Heteroskedasticity Models on the Bombay Stock Exchange

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Abstract

In this article, we study conditional heteroskedasticity in a market index on the Bombay Stock Exchange, from April 1979 to March 1995. We find strong evidence of heteroskedasticity in daily, weekly and monthly returns. The conditional variance of all three data series seem best approximated by a GARCH(1,1) model. The GARCH parameter estimates at all data frequencies exhibit strong persistence in variance.

In the case of monthly returns, we find there is *seasonality* in the volatility, and there is one *regime shift* in the level of unconditional variance of the data. Remarkably enough, after controlling for these, monthly returns are homoscedastic, and there is no persistence. Both, the regime shift and the seasonality, have clear economic interpretations. The regime shift appears in March 1985, and is associated with a sharp turn towards market-oriented economic policies - among other things, this led to an enormous expansion of the domestic IPO market and secondary market trading volumes. The seasonality in the post-March-1985 period is characterised by enhanced volatility associated with each federal budget announcement in end-February.

The results with weekly and daily data are not as drastic – while strong evidence of the regime shift and of seasonality is found in daily and weekly data, even after controlling for these, returns are still ARCH, and still exhibit a fair degree of persistence.

Finally, we use our volatility models to test whether the market prices the observed heteroskedasticity using GARCH-in-mean models. We are unable to reject the null that higher risk is not priced. We offer qualitative arguments suggesting reasons for this behaviour and conjecture that this may change in the near future.

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1 Introduction

Ever since ARCH models were introduced into the literature by Engle (1982), the literature has uncovered evidence of heteroskedasticity in stock market returns in most OECD countries, especially the United States (see Bollerslev, Chou & Kroner (1992) for a comprehensive literature survey). Variance of returns at a point in time shows strong correlations with prior innovations: this has been established using ARMA models estimated for squared returns (as recently explored in Geyer (1994)) and GARCH models for returns of many stock markets in the world (a few of the many papers are Theodossiou & Lee (1995), Errunza, Hogan, Kini & Padmanabhan (1994) and Booth, Martikainen, Sarkar, Virtanen & Yli-Olli (1994)).

1.1 Why Heteroskedasticity in Returns Matters

Heteroskedasticity, if it exists, has numerous ramifications for financial economics. If the data generating process underlying returns contains heteroskedasticity, then it may have to be explicitly accounted for when addressing a whole host of problems, ranging from tests of market efficiency and asset pricing theory to portfolio optimisation and the pricing of derivatives.

On the subject of the data generating process underlying stock market returns, evidence of non-normality of continuously compounded returns in many countries is diminished when examining residuals from ARCH models. At a practical level, this impacts on asset pricing theory and portfolio optimisation which is affected by the heteroskedasticity– examples of this are Ghosh (1992), Schwert & Seguin (1990) or Bera, Bubnys & Park (1988). A powerful impetus for volatility models comes from financial derivatives, where forecasts of volatility are directly used in pricing algorithms for all derivative contracts.

An exploration of what causes heteroskedasticity brings us back to basic questions of market efficiency, and the mechanisms through which prices assimilate information. At the simplest, tests of market efficiency which assume a homoskedastic data generating process are biased towards rejection of the null if heteroskedasticity is present. In one example, Frankfurter & Lamoureux (1988) show that once heteroskedasticity is accounted for, certain kinds of perceived arbitrage opportunities disappear.[1]

1.2 The Bombay Stock Exchange

In this paper, which is part of a larger research program aimed at understanding the Bombay Stock Exchange (BSE), we study heteroskedasticity in returns on the market index.

The BSE has been in operation since 1876, and is one of the oldest stock markets in the world. In the past, domestic firms and investors were restricted in their access to the stock market by a variety of legal constraints, and foreign investors were prohibited. From 1984 onwards, restrictions on domestic agents have steadily diminished, and from 1992 onwards, participation by international investors has begun. These reforms have thus, in the recent past, led to a vast increase in the importance of the stock market in domestic resource allocation on many counts: the share of domestic savings which are channeled through the stock market, the size of the IPO market, the role of equity in the financing of the corporate sector, the share of portfolio investment by international investors in total inflows into the country on the capital account, and the share of BSE market capitalisation owned by foreigners.

As a market index, we will use a long time-series of returns on the BSE Sensex, a widely used market index on the BSE. Our dataset has 3206 observations of daily returns over the period from April 1979 to March 1995. The thirty companies in the BSE Sensex account for only 25% of the market capitalisation of the BSE as of today (though this fraction was around 40% before 1992). This coverage is quite poor, but there is no alternative market index which matches the span of this time-series. The BSE Sensex also has one important advantage as compared to other indexes: while securities on the BSE often suffer from non-synchronous trading, the thirty companies in the BSE Sensex are essentially immune to it. This would reduce the expected spurious autocorrelations generated by non-synchronous trading to a large extent.

[1] They apply timing filter rules to mean-variance efficient portfolios and find that the filter rules do not reveal arbitrage opportunities compared to a buy-and-hold strategy, once heteroskedasticity is accounted for.

The plan of this paper is as follows. We start with the statistical features of the BSE Sensex in section 2. These statistical features are used to guide the specification of time-series models. The econometric theory of these models is reviewed in Section 3. Estimation and diagnostics are presented in Section 4. Inference and analysis – in particular, the issues of regime shifts and seasonality – are taken up in Section 5, and Section 6 asks whether the observed heteroskedasticity is priced. Section 7 concludes the paper, summarising the results and suggesting avenues for further research.

2 Statistical character of the returns vector

The dataset is 3206 points of daily returns. Univariate statistics for daily, weekly and monthly returns are shown below.[2]

		April 1979 to March 1995				
	Number of Observations	Median	Mean	Std. Dev.	Skewness	Excess Kurtosis
Daily	3206	0.051	0.105	1.750	0.109	6.016
Weekly	798	0.276	0.425	3.614	0.144	3.432
Monthly	190	1.575	1.765	8.484	0.511	1.586

Table 1: Summary Statistics for returns on BSE Sensex

The statistical features seen here are consistent with results obtained for stock market indices in other studies, for example, daily data in Koutmos, Lee & Theodossiou (1994) and monthly data in DeSantis & Imrohoroglu (1994). These papers find similar evidence of non-normality in terms of the higher order moments for all of the countries studied, in particular, excess kurtosis.

[2] Continuously compounded returns are calculated as $100 \log(P_{t+1}/P_t)$ where P_t and P_{t+1} are the levels of the BSE Sensex.

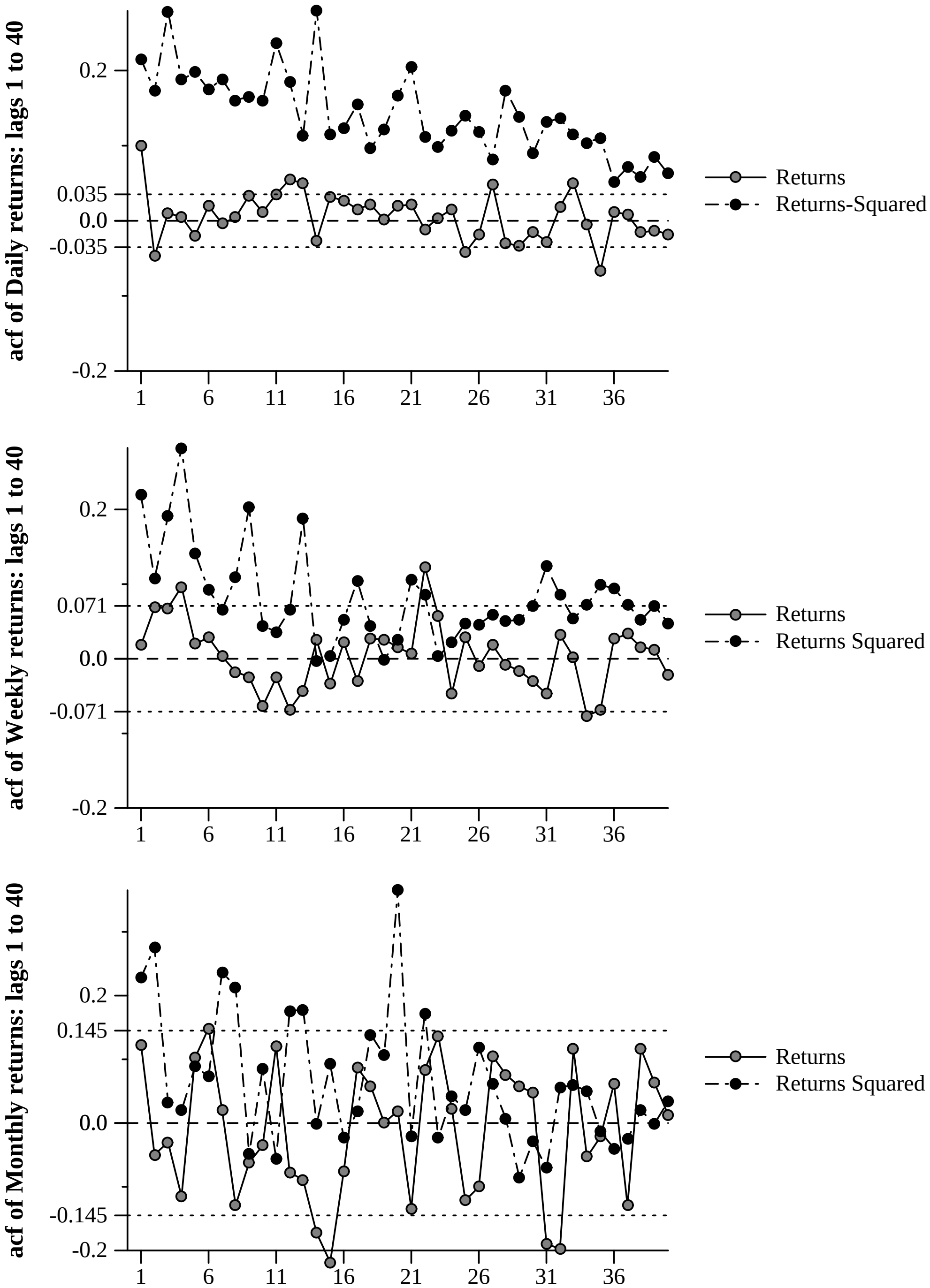

Figure 1: Autocorrelation coefficients for lags 1 to 40

The ACFs in Figure 1 show the time series structure of the returns and the squared returns. The BSE Sensex appears to have strong autocorrelations in returns, at least for first couple of trading days, with significant coefficients in the initial lags of the daily series. In this paper, with the focus on the volatility, we examine the squared returns as a measure of daily variance.

From the ACFs, the autocorrelation in the squared returns suggest that there is a clustering of variance. The correlation appears strongest in daily data with almost every coefficient of the returns squared series being outside the asymptotic bounds.[3] The correlation is weaker for the weekly squared returns and further reduced for the monthly series. But all three series show strong first order correlations in the returns squared series.

The above characteristics of high kurtosis, the variance clustering seen in the ACF and the reduction of correlation in squared terms across aggregation of the data suggest the ARCH specification as a good approximation to the structure of conditional variance of the BSE Sensex.[4] Diebold (1986) first theoretically developed how ARCH returns cause the three characteristics above.

3 ARCH Models for the BSE Sensex

Time series with autoregressive conditional heteroskedasticity (ARCH), were first modeled by Engle (1982). The simplest ARCH model for a time-series y_t is written as follows:

$$y_t = x_t'\beta + \epsilon_t$$

ϵ_t is assumed to be serially uncorrelated and has a unconditional variance of σ^2, and conditional variance σ_t^2 of the form

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2$$

or

$$\sigma_t^2 = \alpha_0 + \alpha(L)\epsilon_t^2$$

The conditional variance equation has q lagged squared residual terms, ϵ_t^2 and the specification is referred to as the ARCH(q) model.

In the GARCH model (Bollerslev 1986), a potentially long lag structure of ϵ_t^2 is replaced by a combination of lagged ϵ_t^2 and σ_t^2. Where the data suggests high values of q, this often produces a more parsimonious specification as compared with a simple ARCH model. The conditional variance takes the form:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \gamma_j \sigma_{t-j}^2$$

or

$$\sigma_t^2 = \alpha_0 + \alpha(L)\epsilon_t^2 + \gamma(L)\sigma_t^2$$

for a GARCH(p,q) model.

[3] The bounds are calculated as $2/\sqrt{T}$, which amounts to 0.035 for the daily data, 0.07 for weekly data and 0.15 for the monthly data.

[4] Akgiray (1989) find that ARCH models estimated for the US stock markets index show reduced ARCH parameters across aggregation of the data.

3.1 Specification of the Mean Equation

The form of the mean equation has ramifications for the time series properties of the variance. Figure 1 showed that there is significant autocorrelation in both the returns and the squared returns. This is a feature documented in returns in the US (Fama 1965, Amihud & Mendelson 1987, McInish & Wood 1991) and on other stock exchanges as well (Cochran, DeFina & Mills 1993).

Models that arose to explain this autocorrelation mostly pointed to institutional factors as responsible for its existance. Hasbrouck & Ho (1987) modelled the autocorrelation as the result of lagged adjustment of limit-order prices. Campbell, Grossman & Wang (1993) modelled it as arising from higher returns for risk-taking on the part of market makers. The risk is increased variance in returns due to the action of "noise" traders.

When different stocks trade on the market at different frequencies, this is known to generate autocorrelation in the market index (Lo & MacKinlay 1990). Thus, the impact of any particular information shock on the market, has a lagged effect through its impact on stocks that trade at different times. This means that for an index even on an "efficient market", the effect of any one shock will die out more slowly than the ideal one-time change in the level of the index.[5] In addition, the non-synchronous trading autocorrelation effect is a relatively short term one, which might also explain why there is a much reduced ACF structure in monthly data of most stock markets studied.

Non-synchronous trading as an explanation of index autocorrelations might have been quite applicable on the BSE, since there is a lot of non-synchronous trading on the BSE. However, it is of limited importance in this article, since the companies in the BSE Sensex trade very well. There are other institutional factors which explain these autocorrelations, and we will not explore them further here.

Thomas (1995) suggests the ARMA(2,1) as a good specification to characterise the daily returns data, ARMA(2,2) for weekly and monthly returns, under the assumption of homoskedasticity. An ARMA model can also be written as an AR model of infinite lags. Since the focus is on the variance structure of the residuals and the exact specification of the mean equation is not the issue, we estimate long-lag AR mean equation models in the following section on estimation.[6] In this paper, we begin estimations using an AR(2) specification for daily data, and an AR(1) for weekly and monthly data.

Thus, the GARCH model that we will estimate for the BSE Sensex takes the form :

$$\begin{aligned} r_t = & \quad \beta_0 + \beta L(r_t) + \epsilon_t \\ \epsilon_t \sim & \quad N(0, h_t) \\ h_t = & \quad \alpha_0 + \alpha(L)\epsilon_t^2 + \gamma(L)h_t \end{aligned}$$

3.2 Model Selection Criteria

Model selection for these models in this paper is based on three metrics: the LR statistic, the Akaike Information Criterion, AIC, and the Schwartz Bayesian Criterion, SBC. All three statistics are based on the log likelihood value at the estimated parameter vector. The LR is a ratio of the restricted to the unrestricted model and is distributed as $\chi^2(k)$ where k is the number of restricted parameters. In this paper, we estimate models with one restriction imposed at a time, and thus use the LR test as a comparison between two models, with $k = 1$.

The AIC and SBC are functions of the log likelihood values as well as the number of free parameters in estimation. They incorporate a penalty for a larger number of parameters, which gives us a bias towards more parsimonious specifications. If a model contains k free parameters, the AIC is $\frac{2}{T}(\log L + 2k)$ and the SBC is $\frac{2}{T}(\log L + (\log T/2)k)$. The AIC often leads to over-specified models as compared with the SBC.

[5] While non-synchronous trading explains index autocorrelations substantially, it has been shown to not completely account for the autocorrelations in the S&P500 index. (Harris 1989, Atchison, Butler & Simonds 1987).

[6] We also estimated ARMA-GARCH models for the data and found very few changes compared with the GARCH parameters estimated with the AR specification of the mean equation.

3.3 Estimation Results

We started by estimating ARCH(q) models (results not shown here) using 22 lagged squared residuals.[7] The estimations offered strong support for the existence of conditional variance. The optimal lag length chosen as per the AIC statistic is $q = 14$ while the SBC statistic was maximised at $q = 4$ for daily data.[8] We take the long lag structure in the variance specification as evidence that the GARCH specification might be a better alternative as a model for conditional heteroskedasticity of the BSE Sensex.

We move on to estimating GARCH models for the BSE Sensex. Given that there is heteroskedasticity inherent in the data, we first re-evaluate the form of the mean equation. Models are estimated for upto four lagged terms of the returns in the mean AR equation for two fixed GARCH specifications – a GARCH(1,1) and a GARCH(4,4) – the log likelihood and selection criteria are tabulated below.

	GARCH(1,1)				GARCH(4,4)			
Mean Terms	Log Likelihood	LR Statistic	AIC	SBC	Log Likelihood	LR Statistic	AIC	SBC
4	-5819.95		3.643	3.660	-5803.91		3.638	3.663
3	-5821.09	2.28	3.642	3.657	-5806.46	5.10	3.638	3.660
2	-5821.86	1.54	3.641	3.654	-5809.68	6.44	3.638	3.658
1	-5825.30	6.88	3.641	3.652	-5813.44	7.52	3.638	3.657
0	-5839.14	27.68	3.648	3.658	-5872.92	28.96	3.646	3.663

Table 2: Selection of Mean Equation Lagged Terms

With the variance specified as a GARCH model, the best fit model of the mean returns for daily data seems to be an AR(1).

We estimate GARCH models for daily data, with the mean equation as an AR(1). Log Likelihood values and the test statistics for the values of $p = 1 \ldots 4$ and $q = 1 \ldots 4$ are shown in Table 3.

p / q	1		2		3		4
1	-5825.30	(1.84)	-5824.38		***		***
	(1.58)		(2.98)		(–)		
aic	3.641		3.642				
sc	**3.723**		–				
2	-5824.51	(3.24)	-5822.89	(5.78)	-5820.00	(0.38)	-5819.81
	(1.52)		(1.42)		(2.80)		(-1.06)
aic	3.642		3.642		3.642		3.643
sc	**3.741**		**3.757**		**3.773**		**3.791**
3	-5823.75	(3.14)	-5822.18	(7.16)	-5818.60	(–)	***
	(3.48)		(5.92)		(5.00)		(1.060)
aic	3.642		3.643		3.650		–
sc	**3.765**		**3.783**		**3.799**		–
4	-5822.01	(5.58)	-5819.22	(6.24)	-5816.10	(5.32)	-5813.44
aic	3.651		3.652		3.652		3.638
sc	**3.783**		**3.800**		**3.817**		**3.658**

(LR) statistics at each addition of a parameter between the LogLikelihood values
aic and **sc** statistics are entered below the LogLikelihood values
(***) estimation did not converge

Table 3: AR(1)-GARCH model statistics

[7] We elected to start with 22 lags as the largest number of trading days in any month in the data.
[8] Models estimated for weekly and monthly returns of the BSE Sensex gave $q = 4$ for weekly and $q = 2$ for monthly.

The increases in lagged h_t terms in the variance yields least by way of improving the Log Likelihood value, in fact, some of the models with the longer lag structure of the lagged h_t terms (i.e. higher p), could not be estimated. In contrast, longer lags in the squared residual (i.e. higher q) yields likelihood gains, though these gains are not significant. The AIC and SBC steadily worsen with increases in either p or q as compard with the GARCH(1,1). As for the estimates themselves, the coefficients on the lagged residual terms have increasing standard errors as the number of lags increase.

4 Inference and Analysis

The moments of the residual based on different GARCH specifications in Table 4 show expected changes in kurtosis. When homoskedasticity is assumed, there is a pronounced kurtosis which changes dramatically when using GARCH(1,1) or GARCH(4,1) to specify the variance. This is consistent with other studies in the literature which find that the evidence for non-normality of returns is diminished when ARCH effects are accounted for.

If the GARCH model is specified correctly, then the residuals standardised by the conditional standard deviation, $\epsilon_t/\sqrt{h_t}$, should be a white noise process. The ACF of $\epsilon_t/\sqrt{h_t}$ should also have smaller coefficients than the ACF of ϵ_t. From Figure 2, we find that the standardised residuals from the GARCH(1,1) model have ACF coefficients that are not significant – they all lie between the asymptotic bounds of $2/\sqrt{T}$. This is even more obvious in the case of the squared standardised residuals except for the term at lag five.

	Moments of the standardised error, $\epsilon_t/\sqrt{h_t}$			
Garch Lags	Mean	Standard Deviation	Skewness	Excess Kurtosis
$(0,0)$	0.032	3.034	0.147	6.207
$(1,1)$	0.018	1.001	0.355	3.724
$(4,1)$	0.051	0.091	-0.102	0.032

Table 4: Daily data AR(1)-GARCH models : Diagnostics

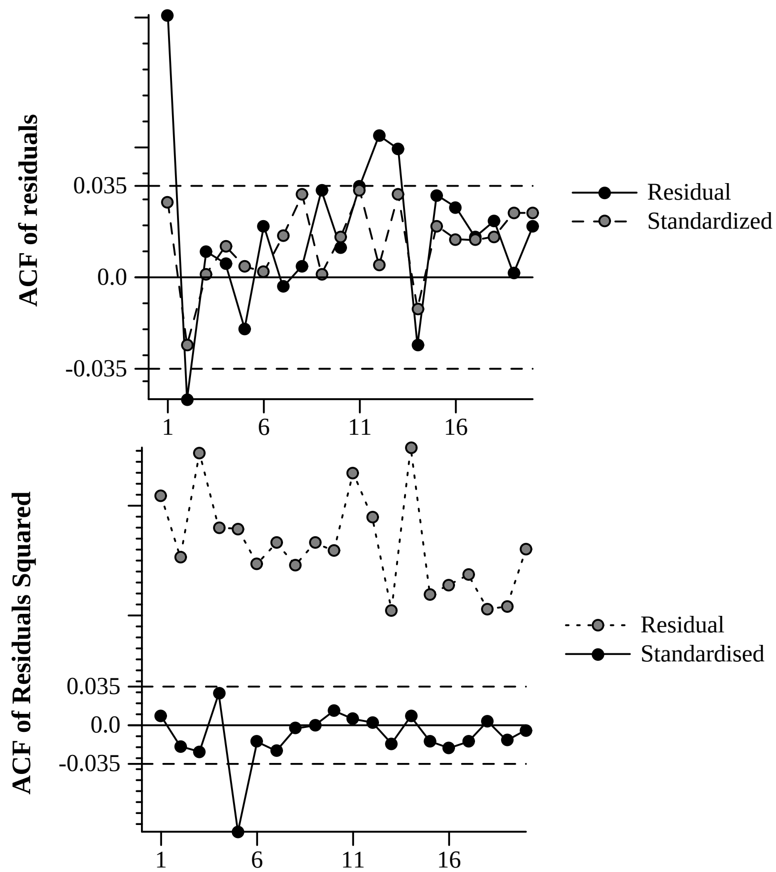

Figure 2: ACF for Residuals in Daily Data at lags 1 to 20

Estimated ARCH models for the weekly and monthly data also show that the model selection criteria favour the GARCH(1,1) amongst models with lags upto four in both the lagged residual squared and the lagged variance terms. Drost & Nijman (1993) demonstrates that given a true GARCH model for a process at a certain frequency, the model for aggregated data is of a higher-order GARCH form. In our case, estimations of the daily, weekly and monthly models are all seemingly GARCH(1,1). This leads us to suspect that the simple GARCH(1,1) might be a misspecification of the time series structure for the volatility of daily returns on the BSE Sensex.

Parameters	Daily AR(1)-GARCH(1,1)	Weekly AR(0)-GARCH(1,1)	Monthly AR(0)-garch(1,1)
β_0	0.062	0.269	1.327
	2.929	2.806	2.330
β_1	0.099		
	5.330		
α_0	0.053	0.234	1.661
	9.851	2.835	1.322
α_1	0.099	0.130	0.105
	12.072	6.694	2.088
γ_1	0.886	0.861	0.879
	115.644	40.516	15.609
$\alpha_1 + \gamma_1$	0.985	0.991	0.984
Moments of standarised error, $\epsilon_t/\sqrt{h_t}$			
Mean	0.019	0.039	0.054
Variance	1.001	0.999	1.003
Skewness	0.356	0.106	0.459
Kurtosis	3.724	1.324	0.279
t-stats below the parameter estimates			

Table 5: GARCH Parameter Estimates

We will now focus on the GARCH coefficient estimates, α_1 and γ_1, in table 5. The sum of these coefficients defines the *persistence* of the variance. The concept of "persistence" here is a measure of the number of time periods for which the impact of any shock to variance is significant. For the models estimated above, the sum is very close to one, which indicates a highly persistent system.[9] Further, in our estimates, this degree of persistence does not seem to change much across data aggregation.[10]

The particular issue of persistence is addressed in the literature in one of two ways: one is that there is indeed long-term persistence in the variance, characterized by a conditional variance which is non-stationary. A non-stationary process implies a system where the effects of a shock are inherent in the returns process forever. From the point of view of efficiency, a market is defined as efficient if prices on the market fully absorbs and internalises information in a short period of time. We expect that information shocks to the returns should have a very short-term effect and the persistence in variance, if any, is relatively small.

An alternative to the above interpretation of persistence is suggested by Lamoureux & Lastrapes (1990*b*), with a model that depicts the perceived persistence as the result of shifts in the levels of unconditional variance. If not specified, these regime shifts in levels show up as highly persistent GARCH parameter estimates, akin to a non-stationary process. These shifts are caused by economic events that affect the behaviour of the variable being studied.

The latter model has more economic appeal than the non-stationary one, especially in the context of a developing country[11], which faces many economic and institutional changes that we expect will have impact on the structural behaviour of the market.

[9] A sum of 1.0 implies unconditional variance of ∞ asymptotically.

[10] Lamoureux & Lastrapes (1990*b*) defines a intuitively appealing notion of the half-life of a shock to the variance, which is the time period over which the shock diminishes to half it's original size. The half life for GARCH(1,1) is $1 - \log 2/\log(\alpha_1 + \gamma_1)$. The half-life for the BSE Sensex as measured by the estimated parameters is 47 days for daily data, 78 weeks and 44 months. This does not make much sense since it implies that a shock fades away faster with daily data as compared with weekly or monthly data.

[11] Geyer (1994) found that persistence of variance as measured by the sum of the GARCH parameters reduced signficantly when a regime shift was account for in the Vienna Stock Exchange.

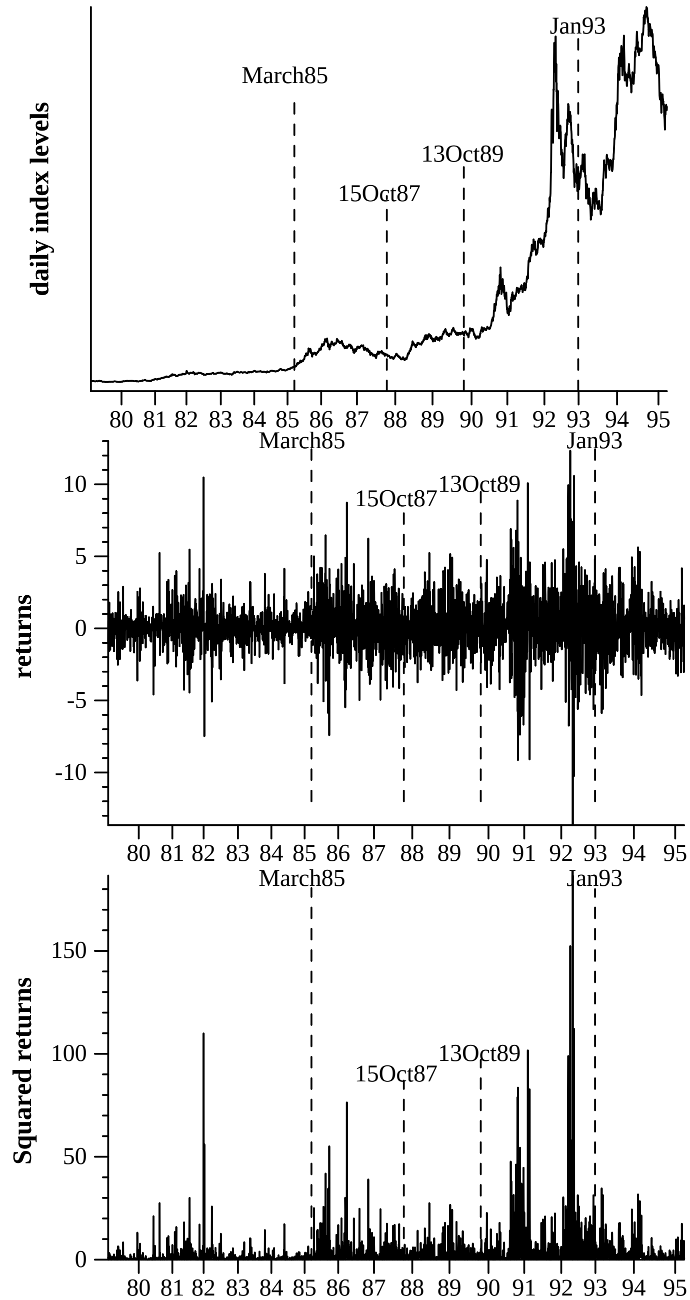

Figure 3: Daily Data: April 1979 to March 1995

4.1 Structural changes in the Indian Economy

The idea of shifts in the variance in the BSE Sensex is particularly appealing because of the many economic changes that have happened in the last decade to the Indian economy and stock market. Of these, the most interesting are the following events:

Events Pre-1990

In 1984, the new administration of Rajiv Gandhi initiated a series of policy measures which mark the beginning of India's turn towards market-oriented economic policies. While the policy environment has evolved substantially over the years, the early thrust of economic policy was on eliminating *internal* entry barriers.

Historically, India had a regime of industrial licensing, where firms had to apply for government permissions in order to start producing a given widget. Industrial licensing was fully abolished in 1991, but from 1984 onwards, the government made many changes which led to licenses being much more freely available than before. This led to an investment boom in the economy as firms rushed to enter industries which were previously characterised by shortages. This had two implications for financial markets:

- Firms often turned to capital markets to raise resources in order to finance the new projects that liberalisation made possible. Thus there was a major increase in the resources raised from the primary market. At the time, the offer prices of IPOs were regulated and very high levels of IPO underpricing were prevalent.
- Incumbent firms (which includes all the companies in the BSE Sensex portfolio) now faced a much altered competitive landscape. Earlier, the incumbent firms were protected by entry barriers. In the following years, many industries became fiercely competitive owing to entry, and profits (and dividends) became much more variable. The impact of news upon the future prospects of the incumbent company was greater than ever before.

India's primary market[12] is unique by world standards in that IPOs are sold directly to lay investors. The enormous growth of the IPO market coupled with the policy-induced high levels of IPO underpricing, served to attract a larger fraction of domestic savings into stocks in two ways: directly, through selling paper, and indirectly, by helping households make the transition from owning no shares to owning some shares.[13] We expect that this increase in volumes in the market also contributed to the increase in volatility to a small extent. [14]

Year	Resources Raised on Primary Market (Rs.bln)	Average Daily BSE Trading Volume (Rs. mln)
1983-84	9.10	130.3
1984-85	8.58	235.1
1985-86	17.45	371.5
1986-87	25.63	586.1
1987-88	17.77	342.3

Table 6: Structural change on the BSE

The regime shift is apparent through a visual examination of the daily data, and we will explore the proposition that a distinct change in the volatility of returns took place from the first few months of 1985 onwards. We will date the regime shift at 1 March 1985.

Events Post-1990

In the more recent past, the three outstanding events which have affected the stock market are the scam, the opening up to foreign portfolio investment, and the ban on forward trading.

The great scam of 1992 was an episode where a speculative bubble was created using an illegal diversion of funds from the banking system. The scam affects returns data from September 1991 till the end of May 1992. The BSE Sensex exhibits pronouncedly lower volatility from July 1992 onwards.

Foreign institutional investors have gradually started investing in India, in response to a gradual elimination of barriers to foreign capital, from 1992 onwards. The integration of Indian financial markets into the world

[12] Details are from a recent study of the IPOs and the Indian primary market conducted by Shah (1995*b*).

[13] Although we do not have long time series data on the percentage of household wealth invested in the stock market, we do know that in the period between 1985 and 1987, public issues as a percentage of savings almost doubled, from 4.6% in 1984 to 7.5% in 1986 and 9.5% in 1987.

[14] The positive correlation between relationship between price variability and trading volumes on the US stock markets has been well studied, as has been carefully researched in Tauchen & Pitts (1983). Since then, Lamoureux & Lastrapes (1990*a*) has also found volume to be a good proxy for information flow that remove ARCH effects from the conditional variance forms of individual stocks on the NYSE.

has also been assisted by large-scale sales of GDRs (global depository receipts) by Indian firms worldwide. Both foreign portfolio investment and GDR issues by Indian firms became significant from the middle of 1993 onwards. Indian investors are still not allowed to invest their wealth abroad.

Owing to these changes, we expect that the Indian stock markets are slowly becoming integrated with worldwide stock markets, as compared with the almost-total isolation that prevailed before. Kim & Singal (1994) study monthly returns from the emerging markets of nine countries and find that there is no increase in volatility after the opening up of the market. In this work, to the contrary, the volatility seems to decrease in the period a year after opening up. In any case, on the BSE Sensex, we hypothesize that the first order effects of increased volumes and thus, increased volatility, has taken a precedence over the effects of diversification so far.

The final event, the ban on forward trading, took place on 12 March 1994. The post-ban time-series is too short for us to analyse in detail. We might expect somewhat higher volatility through the elimination of speculative traders in the period following 12 March 1994. Shah (1995*a*) finds that forward trading diminishes firm-level unsystematic risk, but this need have no effect on the total risk of the market index, which is a well diverisfied portfolio.

Seasonal Effects

In Thomas (1995), we find no discernable monthly seasonality in the mean equation for returns on the BSE. However, there is a strong reason for us to expect seasonality in the volatility.

In India, the annual economic budget is announced on the 28^{th} of February.[15] The budget is a much-eagerly anticipated event, wherein which several policy announcements crucial to industries and firms are announced. For instance, a variety of changes in domestic tax rates, and customs tariffs are announced as part of the budget. Over and above the fiscal operations of the government, the budget speech is commonly used by the finance minister to announce other important economic policy initiatives. We would thus expect a seasonal budget effect in volatilities for the BSE, even though Thomas (1995) does not find any significant month-seasonality in the returns itself.

Rumours, prognoses and leaks about the budget begin in the early part of February and ends with the announcement at the end of February. The weeks following the budget would reflect markets assimilating the news. We attempt to capture the pre- and post-budget announcement effects and model the budget period as a combination of February and March.

The above structural economic changes to the economy coupled with the earlier diagnostic evidence against the GARCH(1,1) specification of volatility motivates studying whether the persistence perceived in the BSE Sensex returns are manifestations of shifts in the variance.

4.2 Estimation of Shifts in levels of Volatility

The problem with estimating regime-shifts-in-variance models is that there has to be a reasonable degree of certainty of when the regime shift took place. Recently, new tests have been developed to detect regime shifts in volatility (Chu 1995), and Hamilton & Susmel (1994) introduce models where the probability of the shift of a regime is endogenously determined as a Markov process. In our case, however, we have a fair idea of the dates involved.

We model the events using dummy exogenous variables in the variance equation, in addition to the GARCH variables. We estimate a AR(1)-GARCH(1,1)-with-dummies model:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \epsilon_t \quad \text{where} \quad \epsilon_t \sim N(0, h_t)$$

and

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} + \eta_k d_k$$

where in the model for the BSE Sensex, the following d_k are used as:

- $d_{\text{post85}} = 1$, if the observation is after February 1985 and zero otherwise. Volatility is much higher in the following period, so the coefficient should be positive and very significant.

[15]There are some exceptions. It was announced on the 15^{th} of March in 1990 and 1995, and on the 19^{th} of July in 1991.

- $d_{\text{scam}} = 1$, if the observation is from the scam period, between September 1991 and July 1992, and zero otherwise. The volatilities in this period was much higher due to the speculative bubble; we expect this coefficient to be positive and larger than that obtained for the post-85 dummy.
- $d_{\text{post93}} = 1$, if the observation is after foreign portfolio investment into India began. We expect the coefficient will be negative.
- $d_{\text{budget}} = 1$, if the observation is from either the months of February or March, and zero if it is not. This coefficient is expected to pick out a higher pre-budget announcement volatility level in the data. We expect this coefficient to be positive.

Models with each of the above dummies in the variance equation are estimated separately. If the dummies cause significant shifts in the variance and account for the seeming persistence, we expect that the values of the GARCH parameters and their sum will also decrease. The same phenomenon should also be observed in the aggregated series.

We estimate models similar to those used in Section 3.3: the AR(1)-GARCH(1,1) model for daily and AR(0)-GARCH(1,1) for the weekly and monthly series.

	α_0	Dummy Coefficient	α_1	γ_1	$\alpha_1 + \gamma_1$	Log Likelihood
$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1}$						
Daily	0.053		0.099	0.886	0.985	-5825.30
	9.851		13.072	115.644		
Weekly	0.237		0.133	0.858	0.991	-2057.77
	2.862		6.648	39.595		
Monthly	1.621		0.099	0.884	0.983	-653.261
	1.287		1.972	15.508		
$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} + \eta d_{post85}$						
Daily	0.057	0.063	0.097	0.869	0.966	-5814.24
	9.537	5.7301	12.043	87.473		
Weekly	0.509	1.471	0.143	0.746	0.889	-2044.97
	3.062	3.048	4.937	13.900		
Monthly	7.529	24.802	0.115	0.557	0.652	-648.077
	0.942	1.016	1.706	1.550		
$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} + \eta d_{scam}$						
Daily	0.055	0.131	0.098	0.884	0.982	-5821.85
	9.932	2.880	12.837	112.544		
Weekly	0.200	1.428	0.103	0.883	0.986	-2057.23
	2.871	2.520	5.217	41.338		
Monthly	2.628	20.941	0.090	0.866	0.956	-652.139
	1.581	0.995	1.634	13.751		
$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} + \eta d_{post93}$						
Daily	0.052	-0.001	0.098	0.887	0.985	-5825.30
	9.780	-0.129	13.0535	116.839		
Weekly	0.258	0.119	0.138	0.851	0.989	-2057.66
	2.826	0.446	6.543	35.605		
Monthly***						
$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} + \eta d_{budget}$						
Daily	0.053	0.004	0.098	0.886	0.985	-5825.26
	9.759	0.502	12.930	113.385		
Weekly	0.191	0.298	0.129	0.862	0.991	-2056.98
	1.923	1.740	6.535	39.898		
Monthly	0.000	12.428	0.099	0.874	0.973	-651.120
	0.000	1.821	1.920	17.282		

*** could not be estimated
t-stats below the parameter estimates

Table 7: GARCH Models with a single dummy in the Variance Equation

- The Post 1985 coefficient is always positive and signficant.
- The Scam coefficient is significant and positive. It is greater than the Post 1985 dummy only for the daily data. This is not so surprising considering that the effects of the high daily variances during that period will have been reduced by the aggregation to monthly.
- The Post 1993 coefficient is insignificant, and has inconsistent sign. We might have expected integration with foreign markets to have a stronger effect on the volatility in the BSE Sensex, but there are two difficulties: we have very few points (only two years of data out of twenty) in this

period, and we have the confounding effect of the ban on forward trading in March 1994.

- The Budget coefficient is positive, as expected.

If the regime shifts in variance are being mistaken for persistence in our models without regime shifts, we would expect that explicitly accounting for these shifts (even in the form of dummies) will cause a change in the sum of the GARCH coefficients, $\alpha_1 + \gamma_1$. In the estimations above, perceptible changes takes place in the case of the Post 1985 regime shift only. The persistence is also reduced across data aggregation, when the Post 1985 dummy is added. This is further support for the hypothesis that the simple GARCH(1,1) model might misspecified.

If the hypothesis that it is the Post 1985 shift in unconditional variance that causes most of the heteroskedasticity in volatility, then estimation of the models using only the Post-1985 or the Pre-1985 data in estimation should show little sign of heteroskedasticity.

Squared returns from monthly data in the Pre-1985 period do indeed have much smaller ACF coefficients, which implies a homoscedastic monthly series before 1985. We find that GARCH models are consistent with homoscedastic monthly returns in the Pre-1985 period.[16] Heteroskedasticity still exists in the post-1985 data, but the model estimates for the Post-1985 data in Table 9 are surprising – we find that the Budget dummy removes all heteroskedasticity for the monthly data.

[16]Estimates for the pre-1985 period are not shown here; it can be seen from Figure 3 that there is not much heteroskedasticity in the data in this period.

	α_0	Dummy Coefficient	α_1	γ_1	$\alpha_1 + \gamma_1$	Log Likelihood
	$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1}$					
Daily	0.103		0.091	0.882	0.983	-4151.79
	7.559		8.715	84.009		
Weekly	2.033		0.157	0.731	0.888	-1379.92
	2.674		4.045	11.096		
Monthly	27.181		0.080	0.640	0.720	-439.417
	1.087		1.113	2.296		
	$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} + \eta d_{scam}$					
Daily	0.104	0.122	0.090	0.881	0.971	-4149.55
	7.584	2.415	8.455	82.216		
Weekly	2.103	2.581	0.129	0.746	0.875	-1378.41
	2.402	1.941	2.900	9.640		
Monthly	24.099	61.744	0.000	0.696	0.696	-435.679
	0.882	0.824	0.000	2.087		
	$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} + \eta d_{post93}$					
Daily	0.125	-0.054	0.089	0.882	0.971	-4147.86
	7.282	-3.707	8.330	78.800		
Weekly	2.120	-0.353	0.153	0.734	0.884	-1379.72
	2.670	-0.711	3.354	10.966		
$Monthly^{***}$						
	$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} + \eta d_{budget}$					
Daily	0.084	0.108	0.091	0.884	0.985	-4144.98
	5.172	4.276	8.206	71.950		
Weekly	2.081	2.724	0.150	0.710	0.860	-1376.91
	2.714	2.450	3.554	10.031		
Monthly	83.255	81.401	0.000	0.000	0.000	-438.769
	7.513	1.395	0.000	0.000		

*** could not be estimated
t-stats below the parameter estimates

Table 8: GARCH Models with single Dummy in the Variance: Post 1985

When the model is estimated with all the dummies together for the Post 1985 period, we see that the signs of the single-dummy estimates are the same across single dummy estimations, which re-inforces the results of table 8.

Parameters	Daily AR(1)-GARCH(1,1)	Weekly AR(1)-GARCH(1,1)	Monthly ar(1)-garch(1,1)
	Parameter estimates of GARCH models		
β_0	0.082	0.300	1.680
	2.333	1.707	1.838
β_1	0.149		0.139
	6.647		1.402
α_0	0.108	2.147	93.986
	5.119	2.515	6.376
α_1	0.088	0.135	0.0
	7.663	3.166	
γ_1	0.879	0.715	0.678
	65.885	9.028	2.040
$\alpha_1 + \gamma_1$	0.967	0.848	0.678
d_{scam}	0.109	2.073	66.494
	2.185	1.375	0.899
d_{post93}	-0.042	-0.199	-7.386
	-2.532	-0.375	-0.686
d_{budget}	0.107	2.398	12.885
	3.945	2.033	0.478
Moments for standarised error, $\epsilon_t/\sqrt{h_t}$			
Mean	0.010	0.021	0.016
Variance	1.000	1.000	1.027
Skewness	-0.185	-0.066	0.338
Kurtosis	1.088	0.955	-0.241

t-stats below the parameter estimates

Table 9: Model with all the dummies in the variance: Post 1985

The model with all four dummies for the daily and the weekly data show marginal changes in the estimated values of the coefficients when estimated with each dummy separately, except in the case of the monthly model, where the GARCH parameters vanish.

The above results establishes that there is definitely some form of heteroskedasticity present in the BSE Sensex. This heteroskedasticity follows a GARCH(1,1) process for the daily and the weekly data. In the monthly series, there is no GARCH process in the variance. Instead, there is a strong pattern to the variance defined by a shift in 1985, and a seasonal pattern defined by the budget announcements in the data after 1985.

Given that some form of heteroskedasticity exists for the returns on the BSE Sensex, and if variance is indeed a proxy for the risk of the returns process and it is predictably modelled as a seasonal process, the question that arises is whether the market prices this seasonal heteroskedasticity.

5 Is Heteroskedasticity priced?

The null hypothesis long accepted as a basic tenet of modern finance is that nondiversifiable risk is priced. In the case of the BSE Sensex, we find that there does exist heteroskedasticity, and that it has seasonal effects. The question is whether the forecastable changes in volatility – caused by ARCH effects and caused by seasonal shifts in variance levels – generate excess returns.

Let us begin with some exploratory data analysis about the budget-related seasonality alone, with an "event study" using the market index around budget announcement dates. The residuals for the event study are are calculated as returns on the market index in excess of the mean returns on non-event dates for the entire time period of April 1979 to March 1995. The excess returns are averaged over 16 events and cumulated over the event horizon of 40 days prior to and after the event. The resulting cumulative average returns plot (the CAR) is graphed in Figure 4.

From the graph of the CAR, we see that there is a significant buildup in excess returns prior to the budget announcement. The period after the budget announcement is not as interesting in the story it tells of the returns process as in the story of the squared returns in Figure 5. Here, we measure volatility at time t in event time by averaging the squared residuals at time t across all events. This shows a marked increase in volatility in the period after the budget announcement as compared to the period before the event. If the point in squared returns at the lag of -35 is discounted as an outlier, then there is a very sharp increase in the variance of returns for the 40 time periods after the budget announcement.

The event study points to increased returns and volatility of returns around the budget announcements. We hypothesize then that the market returns does reflect the increased volatility, and test the hypothesis using the GARCH-in-mean model of returns.

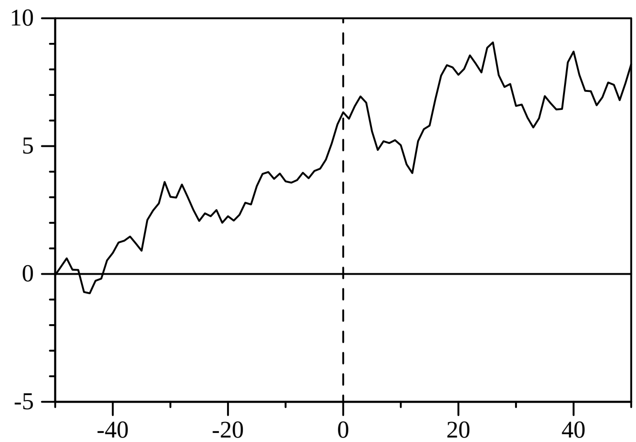

Figure 4: CAR around Budget Announcements : Daily data April 1979 to March 1995

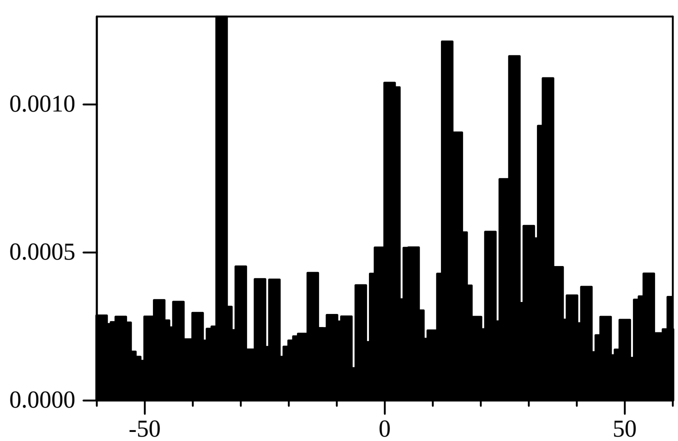

Figure 5: Squared Residuals around Budget announcements : Daily Data April 1979 to March 1995

Economic theory suggests that nondiversifiable risk would be associated with higher returns. The GARCH-in-mean model expresses a linear relationship between return and risk, where the conditional variance is GARCH(1,1). We estimate an AR(1)-GARCH(1,1)-in-mean model for the daily data, defined below as :

$$r_t = \quad \beta_0 + \beta_1 r_{t-1} + \theta_h \sqrt{h_t} + \epsilon_t$$

$$\epsilon_t = \quad \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 h_{t-1} + \sum_{k=1}^{4} \eta_k d_k$$

This model was estimated using both σ and σ^2 as measures of risk; the estimates are not much different and we only show results using σ.

Parameter estimates of GARCH models			
	Daily	Weekly	Monthly
Parameters	AR(1)-GARCH(1,1)	AR(1)-GARCH(1,1)	ar(0)-garch(1,1)
β_0	-0.033	-0.041	0.279
	-0.529	-0.154	1.508
β_1	0.099	0.044	
	5.265	1.090	
θ_h	0.076	0.124	0.190
	1.575	1.269	0.830
α_0	0.062	0.528	3.390
	9.660	2.952	0.739
α_1	0.097	0.130	0.000
	11.783	4.166	
γ_1	0.865	0.753	0.774
	83.365	13.449	4.246
$\alpha_1 + \gamma_1$	0.962	0.883	0.774
d_{post85}	0.081	1.521	13.653
	5.672	3.007	1.205
d_{scam}	0.140	2.354	46.284
	2.382	1.901	1.114
d_{post93}	-0.050	-0.358	-5.333
	-3.019	-0.799	-0.932
d_{budget}	-0.013	-0.114	13.271
	-1.122	-0.451	1.018
Log Likelihood	-5807.70	-2040.25	-645.61
Moments for standarised error, $\epsilon_t/\sqrt{h_t}$			
Mean	0.009	0.009	0.001
Variance	1.001	1.004	1.000
Skewness	0.368	0.036	0.298
Kurtosis	4.224	1.010	0.034
t-stats below the parameter estimates			

Table 10: AR-GARCH(1,1)-in-mean Estimation

The estimation results show a weak relation between the expected return and the conditional volatility. The coefficients in all three cases are the correct sign, but statistically weak. Thus the analysis seems to point out that the heteroskedasticity on the BSE using the GARCH-in-mean specification is not priced. Such results has also been found on many other markets in the world.

Why might this be the case?

The recent literature has tried to use multivariate GARCH models as an alternative to the univariate GARCH-in-mean used here. This is based on the premise that markets over the world are integrated. In the case of such a model, it is not just the variance of the market index which but the covariance of returns with indices of other countries, which is a better descriptor of risk faced by the investor. Because of this, multivariate models that explicitly take covariances into account have better power as tests of the question of heteroskedasticity being priced. Bollerslev, Engle & Woolridge (1988) and DeSantis & Gerard (1994) find that volatility is indeed priced in studies on the index when cross-correlations with other market indices are taken into account.

However, Indian economic policy has been very closed to the world economy. So we would expect the BSE Sensex to be more segmented rather than integrated. For example, in Figure 3, the returns and squared returns around the 15^{th} of Oct, 1987 or Oct, 1989, which are days of high volatility on the S&P500, do not move much on the BSE Sensex. In addition, according to the results in the preceding section, for the long-term monthly data, the primary source of heteroskedasticity is the annual budget announcement. The effect of the Post-1993 dummy, which predates foreign portfolio investment into India, is not very significant in the variance of returns of any frequency for the BSE Sensex.

At the daily level, an examination of the cross-correlation between the returns on the BSE Sensex and the S&P have very weak correlations examined at lags from $-24 \dots 24$. There is even less strength in the correlation of squared returns, which seems to support the idea that there is not much integration between the BSE Sensex and the S&P500.

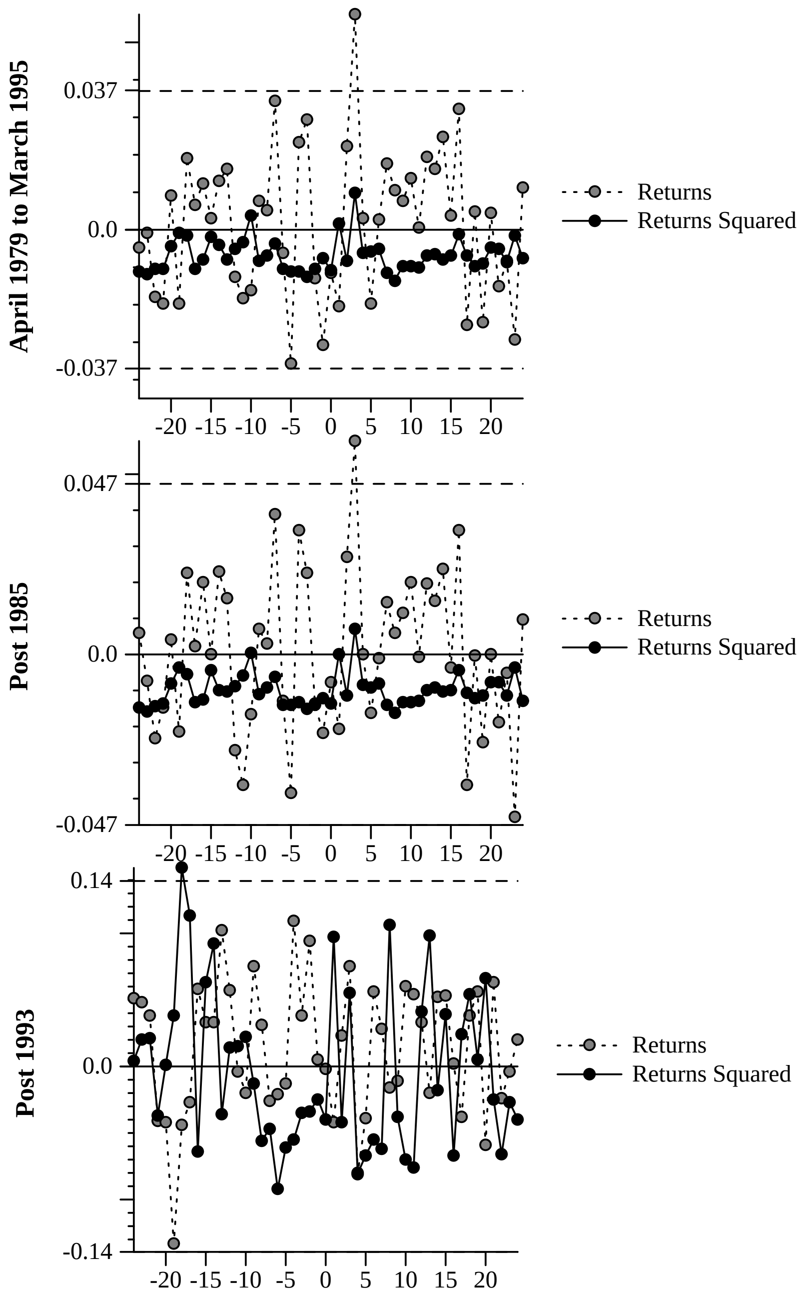

Figure 6: Correlation between the BSE Sensex and the SP500 in three different time periods

The lack of integration between India and the world justifies our univariate analysis. It also suggests an explanation of why heteroskedasticity may not be priced. In the period of estimation, there were many rigidities in financial markets which prevented the free flow of resources in response to ex-ante perceptions of investors about future risk and return. Even movements between stocks and bonds in India are not fluent. An investor who wished to change his risk posture in response to fluctuating perceptions of ex-ante volatility would incur high trading costs in the process, and the microstructure of trading on the BSE imposes some of the highest trading costs in the world upon the investor.

All these factors are likely to change in the future. Indian investors are getting more options – the debt market started functioning in 1994. The rise of online trading in 1995 has generated lowered trading costs. Finally, foreign institutional investors would react to fluctuations in ex-ante risk by moving funds out of India in a way that domestic investors cannot. All these changes are likely to generate a statistically strong θ_h in the future.

6 Conclusion

Our results may be summarised as follows.

1. Daily and weekly returns on the BSE exhibit strong ARCH effects.
2. The simple AR(1)-GARCH(1,1) model seems to be a good model for daily returns, and AR(0)-GARCH(1,1) is a good model of for weekly and monthly returns.
3. There appears to be a regime shift on 1 March 1985, with much higher volatility in the period after this date. This regime shift is likely to be related to the economic liberalisation program which began with the Rajiv Gandhi administration in 1984.
4. The annual federal budget announcement, typically on 28 February, is associated with excess volatility in the market index, especially in the month after the budget announcement.
5. The scam of 1992 is associated with increased volatility.
6. While relatively little data is available after the recent policy initiatives (opening up to foreigners in 1992, and banning forward trading in early 1994), there appears to be no major change in the time series properties of returns in the following period.
7. The regime shift and the seasonality in volatility are apparent in all of daily, weekly and monthly returns. However, in the case of monthly returns, after controlling for the regime shift and seasonality, the returns time series is essentially homoscedastic.
8. In the case of daily and weekly returns, there is evidence of persistence even after controlling for the regime shift and seasonality.
9. GARCH-in-mean models suggest that forecastable fluctuations in volatility of the market index do not appear to be priced.
10. The BSE Sensex and the S&P-500 appear to be quite unrelated, both in returns and in volatility.

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