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IS INDIAN STOCK MARKET MORE VOLATILE IN REFORM PERIOD? EVIDENCE FROM E-GARCH MODEL

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India opened up its stock market from early nineties by allowing FIIs to invest in Indian stock market. It is widely believed that FIIs are the most volatile investors in India stock Market. It is also found that stock market volatility tend to increase following financial liberalization. We tested this hypothesis for India by applying daily as well as monthly returns series from Sensex and IFCG global index. By applying E-GARCH model, we find that volatility has increased marginally in post-reform period. We also conducted structural break test by applying Bai and Perron (1998, 2003) endogenous break methodology. It is clear that stock market reforms as such do not lead to change in volatility persistent. Rather it is related to wide economic policy change/regime shift. At the same time, FIIs activity also not related to break points. When large shocks in stock returns are controlled, there is significant reduction in ARCH effect, however volatility is still persistent.

Keywords: Stock Market, Volatility, ARCH, Structural Breaks, and Financial Liberalisation.

JEL Classification: C12, G00, G14, O16, and F36.

INTRODUCTION

Stock market considered as most efficient in allocating scared capital to its highest-value users. Theoretically, it is proved that stock market helps to increase savings and investment in an economy, which is vital for economic growth. It is also pointed out that stock markets help to reduce risk by diversifying risk across a variety of assets. Thus it has direct implication in reducing cost of capital which in turn spurns investment in the economy. In order to serve these purpose stock markets need to be deep, efficient and stable. Hence, volatility and efficiency are very important aspects of stock markets which ultimately determine the effectiveness of the stock market in economic development.

Volatility is considered as very important indicators of stock market development. Because, volatility has implications for investment, corporate financing and financial stability in the economy. For example, excess volatility weakens investor's confidence which, results in reduction in investment. Lessons from financial crisis reveal that financial asset price variability has the potential to undermine financial stability of an economy. As volatility increases risk also increases simultaneously. So understanding volatility and its magnitude is therefore central to risk management in the economy. Romar (1990) suggested that increased uncertainty associated with financial distress was one of the driving forces behind great depression. Empirical literature also shows that volatility affects corporate financing. Schill (2003) examining the relationship between volatility and corporate financing for US, found that during the period of above normal market volatility, results in 21 percent decline in the number of IPO dollar raised. So increased market volatility generates greater underwriting fees and hence results in IPO under pricing. Relationship between volatility and economic variables are showed below.

Excess volatility $\rightarrow$ Economic uncertainty $\rightarrow$ Market risk $\uparrow\rightarrow$ Financial instability $\uparrow\rightarrow$ Cost of capital $\uparrow\rightarrow$ Reduction in investment $\rightarrow$ Economic growth $\downarrow$.

So the objective of this paper is to estimate time varying volatility and its persistence in Indian stock market both in pre and post liberalisation period. Basically we have two questions to address:

(1) Does Indian Stock Market volatility changed through time and particularly is it more volatile in liberalisation period?

(2) Is it possible to find a relationship between changes in stock market volatility and stock market reforms?

In the asset pricing literature volatility refers to asset price variability. Stock price changes following new information hitting the market. It should however, be noted that discontinuity in price movements in order to reach a new equilibrium price warranted by new information is a feature of information efficient market[1]. But excessive volatility or "noise" trading undermines the usefulness of stock prices as a signal about the true intrinsic value of firm. It has large consequence, which we have already discussed.

The layout of the paper is as follows: section 2 provides the theoretical background. Section 3 outlines literature review. Section 4 presents methodology and Data source. Results and conclusion are reported in section 5.

SECTION 2

Theoretical Back Ground

If integration with the world markets makes the equilibrium process more efficient for stocks in emerging markets, it is reasonable to expect a drop in stock market volatility and a concomitant drop in expected returns. It is argued that, foreign investors are quick to react to changes in short-term economic outlook in emerging economies, making unrestricted capital flows very volatile. This volatility of capital flows may increase the volatility of the stock market. According to finance theory, stock market volatility could increase or decrease when markets are opened up (see for example Bekaert and Harvey, 1997, 2002 and 2003). Markets may become informationally more efficient leading to higher volatility as price quickly react to relevant information; also speculative capital may induce excess volatility. On the other hand, in the pre-liberalisation process, there may be large swings from fundamental values leading to higher volatility. After liberalisation, the gradual development and diversification of the markets could lead to lower volatility. So there is conflicting report about the impact of financial liberalisation on volatility.

A model proposed by Tauchen and Pitts (1983) and subsequently used by Kwan and Reyes (1997), which could explain the impact of financial liberalisation on stock market volatility. The model as follows:

Assume that there are J active traders in the market. Within the day, the market passes through a sequence of distinct Walrasian equilibria. The movement from the (i-1)st to the to the ith equilibrium in a given day is caused by the arrival of new information to the market. The desired net position, Q_{ij} of trader j at the time of the ith equilibrium is assumed to be a linear function of the following forms:

$$Qij = \alpha \, [P^*_{ij} - P_i] \quad (J = 1, 2 \ldots J) \tag{1}$$

Where $\alpha > 0$ – Constant

P^*_{ij} = jth trader's reservation price

P_i = current market price

$$\sum_{J=1}^{j} Q_{ij} = 0 \tag{2}$$

A positive value for Q_{ij} represents a desired long position in a contact while negative value represents a desired short position. Equilibrium requires that the following holds true:

$$\sum_{J=1}^{j} Q_{ij} = 0 \tag{2}$$

This implies that the average of the reservation price clears the market:

$$Pi = 1/J \sum_{i=1}^{j} P^*_{ij} \tag{3}$$

The price change can then be written as:

Where $P^*_{ij} = P^*_{ij} - P^*_{i-1}$, j is the increment to the jth trader's reservation price.

$$\Delta P = 1/J \sum_{J=1}^{j} \Delta P^*_{ij} \tag{4}$$

Assuming a variance – component model with an information component that is common to all traders, φ_i, and one that is specific to the jth trader, ψ_{ij}, Equation (4) can be written as:

$$\Delta P_i = \Phi_i + 1/J \sum_{J=1}^{j} \varphi_{ij} \tag{5}$$

The first two component of the price change are then derived as the following:

$$E\,[\Delta p_i] = 0 \tag{6}$$

$$Var\ [\Delta p_i] = \sigma^2{}_{\varphi} + \sigma_2 / J \tag{7}$$

Equation (7) tells us that other thing being equal, an increase in the number of traders (J) tends to reduce the stock price variance. On the other hand increase in the variance of information sets (σ^2_{ϕ}) available to traders tends to raise the stock price variance. The number of traders (like FIIs) increases in the stock market following opening of a stock market. At the same time information set available to traders also increases[2]. So, when number of traders increase it reduces the volatility of stock price whereas when information set available to traders increase it raises the stock price volatility. The final outcome depends on relative strength.

SECTION 3

Literature Review

Considerable research has focused on stock market liberalisation and stock market volatility (e.g. Bekaert and Harvey 1997, 2000, Bekaert *et al.* 2002a, De Santis and Imrohoroglu 1997, Huang and yang 1999, Aggarwal *et al.* 1999, Kim and Singal 2000, Kaminsky and Schmickler 2003 and Edwards et al. 2003). For example, De Santis and Imrohoroglu (1997) study the behaviour of volatility in some emerging countries and the effect of liberalisation of financial markets. They find significant evidence for time-varying volatility and different effect of liberalisation on volatility across countries. Especially, they find that volatility decreased after liberalisation.

Huang and Yang (1999) analyse the impact of financial liberalisation on stock price volatility in ten emerging markets. Taking as reference the dates of financial market liberalisation from, De Santis and Imrohoroglu (1997), they show that the unconditional volatility of the stock markets in three of the countries (South Korea, Mexico and Turkey) increased after liberalisation, whereas it significantly decreased in another four countries (Argentina, Chile, Malaysia and the Philippines). However, the conditional volatility of the markets of Brazil, Korea, Thailand and Turkey experienced a significant increase while that of the remaining six countries experienced a decrease after liberalisation. In a recent paper, Kim and Singal (2000) analyse changes in the level and volatility of stock returns around the opening to international capital markets. The result reveals that opening of the markets is good for domestic investors. Stock price rise while the volatility tends not to increase.

Financial liberalisation hypothesis predicts a decrease in volatility in asset price in the post reform period. But the empirical findings in this regard suggest a mix conclusion. Singh (1993), Grabel (1995), Levine and Zervos (1998), Kamminsky and Schumkur (2001, 2002), Nilson (2002), and Edwards *et al.* (2003) found that financial liberalisation increases stock market volatility. Studies, which do not find any significant impact of financial liberalisation on volatility, are De Santis and Imorohoroglu (1994), Kim and Singal (1997), Richards (1996), and Bekaert and Harvey (2000). In Indian context, early studies by Samal (1997) and Pal (1998) found that FIIs investment in Indian stock market is the major source of volatility. Another study by Batra (2004) suggests that stock market volatility actually marginally lower in liberalised period.

While the predictions of theoretical models that analayse the impact of financial liberalisation on volatility is at best ambiguous, considerable literature exists that highlights the significant increase in volatility following reforms. Our study gives additional empirical support to the financial liberalisation and volatility hypothesis. So the objective of the paper is to estimate time varying volatility in pre and post liberalisation period.

SECTION 4

Methodology

Beginning with the mean variance analysis of portfolio and asset returns, volatility has become central to much of modern finance theory. In recent times, empirical studies involving high-frequency financial time series data have focused on volatility of asset returns. It has been observe that the asset returns exhibit changes, which are not independent over time.

Rather, large changes tend to be followed by large changes of either sign and small changes tend to be followed by small changes (Mandelbrot 1965, Fama 1965 and French *et al.* 1987).

It is now well-established fact that stock market volatility is a non-constant stochastic process with a non-negligible degree of persistence- if stock market volatility is high today it tends to be high also during near feature. This observation has received much attention from the financial profession due to its implication for asset pricing and portfolio management. The changing volatility and particularly, its persistence have macroeconomic implication, as we have discussed beginning of this paper.

The main objective of modeling temporal variation in variance of return distributions has been drawn from the time varying second order moments. The basis for this has been the fact that a series may be stationary when unconditional variance is constant, but when the variance conditional upon the information set changes over the time the series becomes non-stationary. For example, if security price follows an Autoregressive (AR) one process, the long-run variance is constant but the variance at time t depends on the variance at time $t_{-1.}$ Exploiting the idea of time varying variances, a class of models charactersing such conditional variance has emerged. The first such model introduced by Engel (1982), known as Autoregressive Conditional Heteroscedasticity (ARCH). A typical ARCH model allows the conditional variance of the error term vary over time, in contrast to the standard time series regression models which assume a constant variance. So the ARCH model allows the conditional variance to depend on the past squared residuals in that variance in period t is modeled as a constant plus a distributed lag on the squared residual terms from previous period. Consider following AR (1) model,

$$R_t = \delta + \psi R_{t-1} + u_t \tag{1}$$

Where, R_t = return at period t

R_{t-1}= return at period t-1

u_t = error tem.

Equation one tells us that return in period t depends on its one period past value. The key idea of ARCH is that the variance of u_t at time t (σ^2) depends on the size of the squared error term at time t-1, that is on u^2_{t-1}. So

$$\text{Var } (u_t) = \sigma^2 = \gamma_0 + \gamma_1 u^2_{t-1} + \nu_t \tag{2}$$

Where, ν_t is a white nose process. If the value of γ_1 is equal to zero, the variance is simply constant g_0. Equation (2) is called an ARCH (1) process. But by generalising it we can write for ARCH (p) process. Thus, an ARCH (p) process can be written as

$$\text{Var } (u_t) = \sigma^2 = \gamma_0 + \gamma_1 u^2_{t-1} + \gamma_2 u^2_{t-2} + \ldots\ldots + \gamma_q u^2_{t-q} \tag{3}$$

If the values of $\gamma_1, \gamma_{2,\ldots.} \gamma_q$ is equal to zero, the variance is simply constant γ_0. Otherwise, the conditional variance of u_t evolves according to the autoregressive process given by equation (3).

The ARCH formulations have several extensions. The most prominent of them has been the Genaralised ARCH or GARCH model (Bollerslev 1986), which explains variance by two distributed lags, one on past squared residuals and the second on lagged values of variance itself to capture long-term influences. That is conditional variance is an ARMA process. Now let the error process be such that

$$u_t = e_t h_t^{1/2} \tag{4}$$

Where, $e_t \sim (0, 1)$

$$h_t = \sigma^2_t = \omega + \alpha\, e^2_{t-1} + \beta h_{t-1} \tag{5}$$

$$h_t = \omega + \sum_{i=1}^{q} a_1 e^2{}_{t-i} + \sum_{i=1}^{p} \beta_i h_{t-1} \tag{6}$$

Equation (5) represents GARCH (1, 1) process and equation (6) represents GARCH (p, q) process. Now h_t is the conditional variance, which follows an ARMA process. Now equation (5) allows us to capture various dynamic structure of conditional variance. The size and significance of a indicates the magnitude of the effect imposed by the error term (u_{t-1}) on the conditional variance (h_t). In other words, the size and significance of α implies the presence of ARCH process in the error term. This is called volatility clustering. The significance of β is that it has information about the market structure in general as well as the information that influencing the stock prices. The sum of $\alpha + \beta$ represents the change in the response function of shocks to volatility per period. If $\alpha + \beta = 1$, a current shock persists indefinitely in conditioning the future variance. If $\alpha + \beta > 1$, then the response function of volatility increases with time. If $\alpha + \beta < 1$, this means that shocks decay with time, and the closer to unity unit value of persistence measure, the slower is the decay rate.

The economic interpretation of the ARCH effect in stock markets has been provided within both micro and macro frameworks. According to Bollerslev *et al.* (1992) and other studies, the ARCH effect in stock returns could be due to clustering of trade volumes, nominal interest rates, dividend yields, money supply, oil price index, etc. The GARCH models have been found to be valuable in modeling the time series behaviour of stock returns (French et al.1987; Chou 1988; Akgiray 1989; Ballie and Degennaro 1990; Koutmos 1992; Kim and Kon 1994; Tunaru 2002).

The GARCH models have important limitations. For example, researchers beginning with Black (1976) have found evidence that that stock returns are negatively correlated with changes in return volatility – i.e., volatility tends to rise in response to " bad news" and fall in response to "good news"[3].

GARCH models, however, assume that only the magnitude and not the positivity and negativity of unanticipated excess returns determine future variance. If the distribution of u_t is symmetric, the change in variance tomorrow is conditionally uncorrelated with excess return today. In equation (5), σ^2_t is a function of lagged σ^2_t and lagged e_t^2, and so is invariant to changes in algebraic sign of the e_t's i.e., only the size, not the sign of lagged residuals determines conditional variance. So, this suggests that a model in which σ^2_t responds asymmetrically to positive and negative residuals might be preferable for asset pricing applications.

The second limitation of GARCH models results from the non-negativity constraints on ω and the α_i in (eq. 6), which are imposed to ensure that σ^2_t remains non-negative. These constraints imply that increasing e_t^2 in any period increases σ^2_{t+m} for all $m \geq 1$, ruling out random oscillatory behaviour in the σ^2_t process. Furthermore, these non-negativity constraints can create difficulties in estimating GARCH models.

A third drawback of GARCH modeling concerns the interpretation of the "persistence" of shocks to conditional variance. In many studies of the time series behaviour of asset volatility (e.g., Poterba and Summers (1986), French, Schwert, and Stambugh (1987), and Eangle and Bollerslev (1986a)), the central question has been how long shocks to conditional variance persist. If volatility shocks persist indefinitely, they may move the whole term structure of risk premia, and are therefore likely to have significant impact on investment in long-lived capital goods (Poterba and Summers 1986). According to Nelson (1991), his E-GARCH model overcomes some of the limitations of GARCH family of models. The specification of E-GARCH model follows as below,

$$R_t = \delta + \psi\, R_{t-1} + u_{t\ldots} \ldots\text{(As eq.1)}$$

Where,

$$u_t = e_t h_t^{1/2} \ldots\ldots\text{(As eq. 4)}$$

$$e_t \sim (0, 1)$$

and,

$$\text{In } h_t = \omega + \beta \text{ In} h_{t-1} + \alpha_1 \mid e_{t-1} / \sigma_{t-1} \mid + \alpha_2\, e_{t-1} / \sigma_{t-1} \ldots \quad (7)$$

In this model β is the GARCH term that measures the impact of last period's forecast variance. A positive β implies volatility clustering indicating that positive return are associated with further positive changes in stock return and vice versa. α_1 is the ARCH term that measures the effect of news about volatility from the previous period on current period volatility. α_2 measure the leverage effect. If the coefficient of α_2 is significant then the positive shocks and negative shocks have different impact on volatility. Ideally α_2 is expected to be negative indicating "bad news" has higher impact on volatility than "good news" of the same magnitude. The sum of the ARCH-GARCH coefficients indicates the extent to which a volatility shock is persistent over the time.

Data Source

We use two stock market indices – the BSE Sensex indices and the international financial corporation published IFC Global (IFCG) index. Both daily and monthly return series is used in our analysis. Sensex is the most popular market index and widely used by researchers in India. For daily data, our period of analysis is from 1985 to 2004. We have divided this period into two-sub period such as pre-liberalisation (1985-92) and post liberalisation period (1993-2004). For monthly data, the period of analysis is from 1976-04 for IFCG Data and 1979-2005 for BSE Sensex. The data have been collected from prowess database of CMIE as well from Emerging Stock Market Fact books of S& P. For carrying out empirical analysis the price series are converted to return series in the following way:

$$R_t = \ln (P_t\text{-}P_{t-1})$$

Where, R_t is the logarithmic return on security at time t, and P_t, P_{t-1} closing value of stock price of Sensex at time t and t-1.

SECTION 5

Summary Statistics of Sensex Daily and monthly Return

It is clear from table 1 is that the return series is not normal. Skewness in both the period is not zero. It is positively skewed in the pre-liberalisation period and negatively skewed in post liberalisation period as well as for full sample. The kurtosis for all the period is greater than 3, thereby indicating leptokurtic distribution. Mean returns for pre-liberalisation period is higher than that of post-liberalisation period for both daily return as well monthly returns. The standard deviation in returns is higher in pre-liberalisation period for daily series, indicating stock return is more volatile in pre-liberalisation.

Table 1
Summary Statistics for Daily and monthly Return

Period	*Mean*	*Max.*	*Min.*	*S.D.*	*Skewness*	*Excess Kurtosis*
1985-1992	0.052	12.6	-13.01	1.44	0.22	201.55
1993-2004	0.010	0.07	-11.08	0.71	-0.23	5.17
1985-2004	0.020	12.6	-13.01	0.98	-5.87	200.1
1991-1992	0.059	8.73	-13.02	1.51	-7.17	77.53
			Monthly Return			
1979-1992	0.68	19.13	-11.14	3.41	1.07	5.33
1992-2005	0.29	8.25	-7.48	3.28	-0.43	1.58
1979-2005	0.48	19.13	-11.14	3.35	0.52	2.81

Standard deviation for sub-period (1991-1992) is higher than any other period, indicating this period is most volatile. Similarly, for monthly series, standard deviation for pre-liberalisation period is higher indicating market is more volatile in pre-liberalisation period.

Table 2
Diagnostic Checking of Daily Return Series

Period	*BJ*[A]	*LB*[B]	*ADF*[C]	*LM*[D]
1985-1992	35678.74	42.42	-36.16	372.66
	(0.00)	(0.02)	(0.02)	(0.00)
1993-2004	552.97	39.29	-36.07	164.85
	(0.00)	(0.03)	(0.01)	(0.00)
1985-2004	30326	39.45	-49.81	356.00
	(0.00)	(0.03)	(0.01)	(0.00)
1991-92	2786	22.18	-31.23	21.21
	(0.00)	(0.00)	(0.03)	(0.00)
		Monthly Series		
1979-1992	227.34	18.45	-10.55	13.56
	(0.00)	(0.03)	(0.04)	(0.06)
1993-2005	12.96	14.38	-12.29	12.34
	(0.001)	(0.06)	(0.05)	(0.06)
1979-2005	122.47	18.67	-12.53	17.45
	(0.00)	(0.03)	(0.04)	(0.03)

(a) Bera Jarqua Statistics approximately distributed as central Chi-square (2) under the null hypothesis of normally in the underlying distribution of returns. b) Ljung – Box Statistics to test autocorrelation among residuals of returns .c) Lagarange Multiple Test Statistics to test null hypothesis of no ARCH effect against alternative of ARCH effect, critical values of Chi-square at 1%, 5% and 10% are 15.08, 11.07 and 9.23 respectively.

Before estimating ARCH/GARCH/E-GARCH models to capture volatility, necessary diagnostic statistics are computed and presented in Table 2. Here we assume that daily returns return follows a first order autoregressive (AR (1)) process. The Bera-Jarqua (BJ) statistics, which exceeds critical chi-square value with 2 degree of freedom in all cases, rejects the normality of the underlying distribution. In order to analyse the behaviour of stock returns, Ljung-Box (LB) statistics are obtained to trace the presence of autocorrelation among residuals of the return. It is clear from the table 2 is that in all the cases the presence of autocorrelation is significant. The Augmented Dickey-Fuller (ADF) test statistics indicate that return series are stationary in nature. LM statistics also indicates the presence of ARCH disturbances in the squared residuals. Here, we have considered the order of the ARCH is to be 5. Because, according to the test procedure, the TR^2 statistics (where T is the sample size and R^2 is the coefficient of determination) follows asymptotically a chi-squared distribution with degree of freedom 5.

It follows from the above analysis is that stock returns are not identically and independently distributed. This may lead us to conclude that return variance process is time varying and heteroskedastic in nature and hence ARCH formulation would be appropriate. The result obtained from AR (1) model with disturbance term following ARCH (5) structure is reported in Table 3. The constant term a_0 is found to be insignificant for pre and post liberalisation period as well as for whole sample. it is significant indicating that return process has a drift element. The coefficients of the a1 are found to be significant and less than one, thereby indicating stability in returns. Further, the coefficients of a_1 exhibit daily serial autocorrelation and in this regard the result indicates that there exit positive daily autocorrelations.

The ARCH (5) models have been estimated by maximising the log likelihood function using an iterative procedure based on the method of BHHH. For given values of past realised returns, α_0 and α_i (i = 1….5) are estimated for total return in the market. The constant term α_0 for whole sample is found to be positive and significant, which indicates that volatility could increase even in the absence of any influence. The summation of α_1s is more than one for pre-liberalisation period as well as for whole sample, indicating that the estimated variance is not finite. The lagged coefficients are significant at lags 1,2,3,4, and 5. The coefficients from the market point of view may interpreted as follows: the volatility of previous trading day is carried over to the current period and persisting over a period of four days.

Table 3
Estimation of ARCH (5) Process with AR (1) Model for Daily Returns.

Period	a_0	a_1	a_0	a_1	a_2	a_3	a_4	a_5
1985-92	0.023	0.30	0.50	1.50	0.27	-0.01	0.05	-0.001
	(1.71)	(13.1)	(24.7)	(22.08)	(15.05)	(-8.85)	(1.99)	(-0.26)
1993-04	0.032	0.137	0.191	0.228	0.132	0.111	0.089	0.086
	(2.41)	(6.81)	(16.1)	(9.54)	(5.57)	(6.1)	(4.43)	(4.67)
1985-04	0.006	0.118	0.27	0.24	0.14	0.048	0.64	-0.003
	(0.83)	(10.59)	(37.53)	(10.69)	(5.08)	(4.19)	(52.40)	(-1.39)

Figures in parentheses represent t-ratios.

Another important point that may be noted here is that ARCH error structure and autoregressive parameter of the R_t process interact with each other so that volatility of R_t is increasing in α_i and a_1. The explanation is like this: Any large shock in u_t will be associated with a persistently large variance; the larger is α_i the larger is the persistence. Furthermore, the greater the parameter a_1, the more persistent is the volatility.

In addition to the ARCH (5) models, GARCH (1, 1) model has been estimated. The result is reported at Table 4.

Table 4
Estimation of AR (1) Model with GARCH (1, 1) process

Period	A_0	A_1	ω	α	β	Mean (%)
1985-92	0.026	0.097	0.11	0.128	0.765	0.052
	(1.17)	(12.77)	(9.96)	(31.87)	(64.95)	
1993-04	0.033	0.134	0.02	0.03	0.83	0.015
	(2.55)	(6.46)	(6.71)	(10.06)	(72.98)	
1985-04	0.036	0.18	0.067	0.146	0.769	0.027
	(2.84)	(11.18)	(22.8)	(20.96)	(83.05)	
1991-92	0.037	0.151	0.093	0.135	0.84	0.081
	(0.74)	(2.52)	(2.09)	(3.00)	(23.72)	
GARCH (1,1) model for Monthly Series						
1979-92	0.45	-0.02	0.35	0.062	0.91	0.44
	(2.13)	(-0.34)	(0.72)	(2.38)	(6.57)	
1993-05	0.23	0.05	0.06	0.08	0.95	0.53
	(1.67)	(2.24)	(2.01)	(3.45)	(18.45)	
1979-05	0.297	0.015	0.143	0.051	0.94	0.49
	(1.63)	(0.27)	(1.17)	(2.56)	(39.62)	

Figures in parentheses represent t-ratios.

The results in Table 4 suggests that GARCH (1, 1) coefficients are found to be significant and positive, thus implying that volatility is captured by GARCH (1,1) model. The significance of α coefficients in the model indicates the tendency of the shocks to persist. The sum of the coefficients of lagged squared disturbance (α) and that of past variance (β) is less than one indicating shocks die with time. The sum is marginally higher in pre-liberalisation (0.89) period than post-liberalisation (0.86) period, thus indicating a marginal higher volatility in pre-libaralisation. The mean volatility also indicates the similar pattern. It was 0.052 % in pre-liberalisation period and came down to 0.015% in post-liberalisation period. In June 1991, India declared Structural Adjustment Programme (SAP) following BOP crisis and then a series of economic as well financial reform measures were announced. So, we have sub-periods from June 1991 to end of 1992. This period is highly volatile compared to other period. Mean volatility also very high in this period (0.081) compared to other period. The sum of all coefficients are more than the other periods.

For monthly data, volatility persistent is significantly evident for the whole period as well as for sub-periods. The sum of the coefficients is less than one for pre-liberaliation and for full sample. It is more than one in post-liberalisation. The mean volatility is marginally higher in post liberalization (0.53%) period than pre-liberalisation (0.44%) period, indicating market is more volatile in post liberalisation period. This is just opposite to that of daily series.

As we have already discussed that GARCH models take only magnitude not the sign of lagged residuals. Hence it ignores the leverage effect. Nelson's E-GARCH model overcomes this problem. So, we have estimated E-GARCH (1, 1) model for the sample period. The results are reported in Table 5. The Leverage effect is significant for all the period except for sub-period (1991-92). As expected the coefficient of leverage is negative indicating bad news have higher impact than good news. The coefficient of b is positive and significant indicating volatility clustering. In other words positive stock price changes are associated with further positive changes. The coefficient of ARCH term a_1 is positive and significant. The sum of the ARCH- GARCH coefficients is more than one for whole sample, pre and post liberalisation period, indicating that volatility increases with time. The sum of the ARCH- GARCH coefficients is higher in pre-liberalisation period (1.16) than in post-liberalisation period (1.14), indicating marginal decrease in volatility in post liberalisation period. This result is just similar to GARCH (1, 1) model for daily data.

For monthly data the result is similar to GARCH (1, 1) model. The mean volatility is higher for post-liberalisation period although marginal. Although the leverage coefficient is significant but the sign is positive. So from daily data it is found that volatility is higher in pre liberalisation period but from monthly data we found that a marginal increase in volatility in post liberalisation period. But generally daily data is suffered by "noise' content. Noise plays a big role in high frequency volatility persistence. At less frequent observation, the noise content dies away. Monthly data series is ideal for the volatility analysis. Now the task is to relate whether the marginal increase in volatility is due to reforms as general or due to reform in sock market. The next section we take up this issue.

Table 5
Estimation of AR (1) Model with E-GARCH (1, 1) Process

Period	*Mean (%)*	ω	β	α_1 *(ARCH Term)*	α_2 *(Leverage)*
1985-92	0.052	-0.02	0.891	0.27	-0.013
		(-6.4)	(215.09)	(13.73)	(-2.95)
1993-04	0.015	-0.271	0.93	0.21	-0.068
		(-15.71)	(97.55)	(14.72)	(-7.95)
1985-04	0.026	0.013	0.92	0.21	-0.036
		(40.22)	(265.06)	(22.36)	(-8.91)
1991-92	0.081	-0.0126	0.975	0.17	0.106
		(-4.08)	(31.05)	(4.44)	(8.29)
		E-GARCH Model with Monthly Series			
1979-92	0.44	1.00	0.94	0.005	0.016
		(1.60)	(52.34)	(0.44)	(3.35)
1992-05	0.53	-0.13	0.98	0.07	0.08
		(-13.87)	(54.67)	(11.23)	(5.28)
1979-05	0.48	-0.03	0.99	0.004	0.08
		(-1.39)	(151.33)	(2.32)	(11.82)

Figures in parentheses represent t-ratios.

Structural Breaks in Stock Market Volatility

We are interested now in detecting the events that may have led to changes in the volatility of stock market. Some recent contribution have looked for structural changes in the behaviour of emerging stock market, and detecting the causes of these changes, making special reference to episodes of financial liberalisation and economic policy decisions [Agrawal *et al.* (1999)].

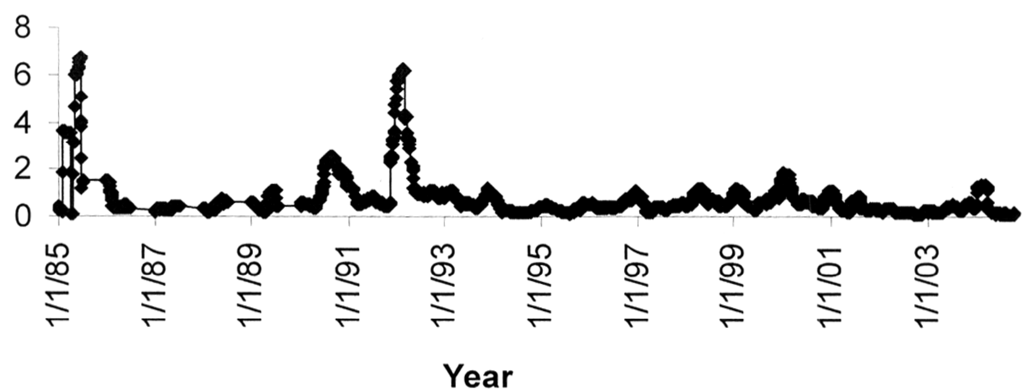
The location of endogenous structural breaks in time series has been a matter of intense research in the last few years (e.g., Banerjee *et al.* 1992, Ghysels *et al.* 1997, and Bai *et al.* 1998). The issue of estimation of the number and location of multiple endogenous structural breaks as also being an active field of research (See for e.g., Andrews et al. 1996, Gracia and Perron 1996, Bai 1997, 1999, Lumsdaine and Papell 1997 or Bai and Perron 1998, 2003 a, b). Most of the techniques in the above papers have been developed for estimation and location of endogenous breaks in the mean parameters of trend models. However, as Bai and Perron (1998) mention, they can also accommodate changes in the variance. We use the general framework in Bai and Perron (1998 and 2003) and their procedure of sequentially locating the breaks with its associated critical values.

As a first step we detect the shift in unconditional volatility. For this purpose we estimate 12-month rolling variance as well 90-days rolling variance. Figure 1 and 2 represents 90-days and 12-month rolling variance. The annualised rolling variance is calculated as follows:

$$\sigma^2 = [12 \sum_{k=0}^{11} (r_{t-k} - \mu_{12})^2 / 12] \tag{8}$$

Where μ_{12} is the sample mean over 12 month window. The 12 before the formula is just a way of annualising the variance.

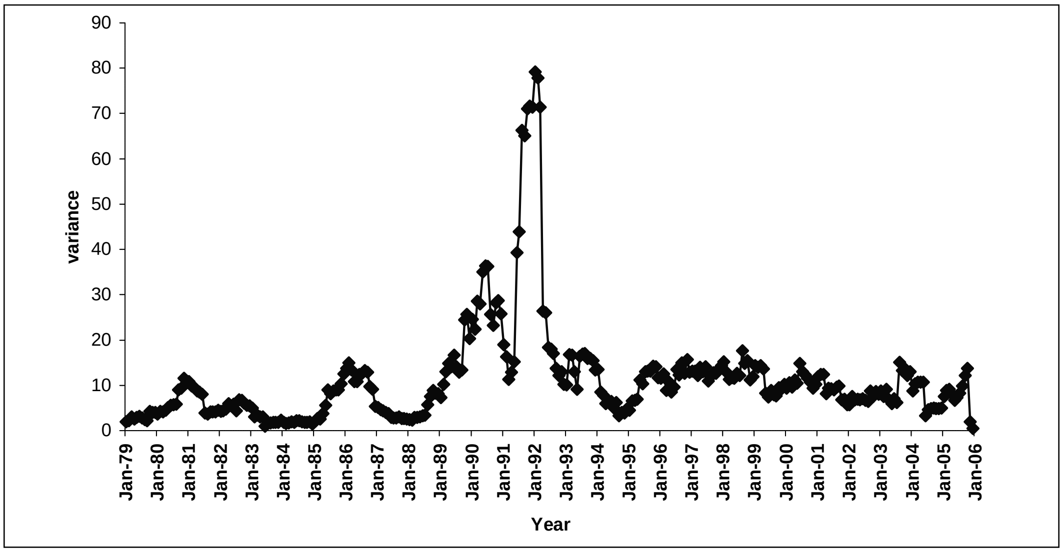
Figure 1
90-days Rolling Variance



From Figure 1 it is clear that there is shift in unconditional volatility around the period 1991-93 during which most the liberalisation measures took place. Since then, the volatility follows a downward trend till 2003. From daily return series it is also clear that the rolling variance shows a continuos increase in volatility until 1991-92, when it reaches its highest level. Since then the volatility shows a downward trend. So the period 1991-93 is the most volatile period.

Though standard GARCH models are able to capture times varying nature of volatility but they fail to capture structural breaks in the series that are caused by low probability events such as a crash and / or political/ economic event. The GARCH model as discussed above can be modified to include sudden changes in the variance. Lastrapes (1989) and Lamoureux and Lastrapes (1990) have shown that when ARCH/GARCH models are applied to data that include sudden change in variance then the conditional variance may be found

Figure 2
Annualised Rolling Variance



to strongly persist over time. According to them, high volatility persistence in GARCH models could be on account of structural changes in the variance process.

We follow the methodology of a combined GARCH as given by Lamoureux and Lastrapes (1990) and followed by Aggarwal et al. (1999) and Batra (2004). The purpose is to test for the structural breaks and then to estimate the time of its occurrence. The structural change analysis is undertaken for unconditional variances in the BSE return series. We test the null hypothesis of no structural breaks against there are (m) numbers of break points in the series. Our result shows that there are three structural break points in the series which is presented in Table 6.

Table 6
Structural Break Points

Variables	*No. of Breaks**	*Dates*	*Events*
BSE Return Series	3	1989: 08	Bofors Scam
		1992:04	Harshad Mehta Scam
		2003:04	SARs effect
IFCG Return Series	3	2000:01	InfoTech Boom
		2001: 08	Terrorist attack on New York
		2003: 04	SARs effect
FII purchase	2	2003:06	
		2004:10	
FII sale	2	1999:09	General Election
		2003:12	
Market Cap.	2	1993:12	
		2003:10	
Turnover	2	1999:06	
		2001:02	Ketan Parekh scam

*According to BIC criteria all the break dates are significant.

It is clear that there is no break point around liberalisation period which is associated with stock market reform per se. At the same time there is no structural change that is related to the entry or buying or selling by FIIs. So FIIs is not the source of volatility persistent. Rather, economic reform in general and some political events leads to structural shift in volatility as it is found from the break dates. In most of the cases we found that scams and international factors that led to structural breaks. Financial liberalisation and particularly, stock market reforms do not lead to a structural break in India.

The E-GARCH model discussed in section 4 could be reformulated to take into account for the structural change by adding dummy variables. The equation (6) can be rewritten as follows:

$$\ln h_t = \omega + \beta \ln h_{t-1} + \alpha_1 \left| e_{t-1}/\sigma_{t-1} \right| + \alpha_2 e_{t-1}/\sigma_{t-1} + \delta_1 d_1 + \delta_2 d_2 \ldots + \delta_n d_n \tag{9}$$

Where d1, d2 and dn are the dummy variables taking the value of one from each point of sudden change of variance onwards and zero elsewhere. We then compare the implied persistence of the model as in equation (9) using the restricted specification to that of the unrestricted specification in (7). Monthly return series is used for break point test. The results are presented in table 7.

Table 7
Volatility with Structural Break Point

Period	*Mean (%)*	ω	α	β	d_1	d_2	d_3
1979-05	0.41	0.125	0.071	0.712	1.44	-1.30	0.697
		(0.48)	(2.38)	(14.5)	(2.98)	(-1.87)	(3.13)
1979-92	0.51	0.20	0.11	0.38	1.11	-0.34	-
		(0.69)	(2.86)	(4.62)	(2.77)	(-1.68)	
1993-05	0.47	0.13	0.06	-0.54	-	-	1.23
		(0.48)	(1.67)	(-2.05)			(2.11)

Out of three dummies, two dummies have a positive impact on volatility. The first dummy (1989: 08) has a positive impact on volatility, and second dummy (1992:04) has negative impact. The third dummy (2003:04) has positive impact on volatility. The result also shows that there is significant reduction in ARCH effect when large shocks are controlled for. But volatility is still persistent even after controlling large shocks. The sum of the ARCH coefficients has come down considerably (from 1.07 to 0.71) for the full sample. In pre-liberalisation period the sum of the ARCH coefficients has come down from 0.96 to 0.38 and for post-liberalisation period declined from 1.13 to -0.54. There is also marginal decrease in mean volatility for all the period.

CONCLUSION

Objective of this paper is that to estimate time varying volatility and compare pre with post liberalisation period. Basically we have addressed two issues: (1) is Indian stock market more volatile in post-liberalisation period? (2) Can we relate the volatility with stock market reforms?

The character of stock returns shows that it not normal and ARCH effect is present. In the presence of autocorrelation and ARCH effect, unconditional variance is not appropriate measure for volatility. The classes of GARCH family models have been found to be valuable in modeling the time series behaviour of stock returns. Our period of analysis is from 1985-2004 for daily returns and 1976-2004 for monthly returns. Our findings indicate that GARCH models are appropriate measure of volatility. Following conclusions are drawn from our analysis:

(1) Volatility persistent is high for all the periods. From daily return we find that pre-liberalisation period is more volatile. But from monthly data it found that post-liberalisation period is marginally higher volatile.

(2) The period June 1991 to 1992 is the most volatile period because of the announcement of SAP programme along with several reforms in several fields of the economy.

(3) From E-GARCH model it is found that leverage effect is present and significant for all the sample period. However, for monthly data, it not significant. In fact, for pre-liberalisation period the leverage effect is positive which contrast to the model.

(4) From structural break analysis we found that there are four break dates and its relation to economic and political events. None of the break dates is related to stock market liberalisation events. Rather it is related to economic policy change/regime shift.

(5) When large shocks in stock returns are controlled, there is significant reduction in ARCH effect; however the volatility is still persistent.

(6) Buying or selling by FIIs does not coincide with change in stock market volatility.

(7) There not much change in the level of volatility in pre and post liberalisation period.

Notes

1. A distinction is made between: (a) weak efficiency, where the market price includes all the information contained in historical prices; (b) semi-strong efficiency, where the market price includes, in addition to information in historical prices, other public information; and (c) strong efficiency, where the market price reveals both public and private information.
2. Financial liberalisation allows domestic stock market to integrate with other stock markets. So, volatility of domestic markets affected through the transmission effect and contagion effects of financial crisis.
3. The economic reasons for this are unclear. As Black (1976) and Christie (1982) note, both financial and operating leverage play a role, but are not able to explain the extent of the asymmetric response of volatility to positive and negative returns shocks. Schwartz (1989 a, b) presents evidence that stock volatility is higher during recession and financial crisis.

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