DOI:10.26524/jms.2012.20

Stock market volatility during dividend announcement a case of selected scripts

DR.S.POORNIMA[1] AND V.CHITRA[2]
[1]*Associate Professor, P.S.G.R.Krishnammal College for Women, Coimbatore*
[2]*Associate Professor, Sasurie Academy of Engineering, Coimbatore*

ABSTRACT: *An attempt has been made in this paper to explain the stock market volatility at the individual script level and at the aggregate indices level. The empirical analysis has been done by using Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model. It is based on daily data for the time period from January 2007 to December 2009. The analysis reveals the same trend of volatility in the case of aggregate indices and three different sectors such as Banking, Information Technology and Cement. The GARCH (1,1) model is persistent for all the five aggregate indices and individual company.*

Keywords: GARCH, Stock Market Volatility

1. INTRODUCTION

Stock market volatility has vital importance for investor‘s decision making, and has considerable influence on investor behavior in the market. In general terms, volatility may be described as a phenomenon, which characterizes changeableness of a variable under consideration. Volatility is associated with unpredictability and uncertainty and is synonymous with risk, and hence high volatility is thought of as a symptom of market disruption whereby securities are not being priced fairly. It measures the variability or dispersion about a central tendency. However, there are some subtleties that make volatility challenging to analyse and implement. Since volatility is a standard measure of financial vulnerability, it plays a key role in assessing the risk/return tradeoffs.

Policy makers rely on market estimates of volatility as a barometer of the vulnerability of the financial markets. The existence of excessive volatility or ―noise‖ also undermines the usefulness of stock prices as a ―signal‖ about the true intr insic value of a firm, a concept that is core to the paradigm of international efficiency of the markets. Considerable research effort has already gone into modeling time–varying conditional heteroskedastic asset returns. It is important because if both returns and volatility can be forecasted, then it is possible to construct dynamic asset allocation models that use time dependent mean–variance optimization over each period. Financial econometrics suggests the use of non- linear time series structures to model the attitude of investors toward risk and expected return. In this context, Bera and Higgins (1993) remarked, ―a major contribution of the ARCH literature is the finding that apparent changes in the volatility of the economic time series may be predictable, and result from a specific type of non-linear dependence rather than exogenous structural changes in variables.‖ When the variance is not constant, it is more likely that there are more outliers than expected from the normal distribution, i.e., when a process is heteroskedastic it will follow heavy– tailed or outlier–prone probability distribution. According to Mc Nees (1979), ―the inherent uncertainty or randomness associated with different forecast periods seem to vary over time, and large and small errors tend to cluster together‖. Although there is a plethora of research concerning stock market volatility, most of the studies have been done for stock market of the developed country as a whole, making use of aggregate information data. There are varying few studies, which have gone into the volatility issues at the level of specific industries or the companies in an industry. **More specifically, this paper is an attempt towards explaining the stock market volatility among three Industries in the service sectors.**

In light of the above, **the objective of this paper is to examine the daily price volatility of the stock return during the dividend announcement among the selected sectors.** The rest of the paper is as follows: Review of literature is explained in section II; section III explains the data and methodology of the study. Section IV, presents the empirical results. Finally, conclusions are presented in section V.

2. RELATED WORKS

Many traditional asset-pricing models (e.g. Sharpe 1964; Merton, 1973) postulate a positive relationship between a stock portfolio‘s expected return and the condition variance as a proxy for risk. More recent theoretical works (Whitelaw 2000, Bekaert and Wu 2000; Wu 2001) consistently assert that stock market volatility should be negatively correlated with stock returns.

Earlier studies for instance French *et.al*. (1987) found a positive and significant relationship and studies such as Baillie and DeGennaro (1990) Theodossiou and Lee (1995) reported a positive but insignificant relationship between stock market volatility and stock returns. Consistent with the asymmetric volatility argument, many researchers (Nelson 1991, Glosten *et.al* 1993, Bekaert and Wu 2000, Wu 2001; Brandt and Kang 2003) recently report negative and often significant relationship between the two.

Researchers have empirically demonstrated (e.g. Harvay 2001, Li *et.al* 2003) that the relationship between return and volatility depends on the specification of the conditional volatility. In particular, using a parametric GARCH-M model, Li, *et.al* (2003) finds that a positive but statistically insignificant relationship exists for all the 12 major developed market. By contrast, using a flexible semi parametric GARCH-M model, they document that a negative relationship prevails in most cases and is significant in 6 out of 12 markets.

Malkiel and Xu (1999) used a disaggregate approach to study the behaviour of stock market volatility. While the volatility for the stock market as a whole has been remarkably stable over time, the volatility of individual stocks appears to have increased.

There are some possible reasons to believe that volatility in the stock market as a whole should have increased over recent decades. Improvments in the speed and availability of information, the growth in the proportion of trading done by institutional investors and new trading techniques all may have increased the responsiveness of markets to changes in the sentiment and to the arrival of new information. The facts, however, at least with respect to the market as a whole, do not suggest that the volatility has increased. They have not looked at the market portfolio but rather at individual stocks and industry average. By looking at the disaggregated volatility of stock prices, they reached a different conclusion that volatility in the stock market has infact increased considerably during the past quarter century. Most of the time series data used in the study are constructed from the 1997 version of CRSP (Center for Research in Security Prices) tape.

Data measuring in the daily return are available from January 1, 1963 to December 31, 1997 and monthly returns are available from January 1926 to December 1997. In the analysis, both exchange traded stocks (New York Stock Exchange (NYSE) and American Stock Exchange (AMSE) and NASDAQ files are used.

In order to study the robustness of their findings of increasing idiosyncratic volatility. They approached the issue from both a correlation structure and diversification perspective. Idiosyncratic volatility is precisely the kind of volatility that is uncorrelated across stocks and thus is completely washed out in a well-diversified index portfolio, According to Capital Asset Pricing Model; such an increasing in the idiosyncratic volatility should not command an added risk premium on the market. Thus, while it is possible to argue that the volatility of individual stock has increased, as long as their systematic risk remain unchanged, there should be no consequence for asset pricing, at least according to Capital Asset Pricing Model holds, an increase in the idiosyncratic volatility will have an important effect on the number of the securities one must hold in a portfolio to achieve full diversification. The general conclusion is that while market as a whole has been no more volatile in the recent decades, the idiosyncratic volatility of the individual stocks has exhibited an upward trend.

Yu (2002) evaluates the performance of nine alternative models for predicting stock price volatility. The data set he used is the New Zealand Stock Market Exchange (NZSE40) capital index, which covers 40 largest and most liquid stocks listed and quoted on the New Zealand Stock Market Exchange, weighted by the market capitalization without dividends reinvested. The sample consists of 4741 daily returns over the period from 1 January 1980 to 31 December 1998.The competing models contain both simple models such as the random walk and smoothing models and complex model such as ARCH type models and a stochastic volatility model. Four different measures are used to evaluate the forecasting accuracy. The main results are (i) the stochastic model provides the best performance among the candidates; (ii) ARCH type models can perform well or badly depending on form chosen the performance of the GARCH (3,2) model, the best model within ARCH family, is sensitive to the choice of assessment measures; and(iii) the regression and exponentially weighted moving average models do not perform well according to any assessment measure, in contrast to the results found in various markets.

Li,*et.al* (2003) examined the relationship between expected stock returns and volatility in the twelve largest international stock markets during January 1980 – December 2001. Consistent with the most previous studies they found the estimated relationship between return and volatility sensitive to the way volatilities are examined. When parametric EGARCH-M models are estimated ten out of twelve markets have positive but statistically insignificant relationship. On the other hand, using a flexible semi parametric specification of conditional variance, they found that negative relationship between return and volatility prevails in most of the markets. Moreover, the negative relationships are significant in six markets based on the whole sample period and seven markets after the 1987 international stock market crash. They have used weekly data from November 1987 to December 2001 for the 12 largest stock market in the world in terms of market capitalization.

Batra (2004) examined the time variation in volatility in the Indian stock market during 1979-2003. The study has used the asymmetric GARCH methodology augmented by structural changes. The paper identifies sudden shifts in the stock price volatility and nature of events that cause these shifts in volatility. He undertook an analysis of the stock market cycles in India to see if bull and bear phases of the market have exhibited greater volatility in recent times. The empirical analysis in the paper reveals that the period around the BOP crisis and subsequent initiation of the economic reforms in India is the most volatile period in the stock market. The time period he has taken for Sensex is1979:04-2003:03 and for IFGC is 1988:01-2001:12.The data have been taken from SEBI, RBI and BSE has been used. As a conclusion one may therefore say that liberalization of the stock market or the FII entry in particular does not have any direct implication in the stock return volatility. Level of volatility does not show much change pre and post liberalization. Significant developments in the market indicators-turn over or market capitalization does not lead to volatility shifts in the stock return. Volatility estimation is important for several reasons and for different people in the market. Pricing of securities is supposed to be dependent on volatility of each market. Raju and Ghosh (2004) used the International Organization of Securities Commission (IOSCO) clarification to categories countries into emerging and developed market. There are six countries from developed capital market and twelve from emerging markets including India. Bloomberg data base is used by them as the data source. For India two indices BSE Sensex and S&P CNX Nifty. Amongst emerging markets except India and China, all other countries exhibited low returns. India with long history and China with short history, both provides as high a return as the US and the UK market could provide but the volatilities in both countries is higher. The third and fourth order moments exhibit large asymmetry in some of the developing markets. Comparatively, India market shows less of skewness and kurtosis. Indian markets have started becoming informationally more efficient. Contrary to the popular perception in the recent past, volatility has not gone up. Intraday volatility is also very much under control and has come down compared to past years.

Shin (2005) examined the relationship between return and risk in a number of emerging stock markets. The main contribution of this study is to present more reliable evidence on the relationship between stock market volatility and returns in emerging stock market by exploiting a recent advance in non parametric modeling of conditional variance. This study employed both a parametric and semi parametric GARCH model for the purpose of estimation and inference. The data for this study covers 14 relatively well-established emerging markets which have stock price index series available from the International Finance Corporation (IFC) emerging market data base. Regionally speaking there are six Latin American emerging markets (Argentina, Brazil, Chile, Colombia, Mexico and Venezuela), six Asian emerging markets (India, Korea, Malaysia, Philippins, Taiwan and Thailand) and two European emerging markets (Turkey and Greece). The sample period is from January 1989 to May 2003, after and before the 1987 international stock market crash. This study examines the impact of the 1987-1998 global emerging stock market crisis on GARCH parameters in the line with Choudhary (1996), who studies the impact of the 1987 stock market crash using monthly data between January 1976 and August 1994.

The findings of this study also suggest fundamental differences between emerging markets and developed markets. Investors in emerging markets are often compensated for bearing relevant local market risk, while investors in developed markets are often penalized by bearing irrelevant local market risk. Another factor could be related to the most commonly known characteristics of emerging stock market-that their stock market volatility is notoriously high compared to developed markets.

3. RESEARCH METHODOLOGY

Section III: Data and Research Methodology

Data and its Sources

The data employed in the study consists of daily prices for the time period from January 2007 to December 2009 for three different sectors such as Banking, Information Technology and Cement. The prices used were daily open and close prices; this data has been collected from the Prowess.

Research Methodology

The impact on the volatility has been computed by using standard deviations, rolling standard deviations, etc., by many researchers (Hodgson et al., 1991, Herbst et al., 1992). However, simply testing for changes in unconditional variance may be inadequate as some researchers show that stock index returns are conditionally heteroskedastic (Bollerslev, 1986). Hence, the GARCH model has been a preferred measure of volatility by many researchers (Antoniou and Holmes, 1995, Gregory et al., 1996) to accommodate for heteroskedasticity in the observed returns.

The assumption of the Classical linear regression model that variance of the errors is constant is known as homoscedasticity. If the variance of the errors is not constant, this is known as heteroscedasticity. It is unlikely that in the context of stock return data that the variance of the errors will be constant over time. Hence, it makes sense to consider a model that does not assume that the variance is constant, and which describes how the variance of errors evolves. The prime motivation behind the development of conditional volatility models emanated from the fact that the existing linear time series models were inappropriate, in the sense that they provided very poor forecast intervals and it was contended that like conditional mean, variance (volatility) could as well evolve over time.

One particular non-linear model in widespread usage in finance is the _ARCH' model. Engle (1982) introduced the ARCH process, which allows the conditional variance to change over time. In ARCH model, the variance is modelled as a linear combination of squared past errors of specified lag. Under the ARCH model, the autocorrelation in volatilities modelled by allowing conditional variance of the error terms, to depend on the immediately previous value of the squared error.

The ARCH models provide a framework of analysis and development of time series models of volatility. However, ARCH models themselves have a number of difficulties. i) It is very difficult to decide the number of lags (q) of the squared residual in the model. One approach to this problem would be the use of likelihood ratio tests. ii) The number of lags of the squared error that are required to capture all of the dependence in the conditional variance might be varying large. This would result in a large conditional variance model that was not parsimonious. Engle (1982) circumvented this problem by specifying an arbitrary linearly declining lag length on an ARCH (4). iii) Other things being equal, the more parameters there are in the conditional variance equation; the more likely it is that one or more of them will have negative estimated values. Non-negativity constraints might be violated.

To overcome these limitations, GARCH model was introduced. In this model artificial constraints have been imposed to make the model satisfy the non-negativity condition. The Generalised Autoregressive Conditional Heteroscedasticity model was developed independently by Bollerslev (1986). GARCH models explain variance by two distributed lags, one on past squared residuals to capture high frequency effects or news about volatility from the previous period measured as lag of the squared residual from mean equation, and second on lagged values of variance itself, to capture long term influences.

4. EMPIRICAL ANALYSIS

This sub section reports the results of the empirical application. This study is based on the daily closing values of three sectors drawn from the National Stock Exchange. The sectors chosen are: Banking, Information Technology and Telecommunication. Since the primary objective of this paper is to understand the volatility process all these three sectors with the selected company scrip's, the study has identified twelve individual companies belonging to various sectors namely, Banking, Information Technology and Telecommunication sector. These companies have been chosen such that they fairly represent the different sectors of the economy. Three companies from each sector have been chosen based on the performance of the ARCH, ARCH-M and GARCH model. The list of nine companies chosen for the study is given in appendix towards the end of the paper. The data is drawn from the PROWESS database. The data are daily closing prices and adjusted for dividends. The study period spans over the period January 1, 2007 to December 31st 2009, thus involving around 3414 number of data points, which provide rich data set for the analysis.

Table 1 Distribution of the closing prices

Sectors & Companies			Average Closing Price	Skewness	Kurtosis
Banking	Allahabad Bank	Pre	50.4033	-0.987	-0.194
		Post	65.6200	0.642	-1.501
	Axis bank	Pre	437.2000	0.357	-0.054
		Post	578.5500	-0.197	-1.096
	HDFC bank	Pre	1044.9900	-0.969	0.062
		Post	1167.7433	1.915	5.987
IT	CMC Ltd	Pre	316.9767	0.561	-1.634
		Post	489.4100	0.728	0.003
	Infosys Technologies Ltd	Pre	1360.1533	0.141	-1.639
		Post	1467.4267	0.388	-1.064
	Sathyam Computer Service	Pre	43.0633	0.313	-1.186

	Ltd	Post	46.4267	0.639	-0.528
Telecom	GTL Ltd	Pre	244.4567	-0.195	-1.547
		Post	258.9567	0.271	-1.781
	Mahanagar Telephone Nigam Ltd	Pre	98.2067	-0.151	-0.356
		Post	96.1867	0.766	-0.420
	Tata Communications Ltd	Pre	569.0900	0.038	-0.764
		Post	495.5800	0.344	-0.805

From the above table it can be observed that in case of banking sector, the skewness value (0.642) of Allahabad Bank has shown positive impact during the post announcement period when compared to the pre announcement period (-0.987) and in case of HDFC bank also the skewness value (1.915) has shown positive impact during the post announcement period when compared the pre announcement period (-0.969). But, in case of Axis bank the skewness value (-0.197) has shown negative impact during the post announcement period when compared the pre announcement period (0.357).

In case of IT sector, it can be observed that all the companies had shown positive impact during both Pre and Post Announcement periods.

It can be observed that in case of Telecom sector, the skewness value (0.271) of GTL Ltd has shown positive impact during the post announcement period when compared to the pre announcement period (-0.195) and in case of Mahanagar Telephone Nigam Ltd also the skewness value (0.766) has shown positive impact during the post announcement period when compared the pre announcement period (-0.151). But, in case of Tata Communications Ltd the skewness value (0.344) has shown negative impact during the post announcement period when compared the pre announcement period (0.038).

It can be concluded that IT sector has shown positive impact compared to other two sectors in the study.

Table 2 Comparison of the closing prices of the first and second half of the month

Industries	**Companies**	**Levene‟s Test**	**P-Value**
Banking Industry	Allahabad Bank	0.000	0.000*
	Axis Bank	0.010	0.000*
	HDFC Bank Ltd	0.628	0.000*
IT Industry	CMC Ltd	0.889	0.000*
	Infosys Technologies Ltd	0.014	0.000*
	Sathyam Computer Service Ltd	0.001	0.001*
Telecom Industry	GTL Ltd	0.160	0.000*
	Mahanagar Telephone Nigam Ltd	0.009	0.221
	Tata Communications Ltd	0.456	0.000*

From the above table it can be observed that Levene‘s test value for Banking sector has shown 0.000 value for Allahabad bank, 0.010 for Axis Bank and 0.628 for HDFC Bank Ltd, it can be inferred that variations is there only for HDFC bank.

It is evident from the above table that IT sector has shown positive fluctuations. Levene‘s test value of CMC Ltd is 0.889, Infosys Technologies Ltd is 0.014 and Sathyam Computer Service Ltd is 0.001. It can be inferred that IT sector has shown volatility in the stock prices.

It can be observed from the above table, GTL Ltd has shown a value of 0.160, Mahanagar Telephone Nigam Ltd has shown a value of 0.009 and Tata Communications Ltd has shown a value of 0.456. It can be inferred that there is fluctuations in the stock prices.

Table 3 Abnormal Returns – GARCH MODEL

Industry		Bank		IT		Telecommunication	
Year	**Event Period**	**AR**	**T stat**	**AR**	**T stat**	**AR**	**T stat**
Year - 1	Pre	-0.012	-0.269	-0.019	-0.480	-0.004	0.011
	Post	-0.022	-0.408	-0.022	-0.186	-0.004	0.007
Year - 2	Pre	-0.022	0.049	-0.006	-0.275	-0.012	0.025
	Post	-0.018	-0.396	-0.007	-0.216	0.003	0.020
Year - 3	Pre	-0.006	-0.217	-0.004	-0.083	-0.003	0.046
	Post	-0.015	-0.319	0.001	0.024	0.006	0.047

It is observed from the above table that average abnormal return and t-statistics of share price have been calculated for Banking, IT and telecommunication industry. For the Banking industry, the average abnormal return for all the years both in pre-event and post-event windows shows negative performance of share price. T-statistics was performed to measure the significant difference among companies in banking industry. During the study period, pre event window of second year (0.049), the industry found significant difference in pre-event window. For all the years, the industry found no significant difference in both pre-event and post-event window. It is tested at 5% level of significant.

Similarly, abnormal return has been computed for IT industry, which shows the excess return of 0.001 during the third year in the Post event window. Other part of pre and post-event window shows negative impact on share price. T-statistics was performed to measure the significant difference among companies in IT industry. During the study period, post event window of third year (0.024), the industry found significant difference in post-event window. For all the years, the industry found no significant difference in both pre-event and post-event window. It is tested at 5% level of significant.

Similarly, abnormal return has been computed for Telecommunication industry, which shows the excess return of 0.003 during the second year in the Post event window and 0.006 during the third year in the Post event window. Other part of pre and post-event window shows negative impact on share price. T-statistics was performed to measure the significant difference among companies in Telecommunication industry. During the study period, for the years, both in pre and post event window (0.011 0.007 0.025 0.020 0.046 0.047), the industry found significant difference. It is tested at 5% level of significant.

Final observation of above table exhibits IT industry had found impact on share price in both pre-event window and post-event window.

Table 4 Variance

Industries / Years	Event Period	Bank	IT	Telecom
		Variance	Variance	Variance
Year - 1	Pre	0.002	0.002	0.000
	Post	0.003	0.014	0.000
Year - 2	Pre	0.002	0.000	0.001
	Post	0.002	0.001	0.000
Year - 3	Pre	0.001	0.003	0.002
	Post	0.002	0.001	0.002

It is observed from the above table that, in case of banking industry high variance is extracted during the post dividend announcement period in the first year, in case of IT industry also high variance is observed during the post dividend announcement period in the first year, but in case of telecom industry, high variance is observed during the third year only.

5. Conclusion

This study in particular addresses the stock market volatility of selected sectors in National Stock Exchange of India using GARCH (1, 1) model. It can be observed that among all the three sectors selected, IT sector had got more volatility during the study period.

The study has tried to dig into the very vast and interesting issue, which requires more elaborated analysis. Due to the limitation of time and resources the study restricted to conclude general findings with limited data set. Future research can be extended for other service sectors by utilizing the more sophisticated techniques of operational research.

6. References

[1]. Baillie and De Gennaro (1990), –Stock Returns and Volatility‖, *Journal of Financial and Quantitative Analysis*,25, pp 203-214

[2]. Bakaert, G and G Wu (2000), –Asymmetric Volatility and Risk in Equity Markets‖, *Review of Financial Studies*, 13, 1-42

[3]. Batra A (2003), –Stock Return Volatility Persistence in India: 1973- 2003‖, Working Paper ICRIER, New Delhi, India.

[4]. Bollerslev, T, R.F Engle and J.M Wooldrige (1988), –Capital Asset Pricing Model With Time Varying Co–variances‖, *Journal of Political Economy*, 96, 1, 116- 131.

[5]. Brandt M. W and Q Kang (2001), –On the Relationship between the Conditional Mean and Volatility of Stock Returns: A Latent VAR Approach‖, Working Paper, University of Pennsylvania.

[6]. Engle R. F (1982): –Autoregressive conditional Heteroskedasticity with estimates of the variance of U.K Inflation‖, *Econometrica*, 50, 987-1008.

[7]. French, K.R, W G Schwert and R F Stambaugh (1987) –Expected Stock Return and Volatility‖, *Journal of Financial Economics*, 19,3-29□ .

[8]. Glosten L. R, R. Jagannathan and D.E. Runkle (1993) –On the Relation between the Expected Value and Volatility of the Nominal Excess Returns on Stocks‖, *the Journal of Finance*, XLVIII, 1779 – 1801.

[9]. Harvey C.R (2001), –The Specification pf Conditional Expectations‖, *Journal of Empirical Finance*, 8(5), pp 573-637.

[10]. Malkiel B.G and Y. Xu (1999) –The Structure of Stock Market Volatility‖, Working Paper, Princeton University Center for Economic Policy Studies.

[11]. Merton,R.C (1973), –An Intertemporal Capital Asset Pricing Model‖, *Econometrica*, 42, 867-87.

[12]. Nelson D. B (1991) –Conditional Heteroskedasticity in Asset Returns: A New Approach‖, *Econometrica*, 59, 347 – 70.

[13]. Pagan, A (1984), –Econometric Issues in the Analysis of Regressions with Generated Regressors‖, *International Economic Review*, 221-247.

[14]. Qi Li, J. Yang, C Hsiao, Y-J Chang (1999), –The Relationship between Stock Returns and Volatility in International Stock Markets‖, Working Paper.

[15]. Raju M.T and A.Ghosh (2004), –Stock Market Volatility – An International Comparison‖, Working Paper Series, No 8, Security Exchange Board of India.

[16]. Sharpe W.F (1964), –Capital Asset Prices: A Theory of Equilibrium under Conditions of Risk‖, *Journal of Finance*, 19(3), pp 425-442.

[17]. Shin J (2005) –Stock Return and Volatility in Emerging Stock Markets‖, *International Journal of Business and Economics*, 4, pp 31-43.

[18]. Theodossiou P and U.Lee (1995), –Relationship between Volatility and Expected Return Across International Stock Markets‖, *Journal of Business Finance and Accounting*, 22(2), pp 289-300.

[19]. Whitelaw R (2000), –Stock Market Risk and Return: An Empirical Approach‖, *Review of Financial Studies*, 13(3), pp 521-547.

[20]. Wu.G (2001) –The Determinants of Asymmetric Volatility‖, *The Review of Financial Studies*, 14, 837-859.

[21]. Yu J (2002), –Forecasting Volatility in New Zealand Stock Market‖, *Applied Financial Economics*, 12, pp 192-202.

*****