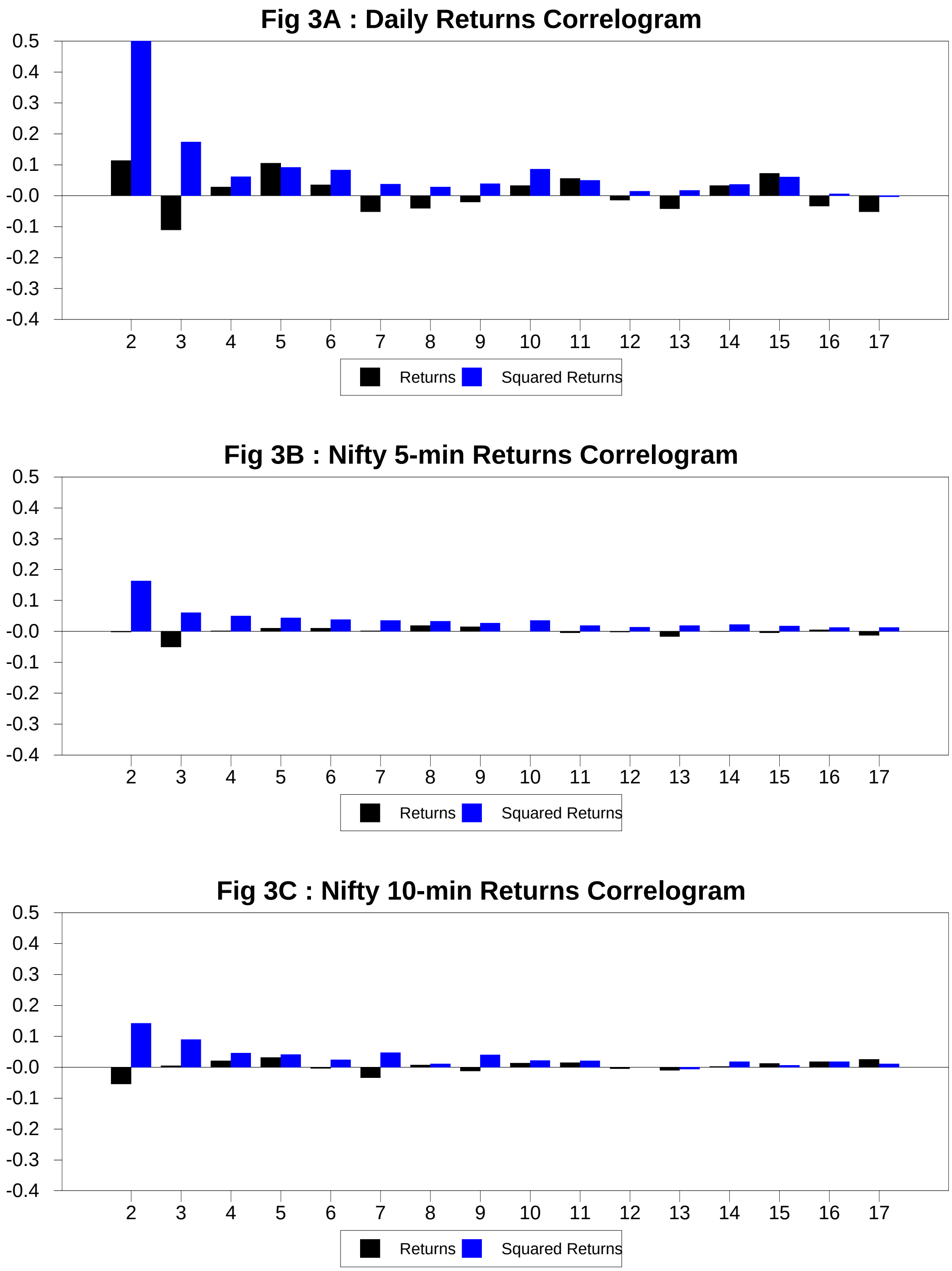

Fig 4: Standardized Residual Correlogram Plots

Fig 4A : Residual correlogram from Daily Data

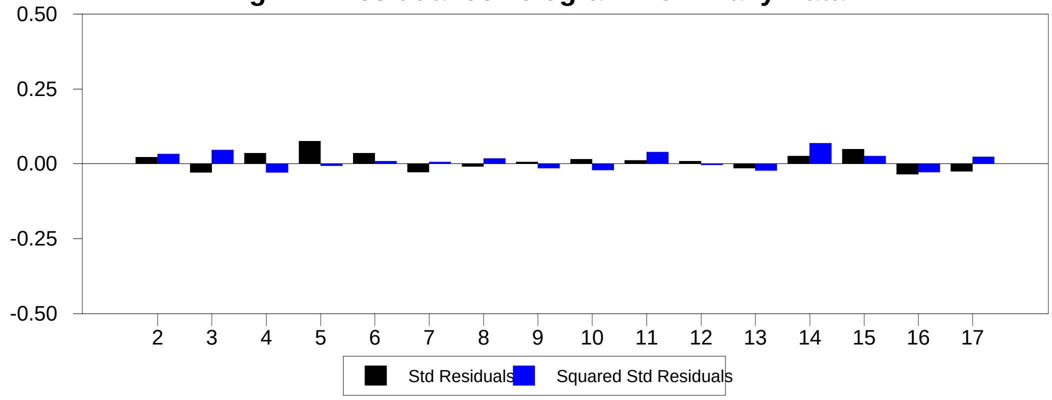

Fig 4B : Residual correlogram from 5-min Returns

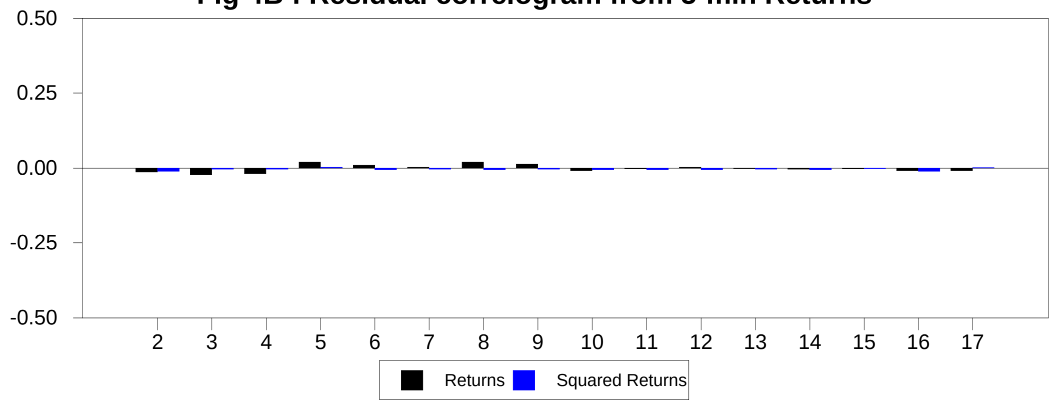

Fig 4C : Residual correlogram from 10-min Returns