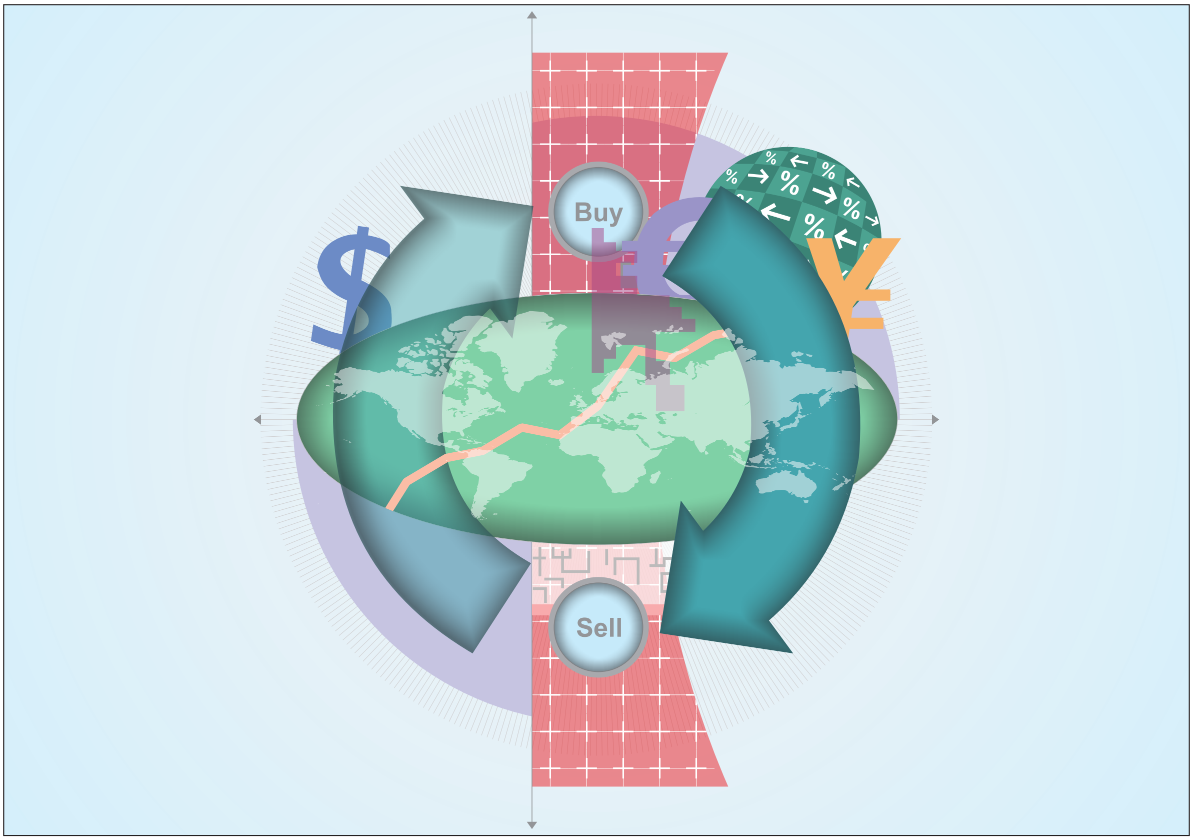

The International Journal of Applied Economics & Finance

ISSN 1991-0886

The International Journal of Applied Economics and Finance 5 (4): 257-268, 2011
ISSN 1991-0886 / DOI: 10.3923/ijaef.2011.257.268

Economic Growth, Expected Stock Returns and Volatility: A Case of Indian Stock Market

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ABSTRACT

Stock market volatility is a matter of great interest for researchers and policy makers. The present study examines the volatility of daily, weekly and monthly stock returns in view of economic growth rate. It investigates the hypothesis that high economic growth rate tend to stabilize the investment decisions and create certainty among the investors. Under such situations, investors prevent to alter their investment decisions spontaneously with regard to good or bad news. A low growth rate, on the other hand, makes their investment decisions highly volatile. The study examines the Bombay stock exchange listed index BSE 100 data for the period from 1996 through 2007, wherein Indian economy has registered high and low growth rates. It also examines additional aspect of volatility with regards to expected and unexpected variations in stock returns by applying AR(1)-GARCH(1,1) model. The findings report that investors are not sensitive to economic growth rate for short period but they become largely sensitive with the long investment horizons. The direct observations can be made here, volatility is invariable to economic growth rate in short time period but investors with long investment horizons are largely affected by economic growth rate. Briefly, high volatility tends to associate with low economic growth rate and low volatility is associated with high economic growth rate.

Key words: Efficient market hypothesis, expected volatility, unexpected volatility, BSE 100, capital asset pricing model

INTRODUCTION

The modern investment theory educates the investors to make investment decisions under the risk and uncertainty. Capital Asset Pricing Models as developed by Markowitz (1952), Sharpe (1964), Lintner (1965) and Mossin (1966) which assume efficient capital market, provide how risky securities are valued in efficient capital market. An efficient stock market fully reflects the available information pertaining to stocks resulting in investors will have homogeneous expectations to stocks performance. Accordingly, investors value the stocks taking into account the risk and return prospectus (Fama, 1991). Number of empirical studies examine stock market volatility resultant to change in economic and financial variables and point out that investors are largely sensitive to these variables (Flannery and Protopapadakis, 2002; Mala and Reddy, 2007; Binder and Merges, 2001). Studies of Aggarwal *et al.* (1999) and Bailey and Chung (1995) report that the period of sudden high volatility tend to be associated with country specific factors like corporate earning, political and govt. decisions having significantly bearings. However, the long trend of volatility should necessarily be associated with economic growth (Officer, 1973; Schwert, 1989). Investors tend to change the risk premium return of their portfolios with regard to changing macro economic fundamentals like inflation, interest rate, exchange rate and industrial production which evolve the long term trend of volatility. The present study examines the hypothesis that high volatility tends to associate with low economic growth rate and low volatility is associated with high economic growth rate. It also tests the relationship of stock returns with expected and unexpected volatility.

Many empirical researches suggest seasonal pattern in stock markets by identifying the autocorrelation is stock returns (Black and Fraser, 1995; Clare *et al.*, 1995; Pesaran and Timmermann, 1995; Moorkejee and Yu, 1999; Caporale and Gil-Alana, 2002; Rothlein and Jarrett, 2002). The auto correlation in time series data such as stock returns signifies that data in time period 't' is correlated with data in time period 't-1'. As a results stock returns exhibits volatility clustering, suggesting that large fluctuations in these series tend to be followed by large fluctuations and small fluctuations by small ones (Koutmos, 1997; Sentana and Wadhwani, 1992; Watanabe, 2002; Karmakar, 2005; Faff and McKenzie, 2007). The holding of such phenomenon marks that past error term which represents non-market risk or unexpected volatility affects current investment decisions. Under this situation, variance captures aggregate fluctuations in stock returns and thereby provides only gross volatility (Jones and Wilson, 1989; Schwert, 1990; Rakesh, 2007). In modeling such phenomenon in stock returns, researchers commonly use autoregressive conditional heteroskedasticity approach (ARCH). If no systematic pattern exists, stock returns may be time variant however, the existence of such systematic variations in the time series of stock returns suggests inefficient market which results earning of extra returns not in line with the degree of risk.

The present study roots its investigation back to study of French *et al.* (1987), wherein attempts are made to examines the relationship of stock returns with expected and unexpected volatility. Their study examined the monthly returns and segregates monthly volatility into its expected and unexpected components. Their study also estimated the relationship between realized monthly returns and two volatility components. They found a significant negative relationship between returns and unexpected changes in volatility as well as a significant positive relationship between returns and expected volatility under the GARCH-M process. Since then a large number of studies support the use of ARCH models in forecasting stock market volatility. Akgiray (1989), Pagan and Schwert (1990), Brailsford and Faff (1996) and Brooks (1998) used U.S. stock market data and found that GARCH models provide better results in forecasting returns and volatility. Using the data set from Japanese and Singaporean stock markets however, Tse (1991) and Kuen and Hoong (1992) found that the exponentially weighted moving average models provides more accurate forecast than GARCH models. Corhay and Rad (1994) used European stock market data and found GARCH (1, 1) better predictors of volatility. Chiang and Doong (2001) further used T-GARCH to examine the volatility of seven Asian stock markets and found asymmetric effect on the conditional volatility when daily return is used. Further, Badhani (2007) postulates a positive relationship between time-varying conditional risk and conditional return on securities. However, unconditional volatility and returns in two switching regimes are found negatively related. There is strong evidence that volatility increases disproportionately with negative shocks in stock returns. Mala and Reddy (2007) examined the volatility in Fiji stock market by using multivariate GARCH model for the period 2001-2005. The study reports that interest rate changes have considerable impact upon stock market volatility.

MATERIALS AND METHODS

The study uses the Bombay stock exchange listed index BSE 100 as the proxy of stock market and the data set used in the study consists daily, weekly and monthly prices. The sample period ranges from January 1996 through December 2007, wherein the Indian economy report mix set of economic environment. The early period (1996-2002) can be categorized as recession phase with 5.6% average low growth rate, however, the later period (2003-2007) was growth oriented, when economy registered an impressive 8.4% average growth rate (Appendix 1). BSE 100 which covers all industry categories stocks, is value weighted index, assigns weights to all stocks in proportion to the share of their market capitalization. The sample stocks account for a major part of the market capitalization as well as trading volume. The number and diversity of stocks lead us to conclude that sample stocks, taken as a whole, is an approximate efficient portfolio of stocks. To examine the impact of economic growth rate on stock market volatility, the study uses a dummy variable (d_t). The study arbitrarily creates two scenarios-when annual economy growth rate was more than 6% and when annual economy growth rate was less than 6 % and assign $d_t = 1$ in the year when growth rate was more than 6% and other wise $d_t = 0$. Given the data set, fluctuations in stock returns mark volatility in stock market, let P_t is the price of index in time period t, P_{t-1} is the price of index in preceding time period t-1, the rate of return R_{it} investors will realize in 't' time period as follow:

$$R_t = [\mathrm{Log}_e(P_t) - \mathrm{Log}_e(P_{t-1})] \times 100 \tag{1}$$

In fact, realized return consist a set of two components-expected return $E(R_t)$ and unexpected return 'ε_t'. Expected return is attributed by stock and economic fundamentals while unexpected return arises due to good or bad news pertaining to stocks. Symbolically, it can be written as follow:

$$R_t = E(R_t) + \varepsilon_t \tag{2}$$

An upswing in ε_t (unexpected rise in return) suggests arrival of good news, on the contrary, a downswing in ε_t (unexpected decline in return) is a mark of bad news. Volatility in stock market resultant to expected variations in stock returns is marked expected volatility while volatility resultant to unexpected variations in stock returns is marked unexpected volatility (French *et al.*, 1987). Investors and policy makers may be interested to see the value of their portfolio in some future point with respect to risk if such trend persistent in stocks prices. In modeling such situations, autoregressive conditional heteroskedasticity (ARCH) approach is used. The approach uses the conditional variance to be function of past error term and allows the variance of error term to vary over time (Engle, 1982). Bollerslev (1986), further, extended the ARCH process by allowing the conditional variance to be function of past error term as well as lagged value of conditional variance. This is based on the idea that past error term which affects current investment decisions, and volatility in the last time period combined together has significant impact over current investment decisions. Following the introduction of ARCH models by Engle (1982) and further generalization by Bollerslev (1986) and Bollerslev *et al.* (1992), these models have been extensively used in explaining and modeling the time series data of stock market. Engle (1982) suggests that the conditional variance (σ^2) is a function of the lagged $\acute{\varepsilon}$ s. It implies that volatility can be forecasted by inclusion the past news as a function of conditional variance. This process is called autoregressive conditional heteroscedasticity which can be written as follow:

$$\sigma_c^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \ldots\ldots\ldots\ldots\ldots\ldots\ldots\alpha_p\varepsilon_{t-q}^2 \quad (3)$$

where, $\alpha_0>0$, α_1, $\alpha_2, \ldots\ldots\ldots\alpha_p\geq 0$ All things being equal, α_i carries more intense influence as compared to α_j. That is, older news bears less impact on current investment decisions which results volatility, than the current news. Bollerslev (1986) generalized the ARCH (q) model to the GARCH (1,1) in which conditional variance depends upon both the squared residuals and its own lagged value:

$$\sigma^2 = \alpha_0 + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \omega \quad (4)$$

The present study uses GARCH (1,1) in forecasting the conditional volatility in Indian stock market, wherein to examine the impact of growth rate on volatility, here a dummy variable is incorporate in this model:

$$\sigma^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \gamma d_t + \omega \quad (5)$$

where, d_t = 1 if GDP growth rate is more than 6% and d_t = 0 otherwise.Where, ω_t is white noise which represents unexpected volatility, whereas first part exhibits the expected volatility. The magnitude and persistence of volatility in current time period directly depends upon the sizes of the coefficients α_i and $\boldsymbol{\beta}_i$. A high '$\boldsymbol{\beta}_i$' suggests that if volatility was high yesterday, it will still be very high today. The shocks to conditional variance will take a long time to die out. In the same fashion, the high value of 'α_i' highlights that unexpected ups and downs in stock returns react quite intensely to market movements resulting in spike volatility. The closer 'α_i' to one, the more persistent is volatility following market shock. In this model, the asymmetric volatility of index return is captured by the estimated coefficient γ. The high growth rate and low growth rate tend to have differential effects on the conditional variance-high growth rate has an impact of 'α' while low growth rate has an impact of $\alpha+\gamma$. If γ = 0, the growth impact is asymmetric on stock returns.

A large number of studies use of GARCH (1,1) and holds it enough to capture volatility in time series data (Bollerslev *et al*., 1992; Aggarwal *et al*., 1999; Sah and Omkarnath, 2006; Dhanakar and Chakraborty, 2007; Mala and Reddy, 2007). However, recent empirical studies indicate that the impact of good or bad news is asymmetric on volatihty (Pagan and Schwert, 1990; Nelson, 1991; Chiang and Doong, 2001). That is, good and bad news carries different magnitude of impact on investment decisions (Bekaert and Wu, 2000). Due to fact that, GARCH models fails to take into account the asymmetric effect between positive and negative stock returns, the models such as Exponential or E-GARCH (Nelson, 1991) and Threshold Autoregressive or TAR-GARCH (Campbell and Hentschel, 1992; Glosten *et al*., 1993, Engle and Ng, 1993; Tsay, 1998) have been used in forecasting and estimating volatility. These models are used to capture the asymmetric affect of good and bad news on investment decisions. This line of research highlights the asymmetric effect of news by emphasizing that negative shock to returns will generate more volatility than a positive shock of equal magnitude. Chiang and Doong (2001) used T-GARCH to examine the volatility of seven Asian stock markets and found asymmetric effect on the conditional volatility when daily return is used. However, study questions this phenomenon in case of monthly return.

RESULTS AND DISCUSSION

Preliminary results: Some of the stochastic properties of the BSE 100 returns are presented in Table 1 which highlights the distribution of risk and returns in these markets for study time periods. The average return in pool are positive, highlights the fact that stock index tend to increase over the period. The negative skewness of daily, weekly and monthly returns in three time periods exhibits that returns are negatively skewed, provides that the returns distribution of the market have higher probability of providing negative return. The kurtosis of monthly returns is leporathic as compared to 3, exhibits return is approximately standard normally distributed, however, the high kurtosis of daily and weekly returns exhibits heavier tail than the standard normal distribution-returns are concentrated to one level. The study uses Jarque-Bera test to examine the normal distribution characteristics of BSE 100 returns with different time intervals. As indicated by Table 1, it is significant at 5% level of significance for all different time intervals, questions the normal distribution of returns thereby the random walk behaviour of BSE 100 returns.

The volatility clustering in BSE 100 daily, weekly and monthly returns can be find out through detecting the autocorrelations in time series returns of sample periods under consideration. The study uses Ljung-Box statistics to test the significance level of autocorrelation at different lags. However, instead of testing randomness at each distinct lag, it tests the overall randomness based on a number of lags. If the stock returns are turned out to be uncorrelated, then Efficient Market

Table 1: Descriptive statistics

Statistics	Daily	Weekly	Monthly
Mean	0.08	0.34	1.52
Median	0.14	0.72	2.49
Maximum	12.24	14.59	17.00
Minimum	-12.26	-14.44	-19.15
St. Dev	1.68	3.63	7.93
Skewness	-0.40	-0.386	-0.42
Kurtosis	7.83	4.59	2.66
Jarque-Bera test	3003.59*	81.10*	4.96**
	(0.000)	(0.000)	(0.083)
Q(5)	607.19*	154.80*	40.62*
	(0.000)	(0.000)	(0.000)
Q(10)	614.31*	160.08*	52.01*
	(0.000)	(0.000)	(0.000)
Q(15)	618.61*	164.82*	55.13*
	(0.000)	(0.000)	(0.000)
Q (20)	634.87*	167.90*	62.01*
	(0.000)	(0.000)	(0.000)
Q (25)	653.23*	187.38*	64.43*
	(0.000)	(0.000)	(0.000)

Note-* significant at 5% level of significance, ** not significant at 5% level of significance

Table 2: Fitting of AR(1)-GARCH (1,1) Model

Mean equation	Daily	Weekly	Monthly	
Return	0.181*	0.489*	1.948*	
	(0.000)	(0.000)	(0.003)	
Variance equatiou				
Returns	α_0	α_1	β_1	γ
Daily	0.069*	0.421*	0.724*	0.038*
	(0.000)	(0.000)	(0.000)	(0.035)
Weekly	1.319*	0.143*	0.787*	-0.377**
	(0.010)	(0.000)	(0.000)	(0.070)
Monthly	73.170*	-0.161*	0.407**	-34.232*
	(0.021)	(0.000)	(0.262)	(0.009)

Note: *significant at 5% level of significance, ** significant at 10% level of significance

Hypothesis (EMH) is accepted thereby rejecting the alternative hypothesis of autocorrelation in stock returns and the stock market in questions are deemed informationally efficient. The holding of such situations highlights the fact that stocks prices are reflecting all inherent information and investors primarily giving weightage to current information in stocks selection. As against to it, if stock returns are found serially correlated, it will report volatility clustering in stock returns. That is high volatility tend to be followed by high volatility and low volatility tend to be followed by low volatility. Such phenomenon involves the rejection of EMH and holds that current stock returns are significantly affected by returns being offered in the past. As indicated by Table 1, L-B statistics 1 through 25 lags are significant; suggesting the presence of autocorrelation is stock returns in all types of returns.

Model estimation, forecasting of conditional volatility: The above tests, report significant non linear dependence in the BSE 100 daily, weekly and monthly stock returns. The 'Q' statistics which examines the autocorrelations in stock returns for lags 1 trough 25, holds volatility clustering i.e., serial correlation is stock returns (Table 1). With finding out this phenomenon, the study uses AR(1)-GARCH (1, 1) which significantly explain the conditional volatility of daily, weekly and monthly returns during the sample period. Table 2 outlines the results of fitted models for sample data and to fit the best model, various criteria like Akaike information and Schwarz criterion are used. The findings report that coefficient α_1 of daily, weekly and monthly returns are significant at 5% level of significance highlighting that investors significantly alter their investment decisions in response to unexpected changes in stock prices due to changes in corporate and economic factors in both short and long run. The coefficient 'β_1' of daily and weekly returns is significant, highlighting that investors adjust their portfolios in response to expected volatility in short time period-volatility in the preceding time period, i.e., variations in stock prices have significant impact upon the volatility in current time period and investors tend to redesign their investment decisions in short time period. However, it is not significant for monthly returns indicating that investors are invariable with their portfolios resultant to expected volatility in stock returns in long run. The study brings out interesting results about stock market volatility resultant to economic growth rate. The coefficient 'γ' is positively significant for daily returns, suggesting that volatility of daily returns is positively related to economic growth rate. However, volatility is significantly negatively related for weekly and monthly returns. It brings out that high volatility period coincide with low growth years and low volatility period is with years when Indian economy reported high GDP growth rate in long run. However, investors are not sensitive to economic fundamentals in short run.

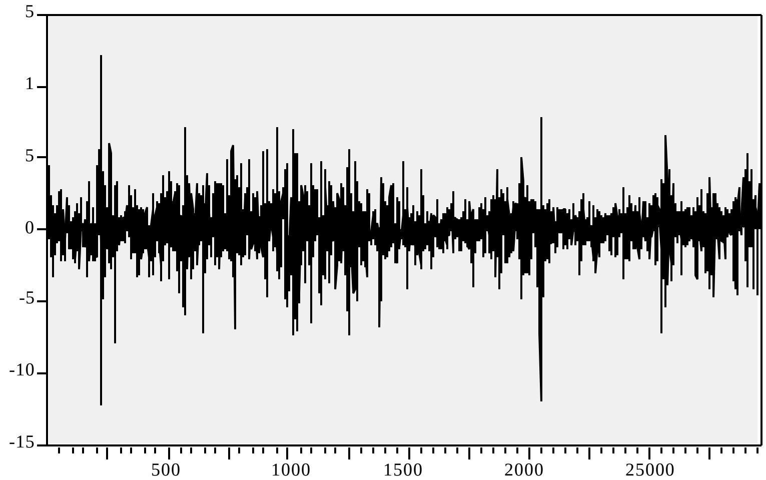

Fig. 1: Volatility of daily returns (1996-2007)

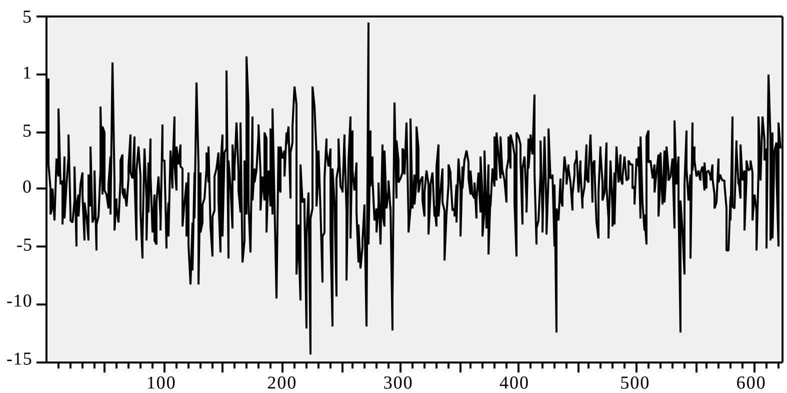

Fig. 2: Volatility of weekly returns (1996-2007)

Figure 1 plots the volatility of daily returns, Fig. 2 volatihty of weekly returns and Fig. 3 volatility of monthly returns. Figure 2 and 3 apparently outlines the years of high volatility. The trend indicate that in 1996 volatility is low and during the same year economy registered growth rate above 6% but volatility in 1997 is very high with economic growth rate below to 6%. In years 1998 and 1999 again volatility is low with growth rate more than 6%. The period ranging from 2000 to 2002 depicts high volatility because of low growth rate. Again the period from 2003 to 2007 highlights low volatility because of impressive growth rate (Appendix 1).

Relationship of stock returns with expected and unexpected volatility: Conflicting empirical evidence are reported with regard to relationship between stock returns and conditional volatility (expected volatility) and standardized residuals (unexpected volatility). Studies (French *et al.*, 1987; Campbell and Hentschel, 1992) find the relation between stock return and conditional return to be positive, whereas number of studies hold this relationship negative (Nelson, 1991; Glosten *et al.*, 1993; Bekaert and Wu, 2000; Wu, 2001). The present study also

Table 3: Relationship between stock returns and expected and unexpected volatility

	Relationship	ϕ_0	ϕ_1	R^2
Daily	Return and expected volatility	0.120*	-0.005*	0.03
		(0.003)	(0.000)	
Weekly	Return and expected volatility	1.167*	-0.056*	0.02
		(0.000)	(0.000)	
Monthly	Return and expected volatility	6.267*	-0.070*	0.05
		(0.000)	(0.003)	
		δ_0	δ_1	R^2
Daily	Return and unexpected volatility	0.160*	1.861*	0.66
		(0.000)	(0.000)	
Weekly	Return and unexpected volatility	0.447*	3.635*	0.93
		(0.000)	(0.000)	
Monthly	Return and unexpected volatility	1.711*	7.735*	0.95
		(0.000)	(0.000)	

Note-* significant at 5% level of significance, ** not significant at 5 percent level of significance

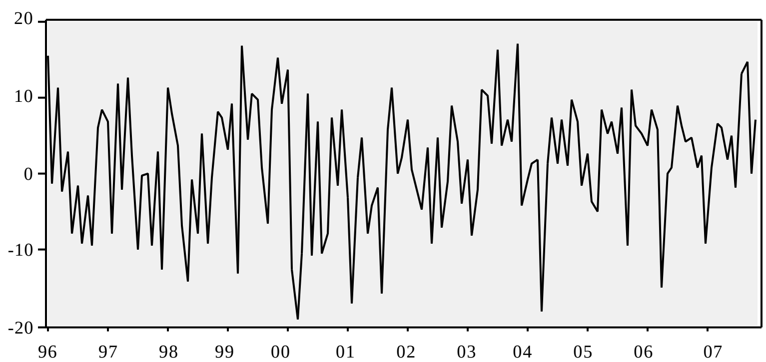

Fig. 3: Volatility of monthly returns (1996-2007)

examines the relationship between stock returns and conditional volatility and residuals by estimating the Eq. 6 and 7, respectively.

$$R_t = \phi_0 + \phi_1 \text{ Exp.Vol.} + \omega_t \tag{6}$$

$$R_t = \delta_0 + \delta_1 \text{ Unexp.Vol}_t + \omega_t \tag{7}$$

Table 3 reports the findings, suggests the relationship between stock returns and expected volatility as measured by ϕ_1 is negatively significant, indicating readjust their expected returns from stocks with regards to expected volatility. However, when measuring the relationship between stock returns and unexpected volatility, coefficient 'δ_1' is positively significant, suggests a positive relationship between stock returns and unexpected volatility. These results bring out the important elements of investment strategy. Investors adjust their risk premium in view of anticipated or expected variations in stock prices resultant to ups and downs in economic fundamentals. The direct observations can be made here that investors react spontaneously to expected variations in stock

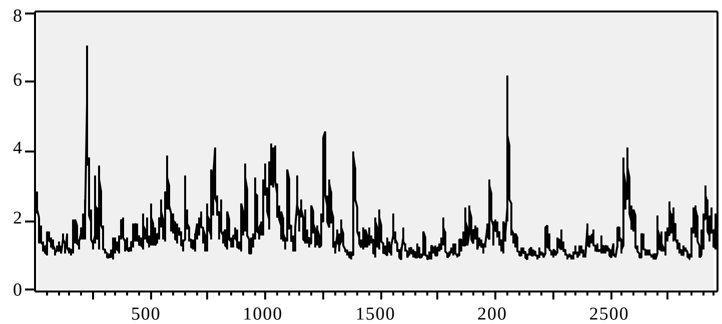

Fig. 4: Conditional volatility of daily returns (1996-2007)

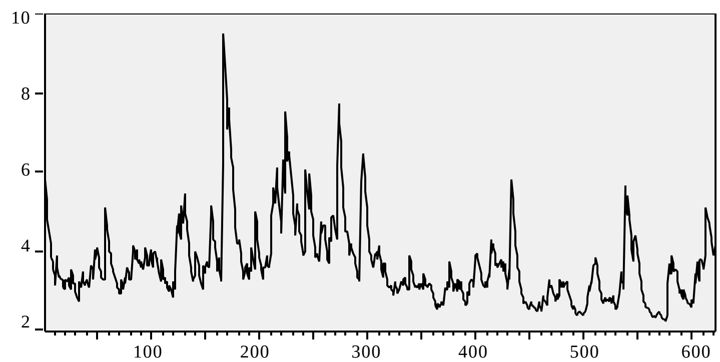

Fig. 5: Conditional volatility of weekly returns (1996-2007)

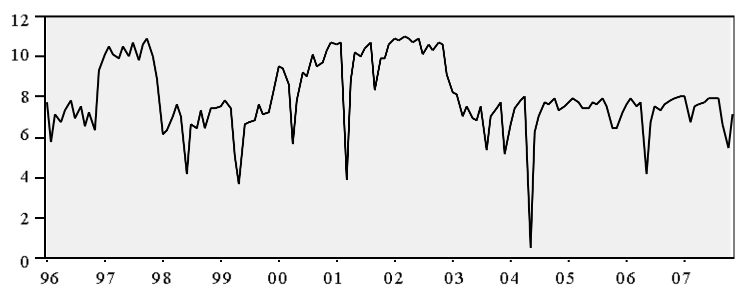

Fig. 6: Conditional volatility of monthly returns (1996-2007)

prices and they readjust their portfolios. The significant positive relationship, however, between stock returns and unexpected volatility brings out the fact that investors expect risk premium for exposing to unexpected variations in stock prices. If efficient market holds true, they will realize higher returns by bearing this risk. Conditional volatihty of daily, weekly and monthly returns has been shown in Fig. 4-6.

CONCLUSION

In the present study attempts are made to examine the investors behaviour with respect to economic growth. The study reports important findings for policy makers and investors. Volatility which results in investors behavior is not sensitive to economic fundamentals in short time period. Investors with short investment horizons over look economic fundamentals but their investment decisions significantly affected by economic fundamentals with increasing the investment horizons. In long run, volatility is negatively linked with economic growth. Additionally, the study reports significant negative relationship between stock returns and expected volatility. It brings out the important element of investment strategy that investors adjust their portfolios in anticipation of expected volatility. However, the relationship of stock returns with unexpected volatility is positive highlighting that extra risk premium is expected for unexpected volatility. These results support the findings of Nelson (1991), Glosten *et al.* (1993), Bekaert and Wu (2000) and Wu (2001).

APPENDIX

Appendix 1: GDP growth rate

Year	GDP growth rate	Year	GDP growth rate
1996-07	7.8	2002-03	4.0
1997-08	4.8	2003-04	8.5
1998-09	6.5	2004-05	7.5
1999-00	6.1	2005-06	8.1
2000-01	4.4	2006-07	9.4
2001-02	5.8	2007-08	9.0

Source-Economic Survey 2007-08

REFERENCES

Aggarwal, A., C. Inclan and R. Leal, 1999. Volatility in emerging stock markets. J. Financial Quant. Anal., 34: 33-55.

Akgiray, V., 1989. Conditional heteroskedasticity in time series of stock returns: Evidence and forecasts. J. Bus., 62: 55-80.

Badhani, K.N., 2007. Intertemporal risk-return relationship in stock indices with alternative model specifications. ICFAI J. Applied Finance, 13: 5-22.

Bailey, W. and Y.P. Chung, 1995. Exchange rate fluctuations, political risk and stock market market returns: Some evidences from an emerging market. J. Financial Quant. Anal., 30: 541-561.

Bekaert, G. and G. Wu, 2000. Asymmetric volatility and risk in equity markets. Rev. Financial Stud., 13: 1-42.

Binder, J.J. and M.J. Merges, 2001. Stock market volatility and economic factors. Rev. Quant. Finance Accounting, 17: 5-26.

Black, A. and P. Fraser, 1995. U.K. stock return: Predictability and business conditions. Mancherster Sch. Econ. Social Stud., 63: 85-102.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. J. Econ., 31: 307-327.

Bollerslev, T., R.Y. Chou and K.F. Kroner, 1992. ARCH modeling in finance. J. Econ., 52: 5-59.

Brailsford, T.J. and R.W. Faff, 1996. An evaluation of volatility forecasting techniques. J. Bank. Finance, 20: 419-438.

Brooks, C., 1998. Predicting stock index volatility: Can market volume help? J. Forecasting, 17: 59-80.

Campbell, J.Y. and L. Hentschel, 1992. No news is good news: An asymmetric model of changing volatility in stock returns. J. Finance Econ., 31: 281-318.

Caporale, G.M. and L.A. Gil-Alana, 2002. Fractional integration and mean reversion in stock prices. Q. Rev. Econ. Finance, 42: 599-609.

Chiang, T.C. and S.C. Doong, 2001. Empirical analysis of stock returns and volatility: Evidence from seven Asian stock markets based on TAR-GARCH model. Rev. Quant. Finance Accounting, 17: 301-318.

Clare, A.D., Z. Psaradakis and S.H. Thomas, 1995. An analysis of seasonality in the U.K. equity market. Econ. J., 105: 398-409.

Corhay, A. and A.T. Rad, 1994. Statistical properties of daily returns: Evidence from European stock markets. J. Bus. Finance Accoun., 21: 271-282.

Dhanakar, R.S. and M. Chakraborty, 2007. Non-linearities and GARCH effects in the emerging stock markets of South Asia. Vikalpa, 32: 23-37.

Engle, R.F. and V.K. Ng, 1993. Measuring and testing the impact of news on volatility. J. Finance, 48: 1749-1778.

Engle, R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of UK inflation. Econometrica, 50: 987-1007.

Faff, W.F. and M.D. McKenzie, 2007. The relationship between implied volatility and autocorrelation. Int. J. Managerial Finance, 3: 191-196.

Fama, E., 1991. Efficient capital markets: II. J. Finance, 46: 1575-1617.

Flannery, M.J. and A.A. Protopapadakis, 2002. Macro economic factors *Do* influence aggregate stock returns. Rev. Financial Stud., 15: 751-782.

French, K.R., G.W. Schwert and R. Stambaugh, 1987. Expected stock returns and volatility. J. Fin. Econ., 19: 3-29.

Glosten, L.R., R. Jagannathan and D.E. Runkle, 1993. On the relation between the expected value and the volatility of the nominal excess returns on stocks. J. Finance, 48: 1779-1791.

Jones, C.P. and J.W. Wilson, 1989. Is stock price volatility increasing? Financial Anal. J., 45: 20-26.

Karmakar, M., 2005. Modeling conditional volatility of the indian stock markets. Vikalpa, 30: 21-37.

Koutmos, G., 1997. Feedback trading and the autocorrelation pattern of stock returns: Further empirical evidence. J. Int. Money Finance, 16: 625-636.

Kuen, T.Y. and T.S. Hoong, 1992. Forecasting volatility in the Singapore stock market. Asia Pacific J. Manage., 9: 1-13.

Lintner, J., 1965. Security prices, risk and maximum gains from diversification. J. Finance, 20: 687-645.

Mala, R. and M. Reddy, 2007. Measuring stock market volatility in an emerging economy. Int. Res. J. Fin. Econ., 8: 126-133.

Markowitz, H.M., 1952. Portfolio selection. J. Finance, 7: 77-91.

Moorkejee, R. and Q. Yu, 1999. Seasonality in returns on the chinese stock markets: The case of Shanghai and Shenzhen. J. Finance, 10: 93-105.

Mossin, J., 1966. Equilibrium in a capital asset market. Econometica, 34: 768-783.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59: 347-370.

Officer, R.R., 1973.. The variability of the market factors of the New York stock exchange. J. Bus., 46: 434-453.

Pagan, A.R. and G.W. Schwert, 1990. Alternative models for conditional stock volatility. J. Econ., 45: 267-290.

Pesaran, M.H. and A. Timmermann, 1995. Predictability of stock returns: Robustness and economic significance. J. Finance, 50: 1201-1228.

Rakesh, K., 2007. Economic growth and volatility in indian stock market: A critical analysis. South Asian J. Manage., 14: 47-59.

Rothlein, C.J. and J. Jarrett, 2002. Seasonality in prices of Japanese securities. Int. J. Bus. Econ., 1: 21-31.

Sah, A.N. and G. Omkarnath, 2006. Do institutional investors destabilize the Indian stock market. The ICFAI J. Finance, 6: 52-65.

Schwert, G.W., 1989. Why does stock market volatility change over time. J . Finance, 44: 1115-1153.

Schwert, G.W., 1990. Stock market volatility. Financial Anal. J., 46: 23-34.

Sentana, E. and S. Wadhwani, 1992. Feedback traders and stock returns autocorrelations: further evidence from a century of daily data. The Econ. J., 102: 415-425.

Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. J. Fin., 19: 425-442.

Tsay, R.S., 1998. Testing and modeling multivariate threshold models. J. Am. Stat. Assoc., 93: 1188-1202.

Tse, Y.K., 1991. Stock return volatility in the Tokyo stock market. Jpn World Econ., 3: 285-298.

Watanabe, T., 2002. Margins requirements, positive feedback trading and stock returns autocorrelations: The case of Japan. Applied Finan. Econ., 12: 395-403.

Wu, G., 2001. The determinates of asymmetric volatility. The Rev. Finan. Stu., 14: 837-859.